A Real-Time Haptic/Graphic Demonstration of how Error Augmentation can Enhance Learning *

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Abstract – **We developed a real-time controller for a 2 degree-of-freedom robotic system using xPC Target. This system was used to investigate how different methods of performance error feedback can lead to faster and more complete motor learning in individuals asked to compensate for a novel visuo-motor transformation (a 30 degree rotation). Four groups of human subjects were asked to reach with their unseen arm to visual targets surrounding a central starting location. A cursor tracking hand motion was provided during each reach. For one group of subjects, deviations from the "ideal" compensatory hand movement (i.e. trajectory errors) were amplified with a gain of 2 whereas another group was provided visual feedback with a gain of 3.1. Yet another group was provided cursor feedback wherein the cursor was rotated by an additional (constant) offset angle. We compared the rates at which the hand paths converged to the steady-state trajectories. Our results demonstrate that error-augmentation can improve the rate and extent of motor learning of visuomotor rotations in healthy subjects. Furthermore, our results suggest that both error amplification and offset-augmentation may facilitate neuro-rehabilitation strategies that restore function in brain injuries such as stroke.**

Index Terms – neuro-robotics, error augmentation, xPC Target, motor learning, and visual distortion

I. Introduction

In recent years, experiments that alter the sensory and motor environment of an individual have explored new and exciting possibilities for tele-assistive teaching and robotically-enhanced rehabilitation techniques. For example, robotic devices can be programmed to provide precise forces that restore a brain injured individual's movement patterns to a healthier pattern [1-4]. However, the use of robotics to promote physical rehabilitation is still in a formative stage, and initial attempts to exploit the intrinsic adaptive capacity of the human sensory-motor system for rehabilitative purposes are ongoing. In a promising study using specially-designed training forces, stroke survivors could make movements they previously could not [5]. This paper presents an initial exploration into the possibilities of a complimentary technique -- error-augmentation -- for facilitating sensory-motor learning.

Several lines of reasoning suggest that augmenting error may enhance motor learning. First, many models and artificial learning systems such as neural networks suggest that error drives learning, so that one can learn more quickly if error is larger [6]. Such error-driven learning processes are believed to be central to adaptation and the acquisition of skill in human movement [7, 8]. Secondly, larger errors are likely to heighten motivation to learn by making the consequence even small errors seem large. It also makes errors more noticeable to the senses and hence may trigger responses that would otherwise be lacking. Error augmentation may lead to larger changes in performance. Finally, intensifying error can also lead to larger signal-to-noise ratios for sensory feedback and self-evaluation.

One issue is clear from adaptive control and learning models, however –learning may become unstable if gains are too high. Motor variability, sensor inaccuracies and other uncertainties can cause endless over corrections that do not converge to satisfactory performance. We hypothesized in this study that there was some optimal amount error augmentation.

Recently we have shown that enhancing error by pushing the arm farther from its intended target can facilitate re-learning of motor commands required to make smooth and straight reaching movements [5]. In that study, stroke survivors experienced training forces that either amplified or reduced their hand path errors. Significant trajectory improvements occurred only when the training forces magnified the original errors, and not when the training forces reduced the errors or were absent. Hence error-enhancing training may be an effective way to promote functional motor recovery for brain injured individuals.

Sensory-motor adaptation has been observed when there is a distortion in the mechanical realm [9-11], but is also observed when there is a distortion in the visuomotor realm [12-15]. In fact, visuomotor adaptation can even trigger recovery of sensory disorders such as hemispatial neglect secondary to stroke [16]. Both mechanical and visuomotor adaptation appear to involve similar neural mechanisms [17]. Hence, we restrict our focus in this initial study to the more easily-implemented visuomotor distortions and healthy adult subjects.

While our preliminary results using error-amplification are encouraging, there are a variety of ways to augment or intensify error. Among these the most obvious are linear affine distortions of gain and offset. The first, gain, is the most obvious way to augment error. If subjects are instructed to move in a straight line to a target, a gain of 2 augmentation would mean that any deviation from the straight line would be displayed 2 times that distance from the line. However, recent work on motor learning suggests that there may be a practical limit to gain augmentation.

