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Custom-designed haptic training for restoring reaching ability to individuals with poststroke hemiparesis

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Abstract—We present an initial test of a technique for retraining reaching skills in patients with poststroke hemiparesis, in which errors are temporarily magnified to encourage learning and compensation. Individuals with poststroke hemiparesis held a horizontal plane robotic manipulandum that could exert a variety of forces while recording patients' movements. We measured how well the patients recovered movement straightness in a single visit to the laboratory (~3 h). Following training, we returned forces to zero for an additional 50 movements to discern if aftereffects lasted. We found that all subjects showed immediate benefit from the training, although 3 of the 10 subjects did not retain these benefits for the remainder of the experiment. We discuss how these approaches demonstrate great potential for rehabilitation tools that augment error to facilitate functional recovery.

Key words: adaptation, control, cortex, force fields, haptics, hemiparesis, human, human-machine interface, impairment, lesion, motor learning, rehabilitation, robots, stroke, teaching.

INTRODUCTION

The range of robotic possibilities for teaching and rehabilitation has yet to be established, but the options do go beyond what a therapist can do—robots are precise, tireless devices that can measure progress with high accuracy. We have been focusing on robotic forces that may facilitate recovery from brain injuries such as stroke. Some conventional therapeutic interventions use guidance and resistance principles to promote motor recovery in the hemiparetic upper limb. Some traditional rehabilitation sources recommend therapeutic intervention that eliminates unwanted muscle activity and muscle tone and then introduces normal movement patterns, which may facilitate rehabilitation [1]. Other theories suggest that facilitating reaching patterns promotes improvements in motor function. One component of this approach is the use of resistance in a direction opposite the movement [2]. However, the most effective rehabilitation algorithms have yet to be determined, which leaves a fertile area for scientific inquiry.

Interestingly, several researchers are exploring robotic techniques that are not necessarily designed to imitate the conventional therapeutic process but to instead uniquely probe new capabilities. For example, one possible technique is to have the robot guide (pull) the hand toward the desired trajectory and have the guidance transition to resistance as recovery progresses [3–4]. Another technique for hemiparetic stroke patients is providing the patient with a bimanual master-slave robot system, which guides the paretic arm by the actions of

Abbreviations: DOF = degrees of freedom, FM = Fugl-Meyer.

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the patient's nonparetic limb [4]. Still another technique is to provide force biofeedback during movement along a constraining rail, which encourages the patient to push in the appropriate direction [4–6]. Others have also attempted sophisticated virtual reality techniques [7–15].

Our research and the work of others suggest that one promising novel approach may be adaptive training [16–20]. In this technique, we use the natural adaptive tendencies of the nervous system to facilitate motor recovery. Motor adaptation studies have demonstrated that when people are repeatedly exposed to a force field that systematically disturbs arm motion, subjects learn to anticipate and cancel out the forces and recover their original kinematic patterns. After the disturbing force field is unexpectedly removed, the subjects make erroneous movements in directions opposite the perturbing forces (aftereffects). This technique has recently been shown to alter and hasten the learning process in nondisabled individuals [19,21].*

Motor adaptation and its related aftereffects have been demonstrated by many investigators under many conditions, ranging from simple position-, velocity-, and acceleration-dependent force fields [22–26] to Coriolis forces caused by movement in a rotating room [27] and skew-symmetric "curl" fields that produce forces in a direction perpendicular to the velocity of the hand [25]. Similar results have also been observed after manipulations of subjects' visual perception that altered the visual feedback of movement [28–31]. Recent results support the view that subjects adapt by learning the appropriate internal model of the perturbation rather than learning a temporal sequence of muscle activations [25–26]. The most encouraging result is that engineering techniques have been successful in predicting both how the arm is disturbed by a force field and the aftereffects of training [24,32–33]. Consequently, one possible rehabilitation method may be for investigators to reverse-engineer the adaptation process by using the models to design an appropriate force field that will eventually result in the desired aftereffect.

Adaptive training will only work, however, if stroke patients can adapt. Several studies have demonstrated that at least a large subpopulation of stroke patients retain their ability to adapt to a force field [16–20] or other disturbances [34–37]. However, severely affected individuals used atypical correction strategies [18], and the amount of adaptation in individuals with more severe impairment is somewhat diminished compared with nondisabled individuals [20]. Our recent work agrees with these findings [38]. Furthermore, our preliminary studies on stroke patients have revealed that aftereffects may persist longer when the aftereffects resemble nondisabled unperturbed movement [16–17,39].

We focused on adaptive training by using robot-applied forces to restore function to hemiparetic stroke patients. This investigation is a pilot study for determining the potential of this approach to rehabilitation. We simply applied a technique to stroke patients that has already proven effective at causing desired results in nondisabled individuals [19]. While straightening slightly curved movements is generally not perceived as the most important clinical goal, it represents our initial effort at testing the promise of this approach in a well-known scientific framework. We addressed two questions. First, we sought to determine whether adaptation can be exploited for restoring movement ability. Second, we sought to determine whether the benefit persists for the duration of the experiment [17].

