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Impact of Visual Error Augmentation Methods on Task Performance and Motor Adaptation

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***Abstract*— We hypothesized that augmenting the visual error feedback provided to subjects training in a point-to-point reaching task under visual distortion would improve the amount and speed of adaptation. Previous studies showing that human learning is error-driven and that visual error augmentation can improve the rate at which subjects decrease their trajectory error in such a task provided the motivation for our study. In a controlled experiment, subjects were required to perform point-to-point reaching movements in the presence of a rotational visual distortion. The amount and speed of their adaptation to this distortion were calculated based on two performance measures: trajectory error and hit time. We tested how three methods of error augmentation (error amplification, traditional error offsetting, and progressive error offsetting) affected the amount and speed of adaptation, and additionally propose definitions for "amount" and "speed" of adaptation in an absolute sense that are more practical than definitions used in previous studies. It is concluded that traditional error offsetting promotes the fastest learning, while error amplification promotes the most complete learning. Progressive error offsetting, a novel method, resulted in slower training than the control group, but we hypothesize that it could be improved with further tuning and indicate a need for further study of this method. These results have implications for improvement in motor skill learning across many fields, including rehabilitation after stroke, surgical training, and teleoperation.**

***Index Terms*— Error augmentation, visual distortion, motor adaptation, robotic rehabilitation.**

I. Introduction

Visual distortion implemented by computer interfaces or prisms has long been used as a tool for motor adaptation research [1]. Recently, it was shown by Patton et al. [2] that forces during training that magnified errors induced significant improvements in adaptation of healthy subjects and rehabilitation of stroke patients, while forces that attenuated errors and zero-force conditions did not induce significant improvements. Lately, there has been interest in whether visual error augmentation would lead to similar results.

Matsuoka et al. showed that visual feedback distortion was able to change the movement patterns of healthy subjects [3] and stimulate functional improvement in stroke patients [4], both demonstrated for a pinching movement using the thumb and index finger. Wei et al. [5] tested the effect of two different visual error augmentation methods on amount and speed of motor adaptation and reported that error offsetting, their novel error augmentation method, significantly improved both the speed and amount of learning, while error amplification with a gain of 2, an existing augmentation method, significantly increased only the speed of learning.

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We hypothesized that error augmentation would improve the speed and amount of training in a point-to-point reaching task, and furthermore sought to find which error augmentation method was most effective. In our experiment, 16 subjects completed a simple target-hitting task using a 2-DOF joystick. A constant counterclockwise 45° rotation of the pointer position with respect to the center of the workspace served to make the task novel.

While our task, environment, and experimental goals were very similar to those of Wei et al. [5], we used a different experimental protocol and an additional performance metric to verify and supplement some of their conclusions and refute others. First, we opted for a blocked experimental protocol rather than catch trials, which we believe might have biased the results of Wei et al. positively for the error offsetting group. Second, in addition to the trajectory error measure, we used hit time measure for evaluating performance and adaptation. Third, in addition to error amplification and traditional error offsetting, we also tested a progressive error offsetting condition. Finally, we arrive at conclusions that are more practical in a real-world context by using different definitions of "speed" and "amount" of learning from Wei et al.

The paper is structured as follows: Section II details the experimental setup, task, participant breakdown, error augmentation conditions, performance measures and data analysis methods. Section III presents the adaptation curves and exponential fit results. Subsequently, results are discussed in comparison to those of Wei et al. in Section IV.

II. Methods

A. Task Description

Subjects completed a target-hitting task using a 2-DOF haptic joystick (IE2000 from Immersion Inc.), though the force-feedback capabilities of the joystick were not used in this study. The visual interface displayed on a computer monitor during the trials is depicted in Fig. 1. The joystick controlled the pointer position, and subjects were required to maintain the pointer at the center location ("home") until a target appeared. Subjects then moved the pointer as quickly as possible to the target while trying to maintain a straight trajectory, and a 0.25 sec stay in the target circle registered as a successful hit. Targets always appeared in one of the

