Visual Limit-Push Training Alters Movement Variability

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***Abstract*—In both movement training and neurorehabilitation, there have been numerous examples of how average performance can be manipulated through practice using enhanced visual feedback. *Objective*: Rather than just influencing the mean, our objective was to use a novel feedback technique called *limit-push* to influence the trial-to-trial variability of motion by distorting vision. *Method*: Limit-push was previously done using robotic forces; the present study employed only visual distortions that imitated the limit-push approach. *Results*: Like the robotic force treatment, our results showed how subjects significantly shifted the distributions of their motions. This effect was even greater than that of the original limit-push experiment that used robotic forces. *Significance*: Such visual distortion interventions do not require a robot for enhanced training. *Conclusion*: The visual limit-push technique appears to be able to selectively alter both the central tendency *and* variability in performance training applications.**

***Index Terms*—Haptics, high-cost, kinematics, motor control, motor learning, motor variability, statistical distribution, virtual environments, visual distortions.**

I. Introduction

ARM movement tasks often afford a luxury of choice. For example, a tennis player must reliably match the ball to the racquet with a wide range of interception points that result in an effective shot. With practice a player can learn these "sweet spots" that result in the best kind of returns within the wide range. Crossing into a region of "high-cost" states with failure outcomes results in a player missing the ball or hitting it outside the court. High-cost regions can be any state where irreparable negative consequences can occur, such as in unsafe or inefficient situations. Whether it is for sports performance training or physical rehabilitation, learning occurs only through experiencing sensory consequences during repetitive practice [1]. As evidenced by the current study and our previous one, it may be that the consequences of experiencing high-cost states motivate learning and shape new behavior [2]. Since high cost states can appear abruptly, we consider the separation between high and low-cost states as a boundary, like falling off a cliff. The central nervous system (CNS) may learn to avoid movement variations that lead to crossing any boundary. It may be possible to harness this learning phenomenon to reshape movement tendencies for performance training and movement rehabilitation. For example, high-cost boundaries could decrease movement-to-movement variability in survivors of stroke and traumatic brain injury who often have disabling motor variability [3]–[5]. Variability control is also of interest in microsurgery and piloting, where tremor may lead to poor performance even though the average path is accurate [6]. We predict that training in the presence of high-cost boundaries implemented with a visual distortion will change not only the central tendencies but also the spread of peoples' movements.

The potential for such changes in movement distributions is evidenced in movement planning research in which the nervous system can manage movement to avoid breaching high-cost boundaries. In fact, it is commonplace for humans to avoid crossing high-cost boundaries for safety and efficiency. In standing, for example, people tend to create *safety margins* away from certain boundaries to avoid position and velocity combinations that precipitate a fall [7]. In a shuffleboard arm movement task with an induced increase of variability healthy subjects limited their movements to lower velocities that traded high score regions for decreased risk of complete failure [8]. Walking subjects adjust their toe height and shift their center of mass over support limb when a trip is imminent [9]. Fear of falling due to standing near a ledge, for example, can not only cause a proactive leaning away from the edge, but also a reactively tighter range as well as faster reaction times to perturbations [10]. However, it is possible that a person's movement variability in certain contexts may be too large to be able to stay within the safe region for some tasks. In such cases movement training in virtual environments with apparently high-cost, although safe, boundaries may be useful.

While high-cost boundaries occur naturally, they can also be created artificially, using devices to influence movement tendencies. Boundaries of instability occur when stepping too wide on a balance beam, and have been shown to change behavior [11], [12]. Visual or haptic feedback simulating events as extreme as "falling off of a cliff" have been shown to dramatically reshape movement choice [13]. Robot-generated haptic environments that simulate instability can change limb impedance properties, leading to altered variance in certain directions [14]. It may be that such approaches resonate with the natural learning tendencies of the nervous system, which may employ a

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boundary-avoidance approach to planning and control of actions. To test this idea, we previously employed a *limit-push* approach, where an abrupt robotic push moved the hand further away whenever the hand exited an invisible box-shaped boundary [2]. This treatment was effective during a projectile interception task, changing the tendencies of movement distributions. What remains to be seen is whether this approach of an artificially-created high-cost boundary might work using similar (and perhaps less expensive) means.