METHODS

Subjects

Fifteen stroke patients without any other musculoskeletal injury volunteered to participate. Their demographic details are listed in **Table 1**. The Northwestern University Internal Review Board approved the research to conform to ethical standards from the 1964 Declaration of Helsinki and Federal mandates that protect research subjects. Before beginning, each subject signed a consent form that conformed to these Northwestern University guidelines. All stroke participants were in the chronic stage, having suffered a stroke 19 to 132 months prior to the experiment. Our exclusion criteria were (1) bilateral impairment; (2) severe sensory deficits in the limb; (3) aphasia, cognitive impairment, or affective dysfunction that would influence the ability to comprehend or to perform the experiment; (4) inability to provide an informed consent; and (5) other current severe medical problems. Subjects were randomly assigned to one of two groups: a treatment group (n = 12) that received custom-designed forces for part of the experiment or a control group (n = 9) that received no forces but otherwise performed the same experimental protocol. We were able to have six subjects return on a separate day for a second visit, so some subjects served as their own controls. The order of

*Wei Y, Patton JL. Forces that supplement visuomotor learning: A 'sensory crossover' experiment. Exp Brain Res. Unpublished observations, 2006.

Table 1.
Subject information for treatment and control subjects of this study (N = 15).

Subject	Sex	Assisted Vision	Dominant Hand	Pathology	Affected Hand	Affected Neural Region
1	Female	Yes	Right	Hemorrhagic stroke	Right	Left intercerebral hemorrhage
2	Male	Yes*	Right	Stroke	Left	Unknown
3	Male	No	Right	TBI followed by 2 strokes	Right	Unknown, left CVA
4	Female	Yes*	Right	Stroke	Left	Right frontal cortex
5	Male	Yes†	Right	AVM hemorrhage	Left	Right frontal and parietal lobe
6	Female	No	Right	Hemorrhagic stroke, RIND 1 yr previous	Left	Right posterior internal capsule infarct
7	Female	No	Right	Hemorrhagic stroke	Left	Right intercerebral hemorrhage
8	Male	Yes	Right	Stroke	Left	Right thalamus
9	Male	Yes*	Left	Stroke	Right	Left parietal lobe
10	Male	Yes	Right	Stroke	Left	Right carotid artery, thrombotic
11	Female	Yes	Left	Stroke	Right	Pons and midbrain
12	Male	Yes	Right	Stroke	Left	Unknown
13	Male	Yes	Right	Stroke	Left	Left subcortical lacunar
14	Female	No	Right	Thrombotic stroke	Right	Left MCA, posterior
15	Male	Yes*	Right	Thrombotic stroke with neurosurgery	Left	Right subcortical

*Vision not assisted for experiment.
†Bifocals used for experiment.
AVM = arteriovenous malformation, CVA = cerebrovascular accident, MCA = middle cerebral artery, RIND = reversible ischemic neurological deficit, TBI = traumatic brain injury.

presentation was randomized. The research therapy staff was blinded to the type of forces the subjects received and performed the modified Ashworth scale to assess spasticity before beginning the experiment. We performed the upper-limb portion of the Fugl-Meyer (FM) examination before and after the robotic experiment to assess general changes in motor capability.

Apparatus

Subjects held the free limb (here referred to as the "endpoint") of a 2 degree-of-freedom DOF robot (**Figure 1**) described elsewhere [26,40]. Endpoint forces and torques were monitored with a 6 DOF load cell that was fixed to the handle of the robot (ATI Industrial Automation, Inc, Apex, North Carolina, model F/T Gamma 30/100). The robot was equipped with position encoders that record the angular position of the two robotic joints with a resolution exceeding 20" of rotation (Gurley Precision Instruments, Inc, Troy, New York, model 25/045-NB17-TA-PPA-QAR1S). The position, velocity, and acceleration of the handle were derived from these two position encoders. We used two torque motors to apply programmed forces to the subjects' hands (PMI Motor Technologies, Wood Dale, Illinois, model JR24M4CH). Motion and force data were collected at 100 Hz. At all times during the experiment, the software generated an additional set of compensatory torques that canceled the inertial effects of the robot-arm linkage and resulted in the feeling of free movement on a slippery surface when the force field was not present.

Protocol

Subjects were seated so that the starting point of the targets was approximately at the center of their theoretical workspace, directly anterior from the shoulder (**Figure 1(b)**). The experiment involved only the hemiparetic limbs of the stroke subjects, which corresponded to the dominant limb in 9 of the 11 subjects (**Table 1**). If subjects had difficulty reaching the center point, we adjusted their chair position slightly. To avoid fatigue, subjects rested their elbow and forearm on a lightweight frictionless linkage (**Figure 1(a)**), and they could choose to rest between movements (subjects rarely rested longer than a few seconds every hundred movements).

Starting from a point centered in front of the shoulder, subjects were presented a target at one of two locations 10 cm distant (out and to the left or out and to the right).