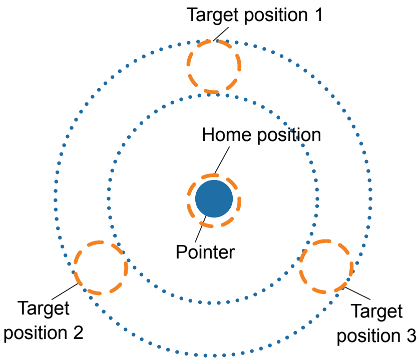

Fig. 1. Visual interface displayed on a monitor during the experiments. Subjects completed center-outwards reaching movements from the home position to one of the target positions and held the pointer in the target circle for 0.25 sec to complete a successful hit. After a hit, the target circle disappeared, and the home circle reappeared at the center. Subjects returned the pointer to the center and waited 1.5-2 sec for the next target to appear randomly at one of the three target positions.

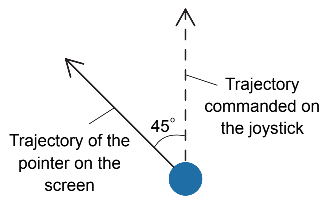

Fig. 2. The effect of the distortion on a straight upward movement of the joystick as observed on the screen. This constant counterclockwise 45° rotational distortion constituted the environment to adapt to.

three target locations shown in Fig. 1, but in a random order. Additionally, the time that subjects were required to wait in the home position before a new target appeared was a random 1.5–2 sec, to obviate the effects of anticipation. Position data was captured at 100 Hz.

The task was made novel by implementing a constant counterclockwise 45° rotational visual distortion of the pointer position as depicted in Fig. 2. Thus, when the visual distortion was active, a northerly movement of the joystick generated a northwesterly movement of the pointer. Subjects were required to adapt to this distortion over the course of training. Different groups of subjects received different forms of error augmentation during this training so that we could analyze how the different methods affected the speed and amount of their training / adaptation.

B. *Experiment Protocol and Participants*

A total of 16 subjects participated in the study. Their ages were 19–39, two were female, and four were left-handed, though one of the left-handed subjects preferred to do the task with his right hand. All had normal or corrected-to-normal vision, none had any movement disorders affecting the dominant hand, and all provided their informed consent as approved by the Rice University Institutional Review Board. The subjects were randomly assigned to one of four error augmentation groups so as to have four subjects in each group. These groups were: (1) Control (no error augmentation), (2) Error amplification (with a gain of 2), (3) Traditional error offsetting and (4) Progressive error offsetting. These error augmentation methods are covered in detail in the next section.

The joystick and the hand of the subject were covered with a curtain throughout the experiment, leaving only the visual feedback from the monitor and proprioceptive feedback available to the subjects. Subjects were instructed to complete the trials as quickly as possibly while maintaining a straight-line motion. The details of the visual distortion and the blocks of the experiment in which it would be encountered were explained to the subjects. Subjects were also informed as to when error augmentation might be present. However, information on the specific error augmentation methods and the group a subject was assigned to was not given.

The experimental procedure is depicted in Fig. 3 and was based on blocks, each of which contained a certain number of trials under the same experimental conditions. In a familiarization block, subjects were presented with 15 trials with no visual distortion or error augmentation in order to acquaint them with the hardware and user interface. An evaluation block consisted of 4 trials with distortion but no augmentation. A training block consisted of 15 trials with distortion and augmentation. Finally, the generalization block consisted of 15 trials with distortion and no augmentation to new target locations, and was intended to test how a subject's motor adaptation generalized to these new directions of movement. Subjects were presented with 3 familiarization blocks, an initial evaluation block, 10 repetitions of training and evaluation blocks, and finally a generalization block, for a total of 25 blocks and 254 trials. It took approximately twenty minutes for a subject to complete the experiment, and subjects were allowed to take brief breaks between the blocks if they felt fatigued.