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Scheidt and colleagues [18] have found that when force is used to disturb motions, subjects incrementally updated their behavior from one movement to the next based on the error they experienced on most recent attempts. This update was best represented by a transfer function that corresponded to lead-lag compensator, in which the average value for the pole was 0.322. Inverting this transfer function suggests that a gain of 3.1 is the approximate limit to which gain could be amplified in order to obtain rapid learning without leading to instability. Since there is recent evidence to show that vision and force distortions are linked [17, 19], we tested the limiting gain of 3.1 as well as a more moderate gain of 2 in this experiment even though we focused on visual rather than force distortions. Specifically, we explored the relationship between learning rate and error gain augmentation using these two candidates.

An alternative approach, error-offset augmentation accentuates error by adding a constant "expected error" to the visual feedback of hand path. Hence, if a subject's error is 2 cm to the right, they might train with a visual feedback that has a 2 cm bias to the right. Offset-augmentation may prove to be superior to gain for several reasons. Magnification using offset is more stable than that of gain because the augmented error display does not grow larger with error. Moreover, in contrast to gain-augmentation, the offset is independent of the size of errors made later in training when the subject is closer to the desired goal. Therefore, offset-augmentation continues to present large errors that continue to motivate learning. One potential problem is that offset error augmentation does not know when to stop -- one can over-learn beyond the desired goal.. While these theoretical assertions could be made about these candidates for error-augmentation, only experimental tests will truly support their validity.

This paper evaluates several of these candidate strategies for error-augmentation on healthy subjects. The magnitudes of error magnification studied in this project involved gain factors of 1 (normal conditions), gain of 2, offset, and a gain of 3.1. The goal of the experiment was to determine which error-augmentation condition best facilitated the learning of a visuo-motor distortion. We hypothesized that: 1) Subjects in all groups could adapt to the visual distortion; 2) Error enhancement would be most evident in the case of offset error augmentation; 3) The groups differ in how they are able to *generalize* what they learned to unpracticed directions of movement. Our results showed encouraging evidence for the use of error augmentation in haptic/graphic systems for robotic teaching, telemanipulation, and rehabilitation.

II. METHODS

A. *Experimental Apparatus*

The experiment was carried out on a planar Manipulandum Robot (Fig. 1), which is consisted of two brushed DC torque motors (PMI model JR24M4CH, Kolmorgen Motion Technologies, NY, USA). The motors are capable of delivering forces at the handle via a Four 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. In this experiment, we only used the motors to remove the modeled inertial effects of the robot, rendering a nearly impedance-free movement of the handle.

While seated in front of the robot and holding the robot handle, subjects were instructed to make reaching movements by following cues presented from an LCD projector on a horizontal projection plane (Fig. 1). Vision of the subject's arm was obscured by the projection plane, and hence a wide variety of visual distortions were possible, including the rotational distortion used in the experiments described below. Previous developments with this robot were controlled by a PC running DOS to acquire the signals and control torques. For this experiment, a real-time control system was developed using MathWorks xPC target TM. The control schematic, shown in Fig. 2, illustrates the two PCs: a 'Host' running with MATLAB-Simulink and MS C++ compiler, and an 'xPC-Target' real-time kernel. Each separate element (referred to as a model) was developed using MATLAB-Simulink. A low-level Target model (Fig. 2, bottom) was first compiled on the Host PC and then passed to the Target. It consisted of position, I/O, and torque blocks and was dedicated to real-time control at 200 Hz. It also receives commands from and broadcasts motion and force data to the Host. The Host model (Fig. 2, top) issued executive commands to the Target, managed the experiment, displayed visual feedback to the user via a calibrated overhead projector, and collected and stored data (100 Hz).