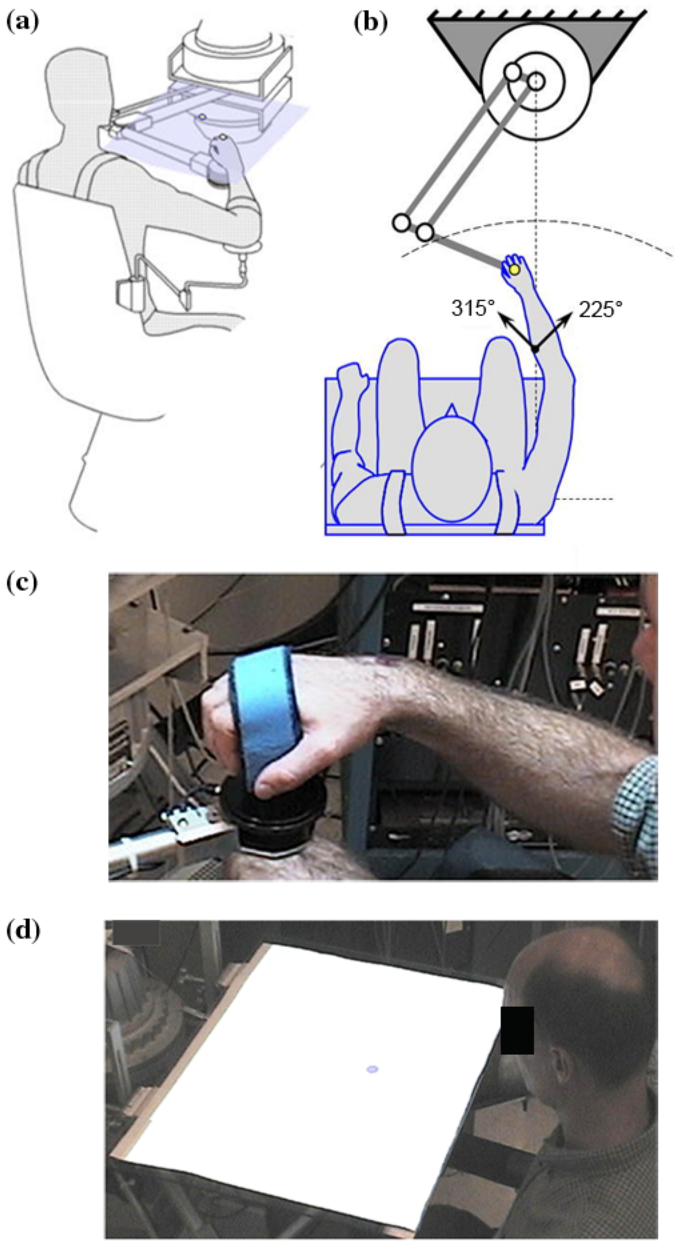

Figure 1.
Experimental apparatus from **(a)** side view and **(b)** top view. **(c)** Hand strap and posture used. Ball handle was on low-friction axle, so it was free to pivot in horizontal plane. **(d)** Subject seated at projection platform with movement target displayed. Only target and cursor representing hand were visible to subject.

These two "main" targets were 90° from each other and formed a "v" pattern that was centered along the paramidline extending from the shoulder (**Figure 1(b)**). Subjects were given a cue to return to the center point after they had either (1) initiated an attempt and 3 seconds had elapsed or (2) reached and stayed in the target (1 cm radius) for at least 0.5 seconds. Subjects' arms were eclipsed by the projection platform. Hence, they could only see the target and a cursor that represented the instantaneous location of the hand. Subjects were neither told about nor shown the desired movement, although they were instructed to try to move to the target at the appropriate speed in a straight line. Only the outward movements were recorded for this experiment. Additionally, we included two extra "generalization" targets that were not practiced but only experienced briefly at the beginning and end of the experiment. These targets were only 30° from each other and formed a "v" in the area between the main targets, also centered on the paramidline extending from the shoulder. The generalization targets were used to determine if any learning was carried to movement directions that were not practiced.

We controlled for a peak speed of 0.288 m/s by giving subjects feedback at the end of each movement using colored dots and auditory tones. These cues let subjects know if they were going too fast, too slow, or within a range of ±0.05 m/s. Consequently, subjects' speeds remained roughly constant across the entire experiment. Subjects were instructed to initiate their movements at a self-determined time after they saw the target appear. To prevent fatigue, we instructed subjects to rest anytime they chose.

