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Force Field Training to Facilitate Learning Visual Distortions: A "Sensory Crossover" Experiment

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Abstract

Previous studies on reaching movements have shown that people can adapt to distortions that are either visuomotor (e.g., prism glasses) or mechanical (e.g., force fields) through repetitive training. Other work has shown that these two types of adaptation may share similar neural resources. One effective test of this sharing hypothesis would be to show that one could teach one using the other. This study investigated whether training with a specialized force field could benefit the learning of a visual distortion. Two groups of subjects volunteered to participate in this study. One group of subjects trained directly on a visual rotation. The other group of subjects trained in a "mixed field" condition. The mixed field was primarily a force field that was specially designed so that, after adapting to its characteristics, the subject would make the appropriate movement in the visual rotation condition. The mixed field condition also contained intermittent test movements that evaluated performance in the visual rotation condition. Results showed that if anything, errors reduced more rapidly in the mixed field condition. We also found that subjects were able to generalize what they learned to movement directions that were not part of the training, but there was no detectable difference between the two groups. Finally, we found no difference in the rate these training effects washed out after subjects returned to normal conditions. This study shows that training with robotic forces can facilitate the learning of visual rotations. The learning may be enhanced in the mixed condition by the addition of cutaneous and proprioceptive force sensors. Moreover, this study can be applied to telerobotics and the rehabilitation of brain injured individuals, where there is often a distortion in hand-eye coordination.

1. Introduction

In order to contend with the visual distortions often observed between movements of the hand and movements of a slave robot, one must practice and adapt to the distortion. One question is whether one can enhance the learning process by exploiting what is known about sensory-motor adaptation.

Because of transmission delays in the nervous system, rapid movements must be pre-planned using an "expectation" or "neural representation" of the outcome [4] that is typically acquired through repeated experience. Research has shown that these internal models can be altered by distorting sensory-motor relationships in a variety of ways. Force fields (forces governed by position and velocity, such as those imposed by a weight, damping, or other governing principle) cause a dramatic change in the movement patterns. One simple example is adaptation to a hand held mass, which occurs within a single motion [1]. More complex loads can take hundreds of movements [2, 3, 4]. This adaptation process is most evident when forces are unexpectedly removed, revealing *after-effects*. After-effects demonstrate that subjects have learned a neural representation of the force field, rather than simply "stiffening" their system to reject the disturbances. It is important to note that both the adaptation and after-effects occur implicitly with minimal conscious attention.

Such techniques for robotic teaching have already been demonstrated. To capitalize on the adaptive phenomenon, forces must be appropriately designed so that a desirable after-effect results from training [5]. The field design problem can be solved using subject-specific models of the biomechanics and neuro-adaptive controller of the arm [5] or, more simply, by determining the necessary forces to shift the arm to the trajectory and training with its inverse [6]. Following the removal of the training forces, the subject's movement is shifted to the "desired" trajectory. An interesting feature of this process is that the desired trajectory is never explicitly revealed to the subject.

Researchers have also observed similar adaptation due to a more easily implemented visuomotor distortion (kinematics). These involve exotic transformations using prisms [7], nonlinear mappings [8], or simple rotations or stretches [9, 10].

There has been a recent debate over whether adaptation to kinetic or kinematic distortions uses the same neural resources. Some have suggested that learning of kinematic (a 30 degree rotation) and kinetic (added mass) distortions were independent processes because there was no interference that is normally seen when training in just kinematic or kinetic alone [12]. Instead, they found that learning a visuomotor rotation was not affected by adaptation to an inertial load presented either simultaneously or 5 minutes later. Flanagan and colleagues also showed similar results with a visuomotor rotation and a viscous force field [13]. However, Tong and colleagues argued that these studies should not show interference because the kinetic and kinematic distortions involved different variables. They demonstrated that when both the force field and the visuomotor rotation depended on position, interference was observed. These results suggested that kinetic and kinematic adaptation occupy common neural resources in motor working memory.

The focus of our study is to subject this claim to more strenuous test and see if one can *exploit* the inter-dependence between kinematic and kinetic adaptation. If the two forms of adaptation use common neural resources, one could use one to facilitate the other, and a switch from one to the other should be seamless. Moreover, learning may be enhanced by experiencing a mix of force and visual distortions.

