Impact of Visual Error Augmentation When Integrated With Assist-as-Needed Training Method in Robot-Assisted Rehabilitation

Furui Wang, Duygun Erol Barkana, and Nilanjan Sarkar, *Senior Member, IEEE*

***Abstract*—The paper investigates the impact of the integration of the visual error augmentation training method with the assist-as-needed training method in robot-assisted rehabilitation training of the upper extremity. A robot-assisted rehabilitation system is developed that integrates an assistive controller, which can provide robotic assistance to the participant as and when needed, with a visual error augmentation mechanism, which amplifies the tracking error to heighten the participant's motivation to improve tracking accuracy. A crossover study is designed to evaluate the impact of the integration of the visual error augmentation method with the assist-as-needed training method. Experimental results on unimpaired participants demonstrate improved performance has been achieved in the integrated training session.**

***Index Terms*—Assist-as-needed training, robot-assisted rehabilitation, visual error augmentation training.**

I. Introduction

STROKE is a highly prevalent condition [1], especially among the elderly, that results in high costs to the individual and society [2]. According to the American Heart Association (2009), in the U.S., approximately 795 000 people suffer a first or recurrent stroke each year [1]. It is a leading cause of disability, commonly involving deficits of motor function. Recent clinical results have indicated that movement assisted therapy can have a significant beneficial impact on a large segment of the population affected by stroke or other motor deficit disorders. Experimental evidence suggests that intensive movement training of new motor tasks is required to induce long-term brain plasticity [3]. In recent years, robot-assisted rehabilitation of stroke patients has been an active research area, providing repetitive movement exercise and standardized delivery of therapy with the potential of enhancing quantification of the therapeutic process [4]–[14].

Various robot-assisted rehabilitation systems are developed for the upper-limb rehabilitation such as MIT-MANUS [4]–[6], mirror image movement enabler (MIME) [7], [8], assisted rehabilitation and measurement (ARM) guide [9], [10] and GENTLE/s [11]. Similarly, robotic systems for wrist rehabilitation have also been reported in recent years [12]–[14]. Studies with these robotic devices verified that robot-assisted rehabilitation results in improved performance of functional tasks. The promising results of robot-assisted rehabilitation systems indicate that robots could be used as effective rehabilitation tools.

Recent research [15] has suggested that in robot-assisted rehabilitation, assisting every movement of a patient is not as beneficial compared to no assistance or assistance as needed. It has also been proposed in [10] and [16] that performance-based therapy showed better results in improving patients' impairment scores than conventional therapies. Thus, a robot-assisted rehabilitation system could be more efficient if the robotic assistance provided to the patient is given as and when needed based on the performance of the patient; this is called the assist-as-needed training method. It has also been demonstrated that movement tracking training that requires cognitive processing achieved greater gains in performance than that of movement training that did not require cognitive processing [17]. Meanwhile, the latest research in many models and artificial learning systems such as neural networks suggest that error drives sensorimotor learning, so that one can learn adaptation more quickly if the error is larger [18]. Such error-driven learning processes are believed to be central to adaptation and the acquisition of skill in human movement [19], [20]. It has been shown that visual error augmentation can improve the rate and extent of motor learning in healthy participants and may facilitate neuro-rehabilitation strategies that restore function in brain injuries such as stroke [21]. Feedback distortion has also been utilized to augment the controllability of human limb motion [22] and shown to elicit functional improvements in patients with chronic stroke and traumatic brain injury [23].

As can be seen from the above discussion, both assist-as-needed and visual error augmentation training methods separately have shown promising results in robot-assisted rehabilitation of the upper extremity. However, none of the existing robot-assisted rehabilitation system, to our knowledge, is designed to integrate these two training methods together. The objective of this work is to investigate the impact of the integration of these two training methods in robot-assisted rehabilitation of the upper extremity. A robot-assisted rehabilitation system that was developed previously by the authors [24] is further enhanced to integrate an assistive controller, which can provide robotic assistance to the participant as and when needed, with a visual error augmentation mechanism, which amplifies

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F. Wang and N. Sarkar are with the Mechanical Engineering Department, Vanderbilt University, Nashville, TN 37212 USA (e-mail: furui.wang@vanderbilt.edu; nilanjan.sarkar@vanderbilt.edu).

D. E. Barkana is with the Electrical and Electronics Engineering Department, Yeditepe University, Istanbul 34755 Turkey (e-mail: duygunerol@yeditepe.edu.tr).

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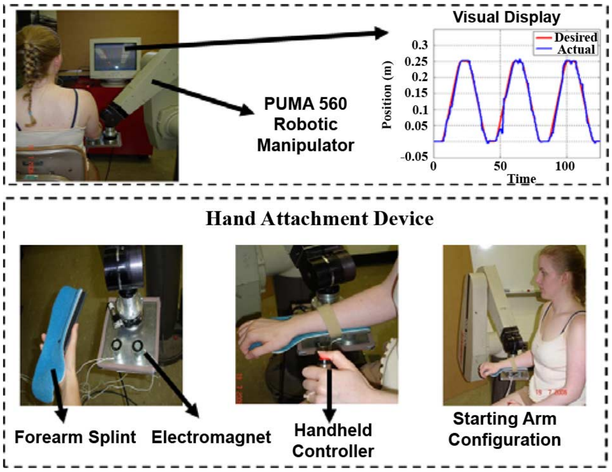

Fig. 1. Participant's arm attached to robot.

the tracking error to heighten the participant's motivation to improve tracking accuracy for this work. A crossover study was designed to evaluate the impact of this integrated training method with 20 unimpaired participants.

This paper is organized as follows. It first presents the robot-assisted rehabilitation system in Section II. The task description, training paradigms, experimental protocol, and task parameters are presented in Section III. Experimental results and analysis are given in Section IV. Section V provides the discussion of the experimental results and the potential contributions of this work. The Appendix concludes the paper and gives the possible future research directions.