This block-based experimental design improves in three significant ways upon the design used by Wei et al. [5], which relied on single unannounced catch trials to capture evaluation data for all groups as well as error profile data for the traditional error offsetting group. First, in our design the conditions prior to and during the initial evaluation are identical for subjects in all groups. This is important because the initial evaluation performance value considerably affects both the amount and speed of learning values deducted from exponential fits. Second, in our block-based design all subjects knew when they were being evaluated, as opposed to a catch-trial-based design where subjects may or may not have noticed the difference between training trials and catch evaluation trials, depending on which augmentation method they experienced. Finally, our data indicates that different error augmentation methods affect quite differently how subjects transition from training trials to evaluation trials. Capturing evaluation data using a block of four trials instead of a single trial allows the confounded data of the first "transition" trial to be discarded, leaving three relatively good trials (one to each target) for analysis.

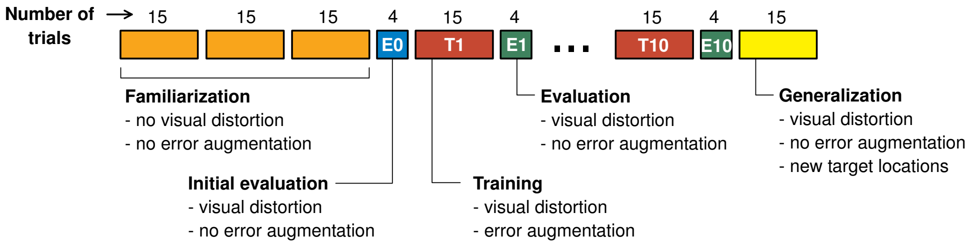

Fig. 3. A break-out of the complete experimental procedure. This information was provided to the subjects before the experiment, and a progress indicator appeared on the screen between every block informing the subjects about the type of block they were about to encounter.

C. *Performance Measures*

The performance measures used were trajectory error and hit time. Trajectory error (TE) was calculated as the mean-absolute deviation from the straight-line path to the target over the course of a trial divided by the length of the path (i.e. the radius to the target). Thus, TE is represented as a percentage. The effective bounds for TE in our experiment are 0% to 100% and actual recorded TE ranged from 0.28% to 43.7%. Lower values of TE are considered better.

Hit time (HT) is the average time taken to complete a trial in seconds. There is no formal lower or upper bound for this measure, though actual values ranged from 0.47 s to 6.25 s. Obviously, lower values of HT are considered better.

D. *Error Augmentation Conditions*

Four error augmentation conditions were used in the training blocks: no error augmentation (control), error amplification, traditional error offsetting and progressive error offsetting.

The group receiving no error augmentation was used as a control. The error amplification group received error amplification as described by Wei et al. [5] with a gain of 2. In this condition, the position of the cursor is calculated by simply doubling the subject's actual TE. Thus, movements in the direction perpendicular to the straight-line path from the center to the target are exaggerated, while movements parallel to this path are unaffected.

Error offsetting was also implemented in a manner similar to that described by Wei et al. [5]. In the initial evaluation block(s), TE was recorded as a function of time in order to generate an error profile. The last 0.25 seconds of this profile were truncated (to account for time spent closing in on a target before the hit was registered) and the length of the remaining profile was normalized to the radius to the target in order to generate an error profile as a function of distance-to-target. The resulting distance-based error profile was referred to as a subject's "baseline error profile." In training blocks, a subject's actual TE at a given distance from the target was summed with the corresponding baseline error to generate the displayed error.

In the traditional error offsetting condition, the baseline error profile was recorded once during the initial evaluation and was used throughout training. In the progressive error offsetting condition, the profile was recorded anew during every evaluation block, so that the error augmentation effectively decreased over the course of a session as a subject's TE improved.

E. *Data Analyses*

The average performance of all four subjects in a group in the final familiarization block (see Fig. 3) was used as the average baseline performance of the group. Similarly, for the average generalization performance of each group, all 15 trials of the generalization block for all subjects in the group were used.

