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Error Amplification to Promote Motor Learning and Motivation in Therapy Robotics

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***Abstract*—To study the effects of different feedback error amplification methods on a subject's upper-limb motor learning and affect during a point-to-point reaching exercise, we developed a real-time controller for a robotic manipulandum. The reaching environment was visually distorted by implementing a thirty degrees rotation between the coordinate systems of the robot's end-effector and the visual display. Feedback error amplification was provided to subjects as they trained to learn reaching within the visually rotated environment. Error amplification was provided either visually or through both haptic and visual means, each method with two different amplification gains. Subjects' performance (i.e., trajectory error) and self-reports to a questionnaire were used to study the speed and amount of adaptation promoted by each error amplification method and subjects' emotional changes. We found that providing haptic and visual feedback promotes faster adaptation to the distortion and increases subjects' satisfaction with the task, leading to a higher level of attentiveness during the exercise. This finding can be used to design a novel exercise regimen, where alternating between error amplification methods is used to both increase a subject's motor learning and maintain a minimum level of motivational engagement in the exercise. In future experiments, we will test whether such exercise methods will lead to a faster learning time and greater motivation to pursue a therapy exercise regimen.**

I. INTRODUCTION

The goal of movement therapy is to improve function and quality of life in impaired individuals (such as hemiparetic stroke survivors or children with cerebral palsy) by maximizing their movement potential. This incorporates physical, psychological, and emotional efforts. Therapy robotics is mainly focused on providing a means of delivering the physical part of the therapy. With the advancements in haptics technology and development of immersive virtual-reality interfaces, robotic therapy regimens that supersede therapists' physical exercises are being developed. While a human therapist initiates the motor learning by showing the correct trajectory of motion to the subject (reducing the trajectory error), in robotic therapy exercises, a promising teaching strategy is to emphasize the amount of trajectory error (augmenting the trajectory error).

Use of feedback distortion and error augmentation in motor learning and adaptation has been extensively studied. In a study focusing on learning of fine motor movements (i.e., grasping), Matsuoka et al. demonstrated that distortion of the visual feedback leads to changes in pinching movement patterns of healthy subjects [1]. Building on this study, the same group showed that such distortion of visual feedback can also be used to improve grasping function in the post-stroke population [2].

Wei et al. compared two error augmentation methods: visual error offsetting and visual error amplification [3]. Introducing maximum error in the reaching trajectory as the performance measure, they studied speed and amount of adaptation to a rotational visual field in a robotic point-to-point reaching exercise. This study proved that these methods significantly increased the speed of learning in both healthy subjects and stroke survivors. With the same task and environment, Celik et al. compared progressive visual error offsetting, their novel error augmentation method, and the two methods used by Wei [4]. They used target hit time as a second measure of performance, in addition to the maximum lateral error in the reaching trajectory, and modified definitions for "speed" and "amount" of learning to further supplement the findings of Wei.

In addition to these visual distortion methods, a physical reaching environment can also be distorted by haptic feedback. Patton et al. showed that training the same point-to-point task, where force feedback in the direction of trajectory errors was provided via the robot's end-effector, facilitated a higher rate of learning in both healthy and clinical populations [5]. Moreover, Patton et al. showed that practicing with error augmentation, reinforced with therapist's verbal feedback, leads to a higher range of motion for post-stroke subjects (using $p<0.1$) [6].

While use of feedback distortion can lead to faster learning of reaching movements, subjects' engagement within such exercises has not been studied. Sustaining an individual's motivation to continue therapy should be a concern in designing new therapy paradigms. In fact, qualitative studies have shown that low motivation to comply with therapy leads to therapy abandonment [7], where more engaging exercises lower the extent of abandonment. Thus, the repetitive nature of massed practice of simple movements (like pinching and reaching) can be considered as a downside of such error-augmenting exercises.

We hypothesize that combining both haptic and visual means of amplifying error can lead to a better learning pattern of point-to-point reaching motions. Moreover, as error amplification makes the repetitive reaching task more challenging, we expect to see a higher engagement during reaching with error amplification. Based on this, we aim to measure the relative effectiveness of each error amplification method in promoting motor learning and increasing subjects'

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engagement in the task, in comparison with the control condition. In our study, 10 healthy subjects completed blocks of reaching tasks similar to those of [3-5] with different levels and methods of error amplification (i.e., low gain vs. high gain and visual vs. visual plus haptic), and reported their satisfaction, attentiveness and dominance during each block.

In Section II of this paper we provide the details of our experimental and analytical methods. Section III covers results, Section IV discusses the results, and Section V concludes by reflecting on the findings of this work.