Therefore, this work tests whether exposing a subject to a high-cost state through an abrupt visual distortion will reduce their movement variability in a critical dimension while attending to a goal directed task. Visual distortions such as mirrors, prisms and computer displays have been well established as a means of inducing the training effects associated with neuroplasticity [15]–[18]. Visual augmentation was also effective in modulating finger pinching tasks [19]. These effects are due to the conflict between visual feedback and proprioception during a visual distortion. In this study, we explicitly test the idea of creating a visual distortion that imitates the robotic limit-push approach, to determine if a visual distortion can similarly reshape movement distributions. We evaluate this *visual limit-push* approach for changes in movement distributions in response to training, and compare this to controls and force-based limit-push group of our previous study [2]. We hypothesized that our treatment would cause people to situate their movement distributions more within the box-shaped boundary. Furthermore, we hypothesized that our new visual variety of limit-push would have similar effects to the force limit-push treatment. Our results build on previous evidence that shows that people's movement variability can be reshaped with the proper training activity. A preliminary version of this work has been reported elsewhere [20].

II. Methods

The experiment included 27 neurologically healthy volunteer subjects who all signed an International Review Board (IRB) consent form as part of the Northwestern University and University of Illinois at Chicago IRB approved protocol for this study. This assured that procedures followed were in accordance with the Helsinki Declaration of 1975, as revised in 2000. Subjects were divided randomly and evenly into a Visual Limit-push Group, Force Limit-push Group, and a Control Group. The latter two groups were taken from Sharp and Patton's 2011 study [2]. Subjects were not informed of their treatment. Subjects sat at the center of the VRROOM (Virtual Reality and Robotic Optical Operations Machine) which provided a 3D, stereoscopic image for a large virtual space superimposed on a robotic workspace. The Control Group and the Force Limit-push Group manipulated the Whole Arm Manipulator (WAM, Barrett Technology, Inc., Newton, MA) in the virtual environment [2]. The new Visual Limit-push Group did not require forces, and so it was collected with our subjects manipulating the lightweight Phantom 3.0 robot (SensAble Technologies, Woburn, MA).

Subjects in all the groups gripped the spherical end effector of a robot to control a virtual environment (Fig. 1, top). The virtual space and robot arm limits were large enough such that the subject could fully extend their arm in front of them while grasping the end effector. The end effector, a tennis ball attached to the end of the distal link of the robot, was used to control a red cube of 5 cm side length that served as a cursor in the virtual space. The virtual space also consisted of a semi-transparent green sphere of 25 cm diameter representing the subjects' workspace and a blue cube projectile of 5 cm side length. Aside from the projectile, cursor and workspace, the environment was black and

