

Investigation of Motor Adaptation to Mirror Visual Feedback

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by

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## ABSTRACT

### Motor Adaptation to Mirror Visual Feedback

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The present study investigated motor adaptation of point-to-point reaching movements to mirror feedback in the sagittal plane. This is a novel paradigm that both displaces and inverts the visual feedback of the right hand, showing it as the left hand. This environment creates a conflict between proprioceptive (and somatosensory) and visual feedback through the direction of errors produced as the result of a movement. Somatosensory, proprioceptive, and visual feedback are used to update internal models of the body and the space surrounding it in order to generate motor commands for upcoming movements. The process of updating internal models has been proposed as an explanation for motor adaptation. The first goal of the study was to characterize learning of the mirror perturbation. The results showed that adaptation occurred within a single training session, however the accuracy of the reaches made in the final perturbation reaches never returned to baseline. The second goal of the study was to determine the effect of mirror feedback on adaptation to a velocity-dependent force applied to the hand by a robotic manipulandum. The results show that subjects were able to adapt to the perturbation generated by the force while receiving mirror feedback at the same rate as when they were given correct visual feedback. These results suggest that visual and proprioceptive feedback can be processed in parallel, which allows the internal models to adjust to the deviating force relying solely on proprioceptive and somatosensory feedback.

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## **Introduction**

We are constantly faced with new objects and tasks in our everyday lives and we adapt to most new situations quickly and effectively. How are we able to adjust our motor commands to such a vast array of environments, including changes in our own body dimensions? The answer lies in the creation of multiple internal models of the world around us. Our ability to complete complex tasks in a variety of environments suggests that there is a mechanism by which the central nervous system uses a variety of inputs to determine the course of action. Internal models have been proposed to be a key component of sensory-motor control and adaptation. Figure 1 illustrates several such models.

These include forward motor models in which the motor commands that will be executed as input generate a prediction of the sensory feedback that will be produced as a consequence of the motor commands. The inverse model takes into account the sensory information from the current position, and takes information from prior movements to estimate the sensory feedback from the desired position, and generates the motor commands that would be necessary to go to that position. The interaction between forward and inverse internal models has been studied (Britain et al., 1996; Kawato, 1999a, 1999b; Wolpert and Kawato, 1998). Support for the existence of internal models has come in large part from studies of arm movement control. Several perturbation paradigms have been developed to study motor learning and adaptation.

In force field experiments, perturbations of reaching movements can be accomplished through an inertial Coriolis force generated by a reaching movement when the body is rotated, or a velocity-dependent force can be mechanically applied to the hand by a robotic manipulandum (Dizio and Lackner, 1995; Dizio et al., 2014; Lackner and DiZio, 1994, 2005). The robotic

perturbation experiments were developed to mimic the Coriolis force experiments to create an analogous force environment. In both cases, reaching movements are initially deviated in path and endpoint. But with repeated reaches, movement paths again become straight and accurate. The adaptation that occurs can be quantified in terms of end point errors and movement curvature. Motor adaptation in a novel dynamic environment is also expressed in the curvature and endpoint errors made in reaches after the force is removed (Shadmehr and Mussa-Ivaldi, 1994). The aftereffects plus the initial adaptation to the perturbations indicate that an internal model is able to adjust the motor commands to produce the desired trajectory towards a target. Studies have shown that both proprioceptive and visual information about arm position is involved in updating the internal model. In the absence of visual feedback, adaptation is slower, but subjects are still able to adapt to a novel force environment (Lackner and DiZio, 2005). Consequently, proprioceptive, somatosensory, and motor information are sufficient for motor adaptation. To see whether a model of the novel forces was developed or whether the adaptation occurred through memorization of the trajectory and the forces necessary to achieve it, one study tested for transfer to other movements made in the same external space, but in different directions. Adaptation was shown generalize to different movements within the same external space thus supporting the internal model hypothesis (Conditt, 1997). Further investigations into generalization of motor learning support the existence of continually updating internal models (Criscimagna-Hemminger et al., 2003; Donchin et al., 2003; Krakauer et al., 2006; Shadmehr, 2004; Tanaka and Sejnowski, 2015)

Another motor learning paradigm has been to study visuomotor adaptation by using a mouse or a joystick to control a cursor on a screen that represents the movement of the hand. The perturbation is achieved by rotating the cursor direction displayed relative to the movement

direction of the hand (Sainburg and Wang, 2002; Wexler et al., 1998; Wigmore et al., 2002). The benefit of these studies is the ability to alter the visual feedback during the reach. Another way that visual input has been perturbed during a reaching movement is through the use of prisms that shift the visual field by a set amount of degrees. Subjects readily adapt to the visual displacement and show aftereffects when prisms are removed (Luauté et al., 2009).

It has been proposed that vision is the dominant sense, and that it generally guides motor adaptation (Scheidt et al., 2005). A study by Scheidt et al. in 2005 investigated how two sensory systems vision and proprioception interact by testing three conditions. One condition where the visual feedback matched the movement, one condition without visual feedback, and one condition with false visual feedback. It showed that when visual information was not available proprioception was enough to guide the adaptation. However, when false visual information was presented, it was found that even though trajectory curvature lessened, the end point errors remained large and the subjects were not able to adapt to the displacement. This study suggested the separation of trajectory and endpoint adaptation. An earlier study showed this same pattern for adaptation to inertial Coriolis forces generated on the arm when reaching movements were made in a room rotating at constant velocity (Dizio and Lackner 1995). Subjects showed transfer of adaptation to the other hand, but only transfer of endpoint adaptation, not of trajectory curvature.

Studies that perturb visual feedback by rotating the position of a cursor relative to the motion of the hand investigate kinematic learning. By contrast, experiments where subjects are exposed to a force perturbation of their movement trajectories rely on dynamic control. Importantly, when two visuomotor perturbations are introduced one after another, interference occurs and the first rotation is unlearned (Wigmore et al., 2002). Interference is also observed

when subjects adapt to a robotic perturbation and then are exposed to a perturbation in the opposite direction directly after inertial adaptation (Brashers-Krug et al., 1996). How internal models created for kinematic (rotational transformation) and dynamic (velocity-dependent force-field produced by a robotic manipulandum) perturbations interact has also been studied by having subjects learn dynamic and kinematic transformations either simultaneously or sequentially (Krakauer et al., 1999). When both internal models were learned separately, there was an increase in the speed of learning them when combined together. When the combined transformation was learned first, it facilitated learning of the kinematic transformation, but not the dynamic transformation. These findings suggest that there is no interference between position-dependent and velocity-dependent adaptation (Flanagan et al., 1999). When a kinematic (rotation transformation), and a dynamic (acceleration-dependent) perturbation using an attached mass was introduced 5 minutes following the first adaptation, no interference occurred regardless of order or learning. This finding suggests independent internal models exist for kinematic and dynamic control of reaching (Krakauer et al., 1999). However, this hypothesis has been challenged by Tong, Wolpert, and Flanagan in 2002. Using a position-dependent kinematic perturbation (visuomotor rotation) and a position-dependent dynamic perturbation, they found interference with consolidating motor learning. Thus, it is still unclear how kinematic and dynamic internal models interact.

Two types of feedback can contribute to updating internal models of arm movement control in a point-to-point reaching task when perturbations are introduced: long-loop cortical reflexes and short-latency spinal reflexes. Long-latency reflexes can identify the effect of the net perturbing torques on the joints of the arm, while short-latency spinal reflexes are able to respond to muscle stretch (Kurtzer et al 2008). The data from long-latency cortical responses reflect the



internal model of the limb dynamics. The long-latency cortical responses can be used to update a forward model that is able to predict the position and velocity throughout a movement and thus produce the compensatory response with a much shorter latency (Shadmehr et al., 2010). It has been suggested that limb position and velocity are represented in the cerebellum and that the cerebellum is a key component in the updating of internal models (Miall et al., 2007). Bayesian approaches propose that predicted feedback from a movement and the actual sensory feedback are weighted depending on the uncertainty of each quantity (Kording and Wolpert 2004). Such Bayesian integration implies that in environments where sensory feedback is limited, the feedback associated with internal models would have more weight.

The paradigms described so far rely on unconscious or implicit adaptation. However, increasing movement accuracy through an explicit strategy can also play a role in adaptation. The interaction between implicit and explicit strategies for learning was investigated using visuomotor rotation paradigm (Mazzoni and Krakauer, 2006). Subjects had to align a cursor with visual targets  $45^\circ$  apart on a circle 10 cm in diameter. To provide them an explicit strategy for adaptation the participants were told that the perturbation was a 45 degree rotation between movement direction and cursor direction. Initially the errors were small and the subjects were successful in reaching towards the desired target; however, over time the errors became larger and larger and it was revealed that the subjects could not maintain an explicit strategy for motor adaptation. Instead they began implicitly adapting to the neighboring target and over time that implicit adaptation was able to override the explicit strategy.