II. Methods

A. Task Description

A five-bar robot previously developed at UBC was used in this study (Fig. 1). Its end-effector sweeps a2-DoF horizontal working area of approximately 50×35 cm^2. Two motors (Parker-Compumotor Dynaserv DR1060B) located at the base (at the "shoulders") actuate the robot, and the two "elbow" joints are passive. The robot's end-effector is a handle instrumented with a 6-axis force-torque sensor (ATI Industrial Automation Inc. "Mini" sensor). In this study, we consider only forces in the horizontal plane. Encoders integrated with the motors supply position feedback. Using TargetDisplay (MathWorks Inc.), the position of the end-effector is visually rendered on a flat screen monitor as a moving dot.

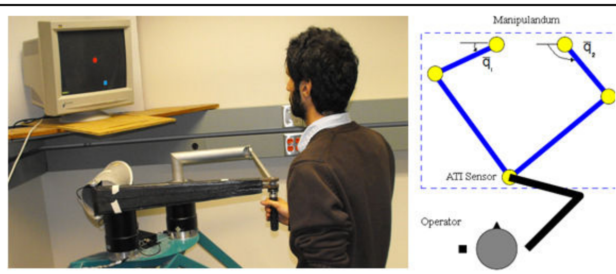

Figure 1. Left: a subject interacting with the robotic manipulandum. The cover that occludes the subject's hand has been removed to show the robot. Right: a schematic top view of the reaching environment.

Subjects were instructed to move the movable dot to visual targets presented on the monitor by manipulating the robot handle with their non-dominant hand. In this massed practice training, the 17" monitor was mounted in front of the subject, with a cover occluding the reaching space to make sure that the only visual feedback was through the monitor. Subjects were told that the moving dot shows the actual position of the handle. Three targets were placed radially, 120° apart, at a constant radius from the start position (i.e., middle of the screen). When a target was highlighted, subjects had to move the robot handle to place the moving dot over the target, and then move back to the start position. We call each three consecutive reaches a cycle, in which the three targets appear in random order.

To implement visual distortion, actual hand movement (handle position) was rotated 30°, and then the rotated position was presented as the moving dot on the monitor. Each subject would then train in 5 exercise blocks, receiving a different method of error amplification (EA) in each block, to learn reaching within the rotated environment.

B. Participants and Experiment Protocol

Ten healthy subjects participated in this study: five males and five females, one left-handed, with an age range of 19-27. Subjects provided informed consent as approved by the Clinical Research Ethics Board of the University of British Columbia. To make sure the subject was cognitively intact and free of significant neurological impairment all subjects were required to score higher than 24 on the Folstein Mini-Mental State Test. All the subjects had normal or corrected vision. Throughout the experiment, skin conductance measures were collected from fingers of the unused hand, but we did not use those data in this analysis. In this within-subjects experimental design, each subject learned to reach within the rotated environment, experiencing the control condition and all the four error amplification methods.

The experimental protocol (Fig. 2) was designed as six exercise blocks. In the first block, subjects performed 14 cycles of reaching tasks without any rotational distortion (i.e., plain motion). Each cycle consists of one reaching motion to each of the three targets in random order. This block aimed to get subjects familiar and comfortable with the robotic reaching task. Following the familiarization block, there were five training blocks.

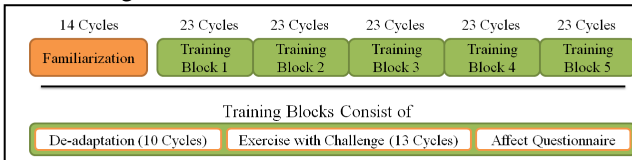

Figure 2. Top: Detailed break-out of the experiment protocol. Subjects were given this information prior to the start of the experiment. Bottom: A break-out of a training block.

Within each of the training blocks, subjects had to practice 10 cycles of plain motion (de-adaptation), and 13 cycles of reaching with one of the designed challenges "within" the rotated environment. The five challenges (one per training block) utilize different methods of EA to promote motor learning. Each subject practiced the challenges in random order. The de-adaptation cycles at the beginning of each training block are designed to wash out the learning effects of the previous training block, so adaptation to a challenge does not carry over to the next challenge.

At the end of each training block, we administered a Self-Assessment Manikin (SAM) affect questionnaire, asking the subjects to self-report their satisfaction, attentiveness, and dominance, all in a range of 1-9 (low to high) [8]. Subjects were given a rest period upon request. On average, each experiment took 90 minutes. We used this blocked experimental design to assess the effects of each training challenge on motor learning and the affect of the subjects.

Five conditions were used as challenges in training exercises for adaptation to the rotational field: reaching without EA (control), reaching with low-gain visual EA, reaching with high-gain visual EA, reaching with low-gain visual plus haptic EA, and reaching with high-gain visual plus haptic EA.