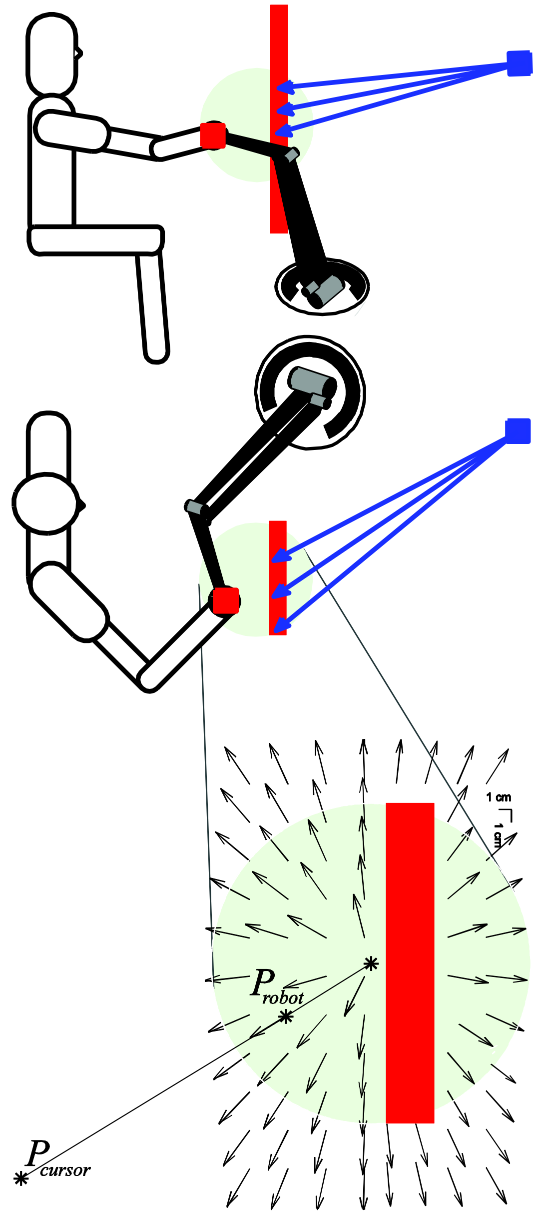

Fig. 1. Side (top drawing) and top down (middle drawing) views of the experiment setup. The boundary (invisible to the subject) is in red. The spherical workspace is in green, and in blue are the projectile and the trajectory lines that the projectile follows upon launch. Top drawings are not to scale. The bottom drawing is a pop-out that shows the distortion field for the visual and force distortions. In the treatment phase each position has a vector associated with it in which the cursor would be distorted. As an example, a subject's hand along with the robot endpoint they held could be at P_{robot}, and in the treatment phase the cursor would be rendered at P_{cursor} which is in the direction of the vector shown at the P_{robot} position. The magnitude of this distortion vector is three times the distance between P_{robot} and the center of the sphere.

the room was pitch-dark in order to avoid outside distractions during the experiment trials.

At the beginning of each of the 600 trials, the blue virtual cube launched towards the subject at 0.8 m/s from approximately one meter away in trajectory chosen randomly from a set of trajectories that always intercepted the semi-transparent green sphere workspace in front of the subject (Fig. 1, top). Subjects were told that their task was to intercept the blue projectile with the red cursor while keeping the red cursor inside of the workspace sphere. The robot provided a small force on the subject each time the projectile was successfully intercepted. After interception, the projectile stopped instantly and reset to its home position which was constant throughout the experiment. Subjects received a rest period of 15 seconds every 25 trials. Each session was about 35 minutes long. The virtual environment was rendered with H3D and manipulated with Python. Position of the hand was recorded at a frequency of 100 Hz.

The study consisted of a Control Group and two treatment groups; the Control Group received no treatment, but the two treatment groups received either a force distortion or a visual distortion. The treatment was applied only during the middle 200 trials of the experiment (trials 201–400). When they moved outside of the invisible box-shaped boundary, the Visual Limit-push Group experienced a visual distortion that made the hand look like it was being pushed further out of the box. This contrasts with the Force Limit-push Group, that experienced an actual force directed approximately away from the box during the treatment phase [2]. There was no limit-push treatment during the 200-trial pre-treatment and post-treatment phases. The invisible box dimensions were: 3.75 cm deep (anterior), 25 cm wide (lateral), and infinitely tall (superior). This box was roughly centered in the workspace (Fig. 1). The Control Group received no distortion in any part of the experiment, but performed the same number of trials. The visual distortion displaced the subjects' cursor away from the box with predetermined magnitude of 0.3 m so that it provided an abrupt shift of the cursor, well beyond the given workspace. The direction of the shift was along the vector direction between the center of the workspace and their current hand position:

$$P_{cursor} = \begin{cases} P_{robot} & \text{inside the boundary} \\ P_{robot} + 0.3U & \text{outside the boundary} \end{cases} \quad (1)$$

where P_{cursor} is the position of the cursor, P_{robot} is the endpoint of the robot held by the subject and U is the unit vector (direction) between the center of the workspace and P_{robot} (Fig. 1, bottom). If the subject acquired a complete knowledge of the boundaries of the box, the subject could stay within the boundary and intercept all projectiles.

Several data processing steps were taken to prepare for analysis. First, we applied a low pass Butterworth filter cutoff at 16 Hz to remove movement frequencies that were beyond meaningful human movements. Additionally, this filter removed duplicate timestamps that were due to rare occasions of spurious recording. The data was then down-sampled to 50 Hz to make it more efficient for analysis. Finally any position observations that were beyond what the body segment lengths of a 95th percentile human could possibly achieve were removed [21]. These happened due to odd occurrences in data collection such as the subject dropping the robot end effector.

