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Forces that Supplement Visuomotor Learning: A "Sensory Crossover" Experiment

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Abstract

Previous studies on reaching movements have shown that people can adapt to either visuomotor (e.g., prism glasses) or mechanical distortions (e.g., force fields) through repetitive practice. Recent work has shown that adaptation to one type of distortion might have implications on learning the other type, suggesting that neural resources are common to both kinematic and kinetic adaptation. This study investigated whether training with a novel force field might benefit the learning of a visual distortion – specifically, when forces were designed to produce aftereffects that aligned with the ideal trajectory for a visual rotation. Participants training with these forces (Force Group) were tested on a visual rotation. After training with this novel field, we found that participants had surprisingly good performance in the visual rotation condition, comparable to a group that trained on the visual rotation directly. A third group tested the rate of learning with intermittent catch trials, where we zeroed the forces and switched to the visual rotation, and found a significantly faster learning rate than the group that trained directly on the visual rotation. Interestingly, these abilities continued to significantly improve one day later, whereas the direct training showed no such effect. All participants were able to generalize what they learned to unpracticed movement directions. We speculate that when forces are used in training, haptic feedback can have a substantial influence on learning a task that heavily relies on visual feedback. Such methods can impact any situation where one might add robotic forces to the training process.

Index Terms

Customization; Force Feedback; Learning

I. Introduction

IN the fields of haptics, telerobotics, and rehabilitation, sensory-motor information is often challenged or distorted, creating demand for training methods to improve performance. Many studies have demonstrated the ability to adapt to visual distortions such as prisms, visual feedback rotations and stretches [1, 2] as well as haptic disturbances such as robot-applied force fields [3–5]. Following adaptation, if visual or haptic distortions are unexpectedly removed, evidence of learning is seen in the form of *aftereffects*, where trajectories are reflective of the distorted condition [6]. One prospect of these phenomena is there may be ways to exploit them to enhance or otherwise alter learning.

While it is generally agreed that adaptation is due to the formation and updating of internal models in the CNS, there has been a long-standing debate whether the neural resources for adapting to visual and haptic distortions are the same. Several studies have tested possible interference effects caused by adapting to multiple novel environments simultaneously. Brashers-Krug, Shadmehr, & Bizzi (1996) showed evidence of retrograde interference where learning of one force field disrupted the retention of a previously learned force field [7]. Krakauer et al. (1999) suggested that tasks should only interfere if they compete for the same neural resources; hence, kinematic and dynamic movement errors were stored and processed separately in working memory. They found that participants learning a visual rotation were not affected by simultaneously learning an inertial load [8]. Flanagan et al. (1999) showed that when participants adapt to a visuomotor rotation and viscous curl field separately, they had greater performance in a combined transformation, but only saw transfer effects subsequently on the visuomotor rotation condition [9]. They suggested that the lack of interference between conditions was due to the formation of two distinct internal models. Tong et al. (2002) later argued interference only occurs when both distortions are based on the same state, hence, interference was observed when both the force field and the visuomotor rotation depended on position [10]. Sing and Smith (2010) found that participants that trained with a velocity-dependent force field and then a field of opposite direction had decreased performance (slower learning rate) with the second task [11]. These results, though not in congruence, suggest that adaptation to kinetic and kinematic distortions occupy similar neural resources in working motor memory.

While many of these previous studies show how mechanisms of adaptation associated with visual and haptic distortions might interfere with one another, we propose that our knowledge about such shared neural resources can also be used constructively to facilitate training. Furthermore, we hypothesize that it is possible to capitalize on the phenomenon of aftereffects and create *positive interference* where aftereffects from force field adaptation causes subjects to perform better with a visual rotation. In a previous study, it was shown that aftereffects could be manipulated with specific training; Patton & Mussa-Ivaldi (2004) were able to “teach” subjects how to move in a curved trajectory by determining the magnitude of force needed to perturb subjects from a straight-line [12]. Although training with forces to learn a visual distortion appears to be an indirect way of learning, we propose that by adding forces to the training procedure, we can capitalize on more sensory inputs (e.g. the cutaneous pressure sensors of the hand, combined with the proprioceptive force and stretch sensors in the muscles) and improve adaptation. Previous work from our lab has shown promising results when testing this idea of “sensory crossover,” where adaptation to a specialized force field improved the learning of a visual rotation [13].