II. Methods

A. Experimental Setup

A PUMA 560 robotic manipulator is used as the main hardware platform in this work. The manipulator is augmented with a force-torque sensor and a hand attachment device (Fig. 1). An assistive controller is developed to provide robotic assistance to the participants. Details of the robotic system can be found in [24] and [25].

B. Task Design

We choose a reaching task that is commonly used for rehabilitation of upper extremity after stroke. In this task, the participant is asked to move his/her arm in the forward direction to reach a desired point in space and then bring it back to the starting position repeatedly within a specified time, i.e., to follow a desired position trajectory. The reaching task designed here requires a combination of shoulder and elbow motion which could increase the active range of motion (AROM) in the shoulder and the elbow in preparation for later functional reaching activities in rehabilitation. The allowable motion is restricted only to the direction of the task. For example, if the task requires the participant to move his/her arm in the Y-direction, then he/she will not be able to move the arm in X or Z directions. The idea here is to improve the ability of the participant's arm movement in one direction at a time by helping him/her improve his/her ability to complete a desired reaching task, which is an important everyday activity.

It has been shown in the literature that a movement tracking task that required cognitive processing achieved greater gains in performance than that of movement training that did not require cognitive processing [26]–[28]. In order to include cognitive processing within this reaching task, the participant is asked to follow a visually presented desired motion trajectory that is intended to command his/her concentration. The participant receives visual feedback of both the actual and the desired position trajectories on a computer screen, which is placed in front of him/her. The participant is asked to pay attention to tracking the desired position trajectory as accurately as possible, which keeps him/her focused on the task. The visual feedback is used not only to inform the participant of how closely he/she is tracking the desired motion but also as a motivational factor to keep him/her focused on the task. During the execution of the reaching task, the number of times the participant needed robotic assistance to track the desired motion is recorded.

C. Assist-as-Needed: Decision of Robotic Assistance Activation During Task Execution

It is intuitive that a robotic system that provides continuous assistance without considering the patient's actual performance will not be as effective as the one that does. Assisting every movement of a patient has been shown to be not beneficial compared to no assistance or assistance as needed [15]. It has also been suggested [16] that performance-based therapy showed better results in improving patients' impairment scores than conventional therapies. In the active-assistance therapy with the ARM Guide system reported in [10], the stroke patients who received robotic assistance when the tracking performance of their upper limbs fell outside a predefined deadband showed significant improvement in the time to complete functional tasks and in supported reaching range and velocity [10]. Thus, a robot-assisted rehabilitation system could be more efficient if the assistance provided to the patient is given only as and when needed. In our robot-assisted rehabilitation system, the assistive controller is designed to provide robotic assistance based on the participant's actual performance of the tracking task. The idea of the assistive controller in our robotic system is to assist the participant when his/her arm position goes out of the predefined acceptable position band. A similar therapy algorithm was implemented with the ARM Guide system in [10].

In this work, a desired trajectory x_d is first defined and then the acceptable position band (Fig. 2) with the upper bound x_{upper} and the lower bound x_{lower} are calculated using

$$\begin{aligned} x_{\text{upper}} &= x_d + (x_d * \text{percentage}) \\ x_{\text{lower}} &= x_d - (x_d * \text{percentage}) \end{aligned} \tag{1}$$

where percentage is the value chosen to set the upper and lower bounds for the defined position trajectory. In order to define the task position trajectories x_d, a generator block using Matlab/Simulink Blockset is developed. This block generates the minimum-jerk position and velocity trajectories with a specified distance, maximum velocity and acceleration using user defined function. If the actual position $x(t)$ lies within the acceptable band, then the participant is considered to be able to track the

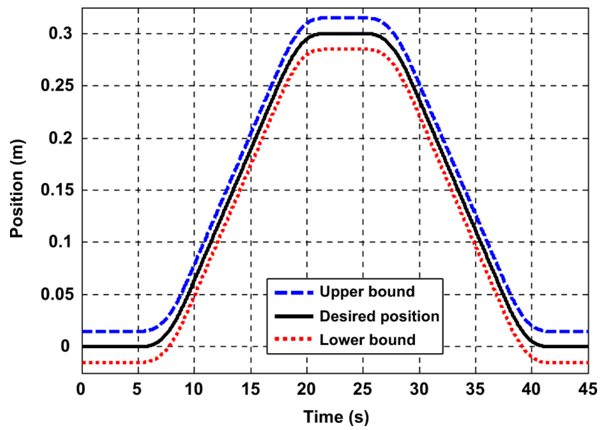

Fig. 2. Acceptable position band.

trajectory without robotic assistance. If the actual position x is not between the upper bound x_{upper} and the lower bound x_{lower}, then the assistive controller is activated to provide assistance to bring the participant's position back into the desired range.

However, note that each participant requires a certain amount of time (settling time) to generate the desired motion. The controller should not be activated until it is determined that the participant is not able to generate the required motion by his/her own effort. Thus, the averages of the participant's actual position x_{ave} (which is different from the instantaneous position in [10]), the upper bound x_{upper}, and the lower bound x_{lower} are calculated in a given time interval. These averages are used to decide whether the robotic assistance is needed. x_{ave}, $x_{\text{upper\_ave}}$, and $x_{\text{lower\_ave}}$ are calculated using the following equations:

$$\begin{aligned} x_{\text{ave}} &= \frac{t_s}{(t_f - t_i)} \bullet \sum_{t_i}^{t_f} x(t) \\ x_{\text{lower\_ave}} &= \frac{t_s}{(t_f - t_i)} \bullet \sum_{t_i}^{t_f} x_{\text{lower}}(t) \\ x_{\text{upper\_ave}} &= \frac{t_s}{(t_f - t_i)} \bullet \sum_{t_i}^{t_f} x_{\text{upper}}(t) \end{aligned} \tag{2}$$

where t_f , t_i, and t_s are the final time, starting time, and sampling time, respectively. The participant's actual position at time t is $x(t)$.