While common variability metrics such as standard deviation or range might characterize the spread of data, these were not specific to the limit-push boundaries. Instead, our primary performance metric was *measure of safety* (MoS). We measured safety as the distance between the robot position and the nearest boundary edge along the anterior-posterior axis. For positions observed *inside* of the boundary, the distances *closest* to the edge were least safe, because they created the greatest risk of entering the high-cost region. However, for positions observed *outside* of the boundary, the least safe distances were *furthest* from the edge because they had the lowest probability for leaving the high-cost region, i.e., crossing back into safety. Hence, to construct MoS, the distances calculated for positions outside of the boundary were assigned a negative value while distances for positions inside the boundary were left positive. The MoS is the minimum of these signed distance values for each trial. The maximum value of MoS is the half-width of the boundary along the anterior-posterior axis, i.e., 0.0188 m. Low MoS values were more "risky" while high MoS values were more "safe". Essentially, MoS assesses the "safety-margin" and spread of the positions observed with respect to the boundary.

The secondary metric *percent outside* (PO) was found for each trial to assess how often subjects were outside the boundary. PO was calculated as the number of timestamps with positions outside of the boundary divided by the total number of timestamps for each trial.

Several analytical steps were taken to extract time points of subject behavior across the experiment. Given a metric value for each trial, in each phase of the experiment we fit those values to the exponential equation,

$$M = P_1 + P_2 e^{-\frac{t}{P_3}} \quad (2)$$

where M is the fitted metric value; P_1, P_2, and P_3 are the parameters of the fit; and t is the trial number (1–200) within a phase. The parameter values that defined the non-linear fit were obtained using a combination of Leavenberg-Marquart nonlinear optimization and simulated annealing to assure the global minimum solution. The endpoints of these fits at the beginning and end of the phases were used as time points. Our analytical techniques resemble our previous experiment [2], comparing how this new visual limit-push altered motion distributions in relation to the force treatment and controls. A mixed effects ANOVA with interactions between our Treatment Group (Force Treatment, Visual Treatment, and Controls) and Time Points (pre-treatment, early treatment, late treatment, early post-treatment, late post-treatment) assessed differences. Three changes between the time points – during treatment, pre to post treatment, and pre to final – evaluated the effect of these treatments over time. Unpaired two-sample t-tests compared average of these time point changes of the three groups, and Bonferroni-Holm corrections accounted for multiple comparisons, with significance thresholds (α) at 0.05. These parametric statistics assume normality, so we examined this assumption with the Lilliefors and Jarque Bera tests for normality which both failed to reject the null hypothesis that the data followed a normal distribution.

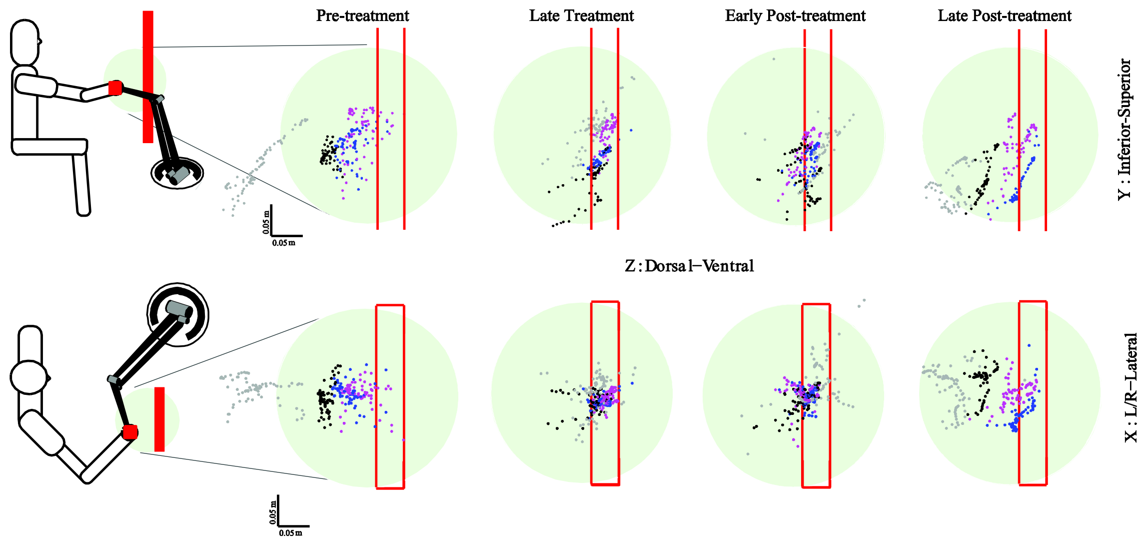

Fig. 2. Position distributions downsampled to 16 Hz. Two views, side and top-down, of the setup and data projections in two dimensions. The green circle is the subject's workspace. The boundary is in red. Each subject's data is in a different color. Horizontal progression represents data from different parts of the phases of the experiment.

