Optimizing Learning of a Locomotor Task: Amplifying Errors as Needed

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Abstract— **Research on motor learning has emphasized that errors drive motor adaptation. Thereby, several researchers have proposed robotic training strategies that amplify movement errors rather than decrease them. In this study, the effect of different robotic training strategies that amplify errors on learning a complex locomotor task was investigated. The experiment was conducted with a one degree-of freedom robotic stepper (MARCOS). Subjects were requested to actively coordinate their legs in a desired gait-like pattern in order to track a Lissajous figure presented on a visual display. Learning with three different training strategies was evaluated: (i) No perturbation: the robot follows the subjects' movement without applying any perturbation, (ii) Error amplification: existing errors were amplified with repulsive forces proportional to errors, (iii) Noise disturbance: errors were evoked with a randomly-varying force disturbance. Results showed that training without perturbations was especially suitable for a subset of initially less-skilled subjects, while error amplification seemed to benefit more skilled subjects. Training with error amplification, however, limited transfer of learning. Random disturbing forces benefited learning and promoted transfer in all subjects, probably because it increased attention. These results suggest that learning a locomotor task can be optimized when errors are randomly evoked or amplified based on subjects' initial skill level.**

I. INTRODUCTION

Robot-aided gait rehabilitation has been presented as a promising technique to improve rehabilitation in patients with neurological injuries [1]. However, up to date, the functional gains obtained after robotic gait training are limited [2], [3]. In fact, robotic devices could potentially decrease recovery if they encourage a decrease in effort, energy consumption, or attention during training [4], [5].

Research on motor learning has emphasized that errors are fundamental signals that drive motor adaptation [6], [7], [8], [9]. Thereby, there has been a progression in the development of training strategies that amplify movement errors rather than decrease them [1]. In patients with chronic stroke, amplifying errors with a robotic force field during reaching resulted in straighter movements when the force field was removed [7], [9]. Increasing limb phasing error in post-stroke participants' gait through a split-belt treadmill induced a long term increase in walking symmetry [8]. Training a reaching task with error amplification was more beneficial for less impaired stroke patients, whereas more impaired patients benefited more from haptic guidance [10]. Similarly, training with amplified errors resulted in better learning in skilled participants than training with haptic guidance when playing a pinball-like game [11]. These results are in line with the challenge point theory, that states that optimal learning is achieved when the difficulty of the task is appropriate for the individual participants' level of expertise [12]. Thus, providing an easy task to a proficient participant would not be predicted to improve learning, since little new information is delivered and new skills are not promoted. Matching the robotic training strategy to the trainee's skill level may provide the greatest opportunity for learning.

An extended approach to error amplification is noise disturbance, i.e. randomly-varying feedforward forces that disturb subjects' movements during training. In a motor learning study, training with noise disturbance resulted in better tracking than unassisted training and than training with a more conventional error-amplification strategy [13]. The question of the most effective training strategies, and their relative benefits compared to unassisted practice still remains unanswered.

Motor learning has been suggested to be of great relevance in neurorehabilitation [14]. Understanding the underlying mechanisms of motor learning during robotic locomotor training is important to improve the efficacy of robotic training in patients. In this study, the impact of three different training strategies on motor learning of a complex locomotor task was tested with twenty three healthy subjects: No perturbation, error amplification, and noise-force disturbance. A one degree-of freedom steeper robot (MARCOS) was employed to conduct the experiment. We expected better motor learning after training with the challenge-based strategies, especially in initially more skilled subjects.

II. METHODS

A. MARCOS

MARCOS (Fig. 1 & 2) is a one degree-of freedom pneumatic robot, developed in our lab, that enables the assessment of brain activation using functional magnetic resonance imaging (fMRI) during gait-like stepping movements. MARCOS is actuated by two pneumatic cylinders per leg. The arrangement of the knee and foot actuation allows predefined flexion and extension movements in the sagittal plane that resemble on-the-spot stepping. A pneumatic cylinder attached to the knee orthosis can move the knee up and down, while the subject's foot is attached to a second cylinder

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that can render forces at the foot sole to mimic the ground reaction forces. Proportional way valves control the air flow to the knee cylinders. The cylinders attached to the feet are controlled with pressure control valves and a proportional way valve in series. The human-robot reaction forces are measured through force sensors located in the knee and foot attachments, and the position of each cylinder piston is measured redundantly. For more detailed information about the robot design, the reader is referred to [16].