If condition: $x_{\text{lower\_ave}} < x_{\text{ave}} < x_{\text{upper\_ave}}$ is satisfied, then the assistive controller is not activated and the participant continues the tracking task without robotic assistance. If condition is not satisfied, then the assistive controller is activated to provide robotic assistance.

D. Visual Error Augmentation

It has been shown that visual error augmentation training, which makes small errors more noticeable to the participant, motivates him/her to make faster responses to correct the error [21]. Faster responses may lead to larger changes in performance of the participant. Additionally, amplified error can also increase signal-to-noise ratios, which may improve cognitive processing and self-evaluation [21]. It was shown that training performance of the patients improved only when the original errors were magnified, but not when the errors were reduced or absent [29]. Hence, visual error amplification training may be an effective way to promote functional motor recovery for people after stroke. However, it is important to select a proper gain K in the visual error amplification. If the gain is too small, the effect of error augmentation will be quite limited; if the gain is too large, it is possible that the sensory-motor learning will become unstable, which may cause sensor inaccuracy, over-correction, and even frustration and anxiety in the participants.

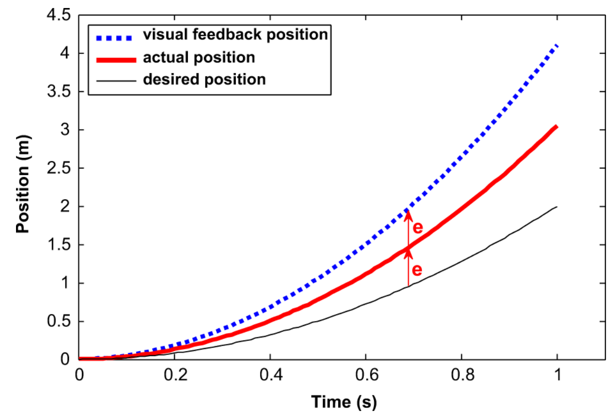

Fig. 3. Illustration of the visual error augmentation method. The thick line is the actual position trajectory, which is not shown on the monitor. The thin solid line is the desired position trajectory and the dotted line is the augmented position trajectory. Those two lines are shown on the monitor.

In this work, the gain is selected as 2, which is shown to elicit the best experimental result in [21]. A gain of 2 means any deviation from the desired trajectory will be displayed as twice the real distance from the desired trajectory (Fig. 3). The error $x_d(t) - x(t)$. Here, $x(t)$ is the actual arm position.

While the participant's performance is expected to be better when visual error augmentation training is applied, a stroke patient may still need assistance from the robot to complete a given task. Thus, the assistive controller described in the previous section will be activated so that the robot will help the patient bring back his/her arm position into the acceptable band to continue the task execution. Note that the errors fed back to the assistive controller are not amplified, which guarantees the robotic system works in an accurate manner.

E. Participants

Two groups of 10 right-handed participants between the ages of 25–35 took part in the experiment. Both groups consisted of seven males and three females. None of the participants had any motor impairment in their arms.

F. Protocol

Participants were seated in a height adjustable chair as shown in Fig. 1 (top left) and were required to place their forearm on the hand attachment device as shown in Fig. 1 (bottom left) when the starting arm configuration was fixed. The height of the PUMA 560 robotic manipulator was adjusted for each participant to start the tracking task in the same arm configuration. The starting arm configuration was selected as shoulder at neutral 0° position and elbow at 90° flexion position. The task required moving the arm in forward flexion to approximately 60° in conjunction with elbow extension to approximately 0° and then coming back to the starting position. The release button of the hand attachment device was given to the participants in case of emergency situations during the task execution (Fig. 1-bottom middle). The participants received visual feedback of the task trajectories and their own position trajectories on a computer monitor in front of them (Fig. 1-top right).

We conducted two sessions of the experiment to evaluate the proposed robot-assisted rehabilitation system with only assist-as-needed training method (AAN Session) and the integration of the assist-as-needed with the visual error augmentation training methods (INT Session). In both sessions, the participants used their non-dominant arms to perform the task. This was done in order to create imperfect tracking condition so that the robotic training had some room to elicit improvement. In the AAN Session, the aim was to evaluate the outcome of the system with the assist-as-needed training method. Participants were required to perform the tracking task with the robotic assistance but without the visual error augmentation training. In INT Session, the aim was to evaluate the outcome of the enhanced system when the visual error augmentation training was integrated. Since the eventual aim is to apply the robot-assisted rehabilitation system to stroke patients who are not likely to complete the task by their own efforts and may need robotic assistance, we make robotic assistance available in both sessions in these experiments.

In order to make a comparison of the two presented training methods, a crossover study was performed to evaluate the difference of the training effects between the two sessions. Group A were asked to participate in the AAN Session first and then followed by the INT Session, while Group B were asked to participate in the INT Session first and then followed by the AAN Session. The two sessions of both groups were conducted with at least two weeks of interval as a washout period. The crossover design is able to increase the precision of comparison because each participant serves his/her own control, so that the comparisons of treatment effect are based on within-participant variability (which is usually less than the between-participant variability). Meanwhile, the carryover effect between the two sessions is also investigated by the between group comparison [30]. This study was approved by the Institutional Review Board of Vanderbilt University (IRB #90736).