Machine Learning and Force-Field Design

As explained in greater detail elsewhere, a time-record of training forces was custom-designed with an iterative machine-learning algorithm [19]. A machine-learning phase iteratively determined the forces that shifted a subject's movement to the "desired" trajectory, $x_D(t)$, by intermittently exerting forces (once every four movements, randomly presented) and adjusting them based on the response of the subject. For this experiment, we used a smooth, minimum-jerk trajectory along a straight line to the target for $x_D(t)$, which was believed to resemble a "healthy" trajectory [41]. For each iteration, a force $F_{D_i}(t)$ was applied to the robot handle in the first 200 ms of the movement, where $F_{D_1}(t) = 0$ and $F_{D_i}(t)$ (for $i > 1$) was adjusted from one movement to the next based on the error between the actual, $x(t)$, and the desired trajectories with the simple machine-learning rule

$$F_{D_{i+1}}(t) = F_{D_i}(t) + \mu(x(t) - x_D(t)) \ .$$

Here, the parameter μ is a learning rate, which has been heuristically found to work in the range from 10 to

30 N•m^{-1}. A μ that is too large leads to unstable learning, and a μ that is too small results in a lengthy machine-learning session. We chose μ = 20 N•m^{-1} for our experiments. The algorithm allowed the subject to initiate the movement when they chose. Forces initiated when velocity exceeded 0.1 m/s or the subject had exited the starting window. All subjects performed a total of 744 movements (trials), broken down into the following experimental phases:

- *Unperturbed familiarization*: 58 movements (~6.5 min) for becoming familiar with the system and the task of moving the manipulandum.
- *Unperturbed baseline*: 10 movements (~1.5 min) for establishing a baseline pattern of reaching movements.
- *Unperturbed baseline, generalization targets*: 10 movements (~1.5 min) for establishing a baseline pattern of reaching movements on the generalization targets described previously.
- *Machine learning*: 200 movements (~25 min) with forces exerted intermittently and randomly once in every 4 movements. The robot gradually learned the average forces necessary to push the subject to the "desired" trajectory. Note that because these forces occurred intermittently and randomly, these movements did not lead to adaptation, because any small amount of adaptation was washed out in the movements between the movements with forces.
- *Second unperturbed baseline*: 10 movements (~1.5 min) for determining if the baseline pattern changed.
- *Second unperturbed baseline, generalization targets*: 10 movements (~1.5 min) for determining if the baseline pattern changed on the generalization targets.
- *Learning*: 222 movements (~30 min) with constant exposure to the training forces. These forces were the vector opposite of the forces that were determined in the machine-learning phase.
- *Aftereffects catch trials*: 80 movements (~10 min) with random, intermittent removal of the force field for 1 in 8 of the movements (catch trials) for determining the aftereffects.
- *Aftereffects catch trials, generalization targets*: 80 movements (~10 min) with random, intermittent removal of the force field for 1 in 8 of the movements (catch trials) for determining the aftereffects.
- *Training refresher*: 2 movements (~15 s) identical to the learning phase.
- *Washout*: 50 movements (~6 min) with no forces applied.
- *Final movements, generalization targets*: 10 movements (~2 min) with no forces applied on the generalization targets.

The movements in each direction were divided equally in each phase. Subjects were also required to take breaks (approximately 1–2 min) after movements 54, 278, 510, and 682 so they could rest and our data collection equipment could be reset. We chose the instance of these breaks to minimally disrupt the learning process and provide the subject with a chance to rest. The subjects in the control group received no forces for the entire experiment but otherwise experienced the same protocol. The entire session lasted approximately 3 hours, which included screening by therapist and pre- and postclinical measures by the research occupational therapist.

Analysis

We restricted our focus in this study to the early part of movements for two reasons. First, stroke patients often make excessively large corrections later in their movements that may depend on earlier errors [42–43]. Second, we were primarily interested in the early phase of the movement that best reflects the operation of a feed-forward controller based on an internal model of the arm-environment dynamics. Our measure, the initial direction error, reflected this early phase of movement by forming a vector from the start point to 25 percent of the distance to the target (2.5 cm). This measurement corresponded to approximately the first 200 to 300 ms of a movement that, if no error corrections existed at the end of the movement, lasted about 1.1 s. Positive error corresponded to a counter clockwise rotation from the actual trajectory to the desired trajectory, and zero corresponded to a straight line to the target. Initial direction error was used for testing our hypotheses on the feed-forward controller and also was found to be highly correlated with the perpendicular distance measure used in other adaptation studies [26,44–45]. Even though we were studying the initial part of movement, we were nonetheless also curious about whether "fixing" earlier stages of movement will correct (or improve) the latter part of movement.

All hypotheses were tested at an α level of 0.05. We tested for a shift in initial direction from baseline to aftereffects and for tendency of the aftereffects to disappear in the washout phase.

RESULTS

For all the movements observed, unperturbed baseline movements for stroke subjects were approximately twice as variable as in nondisabled subjects for the same experimental conditions (**Figure 2**) [19]. All subjects showed significant errors in one or more of the movement directions in the unperturbed baseline phase before any treatment (**Figure 2(a)**). Initial errors averaged 17° of initial direction error. Intermittently in the machine-learning phase, these errors were pushed by corrective forces that evolved to eventually shift movements closer to a straight line (**Figure 2(b)**). The forces resulting from the machine-learning phase ranged from 0 to 12 N and differed from subject to subject.

