ALTERING MOVEMENT PATTERNS IN HEALTHY AND BRAIN-INJURED SUBJECTS VIA CUSTOM DESIGNED ROBOTIC FORCES

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Abstract- **We investigated robotic methods for teaching movements to hemiparetic subjects using novel techniques for neuro-adaptive control. Eight healthy subjects and twelve hemiparetic stroke subjects were exposed to novel viscous forces during planar movement of the hand towards a visual target. These forces were initially responsible for significant movement errors, but were followed by automatic adaptation. The forces were designed so that unexpected withdrawal would result in a pronounced *after-effect*, consisting of movement path errors that were opposite in sign to those induced by initial application of the force filed. For healthy subjects, the desired movement was a curved sinusoid. For the hemiparetics, we chose a replicated normal trajectory. After-effect trajectories in healthy subjects' were significantly shifted toward the desired trajectory. This after-effect fully washed out following the removal of the forces in the final 50-75 movements, regardless of whether the subjects had visual feedback of their position. After-effects also generalized to movement directions that were not practiced. Hemiparetics showed different types of results. While several of them showed minimal improvement, the remaining hemiparetics showed adaptation with beneficial after-effects. Furthermore, several in this group retained diminished features of these after-effects for the duration of the experiment. This approach may be an effective neurorehabilitation tool because it does not require explicit instructions about the desired movement.**

Keywords - Robot, motor control, model, dynamics, adaptation, learning

I. INTRODUCTION

The full potential of robots for teaching and rehabilitation has yet to be determined, but certainly there are options that go beyond what a therapist can do -- robots are precise, tireless devices that can measure progress with high accuracy. We have been focusing on a *force field* approach that may facilitate recovery from brain injuries such as stroke.

Motor adaptation studies have demonstrated that when people are repeatedly exposed to a force field that systematically disturbs arm motion, they learn to anticipate and cancel out the forces and recover their original kinematic patterns [1-7]. When the disturbing force field is unexpectedly removed, where subjects make erroneous movements in directions opposite to the perturbing forces (*after-effect*).

We have recently shown that it is possible to reverse-engineer the problem and determine the forces that will ultimately result in prespecified, "desired" after-effects [8-10]. In this paper we continue to explore the simplest possible approach to this -- a model-free technique using a two-joint planar robot [10]. We present two new results testing the technique on healthy subjects and then turn our attention to stroke subjects. In these initial studies, we restricted our forces to the first 200 ms of the movement to determine whether correcting errors in the early phases of movement would diminish the errors later in the movement. The results should provide initial guidance for more in-depth clinical studies on robot-assisted neurorehabilitation.

II. METHODOLOGY

Our goal was to determine the robotic training forces that ultimately lead to the execution of the desired movement $x_D(t)$ as an after-effect of adaptation. We assume that the adaptation is an alteration of the feedforward plan that cancels out externally applied forces from the robot. The method involves two parts. The first part is an iterative algorithm that determines the forces $F_{Di}(t)$ required to shift the unsuspecting subject's trajectory to the desired trajectory $x_{Di}(t)$ for the first 200 ms. The subscript *i* represents the three target directions (Figure 1). Forces were presented intermittently (1 in every 4 movements, randomly presented) to prevent any expectation. The second part of our method applied $-F_{Di}(t)$, the vector inverse, in prolonged training that would lead to the desired adaptation as an after-effect.

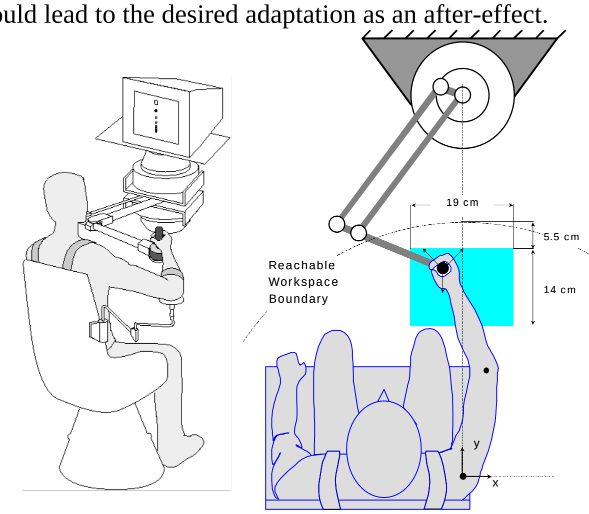

Figure 1. The subject and planar robot, driven by two brushed DC torque motors (Kolmorgen PMI JR24M4CH), controlling forces at a handle via a 4 bar linkage (Figure 1). Digital encoders (Teledyne-Gurley 25/045-NB17-TA-PPA-QAR1S) report angular position, and a force/torque sensor (ATI Gamma 30/100) reports the interface kinetics. Data were collected at 100 Hz.