The present study was undertaken to investigate how visual and proprioceptive information interact in the formation of internal models when there is both a visual perturbation of the seen direction of the hand and a dynamic robotic perturbation of the hand's trajectory. The

novel feature is that by using a mirror aligned with the subjects' sagittal plane and allowing sight of the right hand only as its reflected image in the mirror. The subject sees his or her right hand as being the left, while the right hand is used to reach to a target and can also be perturbed with a robot. Thus, motor commands are being generated in the left hemisphere to move the right hand, but the visual feedback about these movements is seen as being received from the left hand, while the proprioceptive feedback received will be from the right hand. We wanted to investigate how successful the internal models for the motor commands and sensory feedback would be as a result of this misalignment. We discovered that the learning process for the mirror alone is slow when subjects receive visual feedback from their right arm viewed in the mirror, and return to baseline accuracy levels is not achieved within 160 trials with mirror feedback. On the other hand, motor learning of the dynamic perturbation was rapidly achieved both when combined with mirror feedback and when tested without the mirror. Moreover, the sign of the after-effect indicated that the proprioceptive feedback rather than the visual feedback dominated the motor learning – disputing the dominant role of visual feedback.

## **Methods**

### **Subjects**

Ten Brandeis undergraduates volunteered for the study (7 male, 3 female) and were paid for their voluntary participation. The inclusion criteria for the study included the absence of neurological or muscular problems, general good health, and normal or corrected-to-normal vision. Each subject provided informed written consent to the experimental procedures that had been approved by the Institutional Review Board of Brandeis University.

### **Apparatus**

A mirror (45 cm x 42 cm) was mounted at the center of a table. When a subject was seated at the table the mirror was aligned with the projection of the subject's sagittal plane. It completely occluded sight of the left hand but the right hand was visible in the mirror, as if it were the left hand. Direct vision of the right hand was prevented by an adjustable light shield. The mirror was mounted in a slider that allowed it to be moved away from the subject during a non-mirror condition. A 12 x 12 cm piece of aluminum foil was mounted on the table to denote the start position. An ankle bracelet was placed on the subject prior to the beginning of the experiment so that a small current could be detected when the participant was touching the foil, this illuminated the target light, a red light emitting diode (LED). A PHANTOM® Desktop™ Haptic Device (Sensable Technologies, Cambridge, MA, USA) was mounted on the right side of the table. This robot has three joints, allowing for hand movements with six degrees of freedom. It was programmed to generate a lateral velocity-dependent force of 4 Nm/s perpendicular to the movement in the horizontal plane parallel to the desk. A custom built handle allowed subjects to grasp it stably, with the index finger extended to make contact with the table surface at the end of

a movement. A subject grasping the handle is shown in Figure 1. A start position LED was located 10.5 cm from the edge of the table and 15 cm to the right of the mirror. The target LED was 20 cm in front of the start position LED and was lit when the subject made contact with the foil at the starting position. PHANTOM software recorded the position of the robot end tip allowing monitoring of the ongoing position of the subjects tip at 1000 Hz. The experimental setup is illustrated in Figure 4.

## **Procedure**

Subjects sat at the apparatus table for testing. They were asked to sit comfortably and to move only their right arm during the experiment. The subject held the robot handle and aligned their index finger with a groove in the molded grip. The grip of the robot is shown in Figure 2. A schematic of the experimental paradigm is illustrated in Figure 3.

Subjects were assigned to one of two groups. Group 1 (n=5) had 3 days of testing in the following order: force condition, mirror condition, and force with mirror condition. The mirror was moved back for the force condition and the subjects could see their right hand directly throughout the condition. They were instructed to reach to the target in a single smooth, continuous motion as accurately as possible, without slowing down and intentionally correcting their movements, but if they missed the target to try to do better on the next reach. The approximate desired speed of the movement was shown by the experimenter. Subjects were instructed to hold their hand at the endpoint until an auditory cue of “return” sounded and then to return to the start location. They could begin the next trial when they saw the target light switch on. Before the participants began the experiment, they were informed that in some trials they would be asked to look at the target and then close their eyes and keep their eyes closed while reaching to the target and while moving their hand back to the start position. The subjects were

told the robot might perturb their movements but that they should complete them as smoothly and continuously as possible while maintaining the same speed. They were told not to stiffen up their muscles if they felt the force go on. Subjects were told the experiment should take approximately 20 minutes, but they could stop briefly if they needed a break.

Throughout the experiment, the subjects were given feedback about their reaching speed, to help them keep in the range of 350 to 800 m/s. For the mirror condition one week later, subjects were seated comfortably at the table but the mirror was in place and subjects could see the mirror reflection of their right hand as if it were their left hand. The experimental setup during the mirror condition is illustrated in Figure 3. Subjects were instructed to grasp the handle in the same manner as before and to make smooth continuous movements regardless of whether they felt a force perturbing their movements. The participants were asked to return the next day to complete the last condition. The instructions for the participants were identical to those given to them on the first day with the exception that they were to look in the mirror for the entire duration of the experiment with the exception of eyes closed trials.

the participants that were assigned to Group 2 ( $n = 5$ ), completed the conditions in the following order: mirror, mirror and force, and force. The experimental setup for all 3 conditions is shown in Table 1. There were 24 hours between the mirror and the mirror and force-field condition, and seven days between the mirror and force-field and the force-field condition.

## **Computation of dependent variables**

For each experimental session the position at the joint of the robot right above the index finger mold was recorded at a frequency of 1000 Hz. The way that the robot was gripped by the participants is illustrated in Figure 2. The usability of each trial was verified using Matlab® 2013 for Windows 7 (MathWorks, Natick, MA) by ensuring that the peak velocity was between 350 and 800 mm/s and that the duration of the movement was no longer than 1.5 s. If a trial was found to be unusable, it was replaced by a previous or next trial of the same condition. Matlab was used to calculate the following measures about each trial: maximum lateral deviation from a straight trajectory, lateral endpoint deviation, and absolute average deviation from a straight trajectory. Maximum lateral deviation from an ideal straight trajectory was used as a measure of curvature. While previous studies have used maximum lateral deviation and endpoint error alone to account to the errors in movement. After seeing the trajectories of the movements made under mirror feedback, it became clear that maximum lateral deviation would be insufficient to quantify the deviation of the movements. The trajectories showed points of inflection in the curvature during a single movement, and did not show consistency in curvature and endpoint errors. Thus, we developed a measure that took the average deviation from the ideal straight path of each trajectory and added the lateral endpoint error in order to obtain the value that was called ‘Reaching Error’. Thus, we decided to use the absolute average deviation combined with the endpoint error in order to compare learning in the three conditions. For all three conditions the three trial types were created to illustrate learning: (a) ‘Baseline’ was composed the average of trials 13-17 (for the mirror only condition the baseline was taken from the force perturbation only condition) , (b) ‘Initial Perturbation’ which consisted of the average of trials 21-23 for the force condition and 1-3 for the mirror only experimental day, and (c) ‘Final Perturbation’ was

created by taking the average of trials 111-120, or 151-160 for the mirror only condition. To compare learning between the different conditions we used the 'Baseline' value. The amount of learning was determined by subtracting the 'Final Perturbation' from the 'Initial Perturbation' condition. The rate of learning was computed by taking the average reaching error of the first two trials during exposure to the perturbation (trials 1-2 for mirror only and trials 21-22 for the conditions with force) and comparing it to the average of the last 4 trials of the perturbation through a t-test. The first trial to have a significant difference with  $p < 0.05$ , would be a measure of when adaptation began and was used to compare the rates rather than the magnitudes of adaptation.

Next, to investigate the process of adaptation further, for the force and force with mirror feedback conditions, the 'Baseline with Eyes Closed' value was computed as the average of trials 18-20, and for the 'Aftereffect' value trial 122 was used. Since the aftereffect trial was done with eyes closed in order to isolate how the motor plan had been updated as a result of the perturbation, having an eyes closed baseline measure was necessary.

## Overview of analyses

IBM SPSS Statistics 22® for Windows 7 (SPSS Inc., Chicago, IL) was used to perform all statistical analyses. A three-way repeated measures MANOVA was conducted to see if there was a significant effect of group on any of the three dependent variables: reaching error, maximum lateral deviation, and lateral endpoint. The independent variables were set up to be the type of perturbation (Force, Mirror, Mirror and Force) and the stage of the experiment (Baseline, Initial Perturbation, and Final Perturbation). Pillai's trace was used as the test significance. For all the ANOVAs conducted throughout the experiment, if Mauchly's test of sphericity showed that the variances between the conditions were significantly different, the Greenhouse-Geisser correction was used. Next, a three-way repeated measures ANOVA was set up with peak velocity being the dependent variable. A two-way repeated measures ANOVA was designed with 'Rate' as the dependent variable, and group and perturbation type as the independent variables. Thus, we established that the group that a subject was in did not affect any of the dependent variables that we use for future analyses.

A one way repeated measures ANOVAs was used to investigate the effect of the stage of experiment on reaching error, maximum lateral deviation, and endpoint error were conducted for each of the three perturbation conditions. Post-hoc tests, with the Bonferonni correction to account for multiple comparisons were done between each of the stages of the experiment.

To investigate how learning differed between the perturbations 'Baseline', 'Initial Effect', 'Amount of Learning', and rate were compared. Three one way repeated ANOVAs were conducted for both the three variables quantifying the amount of leaning, and post hoc tests were done between perturbations using the Bonferonni correction to test for significance. For the rates, a one way repeated measured ANOVA was conducted with perturbation as the independent



variable, and Least Significant Difference (LSD) post-hoc test was done between each of the perturbations to determine significance.