Subjects then began the learning phase in which the forces learned by the robot were inverted and applied repeatedly (**Figure 2(c)**). These training forces tended to amplify (double) the initial errors we saw in the unperturbed baseline phase. By the end of the learning phase, however, subjects had reduced their errors (**Figure 2(d)**) to a level similar to their unperturbed baseline phase. Beneficial aftereffects were observed in some catch trials, where for a single motion, the forces were removed and the subject was returned to the "normal" world (**Figure 2(e)**). Finally, we tested to see if the effects of the adaptation washed out by leaving the forces off for 60 more movements. For most of the subjects, the benefits were retained until the end, as was the case for the subject shown in **Figure 2(g)**.

However, in this initial investigation, we failed to detect, from direct analysis of the data whether, as a group, subjects statistically benefited from training by having aftereffects lie closer to nondisabled movement. Several subjects did not appear to adapt for one or both of the movement directions (**Figure 3**). We suspected that this was due to a combination of several factors. First, it could have been because of a small (or no) effect size. Second, it could have been because of a large amount of variability in the data. Third, and most importantly, it could have been because some subjects' movements had no room for improvement.

To test the hypothesis that benefit was difficult to detect because there was nothing to improve upon, we singled out subjects' movement directions that actually showed significant error before training (i.e., their baseline movement errors were significantly different from zero). This reduced the analysis to 13 movement directions for the treatment group and 8 movement directions for the control group (about half the data). By this criterion, data from two subjects of the treatment group and four subjects of the control group was not considered further because their baseline movement errors were not significantly different from zero (**Tables 2** and **3**).

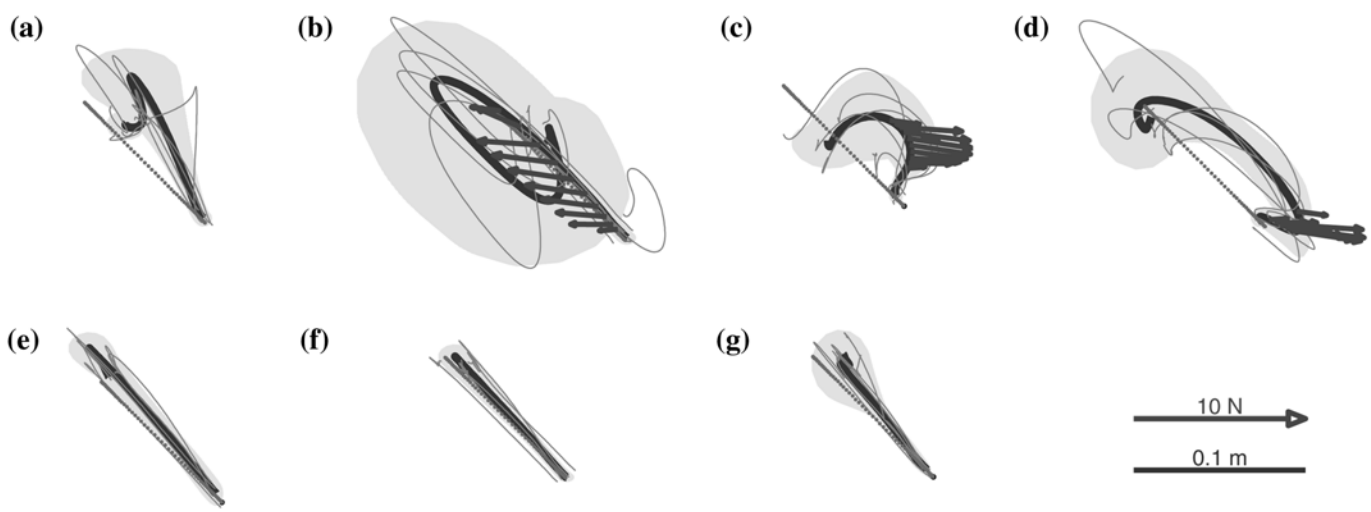

Figure 2.
Typical patterns for successive phases of experiment for single stroke subject: **(a)** unperturbed baseline, **(b)** late machine learning, **(c)** early training, **(d)** late training, **(e)** aftereffects, **(f)** early washout, and **(g)** late washout. Shown 315° movement direction for clarity only. Desired trajectories are bold dotted lines, average trajectories are bold solid lines, individual trajectories are thin lines, and shaded areas indicate running 95% confidence intervals of ensemble. Note that although dotted tracing indicates an ideal trajectory, only target and cursor representing hand were visible to subject.