One might think that using forces to teach a kinematic distortion is an indirect way of learning – learning a visuomotor distortion should be learned best when directly exposed to it. However, the addition of forces may capitalize on more sensory inputs – the cutaneous pressure sensors of the hand combined with the proprioceptive force and stretch sensors in the muscles. Because our recently developed algorithm [6] can design the training forces that result in a desired movement, we hypothesize that learning a visuomotor distortion may be best learned by using forces. Moreover, a mix of force- and vision-training may be optimal.

In this paper, we perform a preliminary test of whether learning of a visual distortion can be facilitated by appropriately designed forces. Half the subjects adapted directly to a visuomotor rotation and the other half adapted to a "mixed" condition where they were exposed to specially designed force field and intermittently switched to the visuomotor rotation. Our results show that people can benefit from forces that are designed to facilitate learning.

2. Methods

Aparatus. The planar robotic manipulandum 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) report absolute angular position, and a 6-axis force/torque sensor (Assurance Technologies, Inc., TI F/T Gamma 30/10, Apex, NC, USA) reports the interface kinetics. A PC acquires the signals and controls torque.

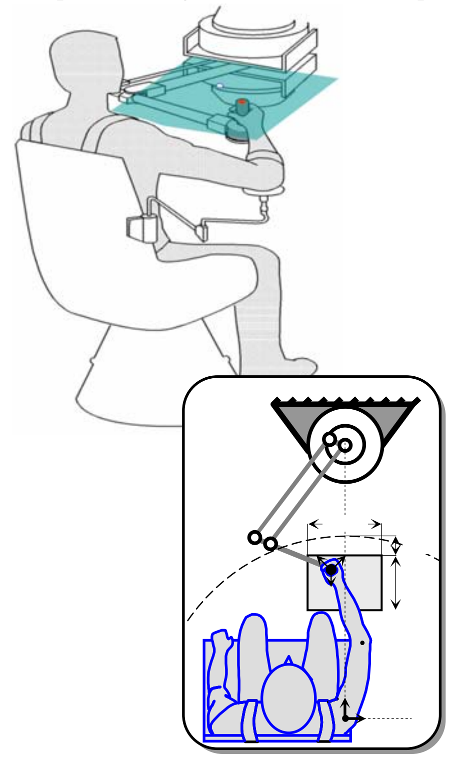

Figure 1. Experimental Setup

Force and position data was collected and controlled at 100 Hz.

Visual Rotation. The planar robotic manipulandum displays a cursor and targets on a plane directly above the arm, obscuring the view of the limb (Figure 1). On certain movements, the visual display was rotated 30° so that the position was truthful only at the starting point.

Force Field Design. As explained in [6], a force field can be designed to train subjects to adapt to a designed trajectory using an iterative machine-learning algorithm. In the machine-learning phase, a force field could is determined that shifts a subject's movement to the desired trajectory by repeatedly testing the response of the subject to an increasing force. For each step *i*, a force $F_{D_i}(t)$ is applied to the robot handle in the first 200 ms of the movement, where $F_{D_1}(t) = 0$, and $F_{D_i}(t)$ are incrementally adjusted from one movement to the next based on the displacement between the handle trajectory, $x(t)$, and the desired trajectory, $x_D(t)$, in the previous movement as:

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

where the parameter μ is a learning rate, which has been found to work in the range of 10-30 Nm^{-1}. A μ that is too large leads to unstable learning, and a μ that is too small results in a lengthy machine learning session. We heuristically determined μ=26 Nm^{-1}. The forces are then reversed and applied persistently during the training session to induce an adaptation.

Protocol. Subjects moved handle of a two-degree freedom (shown in Figure 1 described in [6]) on a horizontal plane at shoulder level from a central starting point to a series of three peripheral targets displayed on the plate. The subjects were instructed to center-out movements to the target. After a 0.5s pause, they were cued to move back to the center point for the next movement. To avoid fatigue, subjects could choose to rest before initiating any movement. Subjects' trunks were restrained from moving with backpack straps on the chair, and their forearms were supported by a passive lightweight linkage (Figure 1). In all experiments, the target set consisted of 3 points spread evenly at 0.1m distance from the center starting point. Targets were presented once the subject moved the handle inside the target point in a random order so that the subjects could not predict the next target point. We controlled for speed by providing a tone after the completion of each movement, indicating that the movement was either too fast (high pitch), too slow (low pitch), or just right (medium pitch, between 0.3 and 0.4 m/s). Force and position data was collected and controlled at 100 Hz.