Before each session, the participant took part in a trial practice first, during which the participant executed the same tracking task several times to get a basic understanding of the task execution. Typically, a participant practiced three forward and backward motions requiring no more than 3 min. Once the session started, the participants were asked to execute the forward and backward tracking task 25 times, which was distributed into five training groups. Thus the participant performed the required task 5 times in each training group without a break. The participant took a 3–5 min break between two training groups. Additionally, after finishing the INT Session, the participant took part in additional practice without visual error augmentation to wash out the possible sensor-motor distortion.

G. Task Parameters

The maximum velocity of the task was defined as 0.02 m/s and the maximum acceleration was $0.008\ \mathrm{m/s^2}$. These two parameters were chosen in consultation with an occupational therapist who works with stroke patients at the Vanderbilt Stallworth Rehabilitation Hospital. The task distance was selected from 0.2 m, 0.25 m, or 0.3 m based on the length of participants' arms. All three parameters were necessary in creating a desirable tracking task for each participant. Once these task parameters were decided, desired position, velocity, and upper bound and lower bound of trajectories were generated by reference blocks in Simulink. Since the participants were healthy subjects, the percentage of position error band was chosen as 5%; x_{ave}, $x_{\mathrm{upper\_ave}}$ and $x_{\mathrm{lower\_ave}}$ were calculated every 4 s $(t_f - t_i = 4)$ using (2); then the criterion $x_{\mathrm{lower\_ave}} < x_{\mathrm{ave}} < x_{\mathrm{upper\_ave}}$ was checked to decide the activation of the assistive controller. Once activated, the robotic assistance would continue for 4 s. The P and I gains of the assistive controller were properly selected, which guaranteed that sufficient robotic assistance was provided to move the arm position back within the acceptable position band in 4 s.

These parameters were chosen to challenge the participants and train them to make fast responses to errors and make the tracking more accurate. It is quite possible that the time interval to determine the activation of robotic assistance and the acceptable position band need to be adjusted in clinical application with stroke patients to encourage the patients without frustrating them to complete the training.

III. Experimental Results

During the experiments, the numbers of times robotic assistance was needed by participants and the actual position trajectories were recorded. For better representation of the experimental results, the participants were sorted in descending order based on their average position errors in the AAN session, i.e., Participant 1 had the largest average position error while Participant 10 had the smallest average position error in the AAN Session of Group 1; Similarly, Participant 11 had the largest average position error while Participant 20 had the smallest average position error in the AAN Session of Group 2. The participant labels were consistent for all the results presented in this work.

A. Activation of Robotic Assistance

The assistive controller of the robot-assisted rehabilitation system monitored the actual arm position and provided robotic assistance to keep the actual arm position within the acceptable position band when needed in both sessions. The activation of the assistive controller to provide robotic assistance for each participant was recorded.

A segment of the activation of the assistive controller for Participant 4 (as an example) is shown in Fig. 4. When the average actual position calculated over a period of 4 s using (2) was out of the position band, the controller initiated robotic assistance, which brought the arm position back into the acceptable range within one period $(4s)$. The position error during this period is shown in Fig. 5.

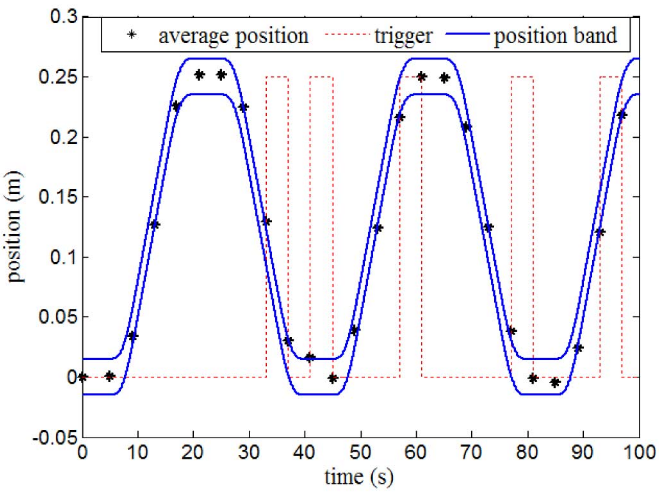

Fig. 4. Calculated average position for Participant 4 in Experiment 1. The robotic assistance was provided when the average position was out of the acceptable position band. The average positions were calculated at $t = 1$ s, 5 s, 9 s, 13 s . . . in this plot.

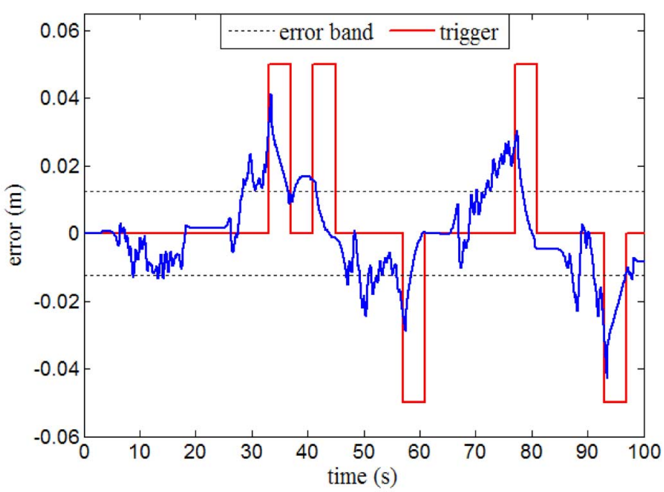

Fig. 5. Position error during robotic assistance for Participant 4. Once activated, robotic assistance continued for 4 s and was sufficient to bring the arm position back into the acceptable error band. Note that, for example, around $t = 30$, the robotic assistance was not activated until $t = 33$ s when it was determined that the average position error in 4 s interval ($t = 29 \sim 33$ s) was out of acceptable error band.

