

The Effect of Haptic Guidance on Learning a Hybrid Rhythmic-Discrete Motor Task

Laura Marchal-Crespo, Mathias Bannwart, Robert Riener, Heike Vallery

Abstract—Bouncing a ball with a racket is a hybrid rhythmic-discrete motor task, combining continuous rhythmic racket movements with discrete impact events. Rhythmicity is exceptionally important in motor learning, because it underlies fundamental movements such as walking. Studies suggested that rhythmic and discrete movements are governed by different control mechanisms at different levels of the Central Nervous System. The aim of this study is to evaluate the effect of fixed/fading haptic guidance on learning to bounce a ball to a desired apex in virtual reality with varying gravity. Changing gravity changes dominance of rhythmic versus discrete control: The higher the value of gravity, the more rhythmic the task; lower values reduce the bouncing frequency and increase dwell times, eventually leading to a repetitive discrete task that requires initiation and termination, resembling target-oriented reaching. Although motor learning in the ball-bouncing task with varying gravity has been studied, the effect of haptic guidance on learning such a hybrid rhythmic-discrete motor task has not been addressed. We performed an experiment with thirty healthy subjects and found that the most effective training condition depended on the degree of rhythmicity: Haptic guidance seems to hamper learning of continuous rhythmic tasks, but it seems to promote learning for repetitive tasks that resemble discrete movements.

Index Terms—Haptic guidance, fading guidance, motor learning, hybrid rhythmic-discrete task

1 INTRODUCTION

THE long-standing Guidance Hypothesis states that physically guiding a movement will impair motor learning¹, because it changes the input-output relationship of the task to be learned [2], [3]. A number of studies have found that haptic guidance that reduced performance errors during training did not aid motor learning but in fact hampered it [4], [5]. Nevertheless, sophisticated robotic mechanisms have been developed to support motor training of complex movements, such as walking or multi-joint arm movements [6]. These devices can haptically guide subjects to move their limbs in a correct kinematic pattern. The rationale is that haptic guidance provides the Central Neural System (CNS) with additional proprioceptive and somatosensory cues, which may facilitate movement planning and enable the CNS to attempt more advanced movement strategies.

Recent studies with therapy robots contradict the guidance hypothesis, suggesting instead that guidance should fade as learning progresses, providing just enough guidance to allow participants to practice the

task, while decreasing the guidance to encourage learning [4], [7], [8], [9]. For example, an experiment conducted with unimpaired children who practiced learning to drive a power wheelchair with fading guidance [7] showed that children who practiced with fading haptic guidance from a robotic joystick learned better than children who practiced without physical guidance. Similarly, subjects trained to perform a tennis stroke with a robotic tennis trainer that faded the guidance as learning progressed learned to time their movements better than subjects who trained with visual feedback [10].

This apparent contradiction with the guidance hypothesis can be explained by emerging evidence that haptic guidance may be specifically useful for learning timing [11], [12], [13]. Several studies showed a benefit of haptic guidance in learning to reproduce the temporal, but not spatial, characteristics of complex spatiotemporal curves [14], [15]. The effect of haptic guidance on learning a visuo-manual tracking task has been evaluated in further studies, which found a positive effect of guidance on the time-related components of a dynamic task, such as an increase in movement speed and smoothness [16], and better learning of temporal force patterns [17]. Training with haptic guidance also benefited learning to play a pinball-like game [18]. In these studies, haptic demonstration of optimal timing, rather than movement magnitude, may have facilitated skill transfer. These results suggest that training with appropriately designed haptic guidance can enhance learning of some motor skills, such as time-critical tasks. However, few studies tested for long-term retention [12], [11], [8], and therefore conclusions on the effect of haptic guidance on motor learning should be taken cautiously [19]. In the following, we refer to short-term training as any training

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1. Motor learning is defined as a set of processes associated with practice or experience that lead to relatively permanent changes in the ability to perform a skill [1].

protocol to achieve motor-learning that is limited to three sessions or less.

Timing of an action plays a crucial role in the proper accomplishment of many meaningful tasks, such as hitting a moving object (discrete timing task), or rhythmically moving an object (continuous timing task). Research in motor control has focused on two main task classes: (i) discrete movements (e.g. target-oriented reaching movements) that include well-defined postures at the beginning and the end of the movement, which are maintained for a non-negligible duration (dwell time), and (ii) rhythmic movements (e.g. walking) that are periodic or at least repetitive movements [20]. Several studies have demonstrated that discrete and rhythmic movements are driven by different control primitives [21], [22], [23]. Indeed, brain imaging studies have shown that the production of rhythmic and discrete movements involve different brain areas [24]. Specifically, rhythmic movements require significantly less cortical and sub-cortical activation, suggesting that discrete tasks may require more complex control mechanisms located at different levels of the CNS.

Regarding rhythmic tasks, different haptic and visual guidance paradigms have been tested for their effect on learning [25]. An extensively studied rhythmic task consists in hitting fixed targets by exciting a virtual second-order (mass-spring-damper) system at its resonant frequency [26], [27]. The effect of different haptic training paradigms on learning this rhythmic task was recently compared to learning a path-following task [28]; results showed that the benefits of the different paradigms depended strongly on the task type.

However, not all motor tasks fall into one of the two classes “discrete” or “rhythmic”, but may lie somewhere between the two. Therefore, one may better designate a movement by its “degree of rhythmicity”. Several measures have been proposed to characterize rhythmicity, for example the “index of harmonicity” [29], which is based on local extrema in the acceleration time series, or the mean-squared jerk [20]. As a robust and intuitive measure, here we characterize the “degree of rhythmicity” of an “almost periodic” [20] movement by the “activity period” as defined in [30], which is 100% minus the percentage of dwell time [20] during one cycle. This means that periodic tasks with negligible dwell time between consecutive movements approach a degree of rhythmicity of 100%, while repetitive discrete tasks with negligible movement time compared to dwell time approach 0% rhythmicity.

A classical example of an ambiguous task is bouncing a ball to a target apex height. The classification of this task depends on the apex height: bouncing a ball to a high apex results in an almost discrete task with long dwell times, while a lower apex can be classified as a continuous task with a high degree of rhythmicity. Modifying gravity in a virtual environment has the same effect on the racket trajectory as changing the apex height: the higher the value of gravity, the more rhythmic

the task becomes. This discrete versus rhythmic behavior in the bouncing ball task was observed in previous studies, which demonstrated that the increase in cycle period did not lead to a simple scaling of the racket trajectory, but to a change in the racket trajectory shape from an approximately sinusoidal profile to a sequence of discrete movements separated by dwell times [30], [31].

Bouncing a ball requires sophisticated motor control. Mathematical analysis of the bouncing-ball model revealed that feedforward control yields satisfactory performance once the racket-ball interaction has settled to the correct steady-state movement [32]. Passive stability related to the bouncing movement implies that small deviations from the desired apex attenuate over successive bounces without involving active corrective motor actions from subjects. This property depends on negative racket acceleration at ball impact. In line with this observation, the racket acceleration at impact has been suggested to be a good performance variable to quantify feedforward control [33] – better performance in feedforward control seems to be related to a lower acceleration at impact. Recent studies have demonstrated that, in addition to feedforward control, subjects may also apply feedback control when an error is observed after a perturbation, and actively correct the racket movement to accelerate the return to the steady state [33].

Motor learning in the ball-bouncing task with varying gravity has been extensively studied [30]. However, the effect of haptic guidance on learning such a hybrid rhythmic-discrete motor task has not been addressed. Here, we use a robotic device to apply different types of haptic guidance while subjects bounce a ball in a virtual-reality paradigm in different virtual gravity environments, in order to investigate the effect of haptic guidance on learning, both in time-critical continuous rhythmic movements (high gravity) and in discrete tasks (low gravity). In particular, we investigate (i) a fixed amount of haptic guidance, (ii) no guidance, and (iii) an amount of guidance that fades as learning progresses. The stated task objective was to reach a target apex height. As reference for the guidance, a model-predictive controller continuously calculates the racket’s optimal movement based on the two-layered hybrid-discrete task model introduced in [30]. The selection of performance measures is crucial to validate training [25]. Here, learning is assessed by two measures: First, a significant reduction of the overall error (difference between the actual ball apex and the target apex). Second, the racket acceleration at ball impact (a time-critical variable), to quantify feedforward control performance [33].

Based on the previous work on time-critical motor learning experiments, we hypothesized that fading guidance may be especially suited to help people learn the task under all gravity levels. Furthermore, we expected better generalization (i.e. transfer of learning gains) to untrained gravities in subjects trained without guidance and, to a lower extent, with fading guidance [34].

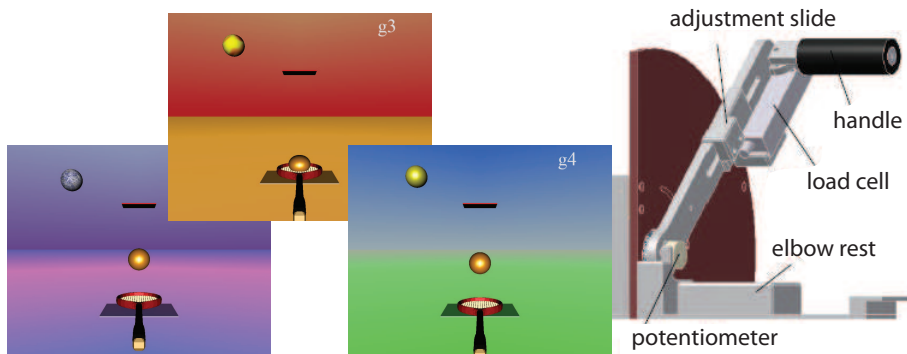


Fig. 1. Virtual display for the 3 gravities trained (g_1 , g_3 and g_4) and assistive robotic device with one degree of freedom.