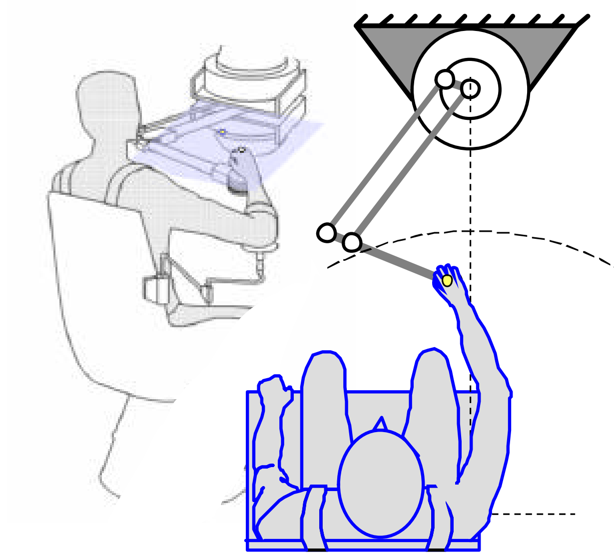

Figure 1. Robotic manipulandum and display apparatus used. Subjects' view of their own arm was blocked by a platform where artificial visual feedback was projected.

The communication between the Target PC and the Host PC was achieved through UDP (User Datagram Protocol), which is a transport protocol that was layered on top of the Internet Protocol (IP). UDP is characterized by its unencumbering nature because it uses a 'send-and-forget' strategy that can ensure reliable real-time control of the robot even when information fails to arrive within a single sampling period.

B. *Subjects*

Sixteen neurologically normal adults (22-30 years old) volunteered. The subjects were divided evenly and randomly into four groups. All subjects gave informed written consent in accordance with the ethics committee (Internal Review Board at Northwestern University). Each subject only participated in one protocol to prevent cross-over effects.

C. *Experimental Protocol*

Subjects were requested to make successive outward reach-and-stop movements to visually displayed targets. Targets were spread evenly along a circle with radius 0.1m. Return movements to the center point were not analyzed. We controlled for a speed of 0.45 m/s by giving subjects feedback at the end of each movement using colored dots and auditory tones to let subjects know if they were going too fast, too slow, or within a range of ±0.05 m/s. Consequently, subjects' speeds remained roughly constant across the entire experiment.

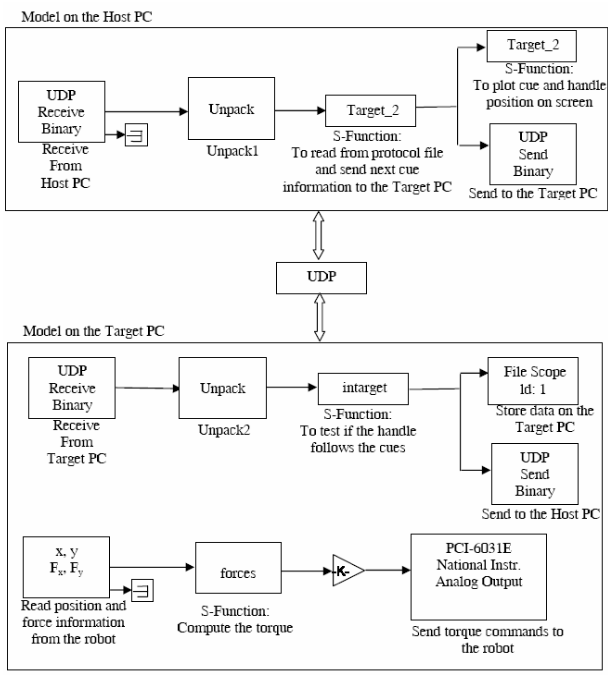

Fig. 2. Control schematics for control using xPC. Two computers operate the robot and display. One manages the experiment, renders a feedback display, and stores data (Host PC); the other is dedicated to reliable control of robotic forces (Target PC).

All four types of error augmentation in this study were derived from a simple affine transformation. That is, the cursor location was moved either by a multiple of the current error vector (a gain, Fig. 3A), or shifted by a constant e_o. (an offset, Fig 3B). A perpendicular vector from the ideal straight-lined movement was used to characterize the current error, and that vector was used to alter the position of the cursor for error magnification. The constant e_o, was the average initial error, determined for each subject in each of the three possible directions of movement at the beginning of the experiment in (Phase 4, described below). To determine e_o, we intermittently exposed each subject to the visual rotation early in the experiment.

Note that the two examples in Fig. 3 appear the same. The final location of the cursor appears in the same spot if the subject performs a movement along the path of the average initial error Phase 4. However, the gain (*2) and offset strategies differ dramatically at other locations. An extreme example is when the subject performs the ideal trajectory. Then error is zero, so the subject experiencing the gain (*2 or *3.1) will see their trajectory match their desired. However, the subject experiencing the offset will still perceive an error. Hence, an offset error augmentation does not decrease with learning like the gain error augmentation does.