B. Times of Assistance Needed

The total number of times assistance was needed by each participant in two training sessions for both Group A and Group B are shown in Figs. 6 and 7, respectively.

Comparing the number of times assistance was needed in two sessions of Group A, who participated in the AAN Session followed by the INT Session, participants significantly improved their tracking performance (i.e., the participants needed less numbers of times of robotic assistance) when the assist-as-needed training method was integrated with the visual error augmentation training method in the INT Session (Fig. 6). The total number of times robotic assistance was needed by each participant decreased significantly, for P1 (33.3%), P2 (56.41%), P3 (39.47%), P4 (76.67%), P5 (75.86%), P6 (23.81%), P7 (16. 67%), P8 (36.84%), P9 (60%), and P10 (17.65%), in the INT Session compared to the AAN Session. The paired *t*-test, which

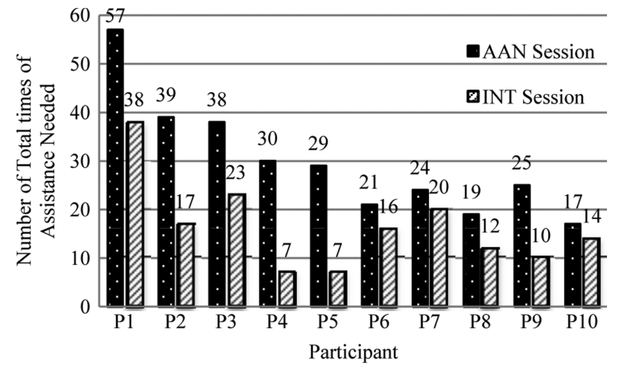

Fig. 6. Comparison of two sessions of Group A. Each participant needed less numbers of times of robotic assistance in the INT Session.

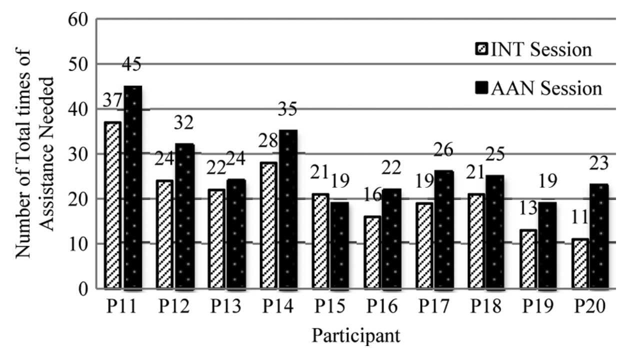

Fig. 7. Comparison of two sessions of Group B. 9 out of 10 participant needed less numbers of times of robotic assistance in the INT Session.

compared the group mean of the numbers of times robotic assistance was needed by the participants in the AAN Session with that in the INT Session, showed that the difference was statistically significant ($p < 0.001$).

Comparing the total numbers of times assistance was needed in the two sessions of Group B, who participated in the INT Session followed by the AAN Session, 9 out of 10 participants achieved better tracking performance (i.e., the participants needed less numbers of times of robotic assistance) when the assist-as-needed training method was integrated with the visual error augmentation training method in the INT Session (Fig. 7), except for Participant 15, who showed a slight decrease in times of robotic assistance needed (9.52%). The total number of times robotic assistance was needed by each participant increased, for P11 (17.78%), P12 (25%), P13 (8.33%), P14 (20%), P16 (27.27%), P17 (26.92%), P18 (16%), P19 (31.58%), and P20 (52.17%), from the INT Session to the AAN Session. The paired *t*-test showed that the difference of times robotic assistance was needed by all participants between the INT Session and the AAN Session was statistically significant ($p < 0.001$).

Note that the carryover effects, which are the training residuals from the first training session into the second training session, might have affected the training performance in the second training session. Thus further analysis of the crossover study was performed to make a comparison of the difference of times robotic assistance was needed by the participants between the two sessions with the existence of carryover effects. Table I shows the number of times robotic assistance was needed by each participant in each session. The steps and analysis of a

TABLE I
NUMBER OF TIMES ROBOTIC ASSISTANCE WAS NEEDED BY EACH PARTICIPANT IN EACH SESSION

Group A					Group B				
ID	AAN	INT	Sum (T1i)	Difference (D1i)	ID	INT	AAN	Sum (T2j)	Difference (D2j)
P1	57	38	95	19	P11	37	45	82	-8
P2	39	17	56	22	P12	24	32	56	-8
P3	38	23	61	15	P13	22	24	46	-2
P4	30	7	37	23	P14	28	35	63	-7
P5	29	7	36	22	P15	21	19	40	2
P6	21	16	37	5	P16	16	22	38	-6
P7	24	20	44	4	P17	19	26	45	-7
P8	19	12	31	7	P18	21	25	46	-4
P9	25	10	35	15	P19	13	19	32	-6
P10	17	14	31	3	P20	11	23	34	-12

general two-period crossover study are briefly described in the Appendix.

First, an unpaired *t*-test was carried out between $\mathrm{T}_{1\mathrm{i}}$ and $\mathrm{T}_{2\mathrm{j}}$ to test the equality of carryover effect. The result of the unpaired *t*-test showed that the difference was not significant ($p = 0.813$). So the carryover effect between the AAN Session followed by the INT Session in Group A had no significant difference from that of between the INT Session followed by the AAN Session in Group B, which indicated that the carryover effect was consistent between the two groups.

To test the difference of the numbers of times robotic assistance was needed by participants in two sessions, knowing that the carryover effect was not significantly different between the two groups, an unpaired *t*-test was performed between $\mathrm{D}_{1\mathrm{i}}$ and $\mathrm{D}_{2\mathrm{j}}$. The result of one-sided unpaired *t*-test showed that the difference of training effects was statistically significant ($p < 0.001$), which indicated that better training performance were achieved by participants in the INT Sessions than in the AAN Sessions.