Reaching without EA was used as a control condition in data analysis. Visual EA was implemented as described in [3] with two gains: a low gain of 1.3 and a higher gain of 1.65. In this condition, cursor location was calculated through a vector summation of rotated hand position and amplified error vectors:

$$x_{\text{cursor}} = x_{\text{hand, rotated}} + (\text{visual EA gain}) \times e \qquad (1)$$

For the remaining two conditions, in addition to the visual EA, haptic feedback was given to subjects based on their instantaneous trajectory error. The haptic force vector, perpendicular to the vector from starting point to the visually presented target, was calculated using the following equation:

$$F_{\text{haptic}} = (\text{haptic EA gain}) \times e \qquad (2)$$

This haptic force was exerted onto the subject's hand via the robot's end-effector. Haptic EA gains were designed to map the trajectory errors to force ranges of 0-5 N and 0-8 N, for low gain and high gain, respectively.

C. Measure of Performance

Each reaching cycle consists of a motion to each of the three targets (i.e., three trials). For each of the trials, the maximum absolute deviation of the actual trajectory from the straight line between start and target points (i.e., the ideal trajectory) was calculated. The average of this value in a cycle (i.e., mean of maximum deviation), was assigned as the measure of performance for that cycle.

III. RESULTS

The data from the "exercise with challenge" cycles (Fig. 2, bottom) were used in analyzing different aspects of adaptation. For each of the five challenge conditions, each subject has thirteen values for the measure of performance (mean maximum error of each of the thirteen cycles). Within each EA condition, the average of these performance metrics was calculated for each cycle, for all the subjects, giving 13 performance metrics for each challenge condition. For each condition, an exponential function, as in (3), was fit to the average performance metrics [3].

$$y = ae^{-t/b} + c \qquad (3)$$

In (3), y is the performance metric and t is the cycle number (0-12). Based on this, c will be the convergence value of the final performance (i.e., the best performance level after training within a specific condition), b represents the time constant of converging to the c value (higher b implies slower learning), and a represents the total amount of learning (i.e., a is the amount of decrease in the maximum error after practicing within the specific EA condition).

Fig. 3 shows reaching trajectories of subject 4 in the five conditions. Dashed red lines are the initial trajectories and blue solid lines are trajectories of learned motions. Note higher initial errors caused by the two visual plus haptic EA methods.

The performance metrics and curve fittings are given in Fig. 4. The following trends can be observed: Low-gain visual plus haptic EA shows the highest amount of learning (i.e., a=45 mm), followed by high-gain visual plus haptic EA, high-gain visual EA, and control. Low-gain visual plus haptic EA also has the fastest learning rate (i.e., lowest b), followed by the other EA conditions in the same order as the amount of learning. Low-gain visual EA has the poorest learning characteristics. However, this order is reversed for the final performance c. To compare the effects of different EA conditions on a, b, and c, we performed a within-subjects multivariate ANOVA, with values obtained through curve fitting to each subject's performance metrics. We found that training with different EA methods does not lead to a significantly different rate of learning and final performance (i.e., b and c). Nevertheless, high-gain visual plus haptic EA leads to a significantly larger amount of learning a, in comparison with both of the visual EA methods (p<0.1).

Subjects' self-reports to the SAM questionnaire showed an increase in the levels of satisfaction (e.g., liking the task)

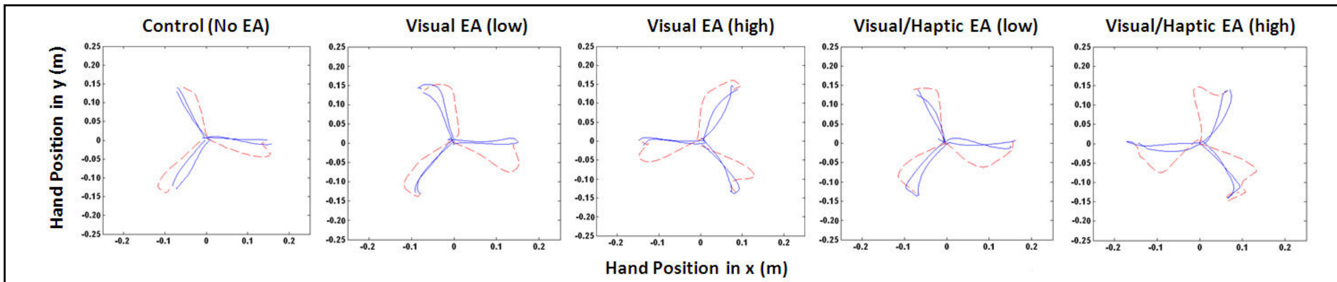

Figure 3. Hand trajectory of subject 4 during each of the challenge exercise blocks qualitatively shows the learning. The dashed red line shows the trajectories during the first reaching cycle, while the blue solid lines show the trajectories during the last two reaching cycles. As learning is independent of the direction of rotational field, the rotation angle was randomly varied between challenges (either -30° or 30°).