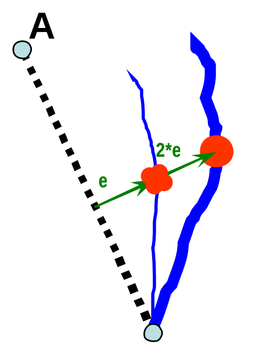

Fig. 3 Illustration of the error-augmentation strategies. The ideal trajectory, appropriate for the rotated environment is indicated as a dotted line. The trajectory that the subject actually moves along is represented by the thin line. Each instant, the cursor (large dot) is displayed by calculating the current error and either multiplying that error (A) or by adding a constant e_0 to that error (B), resulting in the trajectory that the subject sees (thick lines).

For all subjects, the goal was to learn to perform movements to the targets within the allowed range of speeds. All subjects had to do this in the presence of a visual distortion and three of the four groups were subjected to error augmentation. Implicitly they all made movements that were as straight as possible to the target. The first group of subjects was a control that experienced the visual rotation only with no error augmentation (essentially a gain of 1). The second group (*2) experienced a gain of 2 as shown in Fig 3B. The third group (Offset Group) experienced an offset as shown in Fig 3B. The fourth group (*3.1 Group) experienced a gain of 3.1.

Each protocol entailed 12 phases of experimentation that varied only in the values of the gain and offset factors, described below:

1. <u>Familiarization</u>: 15 movements; 5 to each target, to become familiar with the system.
2. <u>Baseline</u>, 15 movements; 5 to each target, with no visual rotation or error enhancement. This established a baseline pattern.
3. <u>Rotated baseline</u>, 15 movements; 5 each to target that were thirty degrees away from t those in Phase 2.
4. <u>Initial Exposure</u>: 120 movements. Here, one movement in eight (totally 15; 5 each to target) was with a 30º rotation of the visual field. There was no error augmentation. The average of these 15 'initial exposure' movements is recorded to e_o as a function of distance from the starting point.

5-7. <u>Early, Intermediate, and Late Learning:</u> In these trials (390 movements in all) the four groups experienced the same visual rotation of thirty degrees, but movements also included error augmentation, dependent upon the group descriptions above. Also during this phase, all of the four groups experienced 'catch-trials' that were randomly presented once every eight movements. During these catch trials their respective error augmentation was removed. Hence for all subjects, these catch trials were the same (30º rotation of the visual field with no error augmentation, occurring at the same movement number). These catch trials were used to monitor and compare learning across all groups.

8. Evaluation: In all 15 of these trials all subjects experienced the same visual rotation of thirty degrees with no error augmentation. This consisted of 5 movements to each target.

9-12. Early, rotated, middle, and late 'washout.' Here, all visual rotations and error enhancements were removed to study how the nervous system de-adapts back to a normal behavior. Phase 9 was composed of 10 movements to each target. Phase 10 consisted of 5 movements to each target, but the targets corresponded to the same target locations in phase 3. Phases 11 and 12 consisted of 40 movements to each target.

D. *Data Analysis*

The measure of interest of this study was the change of the trajectory error compared with an ideal, straight line movement to the target. This ideal closely represented the movements of subjects under normal conditions when there is no distortion or error-augmentation (Fig 1, figures on left side), as observed in previous studies [20, 21]. The trajectory error was defined as the maximum distance (also often called the infinity norm or Chebychev norm) between the actual trajectory and the desired trajectory described above. Other error measures yield similar results.

We made four key different comparisons between the results of four groups of subjects: The *amount* and *rate* of adaptation, the *amount* and *rate* of washout. We also identified the change after the first catch trial among the groups; and the extent generalization.

In assessment of the learning rate of the adaptation to the rotated visual field, the trajectory errors were grouped into 5 trials a block and fit into an exponential curve,

$$A + Be^{-t/C}$$

where A is an offset, B is the amount of learning (the change of the trajectory errors), and C is the rate of learning (time constant for the error to decrease). Data for this analysis was restricted to the catch trials during learning Phases 5-7 and another fit to the data from the washout phases (9, 11 and 12).