C. Analysis of Position Error

The average absolute position errors of each participant in both groups in two sessions were calculated using

$$e_{\rm ave} = \frac{1}{5}\sum_{i=1}^{5}\left(\frac{1}{T_{f,i}-T_{s,i}}\sum_{t_{s,i}}^{t_{f,i}}\left(\left|x_{d,i(t)-x_i(t)}\right|\right)\right) \quad (3)$$

where i is the ith training group, and $T_{s,i}$ and $T_{f,i}$ are the starting and final times of ith training group, respectively. $x_{d,i}(t)$ and $x_i(t)$ are the desired and actual positions in the ith training group, respectively.

In Group A, the average absolute position errors of each participant in the INT Session was much smaller than that in the AAN Session, which meant more accurate tracking performance was achieved by the participants in the INT Session (Fig. 8). The paired *t*-test, which compared the group mean of average absolute position errors of the participants in the AAN Session with that in the INT Session, showed that the difference of average absolute position errors was statistically significant ($p < 0.001$).

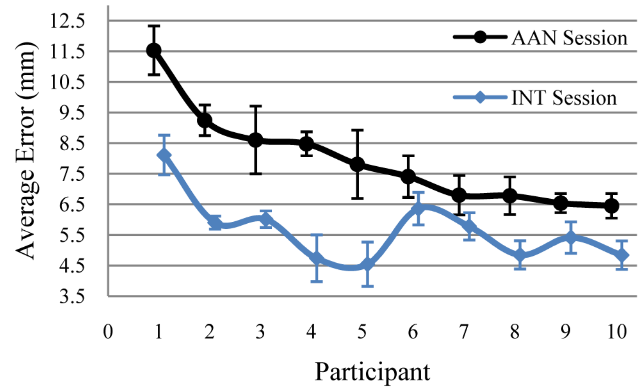

Fig. 8. Average Absolute Position Errors in Two Sessions of Group A. The average absolute position errors of all participants are smaller in the INT Session. Error bar is the standard error of the mean.

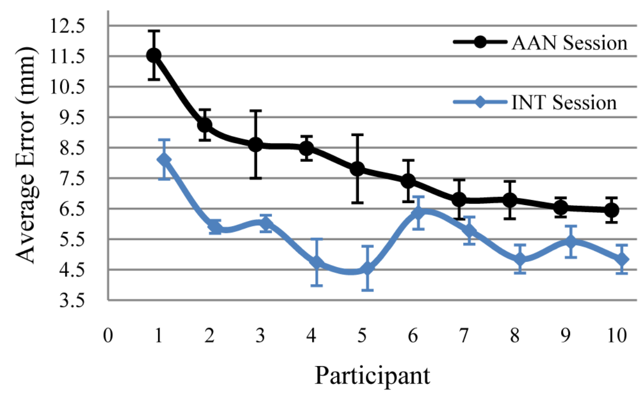

Fig. 9. Average Absolute Position Errors in Two Sessions of Group B. The average absolute position errors of 9 out of 10 participants are smaller in the INT Session. Error bar is the standard error of the mean.

Meanwhile, in Group B, the average absolute position errors of each participant in the INT Session was still smaller than that in the AAN Session, except for Participant 15, which meant that for 9 out of 10 participants of Group B, more accurate tracking performance was achieved in the INT Session (Fig. 9). The paired *t*-test showed that the difference of average absolute position errors between the AAN Session and the INT Session was statistically significant ($p = 0.0014$).

The analysis of the crossover design was performed to test the difference of position error between two training sessions. Table II shows the average error of each participant in both sessions. The unpaired *t*-test between $\mathrm{T}_{1\mathrm{i}}$ and $\mathrm{T}_{2\mathrm{j}}$ showed that there was no significant difference of carryover effect between the two groups ($p = 0.747$). The result of one-sided unpaired *t*-test between $\mathrm{D}_{1\mathrm{i}}$ and $\mathrm{D}_{2\mathrm{j}}$ showed that the difference of training effect between the two groups was statistically significant ($P < 0.001$), which implied the participants were able to perform the tracking task more accurately in the INT Sessions.

IV. DISCUSSION

The primary goal of this study was to explore the impact of visual error augmentation training method, when it was inte-

TABLE II
AVERAGE ABSOLUTE POSITION ERROR OF EACH PARTICIPANT IN EACH SESSIONS

Group A					Group B				
ID	INT	AAN	Sum (T_{1i})	Difference (D_{1i})	ID	INT	AAN	Sum (T_{2j})	Difference (D_{2j})
P1	11.53±0.80	8.11±0.78	19.64	3.42	P11	9.75±0.54	9.98±0.80	19.73	-0.23
P2	9.24±0.50	5.90±0.21	15.15	3.34	P12	7.61±0.77	8.10±0.38	15.71	-0.49
P3	8.60±1.11	6.01±0.27	14.62	2.59	P13	7.36±0.65	7.67±0.46	15.04	-0.31
P4	8.48±0.39	4.74±0.52	13.22	3.74	P14	6.88±0.63	7.54±0.45	14.42	-0.67
P5	7.81±1.12	4.54±0.72	12.35	3.26	P15	7.49±0.67	7.31±0.48	14.80	0.18
P6	7.41±0.68	6.36±0.53	13.76	1.05	P16	5.93±0.75	6.51±0.42	12.44	-0.57
P7	6.80±0.64	5.78±0.44	12.58	1.02	P17	5.47±0.57	6.47±0.35	11.95	-1.00
P8	6.78±0.61	4.85±0.46	11.63	1.93	P18	5.80±0.56	6.31±0.61	12.11	-0.51
P9	6.54±0.31	5.41±0.51	11.95	1.13	P19	5.88±0.61	6.16±0.52	12.04	-0.28
P10	6.45±0.40	4.84±0.46	11.29	1.61	P20	5.48±0.45	6.13±0.37	11.61	-0.65

Note: Values are mean ± standard error of the mean (SEM). Units: mm.