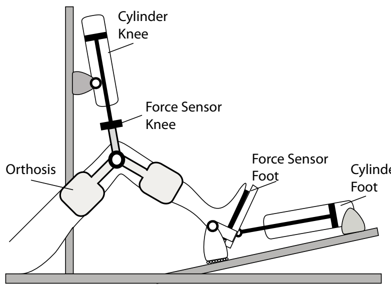

Fig. 1. Sketch of the MARCOS system (only 1 leg depicted for clarity).

B. Training strategies

The experiment consisted in actively tracking a Lissajous figure on the screen (Fig. 2 right) by appropriately coordinating the legs. Subjects trained with three different strategies. The design and evaluation of the training strategies was described in detail in [15], [17]. Here, only a brief summary is given for completeness.

1) No Perturbation: In the no-perturbation strategy, the robot follows the subject's self-selected movement in such a way that the interaction forces between human and robot are minimized. Thus, the robot is compliant and the subject can move without feeling the robot. The control approach for this strategy is a closed-loop force controller, with compensation of the knee orthosis' weight and the dependency of pressure build-up on chamber volume [17].

2) Error Amplification: The robot amplifies the errors generated when trying to follow a desired knee movement. The actuation variable is proportional to the difference between the desired and the measured knee position, i.e. the force generated by the knee cylinder is smaller as smaller is the error and increases with the tracking error. The error-amplification controller works on top of a closed-loop force controller by adding the error-amplification control variable to the control variable from the zero-force controller. We saturated the error-amplification force magnitude to guarantee the subjects' safety and to limit task difficulty.

3) Noise Force Disturbance: A controller that applies random perturbing forces to the knee was designed to test the effect that randomly evoked errors have on motor learning. Every 0.5 seconds, the knee cylinder applies the disturbance as a random magnitude force (between $\pm$ 100 N) that last for 0.1 seconds. Similar to the error-amplification strategy, the noise disturbance works on top of the closed-loop force controller described above.

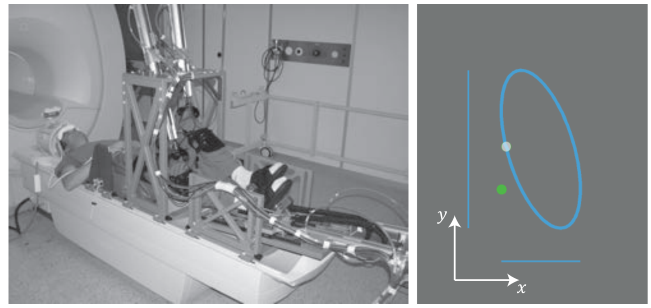

Fig. 2. Left: The fMRI compatible robotic stepping actuator MARCOS [15]. Right: The Lissajous figure to be tracked.

C. Experimental protocol

The study was approved by the local ethical committee. Twenty three healthy right footed subjects (14 male), 26 $\pm$ 3 years old, gave written consent to participate. The study was performed in the MR-Center of University of Zurich. fMRI was used to simultaneously record brain activity; however, these signals are beyond the scope of this paper.

The task was to learn a specific gait-pattern by tracking a white dot that moved on top of a Lissajous figure (Fig. 2). The pattern was achieved by moving the knees up and down following sinusoids of equal frequency (0.5 Hz), but different amplitudes (left leg: 0.16 m; right leg: 0.08 m) and with a diphase between legs of $\pi/3$. The movement of the legs was mapped to the visual display as follows: the up and down movement of the left leg moved up and down a green dot on the display, and the up and down movement of the right leg moved the dot right and left.

Subjects were randomly assigned to three groups (seven subjects in the no-perturbation, and eight in the error-amplification and noise groups). The study started with three trials of 30 s of movement with the robot passively moving the subject's legs in the desired gait-like pattern followed by 10 s of rest, in order to help the subjects to understand the task. During baseline, subjects were instructed to actively track the white dot on the screen during 70 s in no-perturbation mode. Each training session consisted of eight trials of 30 s of movement followed by 10 s rest. The training strategies that amplify or create random errors were applied only to the left leg, while the right leg moved without perturbations. The short term retention test followed the same structure as the baseline. In order to evaluate if transfer of learning occurred, subjects were instructed to follow during 70 s a similar figure but with the right leg performing the largest amplitude, after baseline (baseline-transfer), and after retention (retention-transfer).