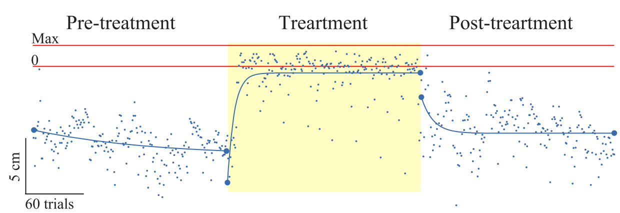

Fig. 3. The measure of safety (*MoS*) across the 600 trials for a typical subject is plotted along with an exponential fit of each phase (200 trials each). This exemplary subject shows a distinct exponential increase in the MoS metric in the training phase. Later in the post-training phase there is an exponential change in MoS back towards baseline values.

III. RESULTS

Multiple tests supported our main hypothesis that visual limit-push treatment prompted people to situate their movement distributions more within the box-shaped boundary (Fig. 2). This was best reflected in our primary outcome measure MoS (Fig. 3). MoS showed an increase for the Visual Group by an average of 7.7 cm from the beginning to the end of (during) treatment (ANOVA MoS; Treatment Group $F_{2,138} = 2.646$, p = 0.0745; Time Point $F_{5,138} = 0.260$, p = 0.9342; Interaction $F_{10,138} = 4.44$, p = 2E-5; *post-hoc* changes during treatment between the Visual Group and Controls: p = 0.019). The Force Group significantly decreased their MoS an average of 5.17 cm during treatment (*post-hoc* changes during treatment between Force Group compared to Controls: p = 0.012; Fig. 4).

We also found significant after-effects of training in the Visual Group by evaluating change from just before to just after treatment (pre to post; Fig. 4; p = 0.016). Consequently, the pre to post treatment increase averaged 4.8 cm in MoS. These after-effects were short-lived, washing out in the post-treatment phase. By the end of the post-treatment phase the values of the Visual Group were no longer significantly different than controls (change pre to final, p = 0.844 for MoS and p = 1.81 for PO). Our secondary metric, PO, agreed with some of these

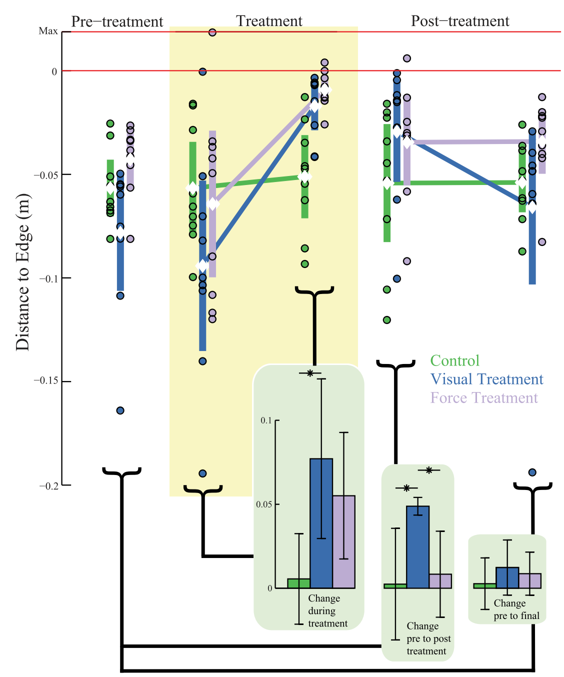

Fig. 4. The MoS values at the end of pre-treatment and the beginning and end of the treatment and post-treatment phases are plotted as circles for each subject with colors representing different groups. The mean MoS values are plotted as white diamonds in the center of bars representing 95% confidence wings. The visual distortion is on for the points that are highlighted in yellow. Zero and maximum possible MoS lines are plotted in red. Insets show the MoS mean changes for each of the changes identified in the top figure for each group. Asterisks represent a significant difference ($p < 0.05$) between groups based on an unpaired t-test with Bonferroni-Holm corrections for multiple comparisons.