Two groups of 7 subjects each (age 22-30; 9 males, 5 females) volunteered and were consented using Northwestern University guidelines. The Visual Group trained only on visual distortion while the Mixed Group trained on primarily forces, but visual distortion movements were intermittently placed (randomly distributed about once in every 5) in order to measure the progress of learning. Since it was believed that the subjects learning also benefited from these intermittent movements, we chose to call it "mixed field" training rather than merely "force field" training. Additional phases were placed in the protocol to test subjects' responses before training, to test generalization to directions that were not practiced (30° counterclockwise from the target directions), and to test how the effects of training washed out. A total of 1155 movements were executed by each group distributed as follows:

1. *Unperturbed Familiarization.* 15 movements to become familiar with the system.
2. *Unperturbed Baseline.* 15 movements to establish a baseline pattern.
3. *Unperturbed Baseline-Rotated.* 15 movements to establish a baseline pattern in the rotated (unpracticed) directions.
4. *Machine learning*:
   - Visual Group: 300 unperturbed movements.
   - Mixed Group: 300 movements with machine learning algorithm: perturbations on intermittent movements, placed randomly once every 4. The computer learns the forces needed to push the subject over to the "desired" trajectory.
5. *Intermittent Exposure to the Visual Rotation*. 120 movements with random, intermittent visual rotation once every 4 movementsto test initial response to the visual rotation.
6. *Intermittent Exposure to the Visual Rotation on the rotated trials*. 120 movements to test to test initial response to the visual rotation on rotated (unpracticed) directions.
7. *Training.* 240 movements
   - Visual Group: Visual rotation.
   - Mixed Group: Forces, with the visual rotation condition occurring once in every 5 movements.
8. *Visual Field Test*. 60 movements to test how subjects response to visual rotation after training.
9. *Visual Field Test-Rotated*. 45 movements to test how subjects response to visual distortion in the rotated directions after training.
10. *Washout*. 210 movements without visual distortion.

Analysis. Two measures were utilized to analyze trajectory error from the ideal trajectory. *Initial direction error* was defined by measuring the error between the ideal and actual initial vectors. Initial vectors were formed by connecting the start point to the point when the trajectory had moved 25% of the target distance. *Maximum distance* (also called the *overall infinity norm* or *Chebychev norm*) was simply the largest distance between the trajectory and the straight line to the target. Statistical analyses used α=0.05.

3. Results

3.1 Learning

Both groups showed evidence of learning. The Visual Group learned the visual distortion. Before training, the typical handle trajectories a subject produced when exposed to the visual rotation were 30°counterclockwise, with no significant differences between the two groups (Figures 2A and 3A). Error from significantly reduced with practice ($p<0.05$; see Figure 2D and 3D).

The trajectory errors decreased gradually through training course on both groups, which was well fit by an exponential function, $A + B * e^{-t/C}$, where B is the amount of the change of the trajectory errors and C is the time constant for the error to decrease with time (Figure 2C and 3C).

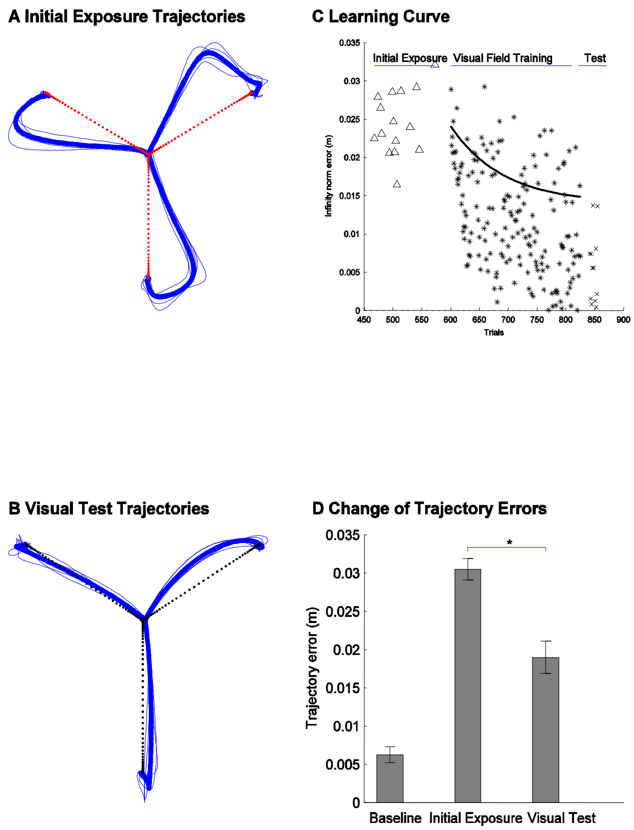

Figure 2. Visual distortion Field Training

An After-effect is a strong indication of the learning. Following the training phase, both the visual distortion field and forces were removed. Subjects behaved differently from their baseline movements – initial direction error for was about 15-18 degrees for both groups.