D. Data Processing and Statistical Analysis

For each trial, the mean tracking error of the left and right legs was calculated as the mean absolute difference between the measured and desired knee positions. To evaluate whether the error increased during training, the error of the left leg in the first training trial was compared to the baseline error using a paired t-test. To determine whether subjects reduced the error of the left leg during training, a paired t-test between the first and last training trials was performed. ANOVAs were used to compare the error of the left leg between groups at the first and last training trials. To determine whether subjects learned, a paired t-test between baseline and retention was performed. We used a linear mixed model to test the effect that different protocol phases (baseline and retention), training strategies, initial skill level, leg (left or right), and the 3-way interaction between phases, strategies and skill level had on the tracking error. Subjects were divided into two groups, depending on the left leg tracking error during baseline. The cut-off value (0.052 m) allowed the creation of two distinct skill groups, thirteen skilled subjects and ten novices. A t-test evaluated whether the skill groups performed differently during baseline.

Transfer could not be evaluated in four subjects (one in no-perturbation, two in noise, and one in the error-amplification), because data was not correctly recorded. This resulted in an imbalance in the skill level groups. Therefore, transfer was evaluated using a mixed model with the sole main effects of the protocol phases (baseline- and retention-transfer), leg (left or right), and training strategy, and the interaction between phases and training strategies. To determine whether subjects presented transfer of learning, a paired t-test between baseline- and retention-transfer was performed. The significance level was set to 0.05.

III. RESULTS

A. Performance during training with different strategies

We found that the training groups responded differently when training started, as seen in an almost significant different error reduction from baseline to the first training trial between groups (Fig. 3, Left, $p = 0.054$). The error-amplification group significantly increased the left leg error ($p = 0.006$), while subjects in the no-perturbation and noise groups did not show significant differences when training started. We also found that subjects learned to deal with the error-amplification strategy, as seen in a significant error reduction from the first to the last training trial (Fig. 3, Left, $p = 0.021$). In fact, subjects trained with error amplification performed almost significantly worse during the first training trial ($p = 0.053$), but they reduced the error as training progressed and reached the same error level as the other groups by the last training trial. Subjects in the no-perturbation and noise groups did not reduce the errors during training.

B. Effect of training strategy and skill level on learning

All subjects learned to perform the task ($p < 0.001$). Subjects in the skilled group performed significantly better during baseline than novices ($p < 0.001$). We found a significant main effect of skill in the linear mixed model ($p < 0.001$). We also found a significant main effect of the leg side: The error created with the left leg (with larger amplitude) was greater than the error created with the right leg ($p < 0.001$). We did not find a significant effect of the training strategy on the error reduction, i.e. training with the different strategies did not result in different learning

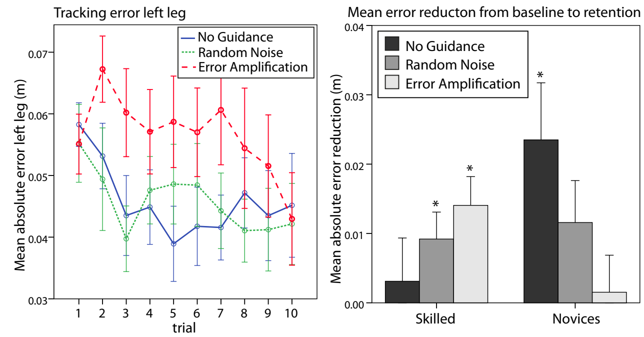

Fig. 3. Left: Left leg tracking error during baseline (trial 1), training (trials 2-9) and retention (trial 10) for the different training groups. Right: Error reduction from baseline to retention. Error bars show +/- 1 SE. $*p < 0.05$.

rates. We found, however, a significant interaction between the training strategy, the initial skill level and the error reduction (Fig. 3, Right $p = 0.004$), i.e. the learning benefit of the training strategies depended on the initial skill level. In particular, no perturbation seemed especially suitable for initially less skilled subjects, while error amplification benefited more skilled subjects. Random noise seemed to enhance learning equally in all subjects.