This paper presents a multi-day experiment that further tested how force field training could facilitate the learning of a visual rotation. Through iteration, forces were specially designed to result in aftereffects that aligned with the “desired” trajectory of the hand for a 30° visual rotation. Three groups of subjects were tested; one group of subjects trained directly on a visual rotation (Visual Rotation Group), one group trained with a customized force field

(Force Group), and the third group of subjects trained with a customized force field with intermittent visual rotation trials (Mixed Group).

II. Methods

A. Apparatus

The planar robotic manipulandum (Fig. 1A) used for the experiment consisted of two brushed DC torque motors (PMI model JR24M4CH, Kolmorgen Motion Technologies, NY, USA) that control forces at a handle via a 4 bar linkage. Rotational digital encoders (model 25/045-NB17-TA-PPA-QAR1S, Teledyne-Gurley, Troy, NY, USA) reported absolute angular position, and a 6-axis force/torque sensor (Assurance Technologies, Inc., TI F/T Gamma 30/10, and Apex, NC, USA) reported the interface kinetics. A personal computer (PC) acquired the signals and controlled torques. Force and position data were collected and controlled at 100 Hz. A calibrated LCD projector was used to display the position of the robot handle and targets on a horizontal plane in front of the subject, which obscured the view of the actual limb and robot. A passive lightweight arm support was positioned under the elbow to support the weight of the arm.

B. Subjects

Thirty healthy right-handed participants (14 females) with a mean age of 25 (±3) and no history of neural or arm injury were recruited and tested at the Rehabilitation Institute of Chicago (RIC). All participants provided informed consent in accordance with Northwestern University Institutional Review Board. Participants were randomly and equally assigned to one of three groups – Force Group, Visual Rotation Group, and Mixed Group.

C. Experimental protocol

Participants moved the manipulandum handle on a horizontal plane at shoulder level from a central starting point to one of three possible targets in the plane 10 centimeters away (shown in Fig. 1A). A second set of targets, called “unpracticed targets”, were presented 30° clockwise from the main target set and used to test generalization. A new target was presented after the subjects moved the handle inside the starting point for 0.5 seconds, targets were presented in a random order so that the subjects could not predict the subsequent target. Participants were instructed to make center-out movements to the target and velocity feedback was given at the completion of each movement. The color of the target indicated if the movement was either too fast (red), too slow (yellow), or just right (green, between 0.3 and 0.4 meters/second). Subjects were allowed to rest before initiating any movement after they had terminated at the target. For movements with visual rotation, the entire visual scene was rotated 30° counterclockwise about the starting point, so that the cursor only truthfully matched the actual position at the origin of each reach (Fig. 1B). The experimental phases were:

1. **Baseline**: 30 movements without force or visual distortion (null field) for subjects to get familiar with the movements.
2. **Robot-learning**: 300 movements with the robot-learning algorithm applying forces one in every four movements. Forces iteratively “grew” until the desired

trajectory was achieved following the previously developed algorithm [12], described in more detail below.

3. **Intermittent Exposure to the Visual Rotation**: 240 movements, with a 30° visual feedback rotation intermittently introduced once every seven movements randomly. These movements assessed the initial errors in response to the visual distortion. The latter 120 movements were tested on a new target set ("generalization" targets).

4. Training:

   - Force Group: 240 movements with force field determined during adaptive-learning phase applied in the negative y-direction. Catch trials of null field were randomly distributed one in seven trials.

   - Visual Rotation Group: 240 movements with a 30° visual rotation. Catch trials in a null field condition were randomly distributed one in seven trials.

   - Mixed Group: 240 movements with force field determined during the adaptive-learning phase. Catch trials of a 30° visual rotation were randomly distributed one in seven trials.

5. **Visual Rotation Test**: 30 movements to test how subjects responded to visual rotation in the training directions after training. For the Visual Rotation Group, this phase is just a redundant training phase. However, for the Force and Mixed Group, this phase tested the continuity of the learning of visual distortion when switched from force field training. The latter 15 movements were on the generalization target directions.

6. **Visual Rotation Test – Day 2**: 30 movements to test how subjects responded to visual rotation 24 hours after training. The latter 15 movements were on the unpracticed target directions to test for the subjects' ability to transfer (or generalize) their learning to unpracticed directions.

7. **Washout – Day 2**: 30 movements without force or visual distortion (null field).

These 7 phases totaled 900 movements for all subjects. Note that Phase 4 was the only phase that differed amongst the three subject groups.