3.2 Benefits of mixed field training

Surprisingly, several pieces of evidence suggested that if anything, the Mixed Group learned better. Subjects in Mixed Group trained with force field that was custom-designed to cause the trajectory that is appropriate for performance in the visual rotation. Periodically, the robot switched to the visual rotation condition to evaluate how well they performed on the objective task of reaching in a rotated visual field (Points in Figure 3C). Figure 4 displays the parameters of the exponential fit, and shows that the mixed group's reduction of error was larger for both measures (Figure 4A&B) and the rate of adaptation of maximum distance reduced more quickly (i.e., a smaller time constant; Figure 4D). However, there was no detectable difference between the time constants (*C*) of the initial direction error (Figure 4C).

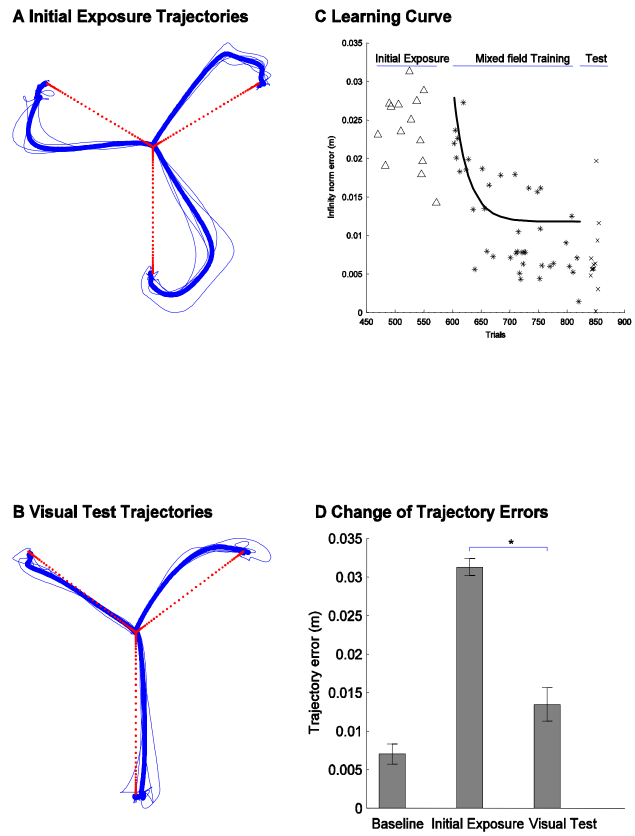

Figure 3. Mixed Field Training

3.3 Generalization and washout

Similar to Patton and Mussa-Ivaldi [6], subjects were able to generalize to nearby directions that were not practiced (Figure 5). On the unpracticed directions, the Visual and Mixed Groups' direction errors decreased 61.2% and 48.8% respectively (both $p<0.05$). Although both training groups could generalize what they learned, we found no detectable difference between the two groups ($p>0.05$).

After training, all subjects experienced a return the normal world, where visual rotations and forces were removed. As expected, all subjects de-adapted. Error decayed rapidly in 50-70 movements. We found no differences on the amount or rate of washout between the two groups.

4. Discussion and Conclusions

This study investigated the possibility of training using sensory crossover, in which kinetic distortions were used to help in the performance on a kinematic distortion of hand-eye coordination. Movement errors decreased dramatically in both groups, indicating that training with