C. Effect of training strategy on transfer of learning

In general, subjects transfer the learning to the untrained task, i.e. they significantly reduced the errors from baseline- to retention-transfer ($p < 0.001$). Results from the linear mixed model showed a significant main effect of leg side ($p < 0.001$). Contrast revealed that the error created with the right leg (with larger amplitude during transfer) was greater than the error created with the left leg ($p < 0.001$). We found a trend on the effect of the training strategy on the error reduction from baseline- to retention-transfer (Fig. 4, $p = 0.150$). Contrast revealed that subjects trained with error amplification tend to reduce the errors by a smaller amount than subjects in the no-perturbation and noise group ($p = 0.057$). In fact, training with error-amplification did not reduce the error in the transfer task, while subjects trained without perturbations ($p = 0.044$) and noise ($p = 0.016$) significantly reduced the errors. A possible reason for the lack of transfer in the error-amplification group could be their reduced initial baseline-transfer error (Fig. 4). Subjects in the error-amplification seemed to perform better during baseline-transfer than subjects in the other training groups. However, the differences between groups were not significant ($p = 0.320$).

IV. DISCUSSION & CONCLUSIONS

Error-amplification was the most difficult training strategy, as suggested by the highest tracking error during training. However, we did not find significant differences in the tracking error between the noise and no-perturbation groups. The noise disturbance had the effect of a short and fast change in the movement's smoothness [15], and thereby perhaps due to the short time that the force was applied the mean tracking error did not increase significantly. Subjects

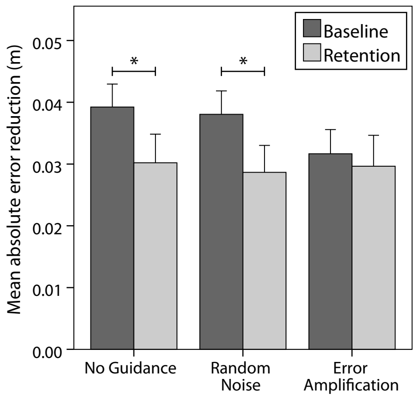

Fig. 4. Tracking error during baseline-transfer and retention-transfer for different training groups.Error bars show +/- 1 SE. $*p < 0.05$.

adapted to the error-amplification strategy during training. Adaptation was expected, since research on motor learning suggests the formation of an internal model when training under error-amplification strategies [6]. Subjects did not adapt to noise disturbance. This finding was also expected, since the disturbing forces were random and an anticipatory model formation was not possible.

Research in motor learning has stated that optimal learning is achieved when the difficulty of the task is appropriate for the individual participants level of expertise [12]. Thus, we hypothesized that training with challenge-based strategies would result in better motor learning in initially more skilled subjects. Results confirmed our hypothesis: the effect of the training strategies on motor learning depended on the subjects' initial skills. Novices benefited more from training without perturbations, while initially more skilled subjects greatly benefited from the amplification of the tracking errors. This finding is in line with recent studies [11]. Error amplification limited learning in novices, perhaps because it made the task too demanding and frustrating. On the other hand, error-amplification seemed to optimally challenge skilled subjects, ultimately boosting learning.

Random noise seemed to benefit learning equally to both skill-based groups, even if the noise force disturbance did not increase the mean tracking error during training. A possible rationale for the positive effect of noise is that subjects could not anticipate the disturbing force, and thus they remained concentrated during training, even if the locomotion task was quite simple for more skilled subjects. The noise strategy was independent of the subjects' performance, thereby it increased subjects awareness and attention when performing the locomotion task, independently of their initial skill level.

We confirmed our hypothesis that the initial skill level plays an important role in the selection of the best training strategy that benefits motor learning of a complex locomotor task. We found, however, that error amplification may limit transfer of learning, while noise disturbance seemed to enhance learning, and transfered the learning gains to similar tasks.

Motor adaptation in healthy subjects has been suggested to have similarities to motor learning in patients [14]. If this is also applicable to the strategies investigated in this study can nevertheless not be assured. Further studies with neurological patients need to be performed.

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