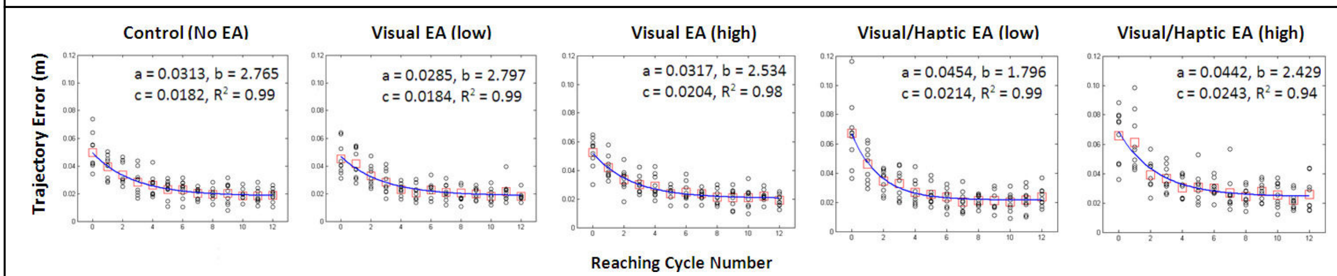

Figure 4. Reaching cycle trajectory error (TE) for all the EA methods. Black circles show cycle mean of maximum TE (performance metric) for each subject. Red squares show the average of performance metric for all subjects. Blue curves show the fitted exponential function (3) to the average of performance metric data. Numerical values for exponential function constants and goodness of fit are given in the right-top corner of each graph.

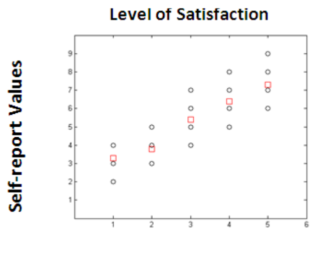

Figure 5. Self-reports of affect for all the EA methods (range from 1-9, 1 being low and 9 being high). x axis shows different methods of EA, numbered as 1) control, 2) low gain visual EA, 3) high gain visual EA, 4) low gain visual/haptic EA, and 5) high gain visual/haptic EA. Black circles show a subject's self-report value during each EA method. Red squares show the mean reported value for all subjects during each EA.

and attentiveness during the task and a decrease in dominance over the task, as the EA methods changed from control to visual EA to visual plus haptic, and from the lower gain to the higher (Fig. 5). A within-subjects multivariate ANOVA shows that the means of each affect measure are significantly different between almost all pairs of conditions (p<0.05). The exceptions are (5 pairs): 1) level of satisfaction between control and low-gain visual EA, and the two visual plus haptic EA methods, 2) level of attentiveness between control and low-gain visual EA, and the two visual plus haptic EA methods, and 3) perceived dominance between high-gain visual EA and low-gain visual haptic EA.

IV. Discussion

Comparing the means of learning speed and amount of learning, low-gain visual-haptic EA proved to be the best, followed by high-gain visual-haptic plus visual EAs. Low-gain visual EA led to the worst learning, suggesting that a gain of 1.3 is not high enough to initiate learning, but it is high enough to make subjects confused and decrease their performance. The ANOVA failed to find significant differences between the final performance of subjects after training with different EA methods, which is acceptable due to the fact that human motor function is not perfect and cannot fully follow ideal trajectories. In accordance with [4], we could not show significant differences between learning properties promoted by each EA, which we believe could be reversed by a more careful tuning of the EA gains. The only exception was the high-gain visual-haptic EA, which significantly improved the amount of learning in comparison to control and visual EA methods, proving our initial hypothesis of achieving better learning characteristics by combining haptic and visual means of providing EA.

Moreover, looking at subjects' engagement in the task, we were also able to confirm our initial hypothesis. Subjects tend to be more satisfied with and more attentive during the visual-haptic EA methods, compared with the visual EA methods. The control condition has the worst score for satisfaction and attentiveness. High satisfaction and attentiveness can be associated with high engagement in the task. Dominance follows a trend in the opposite direction, meaning that comparing the control condition with visual EA methods and also visual-haptic EA methods, the reaching task becomes more difficult and challenging to accomplish. We can argue that a higher challenge within the reaching tasks makes the repetitive nature of them less boring and this can lead to a higher satisfaction with the task. Similarly, completing a more challenging task requires a higher level of attention.

V. Conclusion

This study has replicated the performance improvements seen in previous reaching task studies that have used visual and/or haptic error augmentation to influence motor learning rate and extent. More importantly, we have shown significant differences in affect (specifically: satisfaction, attentiveness and dominance) between progressively more exaggerated error amplification conditions, even when presented in random order to subjects. Understanding these differences will be critical in the subsequent phase of our research, in which we use affect to design a bio-cooperative system that maximizes both learning and the individual's engagement in a reaching task during physical therapy.

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