To analyze the properties of adaptation for different groups, only the data from the last three trials in each evaluation block were taken into account. The first trial in each block was excluded because pilot data indicated that it was susceptible to artifacts due to the transitional effects of removing error augmentation, and thus could not serve as an objective measure of the performance of subjects under visual distortion with no error augmentation. Three performance measure values coming from four subjects in each group constituted twelve values that were averaged to determine the average performance measure value for the corresponding evaluation trial for the group. After calculating all average values for all 11 evaluation trials, an exponential function of the form

$$y = ae^{-x/b} + c \tag{1}$$

was fit to the average data points, where x represents the evaluation block number $(0-10)$, b represents the time constant of adaptation (lower b implies faster adaptation), c represents the value that the function converges to, and $a+c$ represents the initial value of the function y, which represents the performance measures. A generalized visual representation of our exponential fit parameters is provided in Fig. 4. The relative amount of learning, a, is dependent on both the initial and the final value of the function, whereas c is an absolute measure of the performance level attained at the conclusion of training. For TE and HT, lower values of c indicate better performance. Similar to the absolute and relative nature of c and a, we defined a fourth parameter d as a measure of speed of adaptation. The parameter d was defined by using the grand averages (across all subjects) of familiarization (f_g) and initial evaluation ($e0_g$) performance measure values as

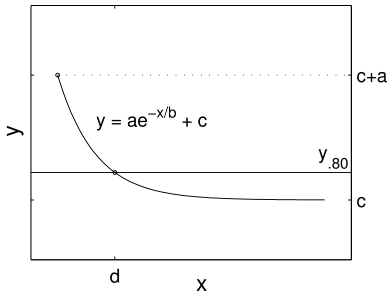

Fig. 4. Exponential fit and the adaptation parameters calculated from the fit. x represents time (trial number) and y represents the performance measure. The parameter a is a relative measure of amount of adaptation, since it is dependent on both the initial and the final performance measure values. In contrast, the parameter c can be used as an absolute measure of amount of adaptation. Parameter b is the time constant of the fit and is a relative measure of speed of adaptation. Similar to a, b is sensitive to the fluctuations of the initial performance measure value. As an alternative, we propose the parameter d, which gives the time period needed to achieve an 80% adaptation level (depicted by the horizontal $y_{.80}$ line in the plot).

$$d = -b\ln\left(\frac{y_{.80} - c}{a}\right) \quad (2)$$

where $y_{.80}$ represents the value of the measure after 80% of overall adaptation occurs and is defined as

$$y_{.80} = f_g + (e0_g - f_g) * 0.20 \quad (3)$$

This specific level of adaptation is shown as a horizontal line on Fig. 4. Similar to the time constant b, d takes lower values for faster adaptation. The main difference between b and d is the use of grand averages in the calculation of d as opposed to group averages in the calculation of b. The reason for choosing an 80% level instead of a 63% level as in the case for b is to avoid negative d values caused by a few of the subjects scoring better than the 63% level at the initial evaluation trial. We believe that c and d, absolute amount and speed of adaptation, constitute more robust measures that are not as vulnerable to the fluctuations of the initial value of the performance measure as a and b. Absolute measures quantify the success of an error augmentation method on a more practical and real-world application basis.

III. Results

Trajectories of the pointer on the screen during evaluation trials for a representative subject from each group are given in Fig. 5. Pointer trajectories in initial evaluation trials are represented by thick dashed curves and trajectories in the final evaluation trials are represented by thick solid curves. The speed and amount of adaptation for each group can be visually inspected on these plots.

A. Trajectory Error

The mean and standard error of the TE measure for all groups and blocks of trials together with the exponential fit curve and fit parameters are given in Fig. 6. The average values and variances for both the familiarization and generalization blocks are similar across groups, indicating that all subjects reached the same level of familiarity with the interface. However, it should be noted that the initial evaluation value varies dramatically between groups, even though all groups have experienced the same experimental conditions until that point. Thus, this is not a good point on which to base definitions for speed and amount of training. Note that the variance of TE for the error amplification group is generally smaller than that of the other groups, especially through the final evaluation trials. For the last four evaluation trials, standard errors of the error amplification group TE values are 13–45% smaller than those of the control group. Contrast this with the variance observed for the progressive error offsetting group, which is quite large. During the last four trials, standard errors of the progressive error offsetting group TE values are 24–137% greater than those of the control group. The error amplification group settles to the lowest c value, indicating that this group performed the best at the conclusion of training and implying that they received the most effective training. As for the speed of adaptation, the traditional error offsetting group shows the fastest adaptation while the progressive error offsetting group demonstrates the slowest adaptation for both the relative (b) and the absolute (d) measures of speed of adaptation. However, note that b indicates a much higher speed of adaptation for the traditional error offsetting group as compared to the error amplification group, while d points to a similar speed of adaptation for both groups. As mentioned, this is due to the misleading sensitivity of b with respect to the initial evaluation value of TE. A group that starts with a worse performance compared to other groups will usually tend to misleadingly demonstrate faster learning by a low b value. For this reason, d is a more appropriate measure for quantifying speed of training.