2 METHODS

2.1 Bouncing-ball simulator

We designed a bouncing-ball game and an assistive robot to perform the desired experiments. The task to be performed was to bounce a virtual ball with a virtual racket. The experiment was implemented using a one-degree-of-freedom haptic device (Fig 1, right) developed in our lab [35]. The robotic device consists of an actuated lever with a handle and an elbow rest. The lever is actuated by a Maxon RE 35 DC Motor (maxon motor, Switzerland), with $U = 48\text{ V}$ nominal voltage, combined with a Harmonic Drive gearbox (HFUC-2UH, size 14, Harmonic Drive AG, Germany) with a transmission ratio of $i = 100$. The combined moment of inertia of motor and gearbox is $9.86 \cdot 10^{-2}\text{ kgm}^2$ at the output shaft. The robot is equipped with an incremental encoder on the motor shaft and a potentiometer on the joint (GL60 Contelec, Switzerland) that redundantly measure the elevation angle, and a force sensor (KD 140 200N, ME-Meßsysteme GmbH, Germany) that measures the torque τ_{user} produced by the subject on the robot. Precision and accuracy of the angle measurement are 0.007° and 0.1° , respectively, and precision and accuracy of the torque measurement are 0.2 Nm and 0.1 Nm , respectively. Coulomb friction in the drive train is approximately 0.1 Nm . The lever can be adjusted to the length of the subject's forearm. In closed-loop zero-impedance control, the residual reflected inertia of the device was identified to be $2.5 \cdot 10^{-2}\text{ kgm}^2$, and the reflected damping to be 1.4 Nms/rad . Force control bandwidth is 8.8 Hz .

The bouncing-ball simulator (Fig 1, left) was developed in MATLAB/Simulink, using the xpc target real-time operating system and the Virtual Reality Toolbox. The simulator consists of a 3-D graphical presentation of a ball that falls under the influence of gravity onto a racket. The rotation of the lever with respect to the elbow joint in supination forearm position is mapped to the vertical motion of the virtual racket. The angular position of the lever θ was linked to the vertical position r of

the virtual racket by a linear mapping where $\theta = r\text{m}^{-1}$. This is a compromise given that we emulated a multi-joint, combined rotational and linear task (hitting a ball with a racket) using a single-joint device. The kinematic limitations of the haptic device only allow a rotational movement of the forearm about the elbow joint, which does not realistically represent racket movements in real tennis playing, where vertical translations would play a role. By mapping linearly, we are consistent with [30], and we make sure that subjects do not reach a near-singular configuration for larger angles, which would reduce their ability to influence the impact location. This mapping does not influence performance or evaluation thereof, as long as subjects are capable of understanding how the haptic lever movement relates to the virtual racket's movement.

The aim of the game was to rebound the virtual ball to a certain apex height shown on the screen, which remained constant through the experiment. Impact with the racket was modeled identical to [30]: The ball velocity \dot{b}^+ after impact is given as a function of ball velocity \dot{b}^- before impact, the coefficient of restitution α and the racket velocity \dot{r}^- before impact:

$$\dot{b}^+ = -\alpha\dot{b}^- + (1 + \alpha)\dot{r}^-. \quad (1)$$

The dynamics of the ball during free flight are ballistic and only a function of the initial conditions and the chosen gravity. This implies that once the ball impacted with the racket, the trajectory of the ball is fully determined and the subject has no more influence on it. It also implies that the task is not a trajectory tracking task; task performance is exclusively determined by the final state of the racket at the instant of impact with the ball.

The game consisted of performing the task under the influence of 5 different gravity values. All environments had the same layout but different background color, to help participants identify the relative gravity by the color of the environment.

2.2 The two-layered hybrid-discrete task model

Rhythmically bouncing a ball is a hybrid task that combines continuous movement of the racket with the control of discrete racket-ball impacts.

To obtain references for haptic guidance, the optimal time till the next impact event, the final racket position and velocity (immediately before impact), as well as the racket's continuous reference position, velocity and acceleration trajectories until impact were calculated at each sampling instant using predictive optimization.

Changing the value of gravity in the virtual environment affects the racket's optimal movement: The higher the value of gravity, the more rhythmic the task becomes, while a lower gravity reduces the bouncing frequency, changing the motor command to a discrete task (Fig 2).

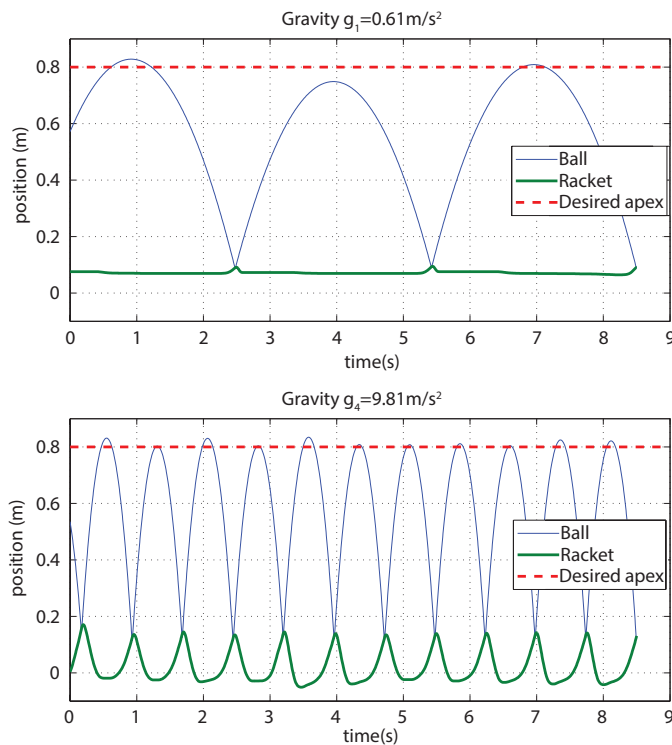


Fig. 2. Examples of racket and ball trajectories under a low gravity level (on top, $g_1 = 0.61 \text{ m/s}^2$) and under “Earth” gravity (bottom, $g_4 = 9.81 \text{ m/s}^2$), while the robotic device stiffly guided the movement. The dashed line represents the desired ball apex height ($h_{\text{des}} = 0.8 \text{ m}$).

The hybrid control architecture was based on a two-layered framework [30], which minimizes a cost functional J over the movement between discrete impact events [30] (To simplify notation, variables are considered dimensionless):

$$J = (r_f - r_{\text{ref},f})^2 + (\dot{r}_f - \dot{r}_{\text{ref},f})^2 + \int_{t_0}^{t_f} [w_r (r(t) - r_{\text{ref},0})^2 + w_e u(t)^2] dt. \quad (2)$$

with reference values denoted by the index ref, initial values by 0, and final values (immediately before impact)

by f. The control input u is the input to a simplified muscle model [30]. The cost functional accounts for the need to reach a final racket position $r_{\text{ref},f}$ and velocity $\dot{r}_{\text{ref},f}$ at impact with little control effort (penalized by the weight w_e). Furthermore, the weight w_r enforces the racket (i.e. the elbow) to remain at the resting position $r_{\text{ref},0}$ when possible, so that the trivial solution where the racket is raised until it contacts the ball at the target apex (and remains there) is avoided. As weighting parameters, the same values as in [30] were employed: $w_r = 0.012\sqrt{g}$, $w_e = 0.00002$. The task is to find the optimal duration $T = t_f - t_0$ of the movement (i.e. the remaining time to impact), the final reference values, as well as the corresponding continuous racket trajectory.

The optimization problem was split into two layers, as in [30]: In an outer loop, the time duration T was iteratively adjusted and final reference values were calculated. In an inner loop, standard LQ control was used to calculate the reference continuous movement between impact events for a given T and final reference values.

In [30], the optimization for the racket movement was run only once between the discrete events. One conclusion of that paper was that it is unlikely that humans re-optimize their internal controller at each impact or time step. However, replicating this for a haptic guidance paradigm is only meaningful when the racket is not allowed to deviate from the a priori calculated trajectory, so in stiff guidance. For guidance with low stiffness, where subjects may deviate from this trajectory, the optimal time to impact and the corresponding optimal movement may change drastically. Compliant guidance along an originally planned trajectory without taking into account de-synchronization between subject and robot can lead to undesired effects, such as the “beat phenomenon” [36] observed for gait rehabilitation robots. Only consistent re-optimization of the trajectory ensures meaningful assistance also at low guidance forces. Thus, a model-predictive controller that performs the minimization at each sampling instant was needed.

The calculations needed in the outer loop are simple: As the ball's movement is ballistic, each T uniquely determines the ball and racket height at impact and the impact equations (1) determine the necessary velocity of the racket to bounce the ball to the desired apex height (so $\dot{r}_{\text{ref},f} = \dot{r}^-$). For this outer loop, we used a golden section algorithm, which guarantees convergence within one sampling step.

For the inner loop, however, the need for on-line optimization led to a challenge: The desired sampling time of 1 ms required a very efficient implementation of the predictive optimization (detailed in the appendix): In contrast to standard algorithms to solve the optimal follower problem, it is not necessary to perform time-consuming online integration (to solve the Riccati equation). The simplification is made possible by recognizing that the inner loop does not need to compute the entire trajectories for each iteration of T , only the cost associated with a given T is needed until the optimal T

is found. With this idea, the cost functional can be reformulated such that it only depends on initial and final conditions, which are found by transforming the continuous differential equations into a discrete mapping from initial to final conditions and vice versa.

2.3 Training conditions

Three control modes were needed for the different training paradigms: First, the robot should allow the subject to try the task without guidance. Second, the robot had to stiffly move the virtual racket to follow the optimal reference trajectory. Finally, the robot should reduce guidance as learning progressed. In the following subsections, the three control strategies designed to achieve these behaviors are described in detail.

2.3.1 No guidance

In the no-guidance condition, the robot followed the subject's movements in closed-loop force control. Thus, the robot was compliant and the subject was able to achieve any elbow flexion with minimal interaction forces caused by the dynamics of the robot. The virtual racket was rendered as a 1 kg object (always experiencing Earth gravity). This force control loop was realized by a proportional force feedback on the measured moment τ_{meas} , combined with feed-forward compensation of the lever weight. The reference moment τ_{rac} was calculated by projecting the virtual racket weight onto the lever. The ball-racket impact was rendered as a 2 Nm torque that was applied at impact and lasted 50 ms. Although the impact duration in real elastic ball-racket interaction experiments was observed to be around 30 ± 9 ms [37], we increased this time to ensure that all subjects perceived the impact forces.