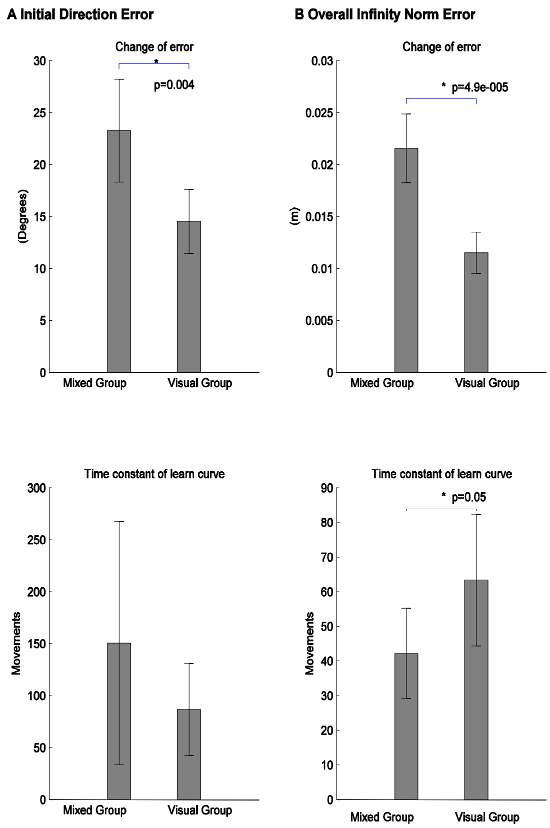

Figure 4. Learning amount and rate

forces can assist in learning visual distortions. This study reveals a viable new strategy for robotic training – one that brings in extra sensory modalities to bear on the objective of learning. Furthermore, these results indicate that the learning of kinematic and kinetic distortions share same neural resources.

During the mixed field training, subjects were exposed to the visual rotation once every 5 movements. This was done in order to measure the progress of the learning process in this experiment. It would be interesting to see if the appropriate learning occurs if pure force field training cured and subjects switched at the very end with no exposure to the visual rotation during the training phase. Our data suggest that the subjects could still learn what is appropriate for performing in the visual rotation, but it remains to be seen if a mixture, such as that used in the present experiment, may be more optimal.

Other research has shown that learning varies depending on the type of distortion. It remains to be seen whether this type of force field training can enhance the learning of other, more difficult visual distortions. Our technique may be limited by the need for large training forces to accomplish the goal.

An interesting item to note is that training using force fields offers the possibility training without any visual display. We speculate that it is possible to learning how to

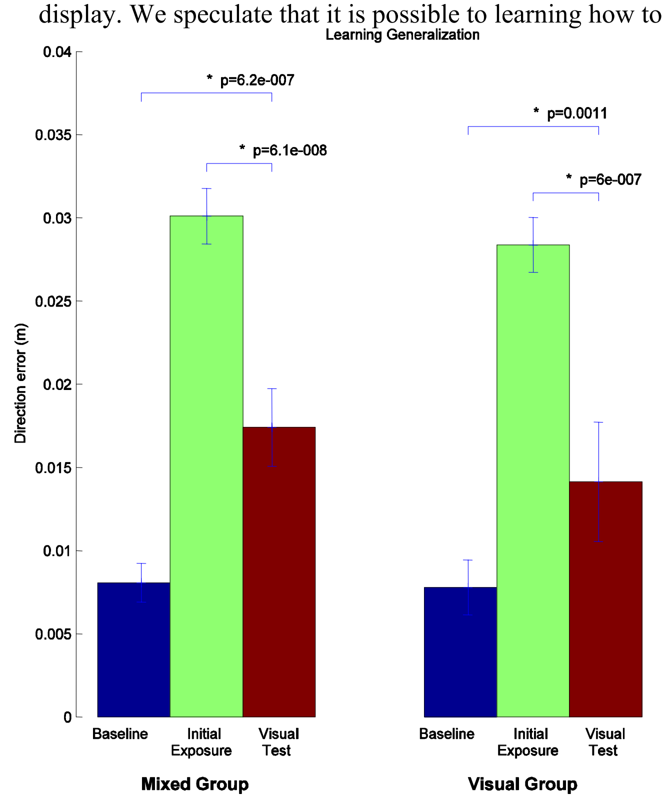

Figure 5. Learning generalization

move in the presence of a visual distortion without seeing anything during the training phase.

De-adaptation (i.e., washout) may be influenced by visual distortions. Previous results have shown that the suppression of visual feedback error leads to the persistence of after-effects [6]. This persistence of the after-effects is an important question in the areas of robotic teaching and robotic neuro-rehabilitation. This study demonstrates that although someone has completed training, the after effects of adaptation persist when they are suddenly perceived as appropriate for the new task (operating in the presence of a visual distortion.) The seamless transition from one sensory training mode to another means that there appears to be another interesting tool to add the arsenal of possible robotic training techniques.

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