TABLE III
AVERAGE VALUE OF EACH GROUP IN EACH SESSION

	Group A		Group B	
Variable	AAN Session (AAN1)	INT Session (INT1)	INT Session (INT2)	AAN Session (AAN2)
Robotic Assistance Needed	29.9±3.81	16.4±2.92	21.2±2.37	27±2.57
Average Error (mm)	7.96±0.50	5.65±0.34	6.77±0.43	7.22±0.38

Note: Values are mean ± standard error of the mean (SEM).

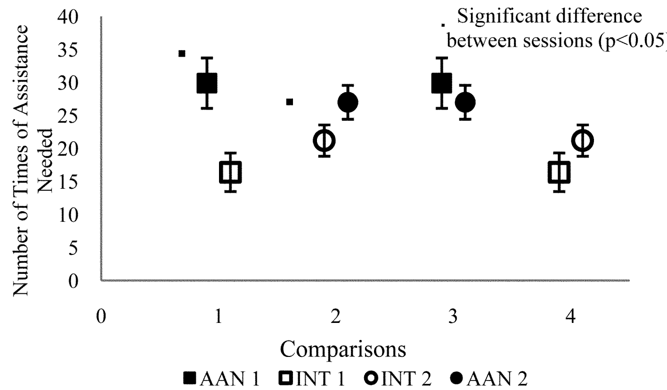

Fig. 10. Average number of times robotic assistance needed in each session. Error bars are the SEM. Note that Comparison 1 and 2 are the paired *t*-tests for the different sessions in the same group. Comparison 3 and 4 are the unpaired *t*-tests for the same sessions in different groups.

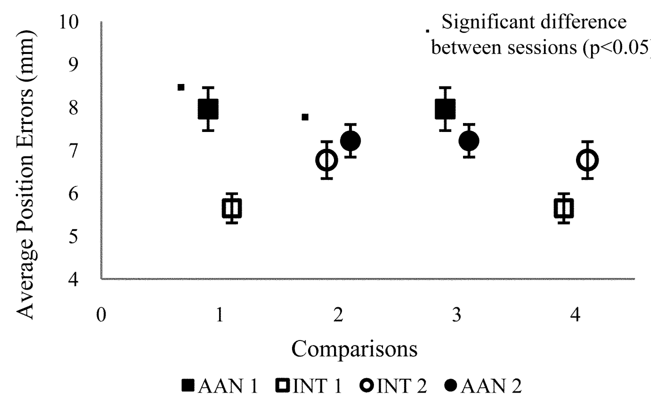

Fig. 11. Average position error in each session. Error bars are the SEM. Note that Comparison 1 and 2 are the paired *t*-tests for the different sessions in the same group. Comparison 3 and 4 are the unpaired *t*-tests for the same sessions in different groups.

grated with assist-as-needed training method in robot-assisted rehabilitation. Both assist-as-needed [10], [16] and visual error augmentation [21], [23], [29] training methods have been investigated separately on healthy subjects and stroke patients for upper extremity. While the algorithmic details differ in these studies, the overall ideas have been similar. In all these studies, improved performances have been achieved across training sessions. We began our investigation knowing that both these training methods, individually, had the potential to improve the rehabilitation outcome. We wanted to extend the understanding of the impact of these two training methods when they were integrated together in robot-assisted rehabilitation. In this study, significant improvements were observed in both AAN Session and INT Session, which was in agreement with the results of the prior works [10], [16], [21], [23]. The detailed performance in each training session was reported in our previous work [31]. Moreover, regardless of the sequence of the two sessions, 19 out of 20 participants needed fewer times of robotic assistance to complete the task in the INT Session. This result indicated that the participants became more capable of executing the task when the visual error augmentation training method had been integrated with the assist-as-needed training method in the robot-assisted rehabilitation system. It was also observed that the tracking performances were better in terms of smaller average position errors for 19 out of 20 participants in the INT Session. Only one participant in Group B, who took part in the INT Session followed by the AAN Session, showed a better performance in the assist-as-needed session.

Comparing the participants' overall performance in the INT Session with that in the AAN Session of the same group, improved training performances were achieved in the INT Session (i.e., fewer times of robotic assistance needed and smaller average position errors, Table III), and differences in the improvements in two sessions were statistically significant (Figs. 10 and 11, Comparison 1 and 2). Thus, it is reasonable to believe that the integration of the visual error augmentation training method with the assist-as-needed training method has contributed towards the improved training performance.

The unpaired *t*-tests performed for the training performance in the same training sessions of different groups did not show statistically significant differences with and without the influence of carryover effect (Figs. 10 and 11, Comparison 3 and 4), which means the training effects in either training session were consistent between groups. Meanwhile, no statistically significant difference in carryover effects was observed between the two groups, which indicated the influence of carryover effects was consistent between groups.

Note that this is a preliminary investigation on complex research questions such as—what is the best training method for stroke rehabilitation? Do these training methods need to be applied separately, or are they more effective when integrated in a specific manner? Although our initial research does not address these issues in relation to stroke patients directly, the findings with unimpaired participants do suggest that an integration of visual error augmentation with assist-as-needed training methods improve the tracking performance significantly. Based on the experimental results presented here, it is reasonable to suggest that integrating visual error augmentation training method with the assist-as-needed training method might have the potential to improve the performance of stroke rehabilitation and should be explored.