2.3.2 Fixed guidance

A stiff PD position controller with proportional gain $K_s = 600$ Nm/rad and derivative gain $K_d = 60$ Nms/rad was implemented to track the optimal reference racket position θ_{ref} and velocity $\dot{\theta}_{\text{ref}}$. A PD controller is a practical solution to prevent errors during a tracking task despite subject interactions. The reference position and velocity at each sampling instant were calculated using the two-layered hybrid-discrete optimization of Sec. 2.2. The ball-racket impact was again rendered as a 2 Nm torque that was applied at impact and lasted 50 ms.

2.3.3 Fading guidance

Fading assistance is a common strategy to include accurate trajectory demonstration of the fixed guidance mode, while still allowing subjects to try the task by themselves [38]. Here, fading guidance was realized by an impedance controller on the measured angle θ_{meas} that guided the movement by a moment τ_{guid} using closed-loop force control (Fig. 3), with

$$\tau_{\text{guid}} = K_s(\theta_{\text{ref}} - \theta_{\text{meas}}) + K_d(\dot{\theta}_{\text{ref}} - \dot{\theta}_{\text{meas}}). \quad (3)$$

The stiffness K_s and the damping K_d are equivalent to the gains of the position controller. The only difference is that in position control, no inner force feedback loop was used, to allow maximal values for K_s and K_d (without risk of instability). Guidance of the impedance controller was systematically faded on a hit-by-hit basis, until an imperceptible force had settled [11]:

$$K_{i,k+1} = f_R K_{i,k}, \quad i \in s, d, \quad (4)$$

where $K_{i,k}$ and $K_{i,k+1}$ represent the impedance gains K_s and K_d in the k -th and $k+1$ -st hit, respectively, and f_R is the robot forgetting factor ($f_R = 0.997$). The initial values of the impedance stiffness and damping gains were set to $K_{s,0} = 300$ Nm/rad, $K_{d,0} = 35$ Nms/rad. As the gains were in the same order of magnitude, the guidance during these first hits was similar to the stiff position controller.

Fading-guidance controllers typically settle the final assistance force to a value that allows subjects to move freely, and the same was done here. Simultaneously, also the virtual racket rendering τ_{rac} , calculated as in the no-guidance condition, was faded hit by hit at the same rate. By the end of the training phase, subjects felt the task dynamics without any assistance. The ball-racket impact was again rendered as a 2 Nm torque lasting 50 ms.

2.4 Experimental protocol

The experiments were approved by the Research Ethics Committee of ETH Zurich, and all subjects provided informed consent. Thirty right-handed subjects (11 females) with no known motor deficits took part in the experiment. The subjects were between 18–31 years old (mean age 25.7 ± 2.5). They were randomly assigned to one of three groups, of 10 members each: the “no-guidance”, the “fixed-guidance” and the “fading-guidance” groups.

The robot was rigidly attached onto a table, and the seat height was adjusted so subjects could rest their elbow in a comfortable position. Subjects sat in front of a computer screen and were instructed to keep the elbow on the elbow rest and grasp the robot handle in supinated posture. Then, they were asked to bounce the virtual ball shown on the screen to match the ball midpoint with a depicted apex in the virtual environment, by moving the virtual racket through the rotation of the robot handle (Fig 1). The virtual apex remained constant throughout the experiment. No other indication of movement accuracy (e.g. number of times that the ball reached the desired apex) was provided, in order not to divert the subjects' attention from the bouncing task itself.

Each subject participated in two experimental sessions on different days (Fig. 4). During the second experimental session (3–4 days after training), only long-term retention was evaluated, to allow for time-dependent memory consolidation [39], [40]. Practicing during a single-day session can already have quasi-permanent

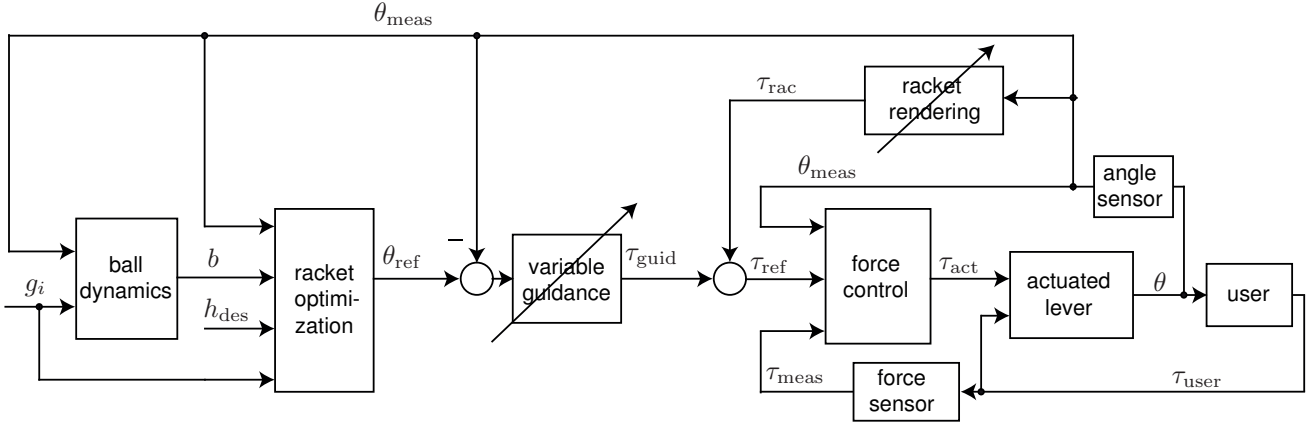


Fig. 3. Impedance controller for fading guidance: In each time step, predictive optimization provides a reference angle θ_{ref} in function of the current ball position b , the current lever angle θ , and the desired apex height h_{des} . Corresponding guiding moments τ_{guid} to the user are rendered by means of an inner force control loop.

effects on the ability to perform a skill [3]. We decided to run a single-day training session because the ball-bouncing task was a relatively easy task that we believed could be mastered in a short time. Therefore, performing multiple-day training sessions could increase the undesirable boredom effect, i.e. performance degradation due to lack of attention.

The first session started with a warm-up period in no-guidance mode, to allow subjects to familiarize with the robot and the virtual reality. During baseline, subjects performed under 5 different gravity levels ($g_1 = 0.61 \text{ m/s}^2$, $g_2 = 1.09 \text{ m/s}^2$, $g_3 = 2.45 \text{ m/s}^2$, $g_4 = 9.81 \text{ m/s}^2$, $g_5 = 15 \text{ m/s}^2$) with no guidance, hitting the ball 26 times under each gravity condition. The gravity values were selected from the gravity levels presented in [30] so that the difference between gravities could be easily recognized. The different gravities have associated different “degrees of rhythmicity”: When performing the task with the lower gravity level g_1 , the dwell time (defined as time between impacts where the racket velocity remains below 5% of its peak value) is 50% of the total time between impacts, whereas the percentage of dwell time is reduced to 10% when performing with the “Earth” gravity level g_4 , and to 25% when performing with the “medium” gravity g_3 [30]. The cycle periods associated with the different gravities are: $T_1 \approx 2800 \text{ ms}$, $T_2 \approx 2100 \text{ ms}$, $T_3 \approx 1400 \text{ ms}$, $T_4 \approx 700 \text{ ms}$, $T_5 \approx 550 \text{ ms}$. The gravity levels were presented in random order, with a pause of 3s between them. The time to complete the baseline condition was 7 minutes. Subjects were informed about the current gravity level through different colors in the virtual environment and through the gravity name (g_1 to g_5) on the screen (Fig 1). Between the baseline and the following training conditions, we allowed for 1–5 minutes rest.

During the training phase, subjects performed the task with 3 different gravities (g_1, g_3, g_4). Training was divided into 9 blocks, each consisting of 50 hits under the same gravity level (3 gravities \times 3 blocks). The 9

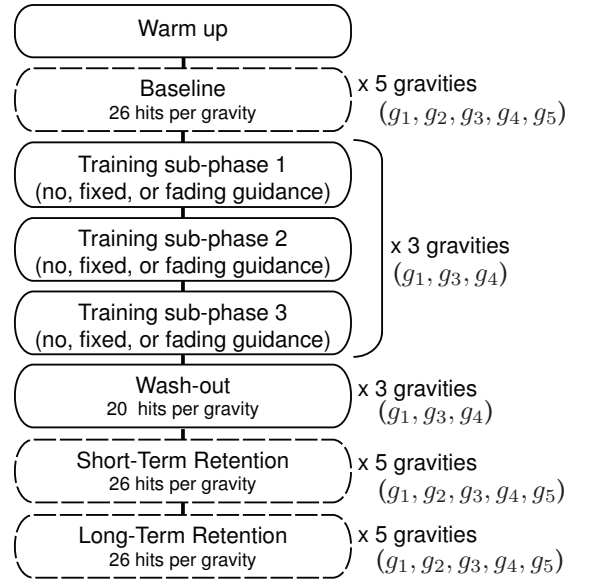


Fig. 4. Experimental protocol

blocks were presented in randomized order, to promote learning of the different gravity levels [41]. To avoid fatigue, subjects were allowed to rest for 1-2 minutes after completing training blocks 3 and 6. We denote as training sub-phases 1, 2 and 3 the resulting training blocks separated by the resting times. During training, subjects in the no-guidance group did not receive assistance from the robot. Subjects in the fixed-guidance group, who were trained with stiff position control, were instructed to actively follow the robot’s movement. The fading-guidance group, which trained while the stiffness of the impedance controller faded throughout the training blocks, were also instructed to cooperate with the robot. Following the training phase, subjects were asked to perform the task again with no guidance under the 3 gravity levels, in order to wash out possible aftereffects (20 hits per trained gravity).