Ten healthy and nine hemiparetic adults volunteered to participate. Before beginning the experiments, each subject signed an approved consent form and was seated so that the center of the range of targets was anterior to the shoulder

Patton, J., Mussa-Ivaldi, F., and Rymer, W. (2001) Altering Movement Patterns in Healthy and Brain-Injured Subjects Via Custom Designed Robotic Forces, EMBC2001, the 23rd Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBS), Istanbul, Turkey

approximately in the center of their reachable workspace. Two hemiparetic subjects were adjusted when it was necessary so that they could reach the starting point with ease.

Each movement was 10 cm in one of 3 randomly chosen directions spaced 120 degrees apart (see Figure 2). Healthy subjects were given visual targets so that they made a series of random-walk reaching movements inside a rectangular area 38 wide by 28 tall. Hemiparetic subjects were given visual targets so that they made center-out reaching movements in the same three directions, but then were cued to return to the center point after each movement. To limit the impact of fatigue, all subjects were allowed to rest before initiating any movement.

We required subjects to perform movements in three directions, broken down into the following experimental phases, all evenly and randomly distributed amongst the three directions:

PART 1

- **Unperturbed familiarization:** 15 movements.
- **Unperturbed baseline:** 15 movements.
- **Machine learning:** 298 movements with random, intermittent perturbations were presented once every four movements. The computer gradually learned the forces required to push the subject over to the "desired" trajectory.

PART 2:

- **Unperturbed familiarization:** 3 movements
- **Unperturbed baseline**. 15 movements to determine if the baseline pattern changed due to PART 1.
- **Learning**. 330 movements of constant exposure to the forces.
- **After-effects**. 120 movements, with random, intermittent removal of the force field once every eight movements (catch trials) to determine the after-effects.
- **Washout**. 75 movements, all without forces. The subject de-adapts.

The desired trajectory $x_D(t)$ that we chose for healthy subjects was a sinusoidal warping of a typical bell-shaped velocity profiled movement (see bold dotted lines in Figure 2). We chose this because it was not considered a movement that is biomechanically or physiologically impossible and because it would involve forces that would not take an excessively long time to learn. For hemiparetic susbjects, we chose a standard straight-line movement with a bell-shaped velocity profile.

This paper presents two new experiments on healthy individuals to further understand the results demonstrating the effectiveness of this technique [10]. The first experiment (*no-vision* experiment) determined whether washout results from the subjects seeing a mistake and thus de-adapting. Five subjects participated. Vision of the moving cursor was blanked during the movement in all but the initial, unperturbed familiarization movements. After the movement had terminated the cursor appeared and the subject could move to the appropriate starting point for the next movement.

The second experiment (*generalization* experiment) determined if after-effects generalize to adjacent directions. We tested the hypothesis that the nervous system is "broadly tuned" so that training in one set of directions can influence others [11]. We evaluated four more subjects with a slightly altered protocol with extra trials in new directions in the baseline, after-effects and final washout sections. These trials were to targets halfway between the original targets.