D. Robot-learning – Adaptive force field design

During the robot-learning phase of the experiment, training forces were custom designed to shift a subject's movement,, $x(t)$, to align with the ultimate trajectory we sought (rotated 30° clockwise), $x_D(t)$. These training forces, initially set to 0 N, were applied intermittently (average of once every 4 movements, randomly presented) and adjusted based on the subject's responses. Specifically, for each trial iteration, i, a force $F_{D_i}(t)$ was applied to the robot handle in the first 200 milliseconds of the movement using the rule previously devolved [12, 13]:

$$F_{D_i}(t) = F_{D_{i-1}}(t) + \mu(x(t) - x_D(t))_i \quad (1)$$

where the learning rate, μ, functioned in the range of 10–30 N/m. When the value of μ was large, forces became unstable and were impossible to learn, whereas a small μ requires a lengthy adaptive-learning phase. We heuristically determined μ to be 26 N/m. As the robot-learning phase progressed, subjects' reaches began to align with the trajectory that would occur under a 30° clockwise visual rotation (Fig. 2, Phase 2). The direction of the force field calculated at the end of the robot-learning phase was reflected over the straight line path during training for the Force and Mixed Group (example in Fig. 1C), so that the after-effects following adaptation (and not the force field itself) would then align with the ideal trajectory. Training forces were calculated for all participants in all groups. The frequency of force trials was based on previous implementations of this approach [4, 12, 13]. Pilot tests were used to ensure that there was adequate iteration for the forces to converge on the solution for each movement direction.

E. Data analysis

Our chosen measure of error was the *initial direction error*, commonly used in motor adaptation studies. It was defined as the angle between the cursor and start position to the straight-line path to the target measured 100 milliseconds after movement onset. We defined positive error to correspond to a counter-clockwise rotation from the actual trajectory to the desired trajectory.

To test our hypothesis that learning would be enhanced for subjects in the Mixed Group (experiencing "sensory crossover") as compared to the Visual Rotation Group, a best-fit exponential model determined the amount and rate of learning during training:

$$E_i = Ae^{-\frac{i}{B}} + C \quad (2)$$

where E is the trajectory error for the trial i during training, A is the amount of learning, B is the time constant indicating the number of trials for the error to decrease 67% of the way to asymptote, and C is the asymptotic (steady-state) error value.

The exponential regression was performed on the visual rotation catch trials of the Mixed Group and trials for the Visual Rotation Group (experiencing the visual rotation condition) at corresponding trials during training. This allowed us to test how force field training transferred to the visual rotation condition even when learning was complete. Separate regressions were also performed to determine if results depended on movement direction. Note that the time constant for the Force Group unfortunately could not be obtained since they received null field trials as catch trials. We instead used the catch trials from the Force Group to measure how their after-effects aligned with the ideal visual rotation trajectory.

The amount of learning, or error change, was measured by the difference between each participant's initial exposure to the visual rotation (Phase 3 – Intermittent Exposure) and errors immediately following training (Phase 5 – Visual Rotation Test). Generalization was measured by comparing the errors during intermittent exposure to visual rotation on unpracticed targets to the final errors on unpracticed targets (the last 15 movements of the Visual Rotation Test and Visual Rotation Test-Day 2). Three statistical tests were performed across groups to evaluate the rate of learning, amount of learning, and transfer to unpracticed targets (generalization). A repeated measures ANOVA tested group differences, and post-hoc pairwise comparisons evaluated pairwise differences corrected using the Bonferroni-Holm method. Significance was declared at the alpha level of 0.05.

III. Results

All subjects showed evidence of learning the visual rotation despite the type of training. Initial values of error did not significantly differ across groups. We found that training with forces to learn a visual rotation achieved comparable error reduction than repetitive practice and improved performance on the following day. Similar to what was previously found in Wei and Patton (2004), the Mixed Group had a faster rate of error reduction during training —10 ± 4 trials, compared to 18 ± 8 trials ($p = 0.0352$; Fig. 3). Following training, the Force and Visual Rotation Groups had comparable change in error from intermittent exposure ($\Delta = -16.6 \pm 1.6$ and $\Delta = -18 \pm 1.9$ degrees respectively, see Fig. 4A), while the Mixed Group decreased error by -13.7 ± 3.7 ($p = 0.008$). Final error was significantly greater for the Mixed Group compared to the Visual Rotation Group ($p < 0.001$; Fig. 4A).