B. Hit Time

Results are given for HT in Fig. 7. Again, generalization and familiarization block values are consistent across all groups, but the initial evaluation value varies for each group. The lowest value of c is noted in the traditional error offsetting group, with the error amplification group having a c value close to that of traditional error offsetting. Variances are smaller for these two groups as compared to others. Both the relative and absolute speed of adaptation measures indicate that the slowest adaptation takes place in the progressive error offsetting group. In terms of b, the control group demonstrates the greatest speed of adaptation, while in terms of d, the traditional error offsetting group adapts more quickly. This is again due to b's misleading nature, and specifically to the higher-than-average initial evaluation HT value observed for the control group. As opposed to the case observed in TE, relative rate of adaptation d indicates a faster adaptation in the traditional error offsetting group compared to the error amplification group while for b the rates of adaptation in these two groups are similar. It can be concluded that results for TE and HT are in agreement only when the absolute measures of adaptation are taken into account.

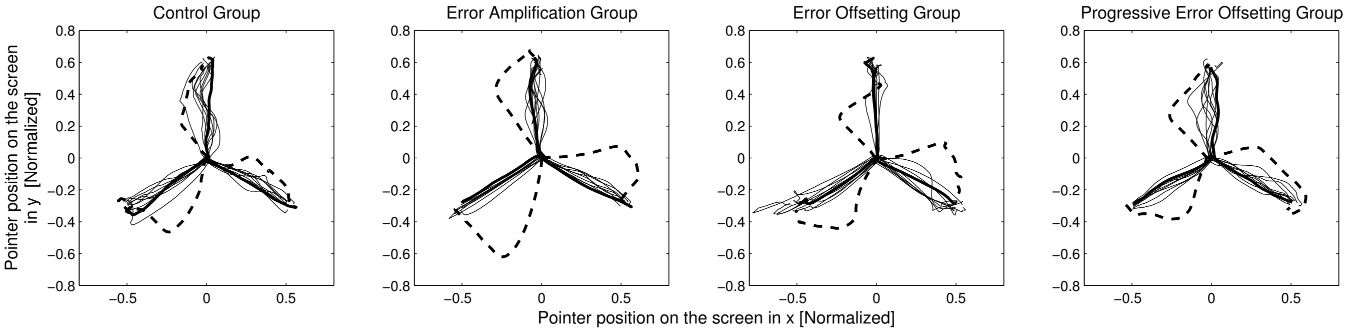

Fig. 5. Trajectory of the pointer on the screen for a representative subject in each of the four groups during evaluation blocks. Thick dashed curves belong to the initial evaluation block while thick solid curves belong to the final evaluation block. Note the adaptation rates and quality for each group. Specifically, note that the subject in the error amplification group adapts faster and demonstrates less TE after adaptation compared to subjects in other groups.