After a short break of 5–10 minutes, subjects proceeded with a short-term retention test. All subjects also returned after 3–4 days for a long-term retention test. Generalization is a crucial aspect of motor learning. It is a type of transfer of learning that occurs from one task to another very similar task [1]. In order to evaluate motor learning generalization, subjects played again under the influence of the 5 gravity levels during the retention tests. We selected two different gravity levels to test for generalization: a gravity level that was between two trained gravities ($g_2 = 1.09 \text{ m/s}^2$), and a second gravity that was higher than the maximum trained gravity ($g_5 = 15 \text{ m/s}^2$). The aim was to test for differences in generalization between a gravity level close to two consecutive trained gravity levels and a gravity level outside the range of the trained gravity levels. Both retention tests followed the same structure as baseline, with 26 hits per gravity.

During baseline, training and retention tests, perturbations were introduced in a pseudo-random manner. A perturbation was defined as a change in the coefficient of restitution—with default value $\alpha = 0.6$ —similar to [42]. A change in α resulted in a ball that rebounded more ($\alpha > 0.6$) or less ($\alpha < 0.6$) than expected. The goal of the perturbations was to compel subjects to practice their feedback control. During baseline and retention tests, two perturbations ($\alpha = \{0.75, 0.45\}$) were randomly introduced after the 5th and 13th trials. During each training block, the perturbing hits were presented as follows: No perturbations occurred during the first 5 hits, neither during the last 12 hits, then each of these 5 perturbations ($\alpha = \{0.45, 0.5, 0.7, 0.75, 0.8\}$) was randomly introduced every 7 hits, in intervals long enough to stabilize the movement before a new perturbation was presented.

The time required to finish the first experimental session was about 30 minutes.

2.5 Data processing and statistical analysis

The overall error during each protocol (sub-)phase was calculated as the mean absolute difference between the actual ball apex height h and the target apex ($h_{des} = 0.8 \text{ m}$), without considering any first hit after a perturbation. We also calculated the mean absolute interaction torque (τ_{meas}) during each protocol block and the mean racket acceleration at impact of the last 5 hits in each protocol block. Note that there were 12 disturbance-free hits after the last perturbation, so subjects had enough time to settle to the steady-state movement. Data from one subject in the fading-guidance group and one subject in the fixed-guidance group were discarded because they did not follow the instructions despite coaching, and instead systematically rebounded the ball to a different apex.

A two-sided t -test was used to evaluate whether subjects in different groups performed differently during baseline. An analysis of variance (ANOVA) with the

overall error during baseline was employed to evaluate if performing with any one gravity level was more difficult than with the others. A two-sided paired t -test was used to evaluate if learning occurred after training: The overall error and racket acceleration at impact over the last 5 baseline trials were compared with the values at retention tests.

The percentage of overall error reduction from baseline to retention test was employed to normalize the data. A repeated-measures ANOVA with the four main protocol phases (baseline, training, short-term and long-term retention) as within-subjects variables, and training conditions as between-subjects condition was performed to evaluate the racket acceleration at impact in the trained gravity levels. We used a linear-mixed model to test the effect that the training conditions and non-trained gravity levels (and their interaction) had on the performance variables during baseline and retention tests. We used a repeated measure ANOVA with baseline and the short- and long-retention test as within-subjects variables and gravity level as between-subject factor to determine whether the gravity level had an effect on the measured torque, and if subjects reduced the torque after training. We performed a univariate analysis with the measured torque during training with the training strategy and the gravity level as fixed factors to evaluate the influence of the training strategy on the measured torque for different gravity levels. Correlations between mean overall error and racket acceleration at impact were tested using Pearson correlation tests. Pairwise follow-up comparisons were performed using Tukey correction. The significance value was set to $p = 0.05$. All statistical analyses were performed using the software package SPSS.

3 RESULTS

3.1 Overall performance

During baseline, we did not find significant differences between training groups in the mean overall error (Fig. 5A) and racket acceleration (Fig. 5B). We found a significant difference between gravity levels in the overall error during baseline ($p < 0.001$); in particular, subjects performed better with g_2 and g_3 , as suggested by a significantly smaller overall error compared to the other gravity levels ($p < 0.05$).

All training groups significantly reduced the overall error from baseline to short-term retention (Fig. 5D, no-guidance: $p < 0.001$, fading-guidance: $p = 0.002$, fixed-guidance: $p < 0.007$) and long-term retention (Fig. 5D, all conditions: $p < 0.001$). We found a significant main effect of training condition on error reduction at long term ($p = 0.023$). Contrast revealed that subjects who trained without guidance reduced the error to a greater percentage than subjects who practiced with fading guidance ($p = 0.006$). We also found a significant interaction between the training condition and gravity ($p = 0.028$).

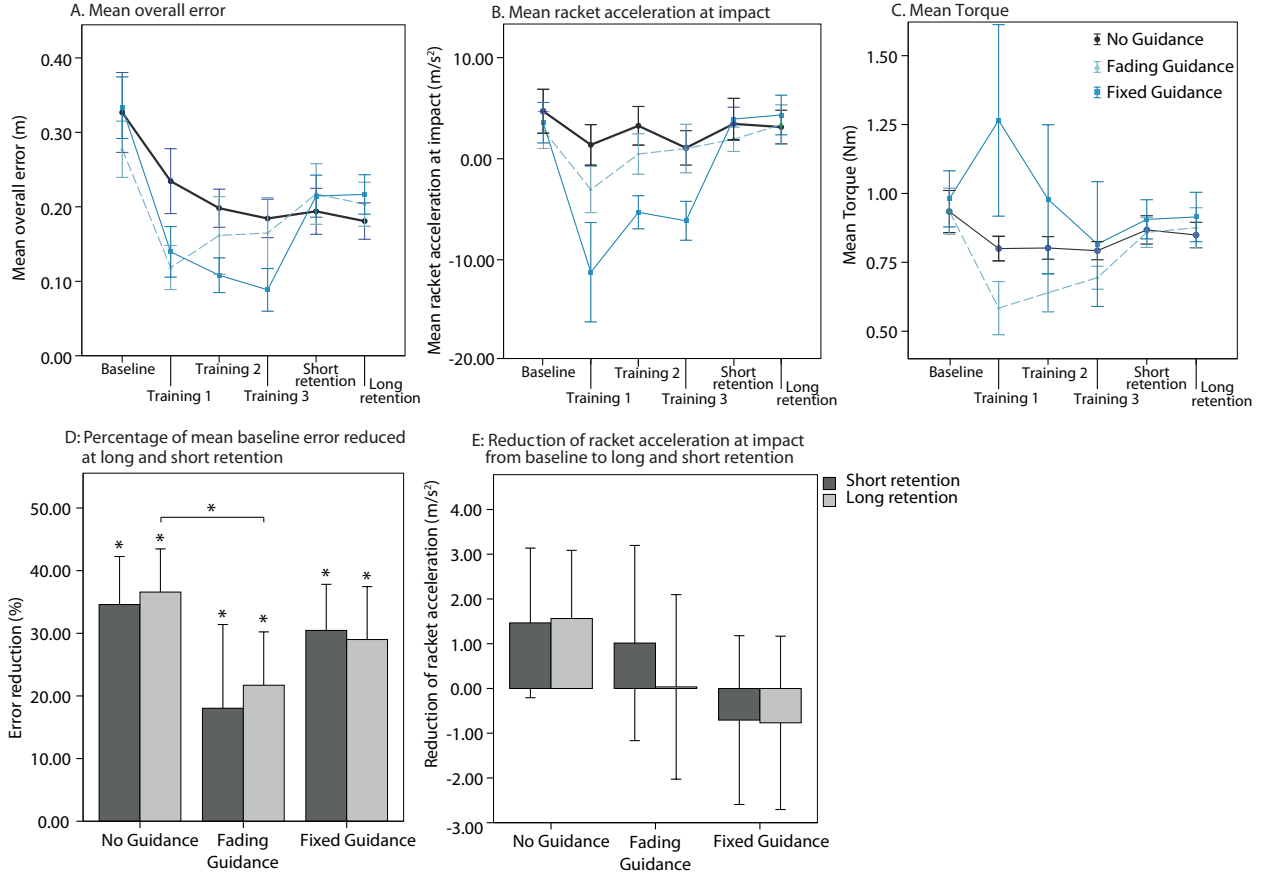


Fig. 5. **A:** Mean overall error during baseline, training, and short- and long-term retention for the three different conditions. **B:** Mean racket acceleration at impact. **C:** Mean interaction torque between subject and robotic device. **D:** Percentage of baseline mean overall error reduced at short- and long-term retention. **E:** Reduction of racket acceleration at ball impact from baseline to short- and long-term retention. Error bars show ± 1 CI. Bars with asterisks show a significant reduction. Significantly different training condition pairs are identified with an asterisk ($p < 0.05$).

Subjects did not significantly reduce their racket acceleration at impact. Only subjects who trained without guidance showed a tendency to reduce the acceleration (Fig. 5E, $p = 0.110$).

We found that subjects significantly reduced the measured torque from baseline to short-term retention (Fig. 5C, $p < 0.001$), and long-term retention ($p < 0.001$). We also found a significant main effect of gravity level on the measured torque ($p < 0.001$). In particular, we found that subjects needed more torque to perform with gravity g_4 than at any of the lower gravity levels ($p < 0.001$), and even more torque to perform g_5 ($p < 0.001$). We found a significant interaction between gravity and protocol phase. In particular, subjects seem to reduce the torque between baseline and retention tests to a higher extent for the higher gravities g_4 and g_5 . We also found that the torque measured during training depended on the training condition (Fig. 5C, $p < 0.001$). In particular, training with fixed guidance increased the torque compared to no guidance ($p = 0.020$) and fading guidance ($p < 0.001$). There was a tendency of more torque when training with no guidance compared to fading guidance ($p = 0.147$). The torque measured during training also

depended on the gravity level ($p < 0.001$), as observed during baseline and retention tests. In particular, training with Earth gravity g_4 resulted in a higher torque than training with g_1 ($p < 0.001$) or g_3 ($p = 0.005$). We found a significant interaction between the training condition and the gravity level: training with fixed guidance resulted in consistently more torque the higher the gravity level was, while the torque measured during training with no guidance and fading guidance did not increase as acutely.