The effect of force field training on learning a visual rotation persisted beyond the immediate evaluation *(Phase 5 -Visual Rotation Test – Phase 5)* (Fig. 4A). The follow-up evaluation on Day 2 (*Phase 6 - Visual Rotation Test – Day 2*) showed additional benefit to force training: the Force and Mixed Groups showed significant change from the previous day (Δerror = 4.9 ± 4.0 and Δerror = −7.4 ± 2.9 degrees). The Visual Group did not change between days (Δ0.5 ± 1.2), and some participants even showed increased error. However, group differences were significant between the Force and Visual Rotation Groups ($p = 0.01$) and the Mixed and Visual Rotation Groups ($p = 0.001$).

All groups showed similar improvement on the unpracticed (generalization) target directions before *(Phase 3 – Intermittent exposure)* and after training *(Phase 5 – Visual Rotation Test)* where Δerror = −14.7 ± 1.9 degrees for the Force Group, Δerror = −15.9 ± 2.0 for the Visual Rotation Group, and Δerror = −11.3 ± 4.0 degrees for the Mixed Group (Fig 4B). The change in error on Day 2 was also similar across groups: Δerror = −5.4 ± 1.0 degrees for the Force Group, Δerror = −4.0 ± 3.9 degrees for the Visual Rotation Group, and Δerror = −4.2 ± 3.9 degrees for the Mixed Group. Final errors on Day 2 differed between the Force and Mixed Group ($p = 0.01$).

There also was evidence that force field training relied on feedforward learning. Feedforward learning is generally associated with the size of aftereffects observed after force adaptation, when forces are unexpectedly turned off. Catch trials for the Force Group during learning revealed that error magnitudes were correlated with the final error in the visual rotation condition (Fig. 5), where $r=0.423$ and $p = 0.015$.

IV. Discussion

This study demonstrated how training with forces might be used to facilitate learning of a purely kinematic transformation – a visual rotation. This was accomplished by specially designing training forces so that the resulting aftereffects aligned with the ideal trajectory for the visually rotated condition. These results reveal a new strategy for robotic training where alternative sensory modalities can contribute to learning, which we term sensory crossover. Trajectory errors during training decreased for all groups, however, when comparing catch trials during training we found that the Mixed Group reduced error more quickly than the control that practiced the visual rotation directly (Visual Rotation Group). While we expected the aftereffects of learning with forces to be beneficial for a visual rotation, it was surprising that it resulted in a similar error change for the Force Group than with repetitive practice. A second aspect of learning often associated with this paradigm, transfer (or generalization) to unpracticed motion directions, was found to be comparable across groups (i.e. no significant difference in the ability of subjects to transfer (or generalize) their learning to rotated targets). Finally, we were able to see that the amount of force field learning directly contributed to transfer for the visually rotated condition – after-effects correlated with errors in the visually rotated condition.

Similar to what was previously found in Wei & Patton [13], force training led to improvements in performance beyond repetitive practice of the visual rotation for both subjects in the Force Group (amount of learning) and the Mixed Group (time constant of error reduction). We saw that when subjects in the Force and Mixed Group returned 24 hours after testing, they continued to improve, indicating that the full benefits of training might not be evident immediately after training. Previous studies have shown that retention of a force-field persists and can even be successfully recalled up to five months later [7]. While error continued to decrease on the second day, the final error for all three groups still did not reach baseline levels, indicating that training was incomplete. Future iterations of this experiment might use catch trials to test if adaptation is complete (as indicated by the evidence in Fig 5), and adjust the length of training accordingly. This test could be performed either using null field catch trials as was done with the Force Group or using visual rotation catch trials as was done with the Mixed Group.

This adaptive training study further demonstrates the ability to *design aftereffects*, and shows how such after-effects can persist when they are suddenly perceived as appropriate for a new task (operating in the presence of a visual distortion). Previous studies have shown that aftereffects can persist for around 385 trials if visual feedback is removed [12]. Our results indicated that it is possible to retain an aftereffect if subjects found their performance to be successful – perhaps if they saw their large movement errors immediately after training they would quickly washout to their original straight-line reaching patterns. The adaptive design of the force field used in training also ensures that the after-effects will produce appropriate arm dynamics for the desired movement. One might also entertain a “force channel” approach that teaches participants the desired arm kinematics, however, previous studies have shown that reaching in a force channel does that facilitate learning to the same extent as learning a dynamic force field and would not facilitate similar after-effects [14, 15]. In this case, de-adaptation (i.e., washout) from the learned force field may have been influenced by visual distortions. This persistence of the aftereffects is an important question in the areas of robotic teaching and robotic neurorehabilitation.