Significance for all statistics was assessed using ANOVAs and Tukey post-hoc Comparisons at α=0.05.

III. Results

Subjects of all four types of error augmentation showed evidence of learning. Subjects made curved trajectories when first exposed to visual distortion (Fig 4, second column of plots), but recovered their ability to produce a straight line at the end of training (Fig 4, third column of plots). When they were returned to normal (un-distorted) conditions, they displayed the characteristic after-effects that curved opposite to initial exposure phase, and these after-effects gradually washed out (Fig 4, rightmost column of plots). Subjects in all the four groups presented large after-effects of adaptation, which was strong evidence that adaptation had taken place.

Quite interestingly, our error augmentation approaches were found to successfully enhance learning in several aspects. First, the Offset group proved to learn significantly more than all other groups (Figure 6, top) ($p<0.002$). Moreover, error augmentation sped up learning for two of the three groups -- Learning for Gain *2 and Offset Groups was both significantly faster than the other groups (Fig. 5, middle two tracings, and Fig. 6, bottom figure) ($p<0.006$). Overall in this experiment, the Offset Group learned best in terms of magnitude and speed of learning.

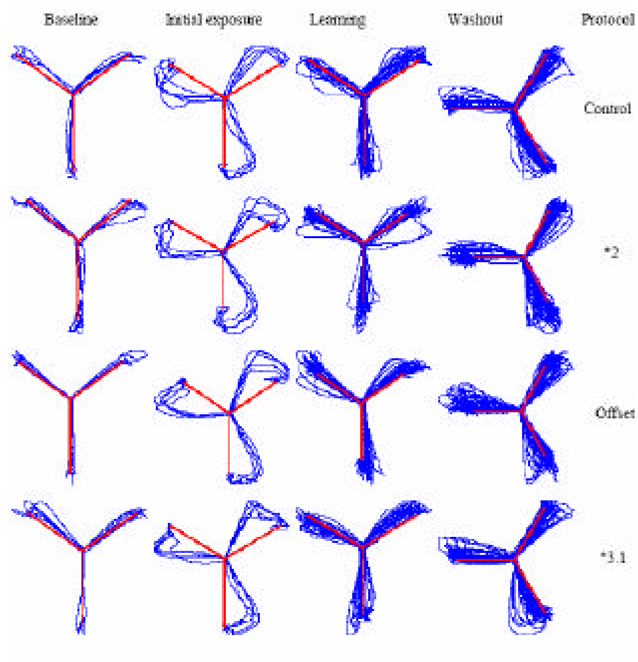

Fig. 4. Representative trajectories of the hand. Each row of plots displays data from a typical subject from each group. Each column represents a critical phase of the experiment. Only the catch trials are shown for the Learning Phase. Red lines indicate the path the subjects should have reached to successfully complete the task.

All subjects de-adapted in about 70 movements after training when the visual distortion was removed. However, we found no significant differences in the magnitude or in rate of de-adaptation (Figure 6, teal bars).

We also tested a gain of 3.1 to see if this large amount of gain might lead to more complete learning after a single trial of exposure. We looked at the trials immediately following the first exposure to 3.1, which was designed to be a catch trial, but we found no significant differences among the groups on the improvements following that single initial catch trial.

Finally, all groups were able to generalize their learning skills well to unpracticed targets, but there was no indication from our data that any one of the groups differed from the others.

IV. Discussion

This paper evaluated several candidate strategies regarding error augmentation to investigate how healthy subjects learn. The goal of the experiment was to determine which error-augmentation condition is optimal for learning a visuo-motor distortion. The smaller time constants for gain