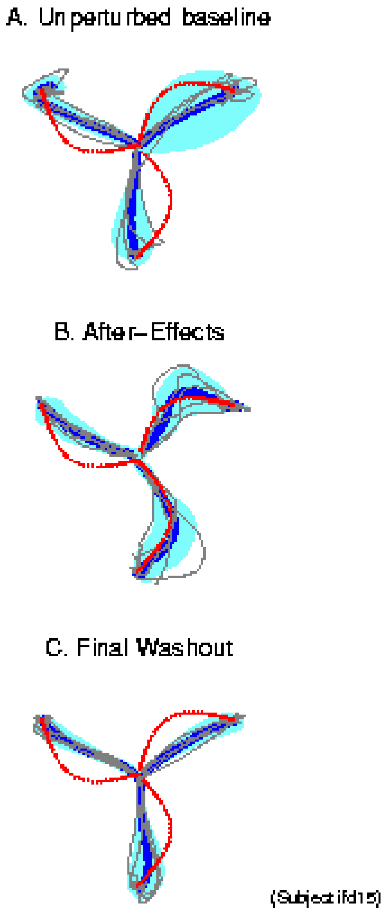

Figure 2. Movement paths for a healthy subject. Desired trajectories are the bold dotted lines, the average trajectory are the bold solid lines, individual trajectories are thin lines, and shaded areas indicate 95% confidence.

For hemiparetic subjects, we chose a standard straight-line movement with a bell-shaped velocity profile. These subjects were allowed to see their cursor at all times.

To promote ready comparison between different studies, we estimated the *initial direction error* to gauge the effectiveness of the approach in shifting the early parts of the movement. This value measured by forming a vector from the start point to 25% of the distance to the target. We defined positive to be counter-clockwise from the each movement's vector to that of the desired trajectory so that a value of zero meant a perfect shift to the desired trajectory. Hypotheses were tested using $\alpha = 0.05$ using paired t-tests to determine significance.

III. RESULTS

III.A. Healthy subjects

As reported previously [10], unperturbed movements approximated straight-lines with bell-shaped velocity profiles (Figure 2A). Then following machine learning and learning phases, the robot forces were suddenly removed and trajectories shifted closer to the desired trajectory (Figure 2B). These after-effects washed out in the final 50-75 movements (Figure 2C).

The results of this additional no-vision experiment provided no clear evidence that washout was attenuated. Hence, removal of vision during the movement phase is presumably not enough to significantly attenuate the washout phenomenon seen in this study.

We found significant after-effects on these non-practiced directions, indicating that subjects' learning generalizes to movements that were not practiced.

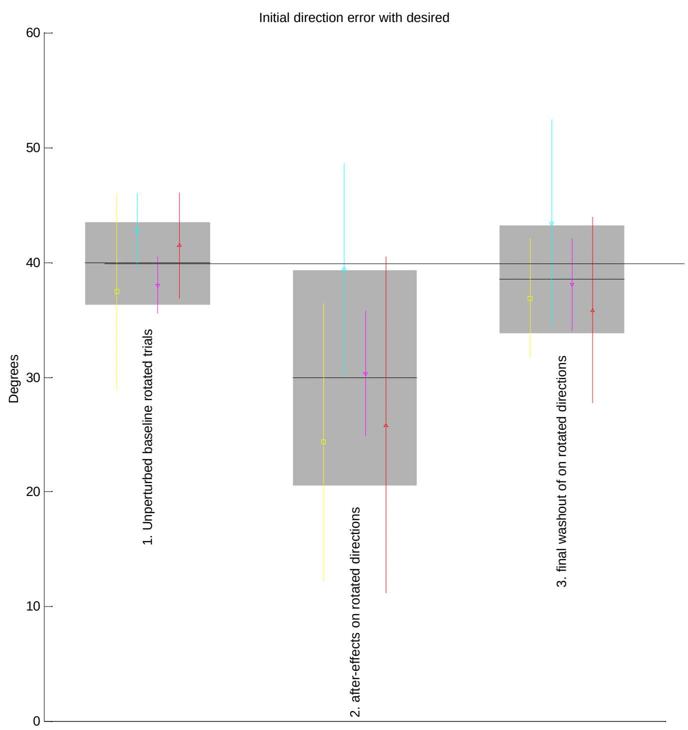

Figure 3. Group results from the Generalization experiment. Initial direction error measure illustrating after-effects and washout on interpolated (untrained) trajectories. Shaded areas represent 95% confidence intervals for the group, while the symbols and bars show the individual subject data. Though these trajectories were not part of the training, there is still a significant shift towards the desired trajectory. As expected, this effect also gradually vanishes in the washout phase.

III.B. Hemiparetic subjects

. Stroke subjects showed less dramatic results, yet for some subjects results were promising. Of the nine subjects that completed the experiments, one subject did not appear to adapt, three subjects were so high functioning that there was nothing to improve in the context of this experiment, and the remaining five showed signs of beneficial adaptation (Figure 4). Three of the five displayed some features of these after-effects for the duration of the experiment (75 washout trials). However, only one of the five of the subjects that showed beneficial adaptation in the beginning of movement also exhibited reduced errors at the end of the movement. This indicates that errors the final phase of movement are not just a over correction of the errors in the beginning of the experiment.