This study explored the idea of sensory crossover, where haptic forces were used to learn a kinetic transformation, as a technique to improve learning. Tong and colleagues [10] originally argued that adaptation to kinetic and kinematic visuomotor rotations interfere with the ability to learn since they occupy common neural resources in motor working memory. We tested their hypothesis with adaptation tasks that are complimentary, demonstrating a constructive facilitation of learning. The Mixed Group in our study was able to switch from one context (force) to the other (visual rotation) without any observable loss of performance or sudden spikes in trajectory error. Their performance, however, showed the least improvement of the three groups in terms of change in error magnitude, possibly indicating a more subtle effect of the multiple training environments. Similar to Tong et al., we tested subjects 24 hours later, i.e. when an aftereffect was no longer expected to be present but after motor memory consolidation is presumed to have been complete [7, 16, 17]. While Tong et al. observed interference a day later, we were still able to see a positive effect a day after training, when the immediate benefits of aftereffects have long-since decayed away. This suggests that the learning process, not the motor learning consolidation process, was shared for both kinematic and kinetic adaptations.

Essentially, this constructive interference is an example of “priming”, where subjects unknowingly perform better in a new environment. Our analysis of catch trials during force field training (Fig. 5) provided further evidence that force field training primed the participant to perform better in a visual rotation condition. Catch trials during training that were more aligned with the ideal trajectory for the visually rotated condition were predictive of lower final errors in the visual rotation condition following training (Fig. 5). Response priming, when exposure to one experience influences the responses under other conditions, has been shown to be quite useful in a number of applications of human performance and learning [18, 19] and retraining of human ability after brain injury [20]. Catch trials also have the ability to slow down or interfere with learning - in the case of the Visual Rotation Group, null field catch trials can briefly interfere, while for the mixed group, catch trials in the VR condition could either offer an opportunity for priming for visual rotation or make it more difficult to adapt to the force. By “tricking” the nervous system into unknowingly performing correctly, participants had comparable and perhaps better performance, retention, and ability to generalize to unpracticed directions.

Our results may also be due in part to a shifting of sensory modalities and use of feedback from haptic sensors. Some researchers have shown that different movement features are learned at different rates (i.e., time constants) [21–23]. For example, time-related features such as movement duration changed faster during learning than magnitude-related features such as peak velocity. The altered learning environment presented to the subjects in this study may cause them to shift their attention or notice errors more easily, resulting in the observed improvement in learning rate for the Mixed Group. The more quickly learned features become more critical to the task so that learning is accelerated. The seamless transition from one sensory training mode to another means that there appears to be another interesting tool to add to the arsenal of possible robotic training techniques.

Regardless of the underlying mechanisms, this work demonstrates certain prospects for motor training (and retraining). Further tests are needed, but one can imagine the utility of custom designed forces for providing a new way to teach transformations in areas such as sports performance, pilot training, surgical maneuvers, musical acts, and neurorehabilitation. However, it remains to be seen whether such work can also be effective in full body actions, in fine motor skills, in three-dimensional activities, or in the recovery from neuropathologies. In any case, such sensory crossover methods appear to be a viable method for either supplementing or completely replacing the training in some contexts.

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Biographies

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Dr. Patton is a member of the IEEE Robotics and Automation and Engineering in Medicine Biology Societies, as well as the Society for Neuroscience. He is the Editor of the proceedings of the IEEE-EMBC conference. He is also an Associate Editor and reviewer of the IEEE Transactions On Biomedical Engineering. He also reviews for the IEEE Engineering in Medicine Biology Magazine, the IEEE Transactions On Robotics and Automation, and the IEEE Transactions On Neural Systems and Rehabilitation Engineering.

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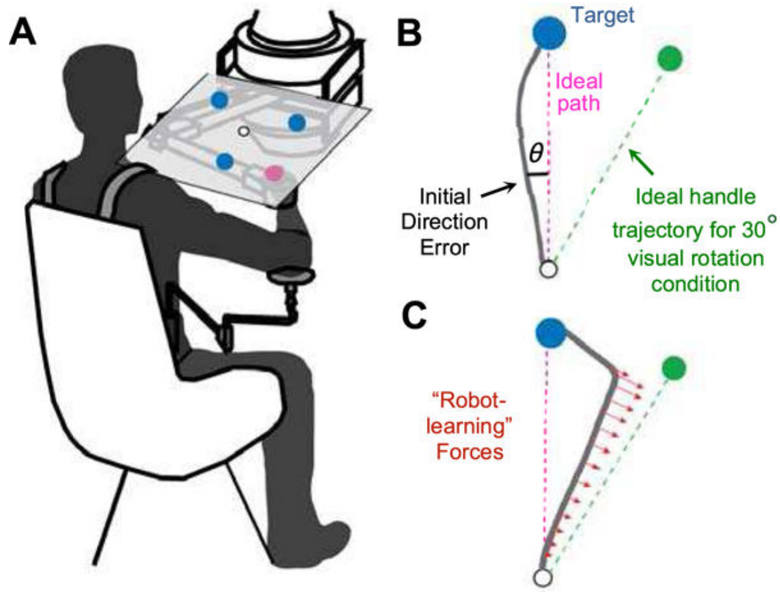