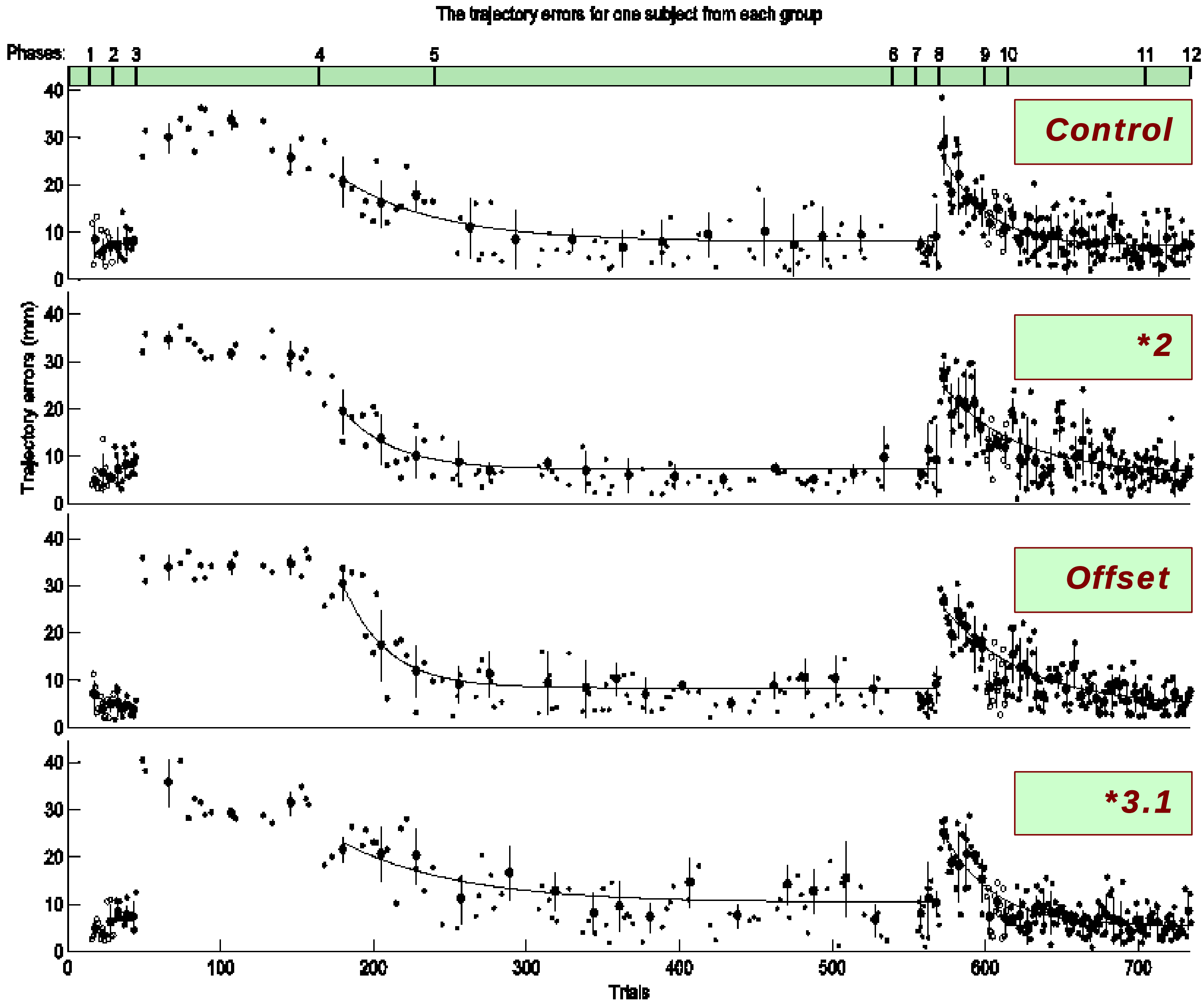

Fig. 5. Learning curves for representative subjects in each group. Small dots represent the trajectory error for a movement, and the bold dots represent the mean trajectory error for 5 successive movements in combination. Learning (5-7) and washout (9-12) phases were each fit to exponential curves (lines). For the learning phases (5-7), only the catch trials are shown because these trials were used for the regression lines that characterize the rate of change and amount of error reduction. For these catch trials, the conditions were the same for all groups (30º rotation of the visual field with no error augmentation, occurring at the same movement number). Conditions were the normal for all groups during the washout phases (9-12), and hence the regression used all trials (as shown).

of 2 and offset demonstrate that error augmentation can increase the rate of learning. Moreover, the Offset Group in learned significantly more the other groups.