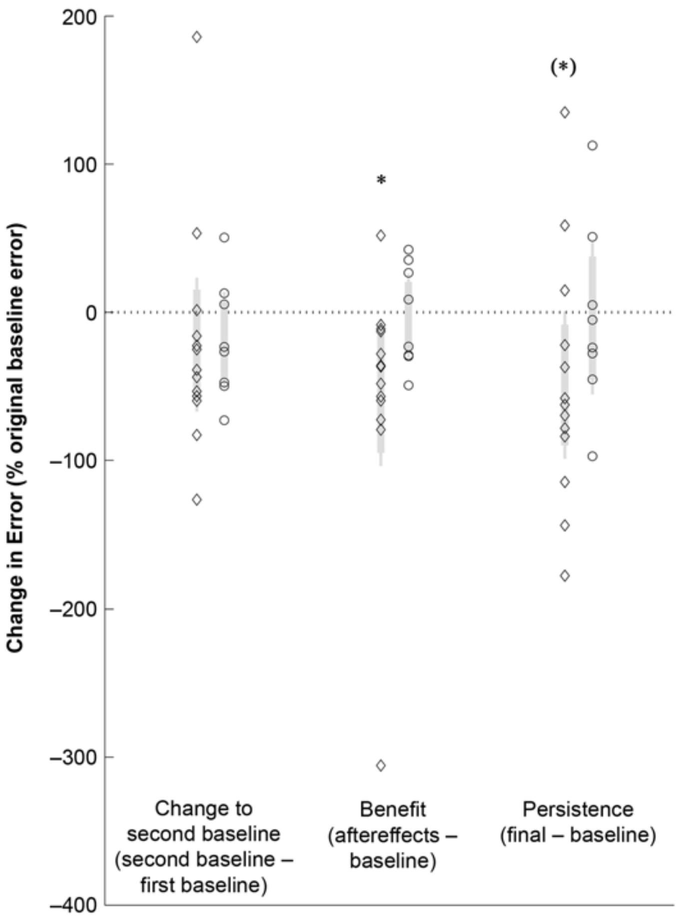

Figure 3.
Percent improvements from training only for movements in which error existed before training. Reduction of errors are negative values and were evaluated at second baseline phase (after end of machine learning; left two columns of data), at aftereffects phase (after force-field training; center two columns of data), or at end of experiment (after forces had been off for 50 movements; right two columns of data). Each subjects' average improvement for each movement direction is indicated by symbol: data from treatment group (◊) and control groups (○) are separated into columns. 95% and 90% confidence intervals are indicated as thin and thick vertical shaded bars behind symbols, respectively, indicating where *t*-tests showed significant benefit from training. Bars indicate significant benefit for treatment group in aftereffects trials and marginally significant persistence of benefit by experiment end. *Indicates significantly different than zero at 0.05 level. (*)Indicates significantly different than zero at 0.07 level.

Surprisingly, all but one of the treatment group movements showed beneficial aftereffects (**Figure 3**, bars, average reduction in error of –54%, $p < 0.05$, *t*-test on percent reduction in error). One subject's error reduction was 300 percent because the training process caused a rotation of the movement direction that went beyond the goal. Nevertheless, if this outlying data point was not considered, the error reduction for all the remaining subjects was still significant ($p < 0.01$). Interestingly, this subject's overcorrection snapped back to almost zero error by the end of the experiment.

The most critical question, however, was whether these beneficial aftereffects could be retained. While we chose this initial experiment not to extend our examination beyond the single 3-hour visit to the lab oratory (days or weeks would be necessary to be clinically convincing), we decided to check if beneficial aftereffects were retained beyond the normal time that nondisabled people wash out their aftereffects (about 20 movements). Similar to the evaluation of aftereffects (**Figure 3**, "Change to second baseline"), the final 10 movements of the 50 movements of the washout phase were also evaluated for a reduction in error from baseline. We found that 10 of the 13 subjects' error remained low and some were even lower than in the aftereffects phase. As a group, this reduction in error was marginally significant ($p < 0.054$, *t*-test on percent reduction in error, **Figure 3,** diamond symbols and bars for "Persistence").

An additional evaluation was whether subjects could generalize what they had learned and perform better in directions that were not practiced. We inspected the reduction in error movements that subjects made in the unpracticed generalization-target trials. However, we found no evidence of benefit either in the aftereffects or by the end of the experiment (not displayed).

Two important intermediate questions were whether (1) the machine-learning phase alone had any influence on movement error and (2) mere practice without forces might also result in some benefit (tested by the control group). Both of these questions are related and relevant to the assertion that a small amount of practice alone might lead to benefits that could confound results from the custom-designed force fields [46]. To test this, we first evaluated the error reduction by the final 15 trials of machine-learning phase and the corresponding trial numbers for the control group (**Figure 3,** "Change to second baseline"). Second, we evaluated the error reduction for the control group for trials that corresponded to those evaluated for the treatment group (**Figure 3,** circles). Although we failed to detect any significant difference between the control and the treatment groups, the treatment group showed a significant benefit while the control group did not (**Figure 3**, circles vs diamonds).

Table 2.
Selected characteristics and experimental data for treatment group (n = 12).