A bivariate correlation using Pearson's coefficient was used to compare the amount of learning (Initial Perturbation – Final Perturbation) between Mirror and Force conditions to investigate whether success at one would predict success with the other.

## Results

### Effect of prior exposure to dynamic perturbation

We first evaluated the effect of prior exposure to the mechanical dynamic perturbation by the robot on the ability of participants to adapt to the perturbation under the mirror condition. Thus, the participants were divided into two groups: one with exposure to the robotic perturbation a week prior to the mirror condition and one with exposure to the mirror a week following the mirror condition. A three-way repeated measures MANOVA was conducted to see if there was a significant effect of group on any of the three dependent variables: reaching error, maximum lateral deviation, and lateral endpoint. Using Pillai's trace, there was no significant effect of group on any of the three dependent variables (reaching error, maximum lateral deviation, and lateral endpoint) ( $F(3, 6) = 0.66; p = 0.608$ ). The peak velocity of the movements was also considered across the three conditions and three stages of perturbation to ensure that the movement speed was consistent. There was no effect of prior exposure to the novel force environment created by the robotic manipulandum on the peak velocity of the movements throughout the various stages of the experimental condition ( $F(1, 8) = 0.09; p = 0.772$ ). There was no difference in velocity across the three perturbations, suggesting that even though participants had larger initial errors, and a slower rate of adaptation to the mirror they were not slowing down to compensate. There was a significant difference in velocities between the stages of the experiment, however the differences were a gradual decrease in the velocities as the experiment progressed which can be attributed to fatigue, and is typical in motor learning experiments. Mean peak velocities with for each of the conditions are shown in Figure 5. Error bars in all the graphs in this paper represent the standard error of the means unless denoted otherwise.

## Motor learning using mirror feedback

Next, we sought to characterize how participants learned the mirror paradigm. We found that the stage of the experiment had a significant effect on reaching error ( $F(1.2, 10.8) = 32.52, p < 0.001$ ). Post-hoc testing was using Least Significant Deviation (LSD) test with the Bonferonni correction. Reaches made during the initial mirror perturbation  $5.19 \pm 0.63$  cm (mean  $\pm$  SEM) had significantly larger errors compared to reaches made in the baseline condition  $0.81 \pm 0.16$  cm ( $p < 0.001$ ), showing that participants are initially affected by the mirror perturbation. Errors made in the initial stage of mirror exposure  $5.19 \pm 0.63$  cm compared to errors made in the final stage of the mirror adaptation  $2.17 \pm 0.22$  cm showed a significant reduction in magnitude ( $p = 0.002$ ), showing that motor learning or the perturbation had occurred. Finally, errors made at the end of the mirror perturbation were significantly larger than baseline reaches ( $p = 0.002$ ), showing that the adaptation to the mirror was not complete. Figure 6 shows the mean reaching error across the three stages of the experiment. Error bars in all graphs represent the standard error of the means.

The same analysis was done on the maximum lateral deviation (MLD), the stage of experiment had a significant effect ( $F(1.3, 11.5) = 16.49; p = 0.001$ ). However a very different pattern emerged compared to the one seen with reaching error when computed as an average lateral deviation and endpoint error. There seemed to be an increase in MLD throughout the perturbation. There was no significant difference in curvature between baseline reaches and reaches during the initial mirror exposure. However, there was a significant difference between the curvature in the initial mirror exposure as compared to the curvature in the final trials using the mirror ( $p < 0.001$ ) and between the curvature of the final reaches in the mirror compared to baseline reaches ( $p = 0.007$ ). One explanation for this result would be for the lack of an effective

mechanism to update the internal models for generating movement and instead a online error processing mechanism that would allow for deviated initial direction and a correction towards the desired endpoint

It was shown that the stage of the experiment has a significant effect on lateral endpoint error ( $F(1.3, 11.3) = 41.48; p < 0.001$ ). Further analysis revealed that there was a significant increase in endpoint error between baseline and initial perturbation trials ( $p < 0.001$ ), and a significant decrease in endpoint error between the initial and the final reaches with mirror feedback ( $p < 0.001$ ), suggesting that participants are able to successfully adapt endpoint error to mirror displacement.

### **Motor learning of dynamic perturbations**

Next, we performed a similar analysis on the robotic perturbation condition. The results are shown in Figure 7. Again, we found that the stage of the adaptation had a significant effect on reaching errors ( $F(1.46, 13.14) = 14.78, p = 0.001$ ). The perturbation produced by the robotic manipulandum produced significant reaching errors, as evidenced by the significant difference in the magnitude of the errors made in baseline versus the initial reaches during exposure to the velocity-dependent force ( $p = 0.004$ ). Subjects were shown to adapt to the mechanical perturbation because the final perturbed reaches were significantly more accurate than the initially perturbed ones ( $p = 0.011$ ). A large aftereffect, that is characteristic of adaptation to a dynamic perturbation, was present as shown by the significant increase in error in the trial after the force was turned off compared to baseline ( $p < 0.001$ ). Finally, adaptation to the perturbation

was complete due to the lack of a significant difference in reaching accuracy between trials at the end of the perturbation period and the baseline trials.

Errors in curvature are characteristic of dynamic perturbations of a velocity dependent force. We showed that the stage of the experiment (baseline eyes closed, baseline eyes open, initial perturbation, final perturbation, and aftereffect) had a significant effect on the curvature of the reaching movements ( $F(2.2, 19.8) = 56.53; p < 0.001$ ). The change in curvature in response to stage of experiment was characteristic of previous experiments with the robotic manipulum. There was no significant difference between the eyes open and closed baseline reaches. There was a significant increase in curvature as compared to eyes open baseline trials when the force perturbation was initially introduced ( $p = 0.001$ ). There was a significant decrease in curvature between initial and final perturbed reaches ( $p = 0.001$ ). Finally, when compared to the baseline eyes closed reaches, the aftereffect reaches showed a dramatic increase in curvature in the opposite direction of the force ( $p < 0.001$ ), showing that the internal model that generates motor commands had been updated to account for the force applied by the robot.

Effect of trial was also shown for endpoint error ( $F(4, 36) = 7.79; p < 0.001$ ). However, there was no significant difference between either baseline and initial perturbation trials, initial and final perturbation trials, or baseline eyes closed and aftereffect trials.

## **Motor learning of a dynamic perturbation with mirror feedback**

The same analysis on force learning with the mirror showed a significant effect on the stage of the perturbation on the reaching errors ( $F(3, 27) = 10.39, p < 0.001$ ). The results are illustrated in Figure 8. The initial mechanical perturbation produced a significant increase in error compared to baseline reaches in the mirror ( $p = 0.006$ ), demonstrating that the mechanical perturbation produced an additional source of error. Subjects showed a significant reduction in error magnitude from the initial to the final mechanical perturbation trials ( $p = 0.009$ ), showing that they were able to adapt to the mechanical force applied by the robot. The aftereffect measure was not significantly different from baseline performance.

An effect of the type of trial (baseline eyes open, baseline eyes closed, initial perturbation, final perturbation, or aftereffect) on the maximum lateral deviation in was shown ( $F(1.6, 14.3) = 19.28; p < 0.001$ ). There was no significant difference between the eyes open and eyes closed trials. There was no significant difference between curvature in the baseline eyes open and the trials with initial perturbation. However, there was a significant difference between the eyes closed baseline reaches and the reaches made during the initial exposure to the force ( $p = 0.026$ ), this may be attributed to additional curvature being generated throughout the movement during mirror feedback trials. There was also a significant difference between the initial and final reaches with the force perturbation ( $p = 0.017$ ). Finally, the most convincing argument for the adaptation of the subject's internal model to the force perturbation is the large

aftereffect (as compared to eyes closed baseline reaches) observed in the opposite direction to the force ( $p = 0.012$ ).

A significant effect of trial type was also found for endpoint error ( $F(4, 36) = 8.29$ ;  $p < 0.001$ ). There was a significant difference between baseline eyes open and initial perturbation trials ( $p = 0.003$ ), as well as baseline eyes closed and initial perturbation trials ( $p = 0.011$ ). However the difference between initial and final perturbation trials and baseline eyes closed and aftereffect trials was not significant.

### **Comparison of motor learning across conditions**

To determine the amount of learning that occurred in the different paradigms, three variables were compared: baseline reaching errors, initial effect of perturbation, and amount of learning. The results of the comparisons are shown in Figure 9. First, the baseline reaches done while looking at the movement of the right hand as significantly differ from baseline reaches while looking at the reflection of the right hand in the mirror ( $F(1,9) = 8.95$ ;  $p = 0.025$ ).

Next, we examined the effect of each perturbation and found that there was a significant effect of the type of perturbation ( $F(1, 18) = 3.61$ ;  $p = 0.048$ ). Further analysis revealed that there was a significant difference between the effect of the mechanical perturbation and the mirror displacement ( $p = 0.036$ ). The amount of learning that occurred throughout the perturbation was independent of the type of perturbation that was encountered ( $F(2, 18) = 1.95$ ;  $p = 0.171$ ).