V. Conclusion

An enhanced robot-assisted rehabilitation system, with the assist-as-needed and the visual error augmentation training methods, is evaluated with two groups of unimpaired participants in two experimental sessions. As a crossover design, Group A participants took part in the AAN training session followed by the INT training session, while the Group B participants took part in the INT training session followed by the AAN training session. The experimental results demonstrate that improved performance, in terms of number of times robotic assistance needed and average position errors, are achieved in the integrated training session on unimpaired participants. The integration of visual error augmentation training method with the assist-as-needed training method might have the potential to improve the performance of stroke rehabilitation and should be further explored.

As future work, a new assistive controller, which can adaptively choose the proper control gains for participants with different levels of motor abilities, will be developed so that participants can achieve better training performance with appropriate robotic assistance. Our previous work [32] has proposed a technique that predicts proper control gains based on parameter estimation and neural network prediction methods for each participant. It is also possible to test various error amplification gains or error offset values in the visual error augmentation training method to achieve a comprehensive understanding of this training method. Additionally, an important direction for future development involves testing the usability of the enhanced robot-assisted rehabilitation system with stroke patients. Functional magnetic resonance imaging procedure can also be introduced to investigate whether the robot-assisted rehabilitation system that integrates visual error augmentation with assist-as-needed training methods result in long-term brain reorganization.

Appendix

Table IV lists all the possible effects in two-period crossover design [30].

In Table IV, μ denotes the overall mean, π_i denotes the ith period effect regardless of treatment, τ_i denotes the ith treatment effect, ρ_i denotes the first treatment's residual or carryover effect into the second treatment in sequence i.

TABLE IV
Possible Effects in a General two Period Crossover Design

Sequence	Period 1	Period 2	Sum	Difference
AB	$\mu+\pi_1+\tau_1$	$\mu+\pi_2+\tau_2+\rho_1$	$\overline{T_1}$	$\overline{D_1}$
BA	$\mu+\pi_1+\tau_2$	$\mu+\pi_2+\tau_1+\rho_2$	$\overline{T_2}$	$\overline{D_2}$

From the table, expectation of sum $\overline{T_1}$ and $\overline{T_2}$

$$\begin{aligned} \mathrm{E}(\overline{T_1}) &= 2\mu + \pi_1 + \tau_1 + \pi_2 + \tau_2 + \rho_1 \\ \mathrm{E}(\overline{T_2}) &= 2\mu + \pi_1 + \tau_1 + \pi_2 + \tau_2 + \rho_2. \end{aligned} \tag{4}$$

Therefore, an unbiased estimator of $\rho_1 - \rho_2$, which measures the difference in carryover effects, is

$$(\rho_1 - \rho_2)_{\mathrm{est}} = \overline{T_1} - \overline{T_2}. \tag{5}$$

If $\rho_1 = \rho_2$, the unbiased estimator of $\tau_1 - \tau_2$, which measure the average difference between treatment 1 and treatment 2, is

$$(\tau_1 - \tau_2)_{\mathrm{est}} = \frac{(\overline{D_1} - \overline{D_2})}{2}. \tag{6}$$

If $\rho_1 \neq \rho_2$, the expectation of an unbiased estimator of $\tau_1 - \tau_2$ is

$$\mathrm{E}((\tau_1 - \tau_2)_{\mathrm{est}}) = (\tau_1 - \tau_2) - \frac{(\rho_1 - \rho_2)}{2}. \tag{7}$$

In this case, an unbiased estimator of $\tau_1 - \tau_2$ is

$$(\tau_1 - \tau_2)_{\mathrm{corrected\ est}} = \overline{X_1} - \overline{Y_1} \tag{8}$$

where $\overline{X_1}$, $\overline{Y_1}$ are the measurements in Period 1 of each sequence.

So the analysis is conducted in three steps.

1) Test the equality of carryover effect between two groups with hypothesis $\rho_1 = \rho_2$.
2) If the carryover effect is not equal, use only the data from the first session to test the difference of times of assistance needed by participants in two sessions.
3) If the carryover effect is equal, use data from both sessions.

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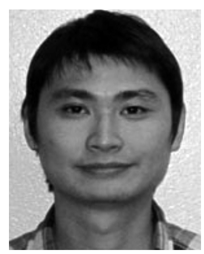

Furui Wang received the B.S. and M.S. degree in mechanical engineering from University of Science and Technology of China, in 2003 and 2006, respectively. He is currently working toward the Ph.D. degree in Robotics and Autonomous Systems Laboratory, Vanderbilt University, Nashville, TN.

His research interests are rehabilitation robotics, hybrid system control, and system dynamics.

Duygun Erol Barkana received the B.Sc. degree from Eskisehir Osmangazi University, Eskisehir, Turkey, in 2001, the M.Sc. and Ph.D. degrees from Vanderbilt University, Nashville, TN, in 2003 and in 2007, respectively.

She is currently an Assistant Professor of Electrical Engineering and Computer Science at Yeditepe University, Istanbul, Turkey. She is interested in dynamics, control, hybrid systems, robot-assisted rehabilitation systems and medical robotics. She directs the Robotics Research Laboratory at Yeditepe University.

Nilanjan Sarkar (SM'10) received the Ph.D. degree in mechanical engineering and applied mechanics from the University of Pennsylvania, Philadelphia.

He is currently an Associate Professor in the Departments of Mechanical Engineering and Computer Engineering at Vanderbilt University, Nashville, TN. He directs the Robotics and Autonomous Systems Laboratory at Vanderbilt University where he along with his colleagues, conduct research in the areas of rehabilitation robotics, human–robot interaction, and intelligent control. He has served as an Associate Editor for the *Journal of Intelligent Systems and Robotics*.

Dr. Sarkar has served as an Associate Editor for the IEEE TRANSACTIONS ON ROBOTICS and as a Guest Editor for IEEE/ASME TRANSACTIONS ON MECHATRONICS.