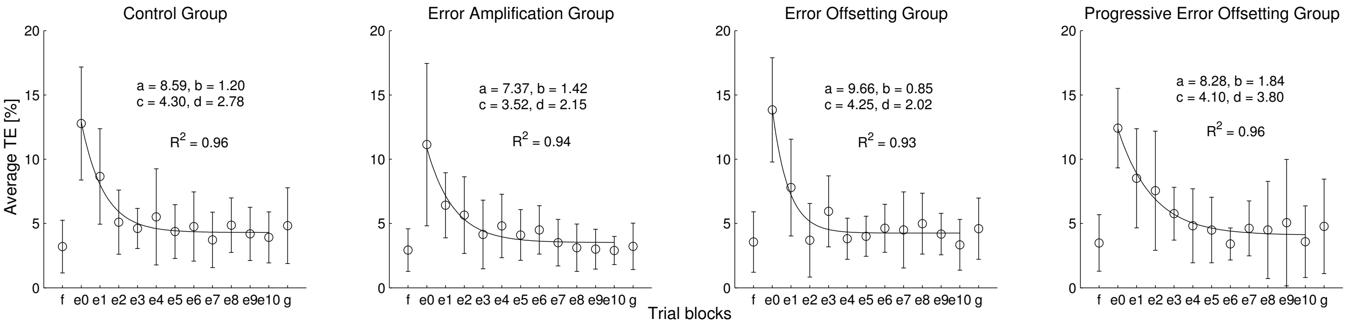

Fig. 6. Trajectory error (TE) block averages for all groups. Note that the variance of TE for the error amplification group is generally smaller compared to the other groups. Contrast this to the variance observed for the progressive error offsetting group. The error amplification group settles to the lowest *c* value, which implies that the largest absolute amount of adaptation occurred for this group.

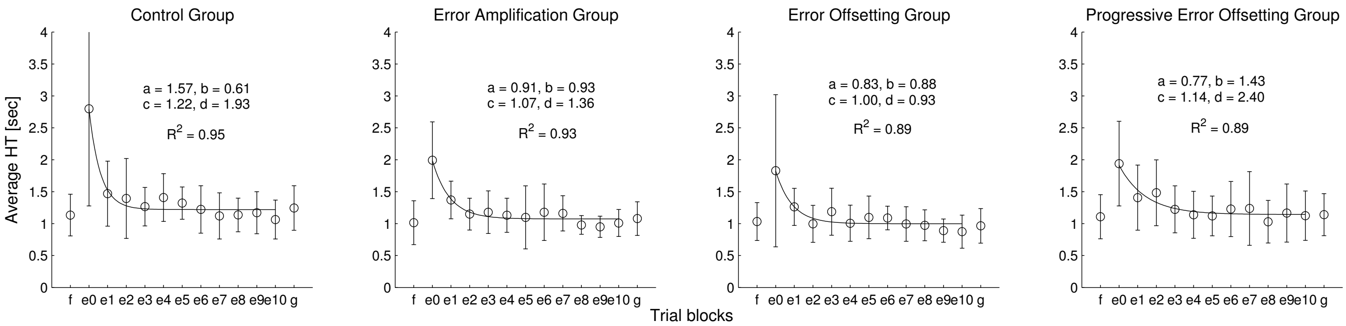

Fig. 7. Hit time (HT) block averages for all groups. The traditional error offsetting group exhibits the lowest *c*, followed by the amplification, progressive offsetting, and control groups. Variances are smaller for the traditional error offsetting and error amplification groups.

IV. Discussion

Our results in many ways verify those of Wei et al. [5]. In particular, we see that the greatest relative amount of TE reduction (a) and greatest relative speed of TE reduction (b) occur in the traditional error offsetting group. However, care should be taken when dealing with semantics here: we are interested in finding the groups with the highest performance at the end of the experiment (c) and shortest amount of time required to achieve a given level of performance (d), not necessarily the group with the highest or fastest performance *improvements* as indicated by a and b. Specifically, we define the most complete training as occurring for the group with the lowest values of TE and HT at the end of training (c). Also, we define the absolute speed of learning d by computing the number of trials to learn 80% of the task. This is in opposition to Wei et al., who chose to interpret their results based on the relative definitions of speed and amount of learning a and b. A relative definition is not realistic in a real-world context since it does not take into consideration the values observed in the population. Also, as demonstrated above, such a definition does not produce consistent results when various performance measures are used.