### **Effect of mirror feedback on learning rate**

The rate of learning was not affected by having prior exposure to the mechanical perturbation ( $F(1, 8) = 0.54, p = 0.482$ ), as shown in Figure 10. However, there was a significant effect of perturbation type on the rate of learning ( $F(2, 18) = 4.41, p = 0.028$ ). There was a significant difference between rates for learning the mirror and learning the force perturbation alone ( $p = 0.028$ ), as well as between learning the mirror perturbation and the force perturbation under the mirror condition ( $p = 0.04$ ). However, there was no significant difference between the rates at which subjects were able to learn the mechanical perturbation whether they were looking in the mirror or not ( $p = 0.616$ ). This means that having the mirror for visual feedback of the movement and receiving contradictory visual and proprioceptive information did not impede the learning of the mechanical perturbation.

No correlation was found between how much (Initial Perturbation – Final Perturbation) people adapt to the visual displacement of the mirror and to the mechanical perturbation of the robotic manipulandum ( $r = -0.055, p = 0.879$ ). There was also no correlation in the rate of learning for the mirror displacement and the mechanical perturbation conditions ( $r = 0.292, p = 0.414$ ). This would suggest that the mechanisms behind adaptation to the two types of perturbations are independent of one another.



## **Discussion**

Motor learning allows humans to adapt to a large variety of environments quickly and successfully due to the presence of multiple systems that are able to separately code for the location of the body in space. However, it is the integration of multiple representations from different sensory modalities that allows us to respond and adapt to various forms of perturbations that occur in our environment. Four representations key to motor behavior include the influence of various motor commands on our body, our body configuration as referenced through proprioception and somatosensation, the location of the body in space as a product of visual and vestibular input, and the representation of the somatosensory and proprioceptive feedback from various movements and locations in space. These four forms of information: motor commands, limb configuration, limb location, and somatosensory feedback from a given position or movement create internal models that guide movement. While different modalities are involved in the composition of these models, it is difficult to decipher the role of each one due to the interconnected nature of all of the representations. An outline of the internal models involved in error processing before, during and after a movement is shown in Figure 1.

To begin to understand the underlying processes behind the creation and maintenance of internal models, various perturbation techniques have been developed and investigated in the field of motor control. Perturbations that create various forms of conflict in the four representations provide insight into the organization of internal models. Prism adaptation

experiments have investigated how one is able to adjust to a sudden shift of the visual field. In this case, the visual representation of the environment would be spatially displaced relative to the body, and during the planning of the movement the desired state would be inaccurate and the inverse dynamic model would produce motor commands, that after being executed by the plant (the actual body motor system) would produce a final state that is different from the desired state that was used as input. The limb would end up deviated past the target in the direction of the visual displacement. The forward dynamic model would also use past experiences to generate a predicted state based on the current state and an efferent copy of the motor commands. Thus, through error processing during and following a movement in the new environment, the difference between the desired/predicted and final state will be computed. Another mechanism of error processing will be going on simultaneously. The predicted state produced by the forward dynamic model will be used by the forward sensory model to generate predicted sensory feedback. Thus, the predicted sensory feedback will be compared to the actual sensory feedback that the participant receives as a result of the movement. The difference between the two representations of the movement can be used to adjust the information about the current and the desired state of the limb. Thus, there will be a new relationship established between the visual representation of the external space and the proprioceptive, motor, and somatosensory information.

In the robotic manipulandum experiments that generate a velocity-dependent contact force on the hand, the motor commands that are initially generated by what the subject knows about the current and desired state of the arm produce a trajectory and endpoint that is not consistent with the predicted or the desired state. The execution of the motor commands will also create proprioceptive feedback throughout the movement that does not correspond to the

predicted proprioceptive feedback. Somatosensory feedback through contact with the robot will also provide additional information that does not correspond to the prediction generated by the internal models, i.e. the hand is perturbed. Finally, if the subject views the hand throughout the movement, the visual feedback contributes to calculating the error. Thus, the combined information from multiple sources leads to updates of the inverse dynamic model to generate motor commands that are necessary to generate a straight and accurate movement.

In our mirror paradigm the visual feedback that the subject receives comes from the reflection of the right hand in the mirror being seen as the left hand. Thus, the question arises: how is the visual feedback predicted and processed in this experiment? Is it possible for the internal models to combine the visual representation of the left arm with the somatosensory and proprioceptive feedback, and motor commands of the right hand? If this does not occur, then is the visual field both “internally” flipped and displaced in order to account for the proprioceptive and somatosensory and visual feedback that occurs as a result of a movement?

The present study establishes that adaptation to the mirror does occur, however it causes incredibly large errors and the learning rate is much slower for the mirror adaptation compared to adaptation to a dynamic perturbation produced by the robot. Before a subject generates a motor command for the reaching movement, he or she is given visual feedback of the right hand reflected in the mirror as the left hand. There are two potential ways that this information could be interpreted. The visual feedback could be processed as coming from the left hand, and thus in order to generate a movement in the right hand, the current and the desired state of the left hand could be combined with the proprioceptive and somatosensory information of the right hand in order to generate motor commands through the inverse dynamic model. If this recalibration were possible prior to the onset of movement, we would predict small errors and quick adaptation to

the new environment, because the errors that would be produced as a result of the movement would then be accounted for by left/right flip between the representations of the right and left hands.

Another possibility is that it is not possible or it is a slow process to be able to combine visual input from the “left hand” with proprioceptive and somatosensory information from the right hand and effectively use this new recalibrated state to generate motor commands. In this case, the subject would generate motor commands that would lead to large errors due to the mirror producing a shift and an inversion of visual input. Thus, the predicted visual feedback would differ significantly from the actual visual feedback of the movement. Also, there would be a contradiction in the error processing between visual and proprioceptive and somatosensory systems. The visual system would process an error to the right as being too far left, and thus the correction would be generated towards the right. However, the proprioceptive and somatosensory feedback would provide an accurate account of the errors’ actual direction and thus generate a correction towards the left. Thus, given this path towards adaptation the participants would have to remap the external space in which the movement is made to the left, and to invert the direction of the error signal from visual input. These two pathways to adaptation are not mutually exclusive, it could be a matter of multiple adaptations occurring on two separate timescales. Given the size of initial errors and the incomplete adaptation to mirror feedback following 160 trials, our data suggest that the visual representation of the left hand is not easily integrated with proprioceptive and somatosensory information from the right hand.

Whether the visual and somatosensory and proprioceptive feedback of the right hand is able to be dissociated throughout adaptation to allow the visual representation of the left hand to be used or whether the visual representation of the right hand (seen as the left hand) adapts to

both the displacement and the inversion was uncertain. However, we examined what would occur when the dynamic perturbation was introduced after the later stages of adaptation to the mirror feedback, as all participants had adapted to the mirror feedback 24 hours prior, and completed 17 reaches again without robotic adaptation. All of the participants had shown a significant decrease in reaching error throughout 160 trials of the mirror condition. When they returned the next day, they had retained the adaptation to the mirror and showed initial errors that were similar in magnitude to the errors that they made towards the end of mirror adaptation. The velocity-dependent force was then applied to their hand by the robotic manipulandum that laterally displaced their movements and caused a significant increase in errors. This displacement exacerbated the error processing contradiction between the visual and the proprioceptive and somatosensory systems. A rightward perturbation would cause proprioceptive and somatosensory feedback to generate a correction towards the left. However, the same perturbation would be processed as a leftward error by the visual system and would thus generate a correction towards the left. We found that the rate of learning of the dynamic perturbation was not affected by conflicting visual feedback. Thus, the subjects were able to disregard the error signals from the visual system and rely on proprioception and somatosensation to adjust their motor commands to counter the velocity-dependent force applied by the robot. It had earlier been shown that proprioception and somatosensation were sufficient to allow adaptation to the Coriolis force generated in rotating environments without visual feedback (Dizio and Lackner 1994). The same experiment had not been conducted for a contact velocity-dependent force generated by a robot. Our paradigm has shown that it is possible to disregard the visual feedback and use a combination of somatosensory and proprioceptive feedback to adjust our inverse dynamic model to generate motor commands. This finding shows that during dynamic

perturbation of movement control vision does not commute or supplant the intrinsic proprioceptive and somatosensory feedback in the ongoing motion of the controlled limb in updating internal models of movement control.