Subject	Age (yr)	Time Since Stroke (mo)	Height (m)	Mass (kg)	Elbow MAS*	Fugl-Meyer Upper Extremity		Initial Significant Error† Movements	Final Mean Δ Error‡
						Pretreatment	Δ Pre- to Posttreatment		
1§	30	129	1.60	70.45	—	26	0	—	—
2	48	55	1.73	75.45	—	37	2	R	–114
3§	37	132	1.75	71.82	—	52	4	R	15
4	76	19	1.73	75.00	—	44	5	R	–143
5¶	56	94	1.80	106.82	2	43	6	R	–58
6	49	54	1.47	60.00	2	32	–1	LR	–124
7¶	51	73	1.60	47.73	2	51	–2	R	–37
8	48	26	1.78	84.09	3	15	1	—	—
9§	72	96	1.70	72.72	2	33	1	LR	–53
10¶	53	113	1.85	90.89	2	22	2	L	–63
11	40	26	1.65	68.18	4	—	—	LR	–10
12	48	110	1.80	102.27	2	23	0	R	135
Mean	50.7	77.3	1.7	77.1	2	34	1.6	—	–45.2

*Scale 0 to 4.
†L indicates movement out and to left and R indicates movement out and to right.
‡Percent of baseline error.
§Subjects served as their own control and were randomized into treatment group first.
¶Subjects served as their own control and were randomized into control group first.
MAS = modified Ashworth scale.

Table 3.
Selected characteristics and experimental data for control group (n = 9).

Subject	Age (yr)	Time Since Stroke (mo)	Height (m)	Mass (kg)	Elbow MAS*	Fugl-Meyer Upper Extremity		Initial Significant Error† Movements	Final Mean Δ Error‡
						Pretreatment	Δ Pre- to Posttreatment		
1§	30	131	1.60	70.45	—	23	1	—	—
3§	37	132	1.75	71.82	—	52	0	LR	–46
5¶	56	93	1.80	106.82	2	47	0	L	–45
7¶	51	72	1.60	47.73	2	46	2	R	–24
9§	72	97	1.70	72.72	2	30	1	R	–28
10¶	53	111	1.85	90.89	2	23	1	R	–5
13	55	11	1.83	79.09	2	43	0	LR	82
14	57	85	1.63	50.91	3	26	–2	—	—
15	46	167	1.80	81.82	—	25	1	—	—
Mean	50.8	99.9	1.7	74.7	2.1	35	0.4	—	–11.1

*Scale 0 to 4.
†L indicates movement out and to left and R indicates movement out and to right.
‡Percent of baseline error.
§Subjects served as their own control and were randomized into treatment group first.
¶Subjects served as their own control and were randomized into control group first.
MAS = modified Ashworth scale.

Finally, the FM clinical scores also improved slightly in the treatment group. For the treatment group, FM scores marginally increased an average of 1.6 (**Table 2**, p = 0.06). No such improvement was seen in the control group (**Table 3**, p > 0.27). This mild improvement was also only loosely correlated to participants' error reduction (i.e., a Pearson correlation coefficient of 0.21).

DISCUSSION

We conducted this initial pilot study to demonstrate how adaptive training might be useful for restoring arm movement. The stroke patients in this study showed less conspicuous results compared with nondisabled subjects exposed to the same algorithm [19]. Nevertheless, when we restricted our analysis to movement directions that were affected by significant error before training, results were quite evident in the stroke group: movements showed beneficial aftereffects after training (error decreased) that persisted in all but three patients. This persistence was twice as long as for nondisabled people. While these results are only an encouraging hint at what might be a possible therapeutic intervention, we believe that these results suggest the need for a longer, more comprehensive look at adaptive training as a means of restoring function following brain injury.

A key assumption of our approach was that motion is impaired because of an ineffective motor plan that can be changed through adaptive training. However, one alternative explanation of impairment is that passive contractures, commonly seen in chronic stroke patients, alter the movement pattern. Indeed, this may explain the three subjects who deadapted to a pattern that was perhaps the most biomechanically optimal for the characteristics of their contracted limb. Another alternative explanation for the three subjects is that some subjects may have less ability to adapt. Indeed, other studies have reported diminished ability to adapt in some stroke patients [18,20,38]. Another alternative explanation is that shifts in movement patterns may have actually been present but were "buried in the noise" of motor variability and therefore statistically undetectable—a statistical power problem. Motor variability is a commonly reported feature of stroke patients [38,43,47–49]. Another possibility may be that subjects could have been so highly functional that no improvement was possible in the context of this experiment—the so called "ceiling effect" in the learning process [50]. But after all movements that did not exhibit significant error before training were stripped away, the remaining movements showed signs of beneficial adaptation.

Whether this technique will lead to benefits that might persist for days or weeks remains to be seen. Another possibility is to consider prolonging this type of training over many days to get ever closer to the desired outcome. As rehabilitation training typically requires a balance of repetitive practice, strengthening, and expert guidance, we believe that the pilot results we present here may inspire other new forms of rehabilitation.

One limitation of our approach is that the forces that push the subject over to the desired trajectory $x_D(t)$ are recorded in a Cartesian coordinate system. The assumption is that these forces can be learned correctly even though the hand is not moving along the desired positions with the desired velocities. Because a nonlinear relationship exists between joint torques and endpoint forces, the torques applied along one trajectory are not necessarily appropriate for another [51]. However, we argue that if that the desired and expected trajectories are within a "domain of proper generalization" [21], the forces applied are a good enough approximation and can lead to desirable aftereffects. Recent studies have presented evidence that motor learning is broadly tuned so that training in one set of directions can influence others [24,26,52–54]. Furthermore, this learning process is quantifiable via an adaptation model [45]. Still, more sophisticated machine-learning algorithms would likely improve the performance by storing the machine-learning forces in the intrinsic (joint or muscle) coordinate system.