3.2 Learning performance at trained gravity levels

3.2.1 Mean overall error

At the lowest trained gravity ($g_1 = 0.61 \text{ m/s}^2$), subjects in the no-guidance and fixed-guidance groups significantly reduced the error from baseline to short-term (no-guidance $p = 0.007$, fixed-guidance: $p = 0.001$) and long-term retention (Fig. 6A, no-guidance: $p = 0.005$, fixed-guidance: $p = 0.006$). The percentage of error reduction at long term was different between training groups ($p = 0.049$). Subjects trained without guidance reduced the error significantly more than subjects in the fading-guidance group ($p = 0.038$).

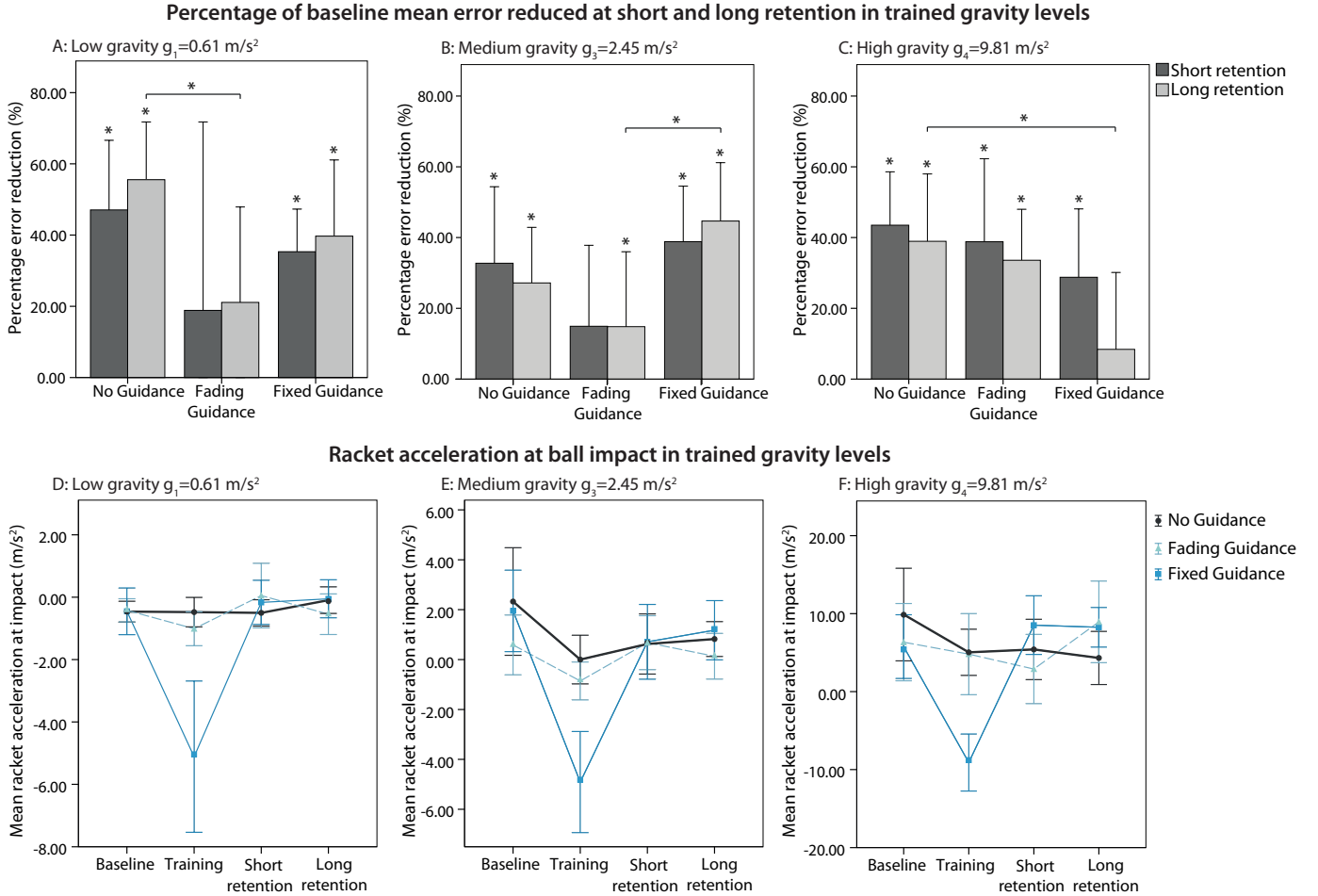


Fig. 6. Percentage of baseline mean overall error reduced at short- and long-term retention for the different training conditions in trained low gravity $g_1 = 0.61 \text{ m/s}^2$ (A), medium gravity $g_3 = 2.45 \text{ m/s}^2$ (B) and high gravity $g_4 = 9.81 \text{ m/s}^2$ (C). Racket acceleration at impact for the different conditions in low trained gravity g_1 (D), medium gravity g_3 (E) and high gravity g_4 (F). Error bars show ± 1 CI.

At the medium gravity ($g_3 = 2.45 \text{ m/s}^2$), subjects trained without guidance ($p = 0.013$) and with fixed guidance ($p = 0.005$) significantly reduced the error at short term. Subjects of all groups reduced the overall error at long term (Fig. 6B, no-guidance: $p = 0.014$, fading-guidance: $p = 0.046$, fixed-guidance: $p = 0.007$), but with a significant difference in error reduction between training groups ($p = 0.043$). Subjects in the fixed-guidance group reduced the error significantly more than subjects in the fading-guidance group ($p = 0.034$).

At the high gravity ($g_4 = 9.81 \text{ m/s}^2$), all subjects significantly reduced the error at short term (Fig. 6C, no-guidance: $p = 0.006$, fading-guidance: $p = 0.006$, fixed-guidance: $p = 0.006$). Subjects in the no-guidance ($p = 0.001$) and fading-guidance ($p = 0.001$) groups also significantly reduced the errors at long term. The percentage of error reduction at long term was different between groups ($p = 0.032$). In particular, the no-guidance group reduced the error significantly more than the fixed-guidance group ($p = 0.035$).

3.2.2 Racket acceleration at impact

Figure 7 shows the ball and racket trajectories, as well as racket acceleration at impact over the last five hits for a representative subject while training with fixed guidance and during short-term retention. A repeated-measures ANOVA with the four main protocol phases (baseline, training, short-term and long-term retention) was performed to further investigate the limited learning for racket acceleration (Fig. 5E).

At the lowest trained gravity, we found a significant difference in the racket acceleration between protocol phases (Fig. 6D, $p < 0.001$): Subjects reduced the acceleration between baseline and training ($p < 0.001$), where training with fixed guidance reduced the acceleration significantly more than no guidance or fading guidance ($p < 0.001$). We neither found a significant acceleration reduction between baseline and retention, nor between groups.

When practicing with the medium gravity, we also found significant differences between protocol phases (Fig. 6E, $p < 0.001$): Subjects reduced the acceleration

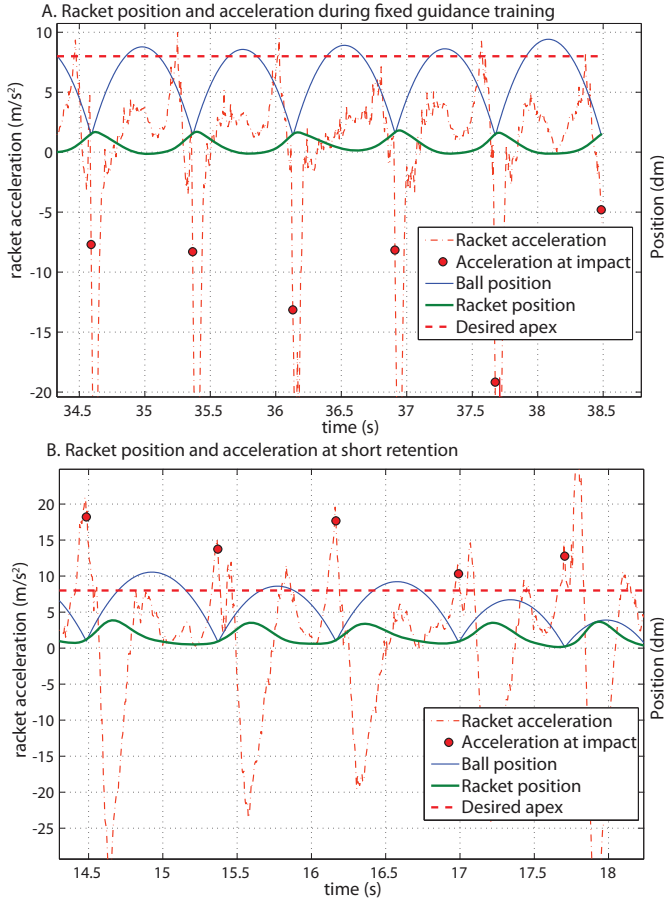


Fig. 7. Ball and racket trajectories and racket acceleration over the last five hits for a representative person under the Earth gravity $g_4 = 9.81 \text{ m/s}^2$ while training with fixed guidance (A), and at short-term retention (B).

significantly from baseline to training ($p < 0.001$), and almost significantly from baseline to long-term retention ($p = 0.057$). The acceleration reduction during training was different between groups: Subjects trained with fixed guidance reduced the acceleration significantly more than subjects in the no-guidance ($p = 0.008$) and fading-guidance groups ($p = 0.002$). However, we did not find significant differences between groups in the acceleration reduction at retention.

When practicing with the high gravity, we also found a significant difference between protocol phases (Fig. 6F, $p < 0.001$). We found a significant acceleration reduction from baseline to training ($p < 0.001$), which was different between groups ($p = 0.012$): Training with fixed guidance reduced the acceleration significantly more than fading guidance ($p = 0.014$). The acceleration reduction from baseline to long-term retention was significantly different between groups ($p = 0.035$). The no-guidance group tended to reduce acceleration more than both the fading-guidance group ($p = 0.061$) and the fixed-guidance group ($p = 0.066$).