## References

- Brashers-Krug, T., Shadmehr, R., and Bizzi, E. (1996). Consolidation in human motor memory. *Nature*.
- Britain, G., Senior, W., and Trust, W. (1996). Forward Models for Physiological Motor Control. *9*.
- Conditt, M. (1997). The motor system does not learn the dynamics of the arm by rote memorization of past experience. *J. ... 78*, 554–560.
- Criscimagna-Hemminger, S.E., Donchin, O., Gazzaniga, M.S., and Shadmehr, R. (2003). Learned dynamics of reaching movements generalize from dominant to nondominant arm. *J. Neurophysiol.* *89*, 168–176.
- Dizio, P., and Lackner, J. (1995). Motor adaptation to Coriolis force perturbations of reaching movements: endpoint but not trajectory adaptation transfers to the nonexposed arm. *J. Neurophysiol.* *74*.
- Dizio, P., Lackner, J.R., Judkins, T., Scheidt, R.A., Franklin, S., Wolpert, D.M., and Franklin, D.W. (2014). Congenitally Blind Individuals Rapidly Adapt to Coriolis Force Perturbations of Their Reaching Movements. *2175–2180*.
- Donchin, O., Francis, J.T., and Shadmehr, R. (2003). Quantifying Generalization from Trial-by-Trial Behavior of Adaptive Systems that Learn with Basis Functions : Theory and Experiments in Human Motor Control. *23*, 9032–9045.
- Flanagan, J.R., Nakano, E., Imamizu, H., Osu, R., Yoshioka, T., and Kawato, M. (1999). Composition and Decomposition of Internal Models in Motor Learning under Altered Kinematic and Dynamic Environments. *19*, 1–5.
- Kawato, M. (1999a). Internal models for motor control and trajectory planning. *Curr Opin Neurobiol* *9*, 718–727.
- Kawato, M. (1999b). Internal models for motor control and trajectory planning. *Curr. Opin. Neurobiol.* *718–727*.
- Krakauer, J.W., Ghilardi, M.F., and Ghez, C. (1999). Independent learning of internal models for kinematic and dynamic control of reaching. *Nat. Neurosci.* *2*, 1026–1031.
- Krakauer, J.W., Mazzoni, P., Ghazizadeh, A., Ravindran, R., and Shadmehr, R. (2006). Generalization of motor learning depends on the history of prior action. *PLoS Biol.* *4*, e316.
- Lackner, J., and DiZio, P. (1994). Rapid adaptation to Coriolis force perturbations of arm trajectory. *J. Neurophysiol.* *72*.

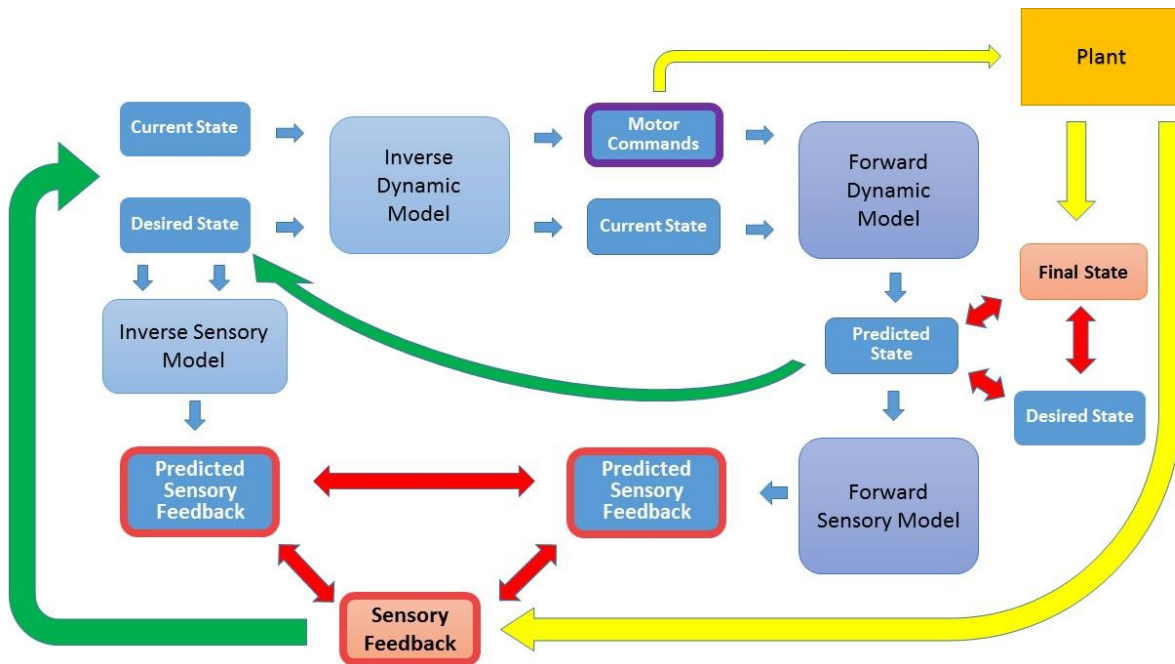
- Lackner, J.R., and DiZio, P. (2005). Motor control and learning in altered dynamic environments. *Curr. Opin. Neurobiol.* *15*, 653–659.
- Luauté, J., Schwartz, S., Rossetti, Y., Spiridon, M., Rode, G., Boisson, D., and Vuilleumier, P. (2009). Dynamic changes in brain activity during prism adaptation. *J. Neurosci.* *29*, 169–178.
- Mazzoni, P., and Krakauer, J.W. (2006). An implicit plan overrides an explicit strategy during visuomotor adaptation. *J. Neurosci.* *26*, 3642–3645.
- Miall, R.C., Christensen, L.O.D., Cain, O., and Stanley, J. (2007). Disruption of state estimation in the human lateral cerebellum. *PLoS Biol.* *5*, e316.
- Sainburg, R.L., and Wang, J. (2002). Interlimb transfer of visuomotor rotations: independence of direction and final position information. *Exp. Brain Res.* *145*, 437–447.
- Scheidt, R.A., Conditt, M.A., Secco, E.L., Mussa-ivaldi, F.A., and Robert, A. (2005). Interaction of Visual and Proprioceptive Feedback During Adaptation of Human Reaching Movements. 3200–3213.
- Shadmehr, R. (2004). Generalization as a behavioral window to the neural mechanisms of learning internal models. *Hum. Mov. Sci.* *23*, 543–568.
- Shadmehr, R., and Mussa-Ivaldi, F. (1994). Adaptive representation of dynamics during learning of a motor task. *J. Neurosci.* *74*.
- Shadmehr, R., Smith, M. a, and Krakauer, J.W. (2010). Error correction, sensory prediction, and adaptation in motor control. *Annu. Rev. Neurosci.* *33*, 89–108.
- Tanaka, H., and Sejnowski, T.J. (2015). Motor adaptation and generalization of reaching movements using motor primitives based on spatial coordinates. *J. Neurophysiol.* *113*, 1217–1233.
- Wexler, M., Kosslyn, S.M., and Berthoz, A. (1998). Motor processes in mental rotation. *68*, 77–94.
- Wigmore, V., Tong, C., and Flanagan, J.R. (2002). Visuomotor rotations of varying size and direction compete for a single internal model in a motor working memory. *J. Exp. Psychol. Hum. Percept. Perform.* *28*, 447–457.
- Wolpert, D.M., and Kawato, M. (1998). Multiple paired forward and inverse models for motor control. *11*, 1317–1329.





## Appendix B: Figures

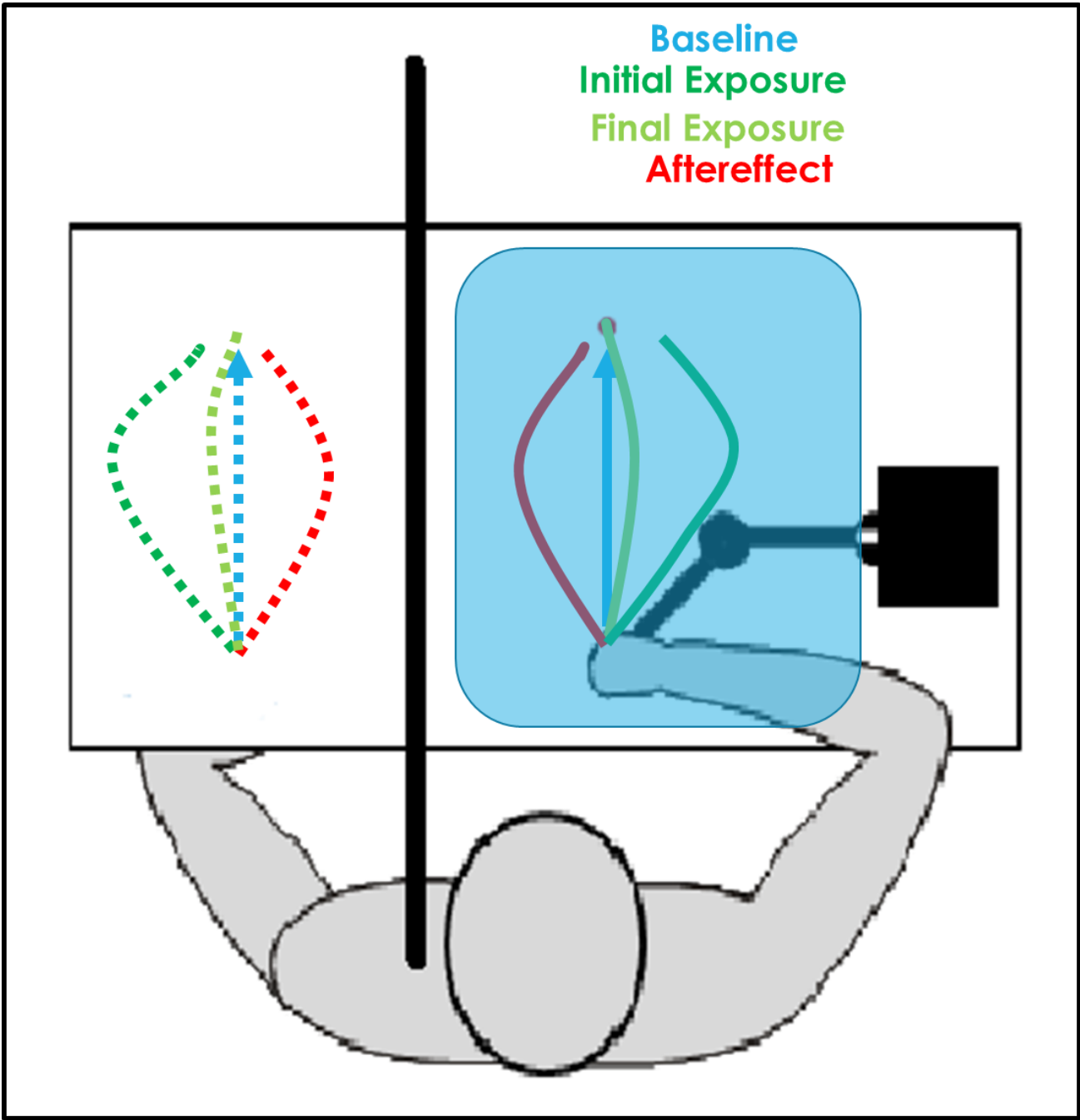
Figure 1: Internal models hypothesis for motor adaptation