Fig. 1.

Experimental setup: (A) Participant moves a robot handle to one of three target locations (blue dots) projected on a horizontal feedback display. (B) Visualization of trajectory error calculation *(initial direction error)* based on subject handle position (gray line). Green dotted line denotes the ideal handle path when participant experiences a 30° clockwise visual rotation. (C) During the *Robot-learning phase*, forces are adjusted iteratively until the participant reaches along the desired trajectory for a 30° clockwise visual rotation.

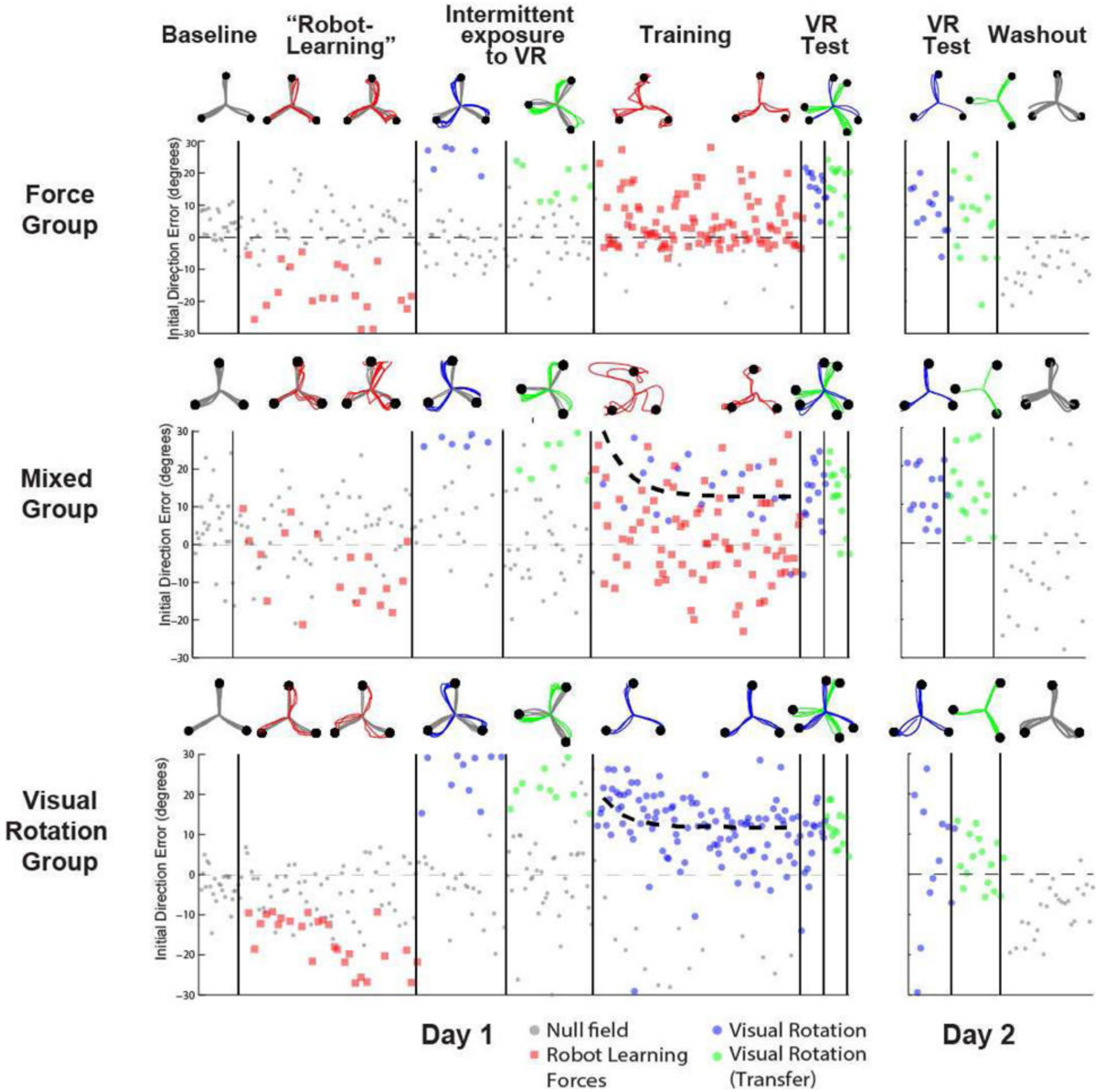

Fig. 2.

Handle trajectories and resulting initial direction error across all trials for representative subjects from the (A) Force Group, (B) Mixed Group, and (C) Visual Rotation Group. All subjects experienced the same conditions except for during the training phase, where the Force Group trained with forces and null field probe trials, the Mixed Group trained with forces and visual rotation probe trials, and