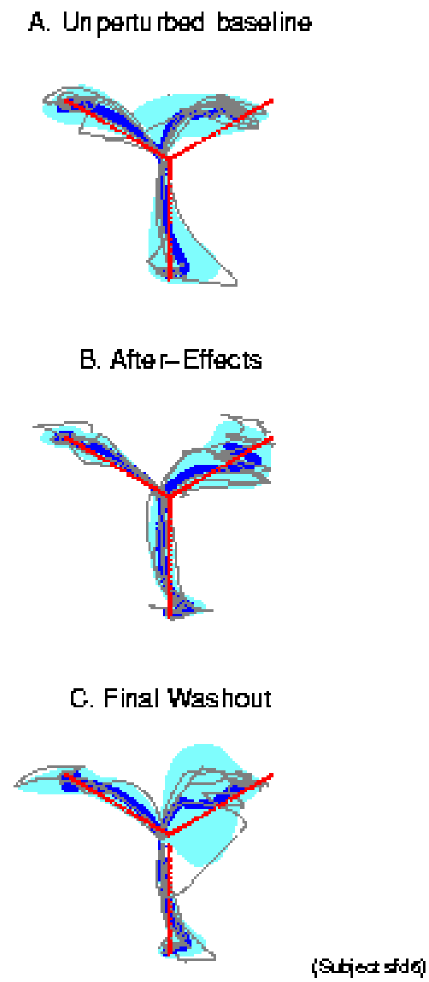

Figure 4. Movement paths before (left) and after (right) training for a stroke survivor (Left L Basal Ganglion). Desired trajectories are the bold dotted lines, the average trajectory are the bold solid lines, individual trajectories are thin lines, and shaded areas indicate 95% confidence. This subject showed the typical synergy pattern for the up-and-to-the-right movement, and showed a beneficial after effect for his direction. Other movements were less dramatic due to a "ceiling effect" in which there was little to improve.

IV. DISCUSSION

This study reports on out preliminary investigations into a new approach for robot-assisted movement teaching that exploits the natural adapting tendencies of the nervous system. Subjects were trained by making movements in the presence of a force field specifically designed so that when the force field was unexpectedly removed a desired trajectory would result. Subjects showed shifts of trajectories towards desired, even though they were never given any knowledge of what the desired was. Depriving a healthy person of visual feedback does not appear to alter the washout. Healthy subjects also show after-effects in target direction that were not practiced. Finally, this system not only can cause the execution of prespecified curved trajectories in healthy subjects, it also provides some encouraging preliminary evidence that this approach can be used to obtain smoother trajectories in stroke patients.

This system is reasonably successful although it neglects to take into account musculoskeletal impedance and spinal reflex properties. A more sophisticated approach may be to model these contributions and factor them in to the estimate of limb dynamics[8]. Our initial attempts at such a model-based approach has proved less successful up to this point [9], but as more precise models are developed, the approach may prove more effective.

Earlier studies on stroke subjects in our laboratory have revealed that after-effects can persist for many movements when the after-effects had the features of normally accurate and smooth movements [12]. The present study furthered this effort to provide forces that were custom-tailored to the subject. No clear evidence yet exists proving that subjects can preserve their after-effects, though some do appear to preserve at least some limited features of the aftereffects for the duration of the experiment. One can also consider prolonging this type of training over many days to get ever closer to the desired outcome. However, only patients whose injury spared the brain regions that are involved in adaptation would potentially benefit from this type of procedure. Other studies using robotics for rehabilitation have also provided tools for assessment and training, demonstrating the potential benefits of robotic rehabilitation [13-16]. Training typically requires a balance of repetitive practice, strengthening, and expert guidance. We believe that the implicit approach presented here provides a new pathway for augmenting motor learning in both the healthy and bran-injured populations.

Acknowledgments: Supported in part by NIH 5 T32 HD07418 & NIH 5 RO1 NS 35673 & NIH F32 HD08658-01. We thank M.E. Phillips for clinical measurements and expertise.

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