**Figure 2: The grip of the robotic manipulandum**



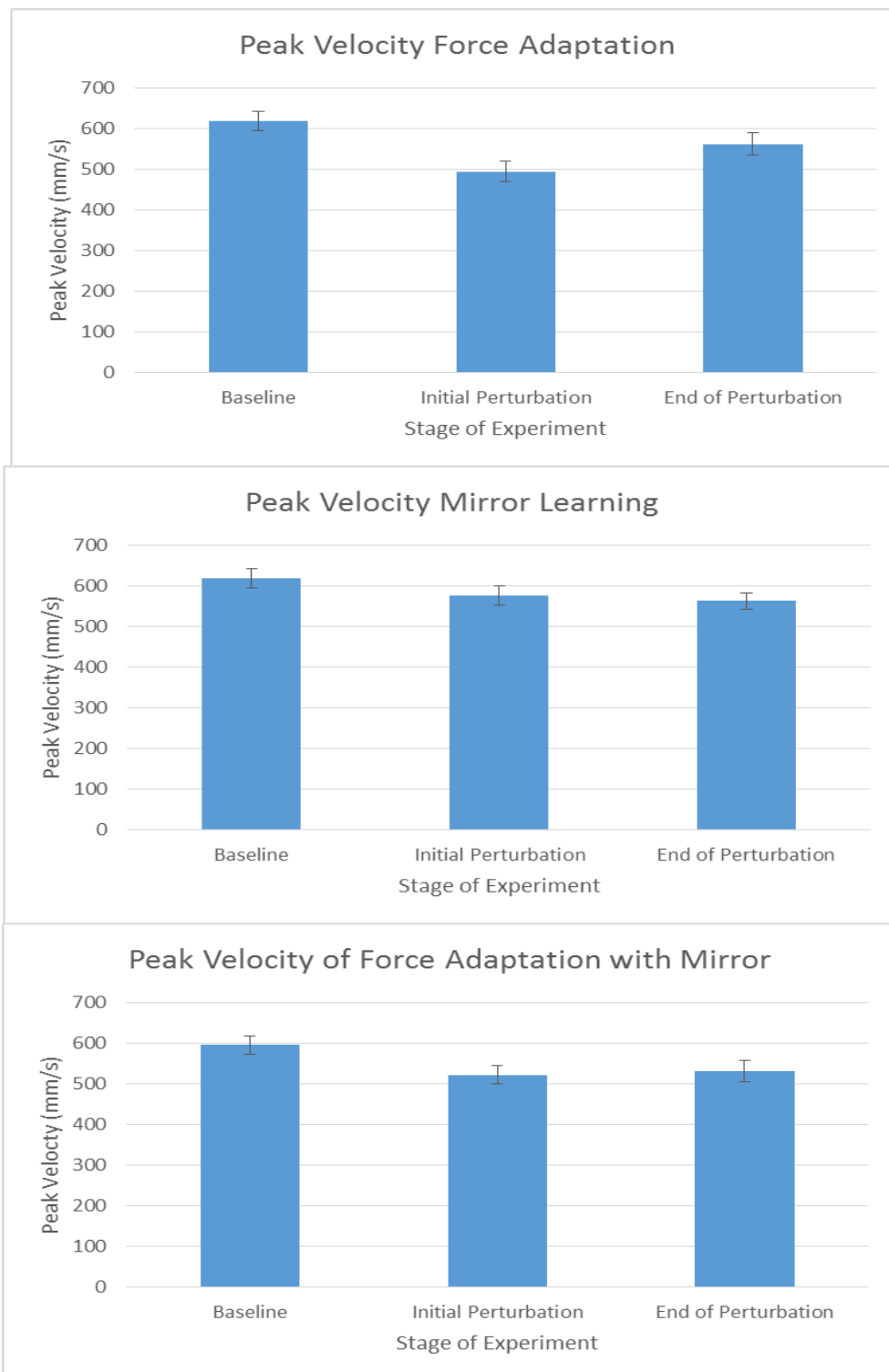
Figure 3: Schematic of experimental paradigm



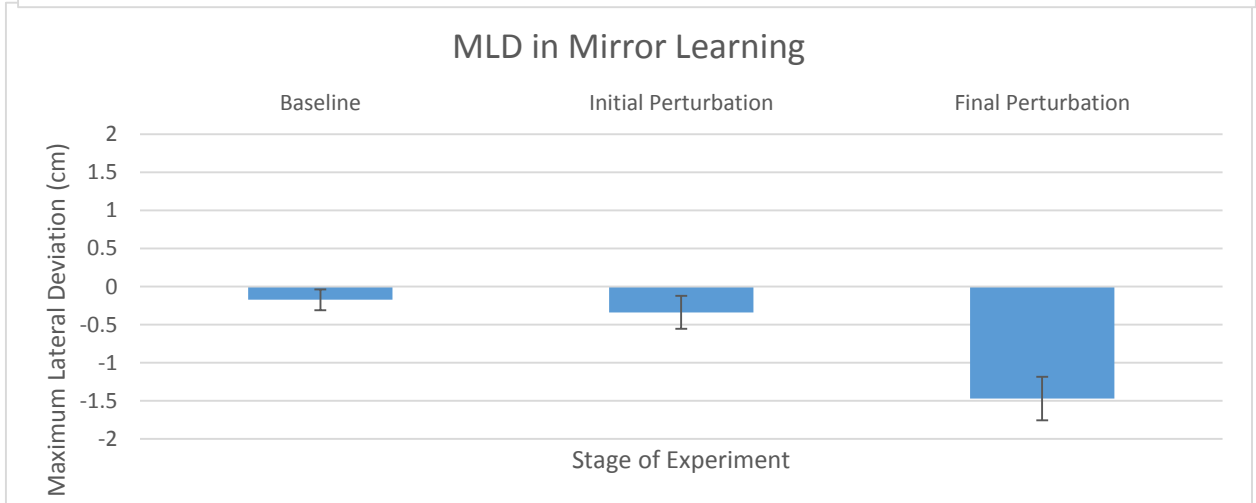
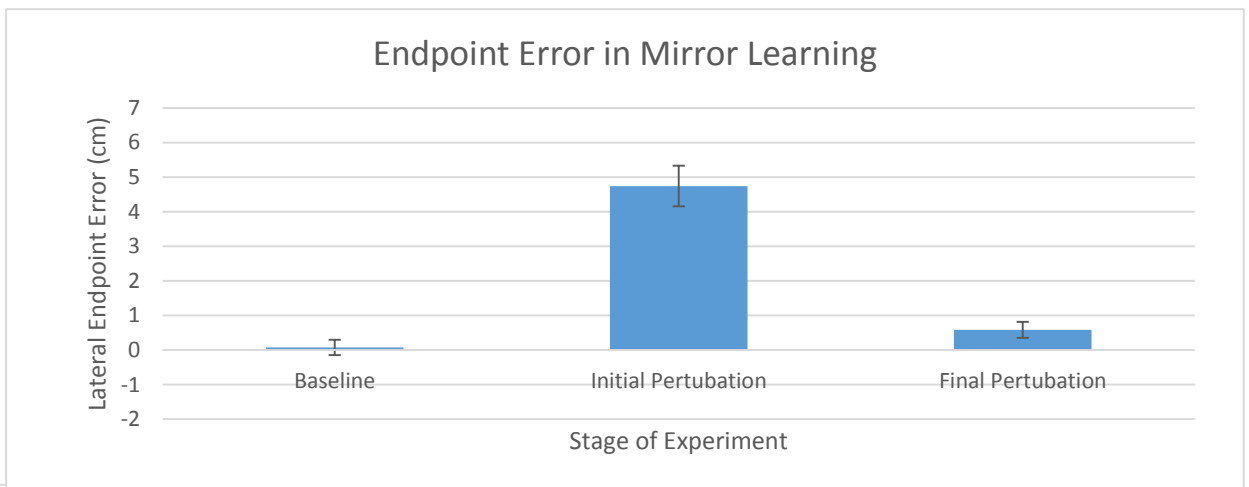
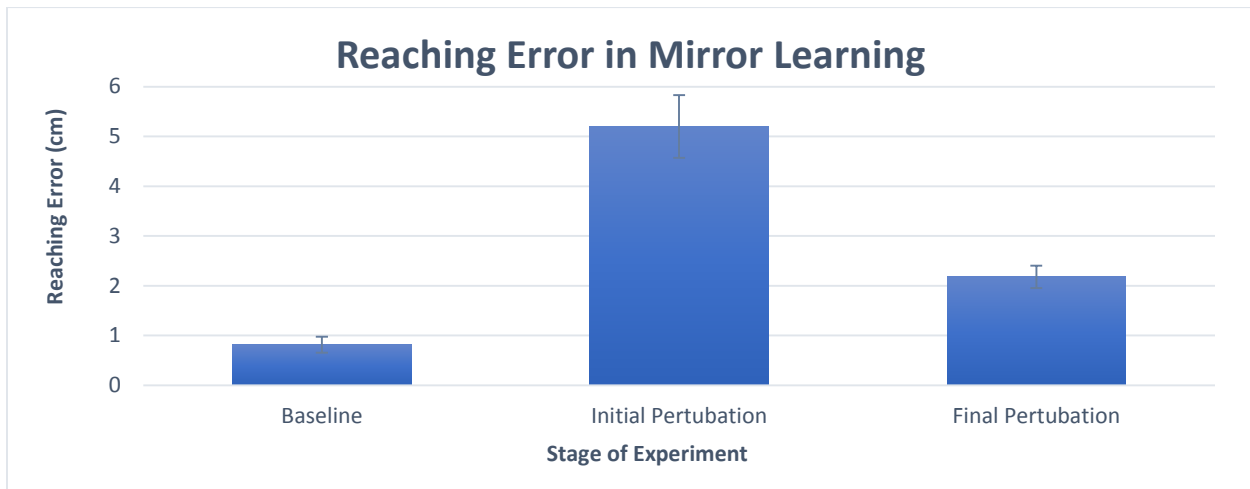
**Figure 4: Photo of experimental setup**