The offset condition, while a less intuitive, appears to allow subjects to adapt to the visually rotated environment more efficiently and accurately than the other methods of augmentation tested. As stated previously, the difference between the offset and gain error augmentation condition is that there is a constant error adding to movements in the Offset Group that does not decrease with improvement. Offset offers one other advantage – it is more stable than the gain-based approach, which can have an unwieldy display of errors when the subject makes a large mistake.

There are several undesired effects from offset condition as well. The Offset Group's larger amount of learning may be due to the fact that they were required, in effect, to learn a rotation of as large as 60 degrees. The offset condition delivers visual feedback that always deviates from proprioceptive feedback the same amount -- 30 degrees in this experiment. This means that offset can lead to learning beyond the goal, which occur in some trials in this experiment. However, the advantage of Offset is that it may overcome the problem of diminishing returns due to small errors that are often seen at the end of the learning process. Therefore a more intelligent implementation may be a 'scheduled' mixture of offset and gain, in which the offset factor is extinguished when the subject learns beyond the goal, may be optimal.

Our results also demonstrate limits on the effectiveness of a gain augmentation strategy. The gain 3.1 in the experiment did no better than the control (gain 1) and worse than gain 2, possibly because the larger gain may have decreased the relative stability of the adaptation process beyond that which subjects were comfortable, thus causing them to down-regulate their internal feedback gain so that the overall gain approached "normal". Had they not done so, noise and sensorimotor uncertainty could possibly lead to overcorrections and consequently unstable learning. Consequently, there is likely an optimal gain between 1 and 3.1. Because there is some recent evidence to show that vision and force distortions are linked [17, 19], our results may not be true for all tasks and contexts. Moreover, error augmentation using sensory feedback such as proprioceptive or haptic forces may be more effective at different gains. Offset, which was not scaled in this experiment, could also have an optimal value. Moreover, some combination of gain and offset strategies may lead to the best possible learning pattern.

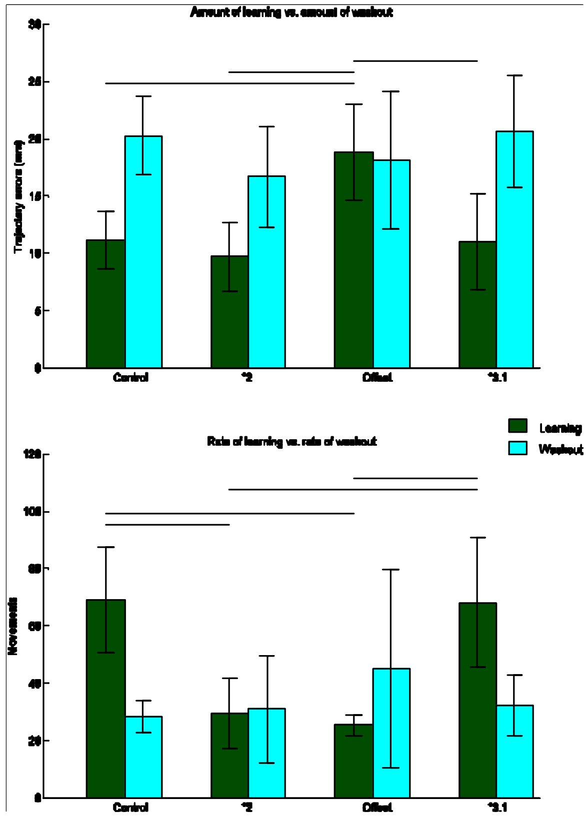

Fig. 6. The amount (top) and time constant (bottom) of error decay during learning (green) and washout (teal) for the four groups. Horizontal lines indicate significant difference between the two groups beneath their tips.

Finally, while our results were on healthy subjects, they have excellent implications for robotic neurorehabilitation. The results of the experiment bring new possibilities to rehabilitation methods which employ robotics. Increased rates of learning via error augmentation would be quite valuable to therapists. The results found in this experiment support and expand upon those found in a recent study [5] that reported when brain injured individuals were subjected to error augmenting vs. reducing forces, error augmenting better healthier movement patterns. The experiment affirms that increasing the error perceived by the subject increases the rate of learning. Error augmentation may 'wake up' an inattentive nervous system and trigger the recovery process by supplying heightened, magnified sensory feedback about a persons' motor deficit. ■

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