results (ANOVA PO; Group $F_{2,138} = 1.115$, p = 0.3310; Time Point $F_{5,138} = 2.294$, p = 0.0487; Interaction $F_{10,138} = 3.037$, p = 0.0017). PO supported our main hypothesis with a decrease of 53.5% during treatment in the Visual Group (p = 0.015). This group also had significant after-effects compared to controls

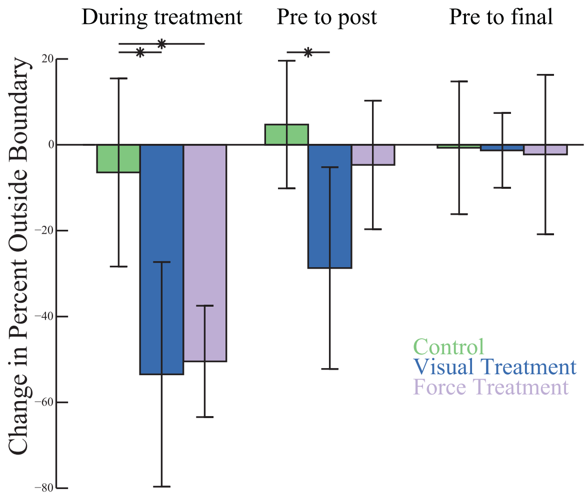

Fig. 5. Mean changes for percent outside of the boundary (PO) for each of the changes identified in Fig. 4 and for each group. Asterisks represent a significant difference ($p < 0.05$) between groups based on an unpaired t-test with Bonferroni-Holm corrections for multiple comparisons.

(pre to post; Fig. 4; $p = 0.023$), but there was no evidence that this effect was sustained (change pre to final, $p = 1.81$).

Most of our results supported our second hypothesis that the Visual Group would resemble the Force Group of our previous study [2]. In fact, during treatment we failed to detect any differences between the visual and force treatments (between group effects $p = 0.404$ for MoS and $p = 0.818$ for PO; Figs. 4 and 5). The immediate after-effect in the Visual Group was larger than in the Force Group only in the MoS metric ($p = 0.007$ for MoS and $p = 0.057$ for PO Fig. 4, top). However, this may be because the Visual Group happened to start off with a baseline further from the boundary and therefore were more motivated to adjust their movements (Fig. 4). Comparing pre-treatment to final between the Force Group and the Visual Group, we failed to detect a difference ($p = 0.844$ for MoS and $p = 1.81$ for PO).

IV. Discussion

We were surprised to find that the visual limit-push distortion could effectively modulate movement distributions, reducing trial-to-trial variability while also shifting central tendencies to be within a bounded region. The treatment directly influenced motion, also leaving an after-effect once the treatment was removed. This after-effect quickly washed out, however. The direct effects of the treatment phase of visual and force limit-push (from our prior study) were indistinguishable from each other, but significantly different than null treatment controls. Such "distorted reality" treatment appears to transiently but selectively recondition movement distributions regardless of modality.

It is encouraging that visual limit-push is effective because it can be implemented without robots. The visual limit-push allows for meaningful practice that is both challenging and repetitive, and it could be implemented with simple and inexpensive position tracking cameras. The Leap Motion sensor and the Kinect are examples of consumer products with position tracking cameras that can achieve similar positional information acquired by the robot in this study. Such sensors would dramatically reduce implementation cost compared to robotic systems, thereby making home systems feasible and potentially provide meaningfully repetitive, daily training for patients.

The limit-push approach is a more general variant of error augmentation, which has been shown to enhance training effects in skilled learning experiments involving repetitive practice. Error augmentation increases performance error to motivate the nervous system to update the motor control system for the next attempt. Subjects exposed to error augmentation treatment learned to make straighter, faster, and more accurate trajectories [22]. This treatment was also effective in three dimensions during learning of complete visuomotor reversal [23]. However, limit-push provides evidence that we simply need a harsh transition between low-cost and high-cost states to motivate a change in movement. Consequently, limit-push allows for a spread (i.e., variability) of movement, influencing subjects' probability *distributions* of their hand location, rather than simply their average tendencies.