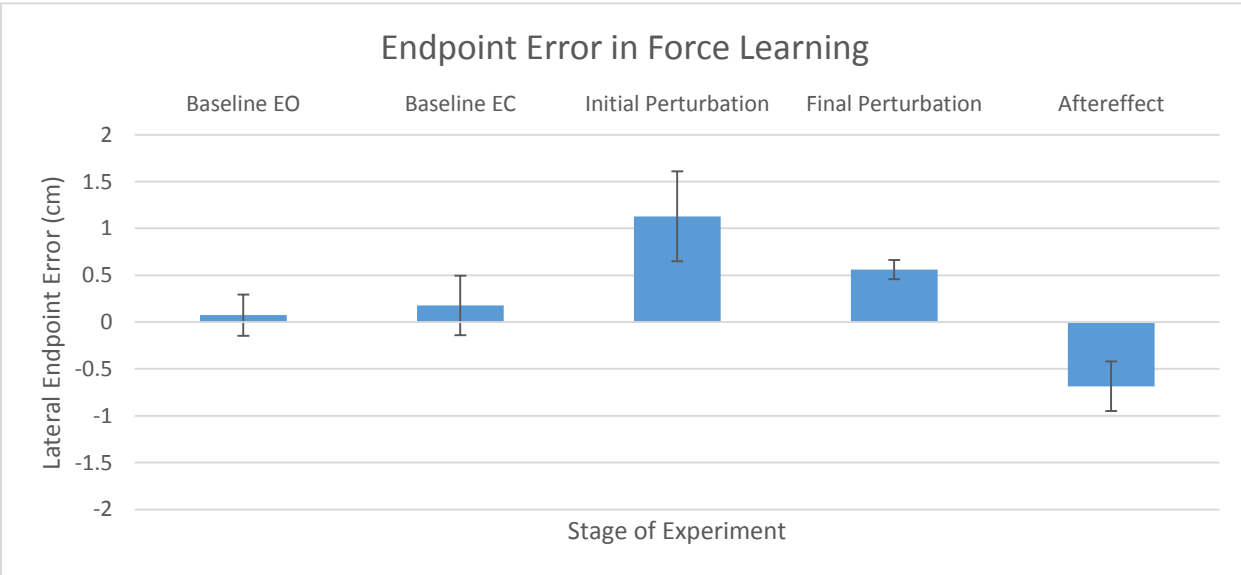
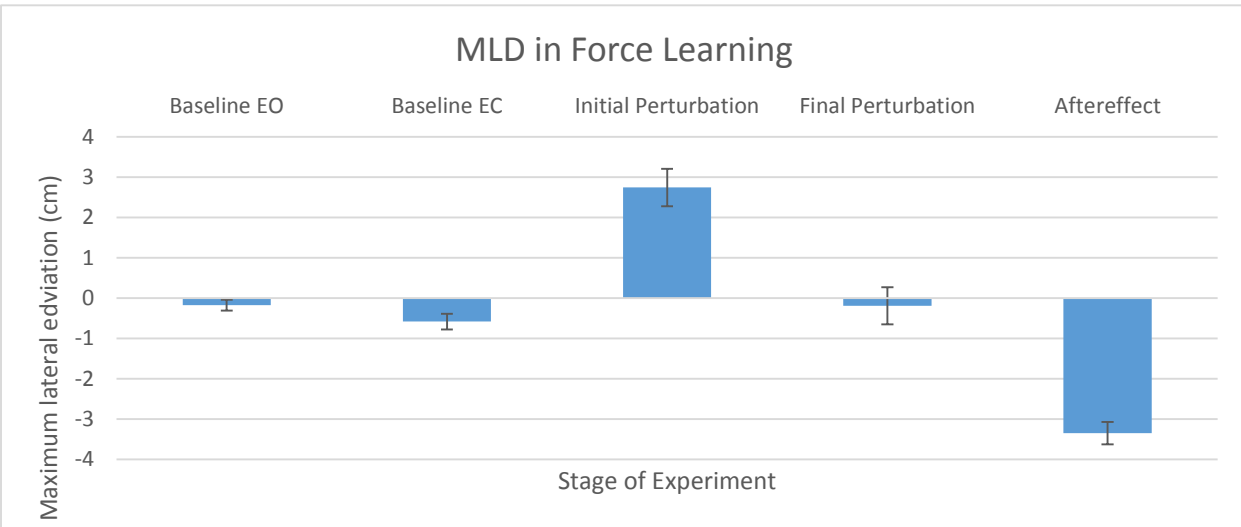
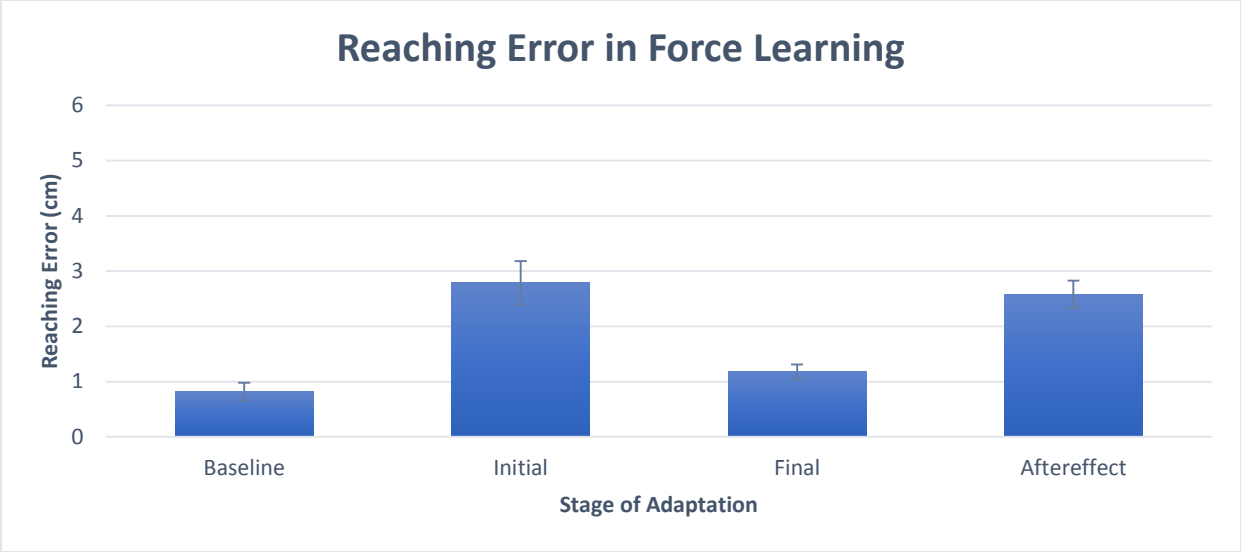
**Figure 5. Average peak velocity across conditions (Mean  $\pm$  SEM)**