the Visual Rotation Group trained with visual rotation and null field probe trials. Exponential regressions were fit to probe trials (black dashed line) during training for the Mixed and Visual Rotation Groups to determine learning rate.

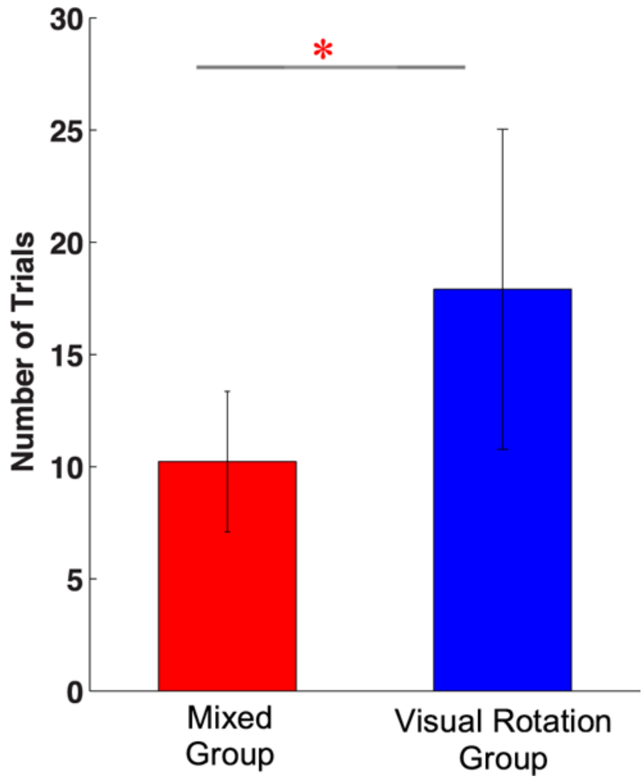

Fig. 3.

Time constant of error reduction during training (Phase 4) is faster (lower number of trials) for the Mixed Group than for the Visual Rotation Group. This analysis used a best fit exponential for each subject, and only considered the catch trials, where the Mixed Group participants intermittently were unexpectedly switched to the visual rotation condition (34 times, randomly distributed). We compared these errors with that our control group (Visual Rotation Group, experiencing the visual rotation) at similar trial numbers. While results varied across participants, the time constant (number of trials for error to decrease by 67%) was lower for the Mixed Group (10±4 trials) indicate group 95% confidence intervals.