Our *measure of safety* metric helped identify how well subjects' movements stayed within the boundaries to reduce the probability of high cost states. This simple metric was useful to test whether subjects learned to better stay within the boundaries with training, and consequently shifted and narrowed their movement distributions. The metric essentially establishes the subjects' range of movement outside of the boundary. Along with the decrease of this range in subjects' movement trends, a shift in the more general central tendency of movement distributions was observed with the decrease of the *percent of movements outside of the boundary*. Based on these two metrics one might speculate that the subjects *learned* where the boundary was, and that they retained a memory of the boundary region after the limit-push treatment was removed.

It is important to note that due to its small depth, staying inside of the boundary was very difficult. However, these metrics show that subjects must have adopted a strategy of avoiding a distorted cursor and staying inside of the narrow region of low-cost while trying to catch the projectile.

Our results suggest that the internal model of a boundary, and hence the potential conceptualization of the boundary, may be easier through the visual distortion than the force distortion. Unlike the force distortion, the visual distortion decouples the cursor position from the subjects' sense of their hand position. Hence, it is possible that the discrepancy between the proprioceptive and visual senses due to visual limit-push contribute information that is easier for the subject to consciously attend to because it defies their expectations of what should happen in the experiment. Such sensory discrepancies may be especially effective because there is evidence that people plan movements in the visually perceived space [24]. This contrasts with the concept that a force distortion may be a more effective stimulus because it contributes both visual and haptic information; the haptic information may be unnecessary. It is possible that the modality of the channel in which information is delivered may influence how much a subject might attend to the cues for learning in the task.

However, neither visual nor haptic distortions could create lasting changes in the distribution of movements of treatment group subjects. Once the distortions were no longer present, subjects reverted to their baseline movement patterns in about 20 trials. This suggests that the visual and haptic distortions, and subsequent conditioning of movement variability to avoid encountering these distortions, may be handled in central planning. It may also be that the conditioned movement distributions quickly washed out because subjects quickly noticed there was no longer a reason to avoid the visual distortion. In fact, the boundary may have been in a less comfortable space or too narrow. The treatment in this study was only designed to change motion distributions and not designed to necessarily yield better task outcomes. Once the distortion was removed subjects may have found that there are better ways to achieve the interception task. Additionally, it is possible that through prolonged training, effects may be less likely to wash out.

The visual distortion made it impossible for subjects to stay inside of the workspace, as they were instructed, without also staying inside of the unseen boundary. This implied that the distortion was "bad" with respect to the given instructions and therefore motivated the subjects to find the safe bounded region inside of the workspace. Therefore, the experiment "clued-in" the subjects to where the boundary might be. However, subjects had no idea of the shape or size of the boundary. Hence, the changes in the metrics above show that subjects, to some extent, conceptualized the boundary based on trial and error through the first five to ten trials of the treatment phase.

These preliminary results should be interpreted with some caution because of the limited nature of this study. The observed changes in variability were limited to the metrics described; changes in other variability measures such as standard deviation and range were not seen. Secondly our results may be limited to only the interception task, so further study should investigate how well this approach translates to other activities. Another limitation is in maintaining new movement tendencies beyond the distorted phase. Subjects quickly de-adapt in the post treatment phase, possibly because these healthy subjects preferred their typical movement tendencies over the ones imposed by the boundary. Another concern is that it is difficult to be certain that our performance metrics reflect the intentions of the nervous system to "avoid bad". It may be that other metrics are being used to learn and control [25]. Nevertheless, our engineering goal – to obtain a response to the visual limit-push treatment – was attained in this task.

V. Conclusion

This study adds important supporting evidence for visual limit-push in the repertoire of movement training algorithms. While the effects of such distortions washout rapidly, this is typical in such paradigms, and further work can investigate methods to refine training, perhaps making this approach useful in reducing unwanted variability in skilled activities. Visual limit-push may also be used to train for reduced variability in the neurorehabilitation of stroke or traumatic brain injury patients that would benefit from an inexpensive, easily accessed system. It is encouraging that this study motivates the exploration of the use of robotic and virtual reality systems to both improve and discover new aspects of human movement control.

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