**Figure 6: Motor Adaptation with Mirror Feedback (Mean  $\pm$  SEM)**

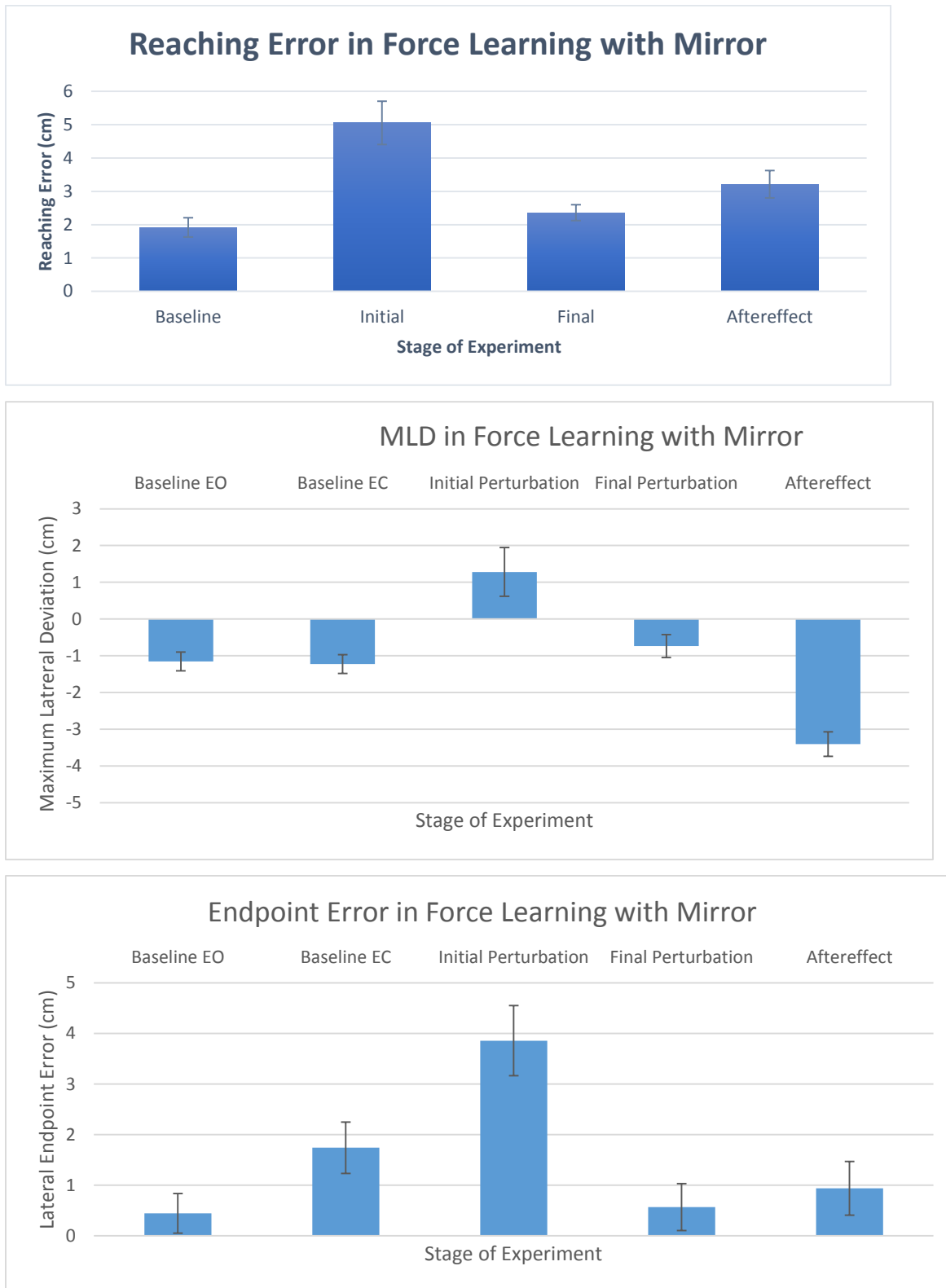


**Figure 7. Motor adaptation to a dynamic force perturbation (Mean  $\pm$  SEM)**

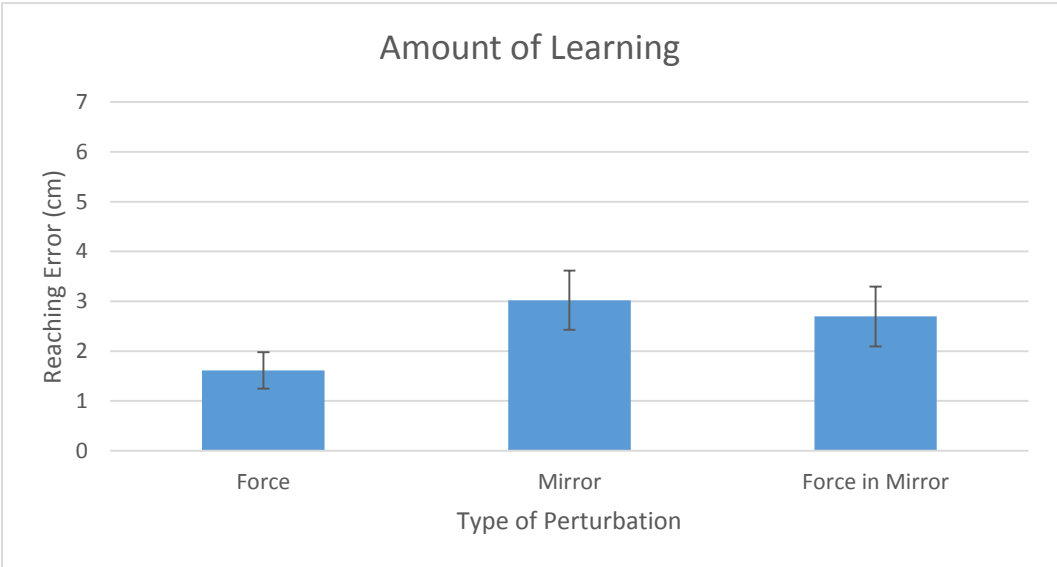
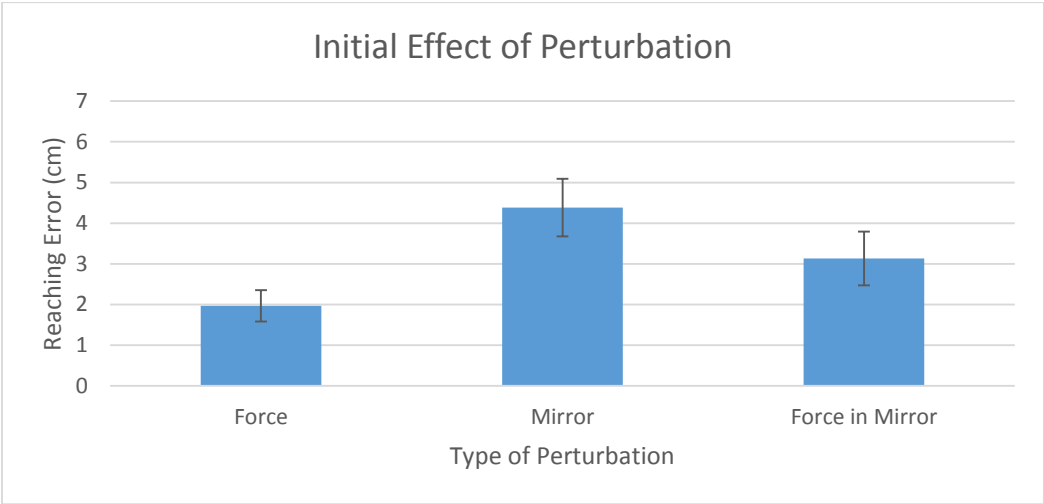
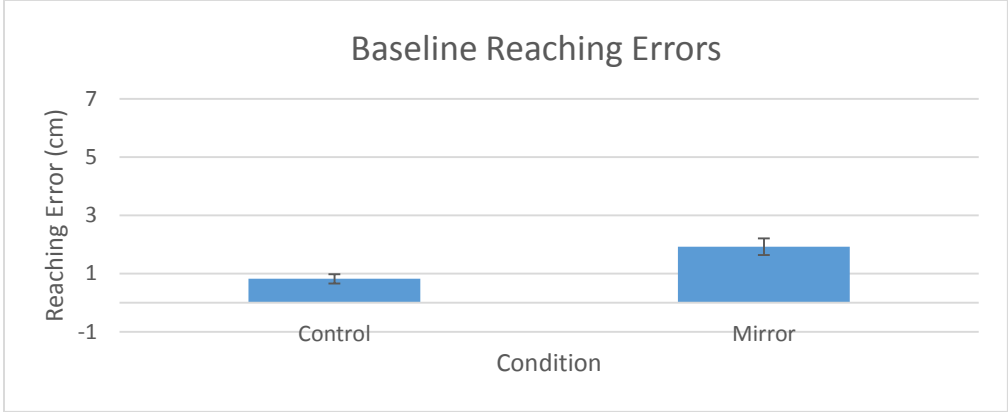




**Figure 8. Motor adaptation to dynamic force perturbation with mirror feedback (Mean  $\pm$  SEM)**



**Figure 9. Comparisons of amount of learning between conditions (Mean  $\pm$  SEM)**



**Figure 10. Comparison of rate of motor learning across conditions (Mean  $\pm$  SEM)**