Most subject data (10 of 13) displayed persistent benefits for the duration of the experiment (50 washout movements)—beyond the time a nondisabled subject would take to deadapt. Consequently, the data strongly suggests that the benefits of the aftereffects are retained because they are perceived to be an improvement. The motor control system may respond to and retain the benefits of this type of adaptive training for several reasons. One reason may be that stroke patients have the confusing challenge of being able to use only a few remaining motor pathways after their injury. The brain attempts to send conventional (preinjury) motor command signals, which are now inappropriate because of injury, to the descending motor pathways. The training methods of this experiment may coax the nervous system to attempt a new motor strategy that is not intuitively obvious to the injured system but becomes a "motor epiphany" following the removal of the training forces. In this scenario, the nervous system is essentially shown the right way to execute the task, much like a coach may get an athlete to try a new strategy.

One might also speculate that change in reflex tone leads to better movement. Reflex torque elicited by an imposed stretch of the elbow has been shown to cause decreases on average of 50 percent with tens of stretches in a single experiment on flexor but not extensor muscles [55]. However, if a spastic muscle pulls the limb to the side and then a robot pushes to increase the error as is done in this experiment, the spastic muscle would be shortened. Therefore, this muscle would have less stimulation that might cause a spastic response.

Another reason adaptive training could lead to benefits is that the impaired nervous system does not react to nor does it try to learn from small errors in movement. Our approach might promote learning by making errors more noticeable. One can imagine many possible strategies for amplifying error, and recent research in our group has shown promising results with several different types [38,56]. Models of learning systems, such as neural networks, suggest that error drives learning. As a consequence, these systems can learn better and faster if error is larger [18,57–59]. Such error-driven learning processes are believed to be central to the acquisition and adaptation of skill in human movement [59–60]. Augmenting error may heighten motivation and attention or lead to anxiety, which has been suggested to correlate with learning [61]. Moreover, intensifying error can raise the signal-to-noise ratio for sensory feedback and self-evaluation. Errors that are more noticeable may trigger responses that would otherwise not be perceived. Other studies agree with the hypothesis that error augmentation can enhance learning and “trick” the nervous system into certain behaviors by giving altered sensory feedback [62–71]. Conversely, suppression of visual feedback can slow down the deadaptive process [19]. However, not all kinds of augmented feedback on practice conditions have proven to be therapeutically beneficial in stroke [72]. Hence, limits may exist to the amount and type of error augmentation that is useful [64,73].

Straightening movements may be considered a small clinical goal compared with extending the functional workspace or enhancing reach-and-grasp capability. This initial effort merely tested the promise of this approach in a well-known framework. More protracted studies lasting weeks—currently underway in our laboratories—are needed to provide more clinical significance to this approach by demonstrating lasting and functional benefits of repeated treatments.

Encouraging evidence points to future studies that exploit the natural adaptive tendencies in the nervous system for restoring function. Perturbation and electromyographic studies may challenge the hypothesis of reflex modulation. Imaging and transcranial magnetic stimulation studies may determine if alternate motor pathways are used or if the cortex is used differently after training. Lesion site locations from magnetic resonance images may indicate whether damage to certain functional areas leads to limits in one’s ability to recover via adaptive training.

While this research focuses on adaptation to forces (kinetics), researchers have also observed similar adaptation to a more easily implemented visuomotor distortion (kinematics). These distortions involve complex transformations using prisms [74], nonlinear mappings [65], or simple rotations or stretches [75–76]. All of these distortions appear to also induce an adaptation process and can trigger rapid recovery from sensory disorders, such as hemispatial neglect, seen in stroke patients [36], which shortens the recovery process from months to hours. Moreover, adaptation to both visual and mechanical distortions appears to involve the same mechanism [77].* One sensory system can facilitate the other, and a combination is the most powerful. One might consider distortions to induce an inappropriate and indirect form of learning, but the addition of more sensory inputs, such as the cutaneous sensors in the hand, the proprioceptive muscle spindles, and Golgi tendon organs may facilitate the learning process by providing more signals. Combining haptics (robotic forces) with sophisticated graphics (such as virtual reality) may provide the most promising form of rehabilitation for individuals with brain injury. However, recent work suggests going beyond virtual reality to distorted reality in order to facilitate functional recovery. This is currently of great interest to our group [14].

CONCLUSIONS

New opportunities for recovery after stroke are offered by extending intensive therapy beyond present inpatient rehabilitation stays, and robotic therapy may be one way to economically accomplish this [78]. While specialized forces are useful for inducing adaptive responses, they are likely to be most effective if combined with other rehabilitation strategies. We believe that the error-amplification approach presented here for individuals with stroke provides a new pathway for augmenting motor relearning in individuals with brain injury.

*Wei Y, Patton JL. Forces that supplement visuomotor learning: A ‘sensory crossover’ experiment. Unpublished observations, 2006.

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