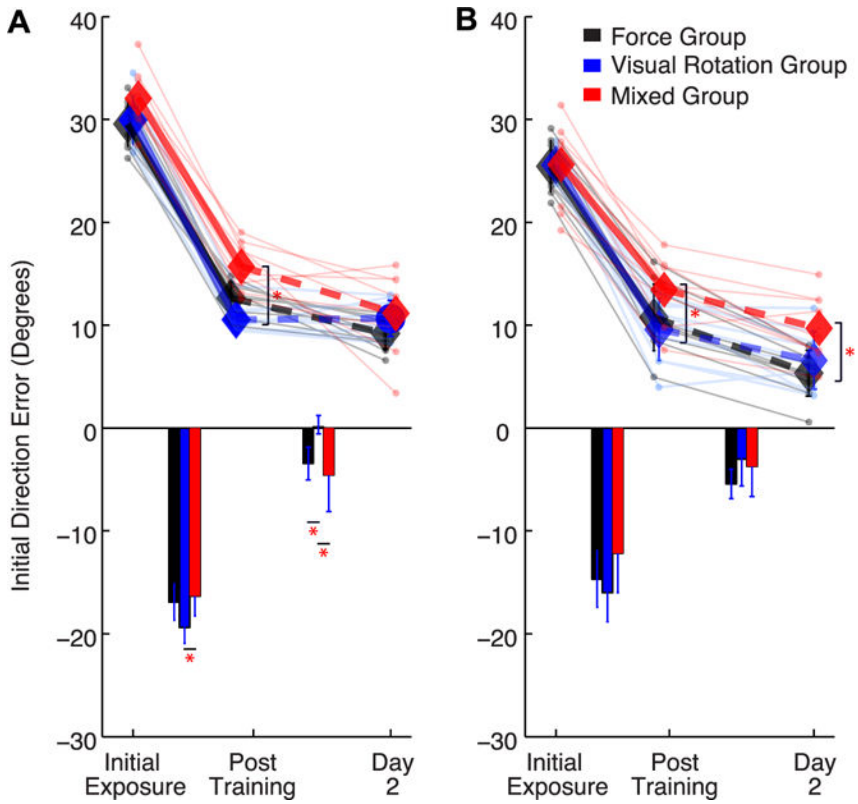

Fig. 4.

Change in initial direction error following training *(Visual Rotation Test)* and 24 hours post training (*Visual Rotation Test – Day 2*) for (A) practiced targets and (B) unpracticed (generalization) targets. Each participant's mean error and change between is shown with transparent circles and lines. The mean error is shown above (diamonds) and mean error change is shown below (bars with 95% confidence wings); negative values indicating a reduction in error. Following training, there the Visual Rotation Group had significantly lower error then the Mixed Group ($p < 0.001$) and change between from pre- to post-training was larger for the Visual Rotation Group than the Mixed Group. Between Day 1 and Day 2, the Mixed and Force Group shown additional improvement beyond the Visual Rotation Group ($p = 0.01$ and $p = 0.001$ respectively). Training had a similar effect on unpracticed targets. The Mixed Group had larger error than the Force Group immediately following training and on Day 2 ($p = 0.01$).

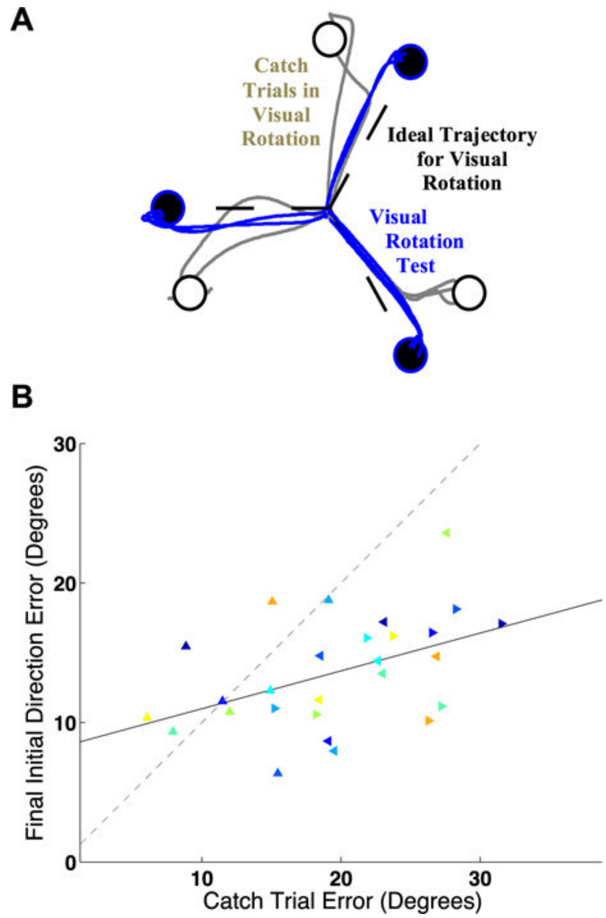

Fig. 5.

Catch trial performance predicts transfer to the visual rotation condition for the Force Group subjects. (A) Catch trials (gray lines) during training (Phase 5) from a Force Group subject show how after-effects begin to align with the ideal trajectory for a visual rotation (black dashed line). Test trials in the visually rotated condition (Phase 6) are shown in blue. (B) Subjects with lower catch trial error performed better in the visual rotation test condition ($r = 0.423$, $p = 0.015$). Each triangle represents one target direction for subjects in the Force Group.