3.3 Learning performance at non-trained gravities

3.3.1 Mean overall error

Subjects in the no-guidance ($p = 0.002$), and fixed-guidance groups ($p = 0.001$) significantly reduced the overall error at short term in the non-trained gravity levels. Subjects in all training groups improved their hitting performance at long term (Fig. 8A, no-guidance: $p < 0.001$, fading-guidance: $p = 0.004$, fixed-guidance: $p = 0.001$). We found neither a main effect of the training condition, nor of the gravity in the linear mixed model analysis. The interaction between training conditions and gravities was also non-significant.

3.3.2 Racket acceleration at impact

None of the training groups significantly reduced their acceleration at impact in the non-trained gravity levels (Fig. 8B). We found neither a main effect of the training condition, nor of the gravity in the mixed linear model. The interaction between conditions and gravities was also non-significant.

3.4 Correlation between performance measures

The overall error reduction from baseline to short- and long-term retention tests was not accompanied by a reduction of the racket acceleration at impact, as suggested by a lack of correlation between the reduction of the two performance measures; we neither found correlations for any gravity level, nor for all gravities together.

4 DISCUSSION

This study investigated which form of robotic guidance — no, fixed, and fading haptic guidance — would be more beneficial in learning a hybrid rhythmic-discrete motor task. We found that the most effective training condition in terms of error reduction depended on the *degree of rhythmicity* of the movement. Further, training with haptic guidance seems not to have any effect on racket acceleration at impact. These findings contradict results from previous studies, which found that fading guidance was more beneficial to learn time-related continuous tasks [15], [16]. In the following subsections, we discuss the results in detail.

4.1 The most effective training condition depends on the degree of rhythmicity

The Challenge Point theory states that optimal learning is achieved when the difficulty of a task is adjusted to the individual participant's level of expertise (i.e. when the challenge point is reached). Thus, low-skilled subjects would learn less when training a too difficult task than when training at an appropriate level of difficulty. Likewise, proficient subjects would not learn optimally when practicing a task that is easy for them. Thus, reducing task difficulty via haptic guidance could have a positive impact on learning when subjects are training an overly

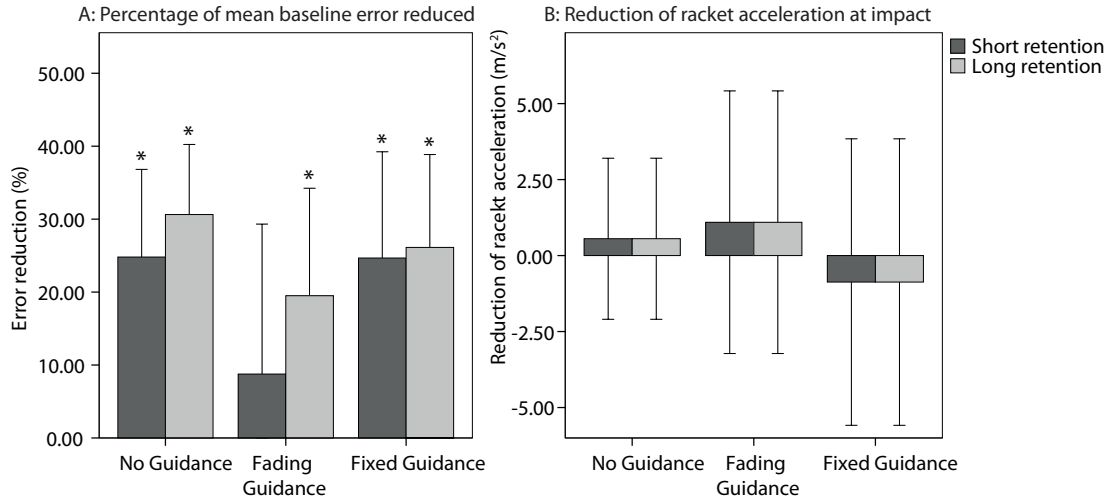


Fig. 8. Performance changes in non-trained gravities. **A:** Percentage of baseline’s mean overall error reduced at short- and long-term retention for no-guidance, fading-guidance and fixed-guidance groups. **B:** Reduction of racket acceleration at ball impact from baseline to short- and long-term retention. Error bars show ± 1 CI.

difficult task. In fact, haptic guidance has been found to be more beneficial for less skilled participants in some recent studies [10], [18], [11], supporting the Challenge Point theory. Likewise, haptic guidance could have a negative impact when applied during training of tasks that are already easy for subjects.

In our study, the higher gravities seemed more “challenging”, because subjects performed significantly worse during baseline with g_4 and g_5 than with the lower gravities g_2 and g_3 (A possible rationale may be that faster movements allow less opportunity for online error correction, and thus the performance under higher gravities degraded, especially given that subjects encountered the task for the first time during baseline). According to the Challenge Point theory, a positive impact of haptic guidance on learning could be expected when practicing g_4 , and a negative impact for g_3 .

Our results contradict the Challenge Point theory: Training with fixed guidance improved learning in terms of error reduction in the gravity level that subjects mastered better during baseline (g_3), while training without guidance resulted in better learning in gravity g_4 than training with fixed guidance.

Thus, the differences in the most effective training condition do not seem to depend on the “level of difficulty”, but rather on the “degree of rhythmicity”: For the periodic discrete task (low gravity), no guidance and fixed guidance resulted in better performance after training. Fixed guidance also improved learning in more mixed tasks that fall in between discrete and rhythmic classes (medium gravity). However, for the continuous rhythmic movement (higher gravity), no guidance seemed to be especially suitable to learn the task. The positive effect of fixed guidance is in line with recent studies that showed that guidance is especially beneficial to learn discrete timing tasks, such as the best moment to turn in sharp curves [11] or the moment to start a tennis stroke [10].

Fixed guidance seems inappropriate for tasks with a high degree of rhythmicity, i.e. continuous, repetitive movements with negligible dwell times.

4.2 Haptic guidance did not benefit learning of the racket acceleration at impact

Subjects systematically hit the ball with a racket acceleration higher than the negative acceleration observed in experienced subjects [33]. Subjects hit the ball using a negative racket acceleration only during training with fixed guidance (Fig. 6). However, when the guidance was removed, subjects systematically hit the ball at a very low position, shortly before the racket reached maximum velocity, so with small positive acceleration. This strategy contradicts previous work [30], [33]; instead it is more consistent with what the hypothesis of energy minimization would predict: The energetically optimal contact should be at maximum racket velocity (i.e. acceleration zero) [31]. A possible rationale for this discrepancy could be that parameters of the cost function might have to be further adjusted to match human behavior well enough to be suitable for haptic guidance. These parameters were taken from [30], where the aim was to show a similarity between model predictions and human behavior concerning the varying degree of rhythmicity with varying gravity. However, [30] did not give a quantitative comparison between predicted and observed activity periods. Furthermore, discrepancies may arise from the differences between the devices employed: We used a transparent actuated lever with rotational movement about the elbow as a pivot, while subjects in [30], [33] moved a sensorized racket without constraints on the arm, and apparent dynamics of the apparatus were not reported. Difference in setups might have led to a biased trade-off between energy optimality and passive stability [31].

The finding that subjects did not reduce the racket acceleration at impact contradicts recent evidence that haptic guidance may be specifically useful to reproduce the temporal characteristics of spatiotemporal patterns [14], [15], [16]. One might argue that we tested for long-term effects of haptic guidance, while previous work mainly tested performance gains at short term. However, we did not find any benefit at short-term retention either, so this cannot explain the differences.

The lack of any significant correlation between racket acceleration at impact and mean overall error, during baseline and during the retention tests, suggests that racket acceleration at impact may not be a time-critical feature of the ball-bouncing task. In fact, we did not find a correlation between the reduction from baseline to retention of the mean overall error and the acceleration at impact, thereby suggesting that subjects explored strategies to improve their hitting success different from reducing the racket acceleration at impact as observed in previous research [30], [33]. This is in line with recent work on the ball-bouncing paradigm, which suggests that subjects actively regulate their movements on every cycle based on perceived variables, i.e. they employ feedback control more actively, in detriment of feedforward control [43], [44]. Thereby, the lack of benefit from haptic guidance may be explained by the inappropriate selection of racket acceleration at impact as performance measure.

4.3 Subjects generalized to non-trained gravities

We hypothesized that training without guidance would generalize better to untrained gravities. Indeed, subjects in the no-guidance group significantly reduced the overall error at both untrained gravities. However, also subjects trained with fixed and fading guidance significantly reduced the overall error at untrained gravities. This result contradicts our recent study, which found that haptic guidance limited generalization in a timing-based task [34], while training without guidance did benefit generalization. In this previous experiment, we speculated that the limited generalization arose because subjects who received guidance experienced a narrower range of training examples. A possible rationale for the discrepancy is that bouncing a ball at the non-trained gravity levels was indeed similar to the experience gained when practicing with the trained gravities, and thus training with guidance also allowed to create a “rich and varied experience” [34] that improved learning of the untrained gravity levels. In fact, a cycle with the low untrained gravity g_2 was only 25% shorter than a cycle with the low gravity g_1 , and a cycle with the untrained high gravity g_5 was only 21% shorter than with the high trained gravity g_4 .

4.4 Why did fading guidance not improve learning?

We hypothesized that fading guidance would improve learning at all gravities. However, we did not find any

positive effects of this special form of guidance on learning the bouncing task.

Fading guidance might be seen as compliant guidance that leaves subjects freedom to choose a strategy, but still to benefit from the error-correcting functionality of the device. While guidance faded, instead of adopting the initially demonstrated robust, self-stabilizing strategy with negative acceleration at impact, subjects consistently converged towards a more energy-efficient, but less robust strategy with racket acceleration close to zero, like subjects trained without guidance (as seen in Fig. 5B). The fading guidance, however, allowed them to employ this strategy during training and still reach high performance, as can be seen in the low overall error during training in Fig. 5A. This could be explained by the constant re-calculation of the optimal trajectory, which kept performance high even without self-stabilizing properties of the strategy. This gave subjects an erroneously good impression of their performance, reducing error as driving factor for learning to occur. Further, the dynamics of the task were not displayed in full, due to the compliant assistance, which is also reflected in the lower interaction moments as compared to no guidance conditions (Fig. 5C). Only the last hits of the training phase, when assistive forces approached zero, gave subjects a realistic impression of the task dynamics, so they had only limited training possibilities. When the correction from the device was not available anymore during retention trials, subjects accordingly displayed bad performance.