The group with the lowest TE, and hence maximum performance, at the conclusion of training is in fact the error amplification group ($c = 3.52\%$), followed by the progressive error offsetting ($c = 4.10\%$) and traditional error offsetting ($c = 4.25\%$) groups, respectively. Thus, all error augmentation algorithms implemented in the study resulted in more complete learning as compared to the control group ($c = 4.30\%$). In terms of absolute rate of learning, the fastest training occurred for the traditional error offsetting group ($d = 2.02$), followed closely by the error amplification group ($d = 2.15$). Progressive error offsetting ($d = 3.80$) actually slowed down the learning considerably as compared to the control group ($d = 2.78$).

In terms of HT, parallel results were obtained. The traditional error offsetting group exhibited the best performance ($c = 1.00$ sec), followed closely by the error amplification ($c = 1.07$ sec) and progressive error offsetting ($c = 1.14$ sec) groups. All three error augmentation groups showed more learning than the control group ($c = 1.22$ sec). The order from fastest to slowest learning as indicated by the absolute rate of learning measure was: traditional error offsetting ($d = 0.93$), error amplification ($d = 1.36$), control ($d = 1.93$) and progressive error offsetting ($d = 2.40$) groups. It is important to note that the same parallelism in results for both performance measures did not emerge in terms of the relative measures of adaptation.

A between-subjects multivariate ANOVA analysis that used the values of a, b and c estimated separately from each subject's adaptation curve fit failed to show significant differences among the groups. We identified that a few of the subjects tried to intentionally compensate for the visual distortion starting from the very first evaluation trial instead of experiencing the effects of it and then gradually adapting to it for compensation. This aspect placed them as outliers in terms of both measures and is considered to be a major contribution to the lack of statistical significance of the results. We plan to explicitly instruct subjects to avoid such behavior in future studies. We believe that achieving statistically significant results would be possible by increasing the statistical power of the experiment by increasing the number of subjects. Unfortunately the nature of the experiment does not allow a repeated measures experiment design, since it would lead to significant cross-over effects.

We believe that balancing the groups can improve the accuracy and validity of the results of error augmentation method comparison, regardless of using relative or absolute measures. To ensure balanced groups with respect to the initial evaluation trial, we propose a two-session experiment protocol for future work. In the first session, subjects will complete the portion of the experiment concluding with the initial evaluation block. Assignment of subjects to groups will be completed based on their performance at the initial evaluation. The remaining portion of the experiment will be conducted in a second session after all groups are formed.

We showed that imposing a constant speed constraint is not necessary for being able to implement an error offsetting type of error augmentation. By transforming the recorded initial evaluation trajectory of the subject from the time domain to the spatial domain, such a method is still applicable to tasks with no speed/time constraints. Furthermore, such a method allows the utilization of hit time as an additional performance measure. The effects of our implementation of error offsetting on training were similar to the effects of the implementation used by Wei et al. [5].

We tested a previously unreported method of error augmentation —progressive error offsetting— and showed that even though this method was able to increase the amount of adaptation, it considerably decreased the rate of adaptation. We believe that this drop in speed of adaptation can be explained by the rapidly diminishing nature of the feedback. The speed of adaptation slows drastically over time because the amount of feedback is reduced according to concurrent performance improvements. Error amplification predictably exhibits the same trend. Thus, neither can compete with traditional offsetting in terms of speed of training. We propose that a balance between traditional and progressive offsetting can be reached that maximizes training speed while minimizing the likelihood of overtraining.

V. Conclusion

Visual error augmentation has the potential to increase speed and amount of adaptation with possible applications in motor learning and rehabilitation. We report speed and amount of motor adaptation to a rotational visual distortion during a target-hitting task where subjects were randomly assigned to one of the four different error-augmentation conditions: control (no error augmentation), error amplification, traditional error offsetting, and progressive error offsetting. We used new absolute definitions for the completeness and speed of adaptation that are practical and robust, as evidenced by the agreement of results for two performance measures (trajectory error and hit time) and insensitivity to the initial performance value before adaptation. We found that traditional error offsetting provides the fastest adaptation, while error amplification induces the most complete adaptation. We used a method for implementing error offsetting without a time or speed constraint for the task. Such a method also allows hit time to be used as another performance measure. We also tested a novel progressive error offsetting condition, which resulted in more complete adaptation, though it slowed down the adaptation.

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