The selection of a fixed fading gain in (4), independent of the subjects’ individual performance, was done to assure that all subjects were exposed to the same level of guidance during the experiment. The reduction of the robotic guidance may have been too fast or too slow for a subject’s specific learning rate. A guidance-as-needed algorithm that aims to systematically reduce guidance but can also increase guidance based on a subject’s current performance level may have resulted in better learning [11].

4.5 Technical limitations

The present study is influenced by several technical limitations, in particular concerning the haptic performance of the robotic device, the realism of the virtual reality, as well as the cost function used to calculate the optimal racket trajectory. The haptic device does not perfectly reflect a freely moving racket. Friction and sensor noise play a role and reduce achievable precision and accuracy in all conditions. For the cost function, we used the same cost function and weighting parameters as [30], as this approximated the fraction of dwell times observed in human movement in preliminary experiments. More evidence would be needed in how far this particular cost function and its parameters indeed reflect or reproduce the human’s internal strategies. However, this is outside the scope of the present study. Finally, the displayed virtual reality is inspired by the task of playing tennis, but it

does not reflect this task in a realistic manner. However, we believe that specific features of the task, in particular the rhythmic-discrete nature, are still maintained and worth investigating even in this more artificial task.

5 CONCLUSION

In this study, we investigated the influence of haptic guidance on learning of hybrid rhythmic-discrete motor tasks: Subjects played a ball-bouncing game with varying amounts of haptic guidance at different gravity levels, provoking different *degrees of rhythmicity*.

We found that the most effective training condition in fact depended on the degree of rhythmicity of the movement: Fixed haptic guidance seems inappropriate for tasks with a high degree of rhythmicity, thus tasks that are close to continuous, repetitive movements with negligible dwell times. However, training with haptic guidance seems to be beneficial in improving performance for tasks that resemble discrete movements, similarly to training without guidance.

Additional studies are needed to further validate these observations. It is still an open question whether the benefit of haptic guidance in fact only depends on the movement class analyzed, independent of the task difficulty level.

Furthermore, we could not find benefits of fading guidance compared to fixed or no guidance, and we could not reproduce previous findings on the dominance of negative accelerations at impact, which indicate subjects' strategies for passive self-stabilization. Instead, our subjects seemed to systematically prefer more energy-efficient movement patterns. We could not find a relationship between task performance and accelerations at impact either.

APPENDIX A

A highly efficient algorithm for model-predictive control of the racket position in the ball-bouncing task was derived, in order to allow fast on-line computation in each sampling step. First, the cost functional (2) was rewritten in the form of a standard linear-quadratic regulator (LQR) problem:

$$J = \|\mathbf{x}_f - \mathbf{x}_{ref,f}\|_{\mathbf{S}}^2 + \int_{t_0}^{t_f} (\|\mathbf{x}(t) - \mathbf{x}_{ref}(t)\|_{\mathbf{Q}}^2 + \|\mathbf{u}(t)\|_{\mathbf{R}}^2) dt \quad (5)$$

with the weighting matrices $\mathbf{R} = w_e$, $\mathbf{Q} = \text{diag}(w_r, 0, 0)$, and $\mathbf{S} = \text{diag}(1, 1, 0)$, and the state vector

$$\mathbf{x} = (r \quad \dot{r} \quad a_m)^T, \quad (6)$$

where a_m is muscle activation, r is racket position, and \dot{r} is racket velocity. The system is governed by the dynamics [30]:

$$\dot{\mathbf{x}} = \mathbf{A}\mathbf{x} + \mathbf{B}\mathbf{u}, \text{ with} \quad (7)$$

$$\mathbf{A} = \begin{pmatrix} 0 & 1 & 0 \\ 0 & -\gamma/I & 1 \\ 0 & 0 & -1/\tau_m \end{pmatrix}, \mathbf{B} = \begin{pmatrix} 0 & 0 & 1/\tau_m \end{pmatrix}$$

The parameters are: Damping coefficient $\gamma = 0.25 \text{ N/(m/s)}$, moment of inertia of arm and racket $I = 0.05 \text{ N/(m/s}^2)$, and muscle time constant $\tau_m = 50 \text{ ms}$. By suitable coordinate definitions, $r_{ref,0} = 0$ and thus $\mathbf{x}_{ref}(t) = \mathbf{0} \forall t \in \{t \in \mathbb{R} : t_0 \leq t < t_f\}$, and $\mathbf{x}_{ref,f} = (r_{ref,f} \quad \dot{r}_{ref,f} \quad 0)^T$.

The solution to this optimal follower-controller problem is given by the control law [45]:

$$\mathbf{u}(t) = -\mathbf{R}^{-1}\mathbf{B}^T\mathbf{P}\mathbf{x}(t) + \mathbf{R}^{-1}\mathbf{B}^T\mathbf{p}(t), \quad (8)$$

where the matrix function $\mathbf{P}(t)$ is the solution of the Riccati equation, and the vector function $\mathbf{p}(t)$ reflects the influence of the reference trajectory:

$$\dot{\mathbf{P}} = -(\mathbf{P}\mathbf{A} + \mathbf{A}^T\mathbf{P} - \mathbf{P}\mathbf{B}\mathbf{R}^{-1}\mathbf{B}^T\mathbf{P} + \mathbf{Q}), \quad (9)$$

$$\mathbf{P}(t_f) = \mathbf{P}_f = \mathbf{S}, \quad (10)$$

$$\dot{\mathbf{p}} = -((\mathbf{A} - \mathbf{B}\mathbf{R}^{-1}\mathbf{B}^T\mathbf{P})^T\mathbf{p} + \mathbf{Q}\mathbf{x}_{ref}), \quad (11)$$

$$\mathbf{p}(t_f) = \mathbf{p}_f = \mathbf{S}\mathbf{x}_{ref,f}. \quad (12)$$

Because of the two-step optimization, it is not desirable to compute the complete solution in each iteration of T . Instead, only the optimal *cost* for a specific duration T is needed, until the optimal T is found.

This can be achieved in a very efficient manner by rewriting the cost functional (5) in the form (The derivation follows [46]):

$$J = \mathbf{x}_{ref,f}^T \mathbf{S} \mathbf{x}_{ref,f} - \mathbf{x}_f^T \mathbf{S} \mathbf{x}_{ref,f} + \mathbf{x}_0^T \mathbf{P}_0 \mathbf{x}_0 - \mathbf{x}_0^T \mathbf{p}_0. \quad (13)$$

The fundamental advantage of this expression is that it does not involve the entire trajectories of \mathbf{x} nor \mathbf{u} , but instead only needs some initial and final values: The matrix \mathbf{P}_0 only depends on the duration T and can be found by backward integration of (10). The value of \mathbf{p}_f is a function of the reference final value $\mathbf{x}_{ref,f}$, as given in (11). The value of \mathbf{p}_0 depends both on the duration T and on the final value \mathbf{p}_f . However, as this is a linear system, transition matrices Φ_p can be found that immediately map \mathbf{p}_f to \mathbf{p}_0 for a particular T :

$$\mathbf{p}_0 = \Phi_p(T)\mathbf{p}_f \quad (14)$$

These transition matrices are found off-line: First, (11) is integrated backward for a maximally expected duration T_{max} , with three arbitrary, but linearly independent values for \mathbf{p}_f , in order to find the corresponding values for \mathbf{p}_0 . Then, for each T , the transition matrix is found by solving (14) for the entries of Φ_p . Similarly, the final racket states \mathbf{x}_f , immediately before the next impact, are found via convolution:

$$\mathbf{x}_f = \Phi_x(T)\mathbf{x}_0 + \Gamma(T)\mathbf{p}_f \quad (15)$$

with the transition matrices

$$\Phi_x(T) = \Phi_p^T(T), \Gamma(T) = -\int_0^T \Phi_x(\tau)\mathbf{B}\mathbf{R}^{-1}\mathbf{B}^T\Phi_p(\tau)d\tau \quad (16)$$

The transition matrices only depend on the duration T , they are independent of initial and final conditions. Therefore, the values for \mathbf{P}_0 , \mathbf{p}_0 , $\mathbf{\Gamma}$, $\mathbf{\Phi}_p$ can be pre-computed and stored as matrix or vector functions of T , respectively, with a sufficiently large domain of T values for the specific gravity condition. As a resolution for T , we choose the sampling frequency of the haptic system, 1 ms.

Also when the optimal T is found, the predictive controller only needs the first values of \mathbf{u} and \mathbf{x} , which are also found immediately from (8) and (7), respectively.

This procedure reduces computational requirements to a minimum; no on-line integration is necessary.

ACKNOWLEDGMENTS

The authors gratefully acknowledge the contribution of Peter Wolf and Alexander Duschau-Wicke for their enriching comments.

The contents of this publication were partially developed under two grants from the US Department of Education, NIDRR grant numbers H133E070013 and H133E120010. However, those contents do not necessarily represent the policy of the US Department of Education, and you should not assume endorsement by the Federal Government of the United States of America. Laura Marchal-Crespo holds a Marie-Curie international income fellowship PIIF-GA-2010-272289, and Heike Vallery holds a Marie-Curie career integration grant PCIG13-GA-2013-618899.

REFERENCES

- [1] R. Schmidt and T. Lee, *Motor Control And Learning: A Behavioral Emphasis*. Human Kinetics Publishers, 2005.
- [2] A. Salmoni and R. Schmidt, "Knowledge of results and motor learning: a review and critical reappraisal," *Psychol Bull*, vol. 95, no. 3, pp. 355–86, 1984.
- [3] R. A. Schmidt and R. A. Bjork, "New conceptualizations of practice: common principles in three paradigms suggest new concepts for training," *Psychological Science*, vol. 3, no. 4, pp. 207–217, 1992.
- [4] C. J. Winstein, P. S. Pohl, and R. Lewthwaitek, "Effects of physical guidance and knowledge of results on motor learning: support for the guidance hypothesis," *Research Quarterly for Exercise and Sport*, vol. 65, no. 4, pp. 316–323, 1994.
- [5] J. D. Hagman, "Presentation- and test-trial effects on acquisition and retention of distance and location," *Journal of Experimental Psychology: Learning, Memory, and Cognition*, vol. 9, no. 2, pp. 334–345, 1983.
- [6] L. Marchal-Crespo and D. Reinkensmeyer, "Review of control strategies for robotic movement training after neurologic injury," *Journal of NeuroEngineering and Rehabilitation*, vol. 6, no. 1, p. 20, 2009.
- [7] L. Marchal-Crespo, J. Furumasu, and D. Reinkensmeyer, "A robotic wheelchair trainer: design overview and a feasibility study," *Journal of NeuroEngineering and Rehabilitation*, vol. 7, no. 1, p. 40, 2010.
- [8] S. Agrawal, X. Chen, C. Ragonesi, and J. Galloway, "Training toddlers seated on mobile robots to steer using force-feedback joystick," *Haptics, IEEE Transactions on*, vol. 5, no. 4, pp. 376–383, Fourth 2012.
- [9] S. Banala, S. Agrawal, and J. Scholz, "Active leg exoskeleton (alex) for gait rehabilitation of motor-impaired patients," in *Rehabilitation Robotics, 2007. ICORR 2007. IEEE 10th International Conference on*, June 2007, pp. 401–407.
- [10] L. Marchal-Crespo, M. Raai, G. Rauter, P. Wolf, and R. Riener, "The effect of haptic guidance and visual feedback on learning a complex tennis task," *Experimental Brain Research*, vol. 231, no. 3, pp. 277–291, 2013.
- [11] L. Marchal-Crespo, S. McHughen, S. Cramer, and D. Reinkensmeyer, "The effect of haptic guidance, aging, and initial skill level on motor learning of a steering task," *Experimental Brain Research*, vol. 201, no. 2, pp. 209–220, 2010.
- [12] A. Basteris, L. Bracco, and V. Sanguineti, "Robot-assisted inter-manual transfer of handwriting skills," *Human Movement Science*, vol. 31, no. 5, pp. 1175 – 1190, 2012.
- [13] J. Lüttgen and H. Heuer, "The influence of robotic guidance on different types of motor timing," *Journal of Motor Behavior*, vol. 45, no. 3, pp. 249–258, 2013.
- [14] J. Luetgten and H. Heuer, "The influence of haptic guidance on the production of spatio-temporal patterns," *Human Movement Science*, vol. 31, no. 3, pp. 519 – 528, 2012.
- [15] D. Feygin, M. Keehner, and R. Tendick, "Haptic guidance: experimental evaluation of a haptic training method for a perceptual motor skill," in *Proceedings of the 10th Symp. On Haptic Interfaces For Virtual Envir. and Teleoperator Sysys. (HAPTICS.02)*, 2002, pp. 40 – 47.
- [16] J. Bluteau, S. Coquillart, Y. Payan, and E. Gentaz, "Haptic guidance improves the visuo-manual tracking of trajectories," *PLoS ONE*, vol. 3, no. 3, p. e1775., 2008.
- [17] D. Morris, H. Tan, F. Barbagli, T. Chang, and K. Salisbury, "Haptic feedback enhances force skill learning," *WHC '07: Proceedings of the Second Joint EuroHaptics Conference and Symposium on Haptic Interfaces for Virtual Environment and Teleoperator Systems*, pp. 21–26, 2007.
- [18] M. Milot, L. Marchal-Crespo, S. Cramer, and D. Reinkensmeyer, "Comparison of error amplification and haptic guidance training techniques for learning of a timing-based motor task by healthy individuals," *Experimental Brain Research*, vol. 201, no. 2, pp. 119–31, 2010.
- [19] C. Williams and H. Carnahan, "Motor learning perspectives on haptic training for the upper extremities," *Haptics, IEEE Transactions on*, vol. PP, no. 99, pp. 1–1, 2014.
- [20] N. Hogan and D. Sternad, "On rhythmic and discrete movements: reflections, definitions and implications for motor control," *Experimental Brain Research*, vol. 181, pp. 13–30, 2007.
- [21] B. C. M. Smits-Engelsman, G. P. Van Galen, and J. E. J. Duysens, "The breakdown of fitts' law in rapid reciprocal aiming movements," *Experimental Brain Research*, vol. 145, no. 2, pp. 222–230, 2002.
- [22] J. Buchanan, J.-H. Park, Y. Ryu, and C. Shea, "Discrete and cyclical units of action in a mixed target pair aiming task," *Experimental Brain Research*, vol. 150, pp. 473–489, 2003.
- [23] A. M. van Mourik and P. J. Beek, "Discrete and cyclical movements: unified dynamics or separate control?" *Acta Psychologica*, vol. 117, no. 2, pp. 121 – 138, 2004.
- [24] S. Schaal, D. Sternad, O. Rieko, and M. Kawato, "Rhythmic arm movement is not discrete," *Nat Neurosci*, vol. 7, no. 10, pp. 1136 – 1143, 2004.
- [25] J. C. Huegel, O. Celik, A. Israr, and M. K. O'Malley, "Expertise-based performance measures in a virtual training environment," *Presence: Teleoperators and Virtual Environments*, vol. 18, no. 6, pp. 449–467, 2009.
- [26] M. K. O'malley, A. Gupta, M. Gen, and Y. Li, "Shared control in haptic systems for performance enhancement and training," *Journal of Dynamic Systems, Measurement, and Control*, vol. 128, no. 1, pp. 75–85, 2006.
- [27] A. Israr, H. Kapson, V. Patoglu, and M. O'Malley, "Effects of magnitude and phase cues on human motor adaptation," 2009, pp. 344–349.
- [28] D. Powell and M. O'Malley, "The task-dependent efficacy of shared-control haptic guidance paradigms," *Haptics, IEEE Transactions on*, vol. 5, no. 3, pp. 208–219, 2012.
- [29] Y. Guiard, "On fitts's and hooke's laws: Simple harmonic movement in upper-limb cyclical aiming," *Acta Psychologica*, vol. 82, pp. 139 – 159, 1993.
- [30] R. Ronsse, K. Wei, and D. Sternad, "Optimal control of a hybrid rhythmic-discrete task: the bouncing ball revisited," *J Neurophysiol*, vol. 5, pp. 2482–2493, 2010.
- [31] R. Ronsse, J.-L. Thonnard, P. Lefèvre, and R. Sepulchre, "Control of bimanual rhythmic movements: trading efficiency for robust-

- ness depending on the context," *Experimental Brain Research*, vol. 187, no. 2, pp. 193–205, 2008.
- [32] D. Sternad, M. Duarte, H. Katsumata, and S. Schaal, "Bouncing a ball: Tuning into dynamic stability," *Journal of Experimental Psychology: Human Perception and Performance*, vol. 27, no. 5, pp. 1163–1184, 2001.
- [33] K. Wei, T. M. H. Dijkstra, and D. Sternad, "Stability and variability: Indicators for passive stability and active control in a rhythmic task," *Journal of Neurophysiology*, vol. 99, no. 6, pp. 3027–3041, June 2008.
- [34] L. Marchal-Crespo and D. J. Reinkensmeyer, "Effect of robotic guidance on motor learning of a timing task," in *Proceedings of the Second IEEE/RAS-EMBS International Conference on Biomedical Robotics and Biomechatronics*, October 2008.
- [35] H. Vallery and R. Riener, "How Can We Enhance Motor Learning in Position Control?" in *Proceedings of the International Workshop on Computational Principles of Sensorimotor Learning*, Kloster Irsee, Germany, 2009.
- [36] D. Aoyagi, W. E. Ichinose, S. J. Harkema, D. J. Reinkensmeyer, and J. E. Bobrow, "A robot and control algorithm that can synchronously assist in naturalistic motion during body-weight-supported gait training following neurologic injury," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 15, no. 3, pp. 387–400, 2007.
- [37] H. Katsumata, V. Zatsiorsky, and D. Sternad, "Control of ball-racket interactions in rhythmic propulsion of elastic and non-elastic balls," *Experimental Brain Research*, vol. 149, no. 1, pp. 17–29, 2003.
- [38] J. L. Emken, R. Benitez, and D. J. Reinkensmeyer, "Human-robot cooperative movement training: learning a novel sensory motor transformation during walking with robotic assistance-answered," *Journal of Neuroengineering and Rehabilitation*, vol. 4, no. 8, March 2007.
- [39] R. Shadmehr and H. H. Holcomb, "Neural correlates of motor memory consolidation," *Science*, vol. 277, no. 5327, pp. 821–825, 1997.
- [40] J. L. McGaugh, "Memory—a century of consolidation," *Science*, vol. 287, no. 5451, pp. 248–251, 2000.
- [41] J. B. Shea and R. L. Morgan, "Contextual interference effects on the acquisition, retention, and transfer of a motor skill," *Journal of Experimental Psychology: Human Learning and Memory*, vol. 5, no. 2, pp. 179–187, 1979.
- [42] A. de Rugy, K. Wei, H. Müller, and D. Sternad, "Actively tracking 'passive' stability in a ball bouncing task," *Brain Research*, vol. 982, no. 1, pp. 64–78, 2003.
- [43] R. Ronsse and D. Sternad, "Bouncing between model and data: Stability, passivity, and optimality in hybrid dynamics," *Journal of Motor Behavior*, vol. 42, no. 6, pp. 389–399, 2010.
- [44] I. Siegler, C. Bazile, and W. Warren, "Mixed control for perception and action: timing and error correction in rhythmic ball-bouncing," *Experimental Brain Research*, vol. 226, no. 4, pp. 603–615, 2013.
- [45] A. Bryson, *Applied Linear Optimal Control*. Cambridge University Press, 2002.
- [46] M. Papageorgiou, *Optimierung. Statische, dynamische, stochastische Verfahren für die Anwendung*. Oldenbourg-Verlag, 1991.

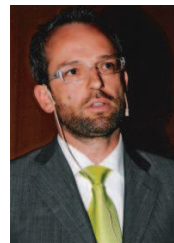


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