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Robotic Teaching By Exploiting the Nervous System's Adaptive Mechanisms

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Abstract. We tested the idea of teaching arm movements implicitly, based on recent studies of adaptive control. Eight subjects were repeatedly exposed to predetermined training forces during movement so they would develop an expectation and cancel them out. Forces were unexpectedly removed to cause a predictable after-effect. Forces were designed so that a "desired" movement would result as this after-effect. This method does not require any explicit instructions about the desired movement. Results showed a significant shift of trajectories toward the desired, although the after-effect washed out following the removal of the forces in about 75 movements. This approach may be effective for teaching healthy movement patterns to brain injured patients because their movement alterations can be perceived as improvements.

1. Introduction

Robot-assisted teaching has great potential because training can be highly accurate, can be sustained for very long periods of time, can measure progress, and can produce a wide range of forces or motions. An important question is, what is the best method to apply these forces to facilitate learning and/or rehabilitation. The most effective training algorithm has yet to be determined. One of our long-term goals for this type of application is to develop a robot-controlled training procedure that could facilitate the recovery of motor skills lost to brain injury such as stroke. The first step, however, is to develop and test this robotic approach on healthy subjects. Rather than straightening out the crooked trajectories of impaired subjects, this initial study demonstrates the robot's ability to bend healthy subjects' trajectories to a prespecified trajectory not known to them.

Recent studies on motor adaptation have demonstrated that when people are repeatedly exposed to a force field that systematically disturbs arm motion, they are able to recover their original kinematic patterns [1]. Subjects do this by canceling the forces of the field in a feedforward manner (i.e., the canceling forces are preplanned), The feedforward control is evidenced by characteristic after-effects when the disturbing force field is unexpectedly removed, where subjects make erroneous movements in directions opposite to the perturbing forces [1]. The adaptation and its after-effect have been demonstrated in a number of different types of systematic disturbances [1-7].

One important feature of after effects is that they are predictable. Subjects anticipate the forces with an adjustment in feedforward joint torques [1]. The adjustment cancels the forces of the field, resulting in a normal-looking movement when the force field is on, and an abnormal movement that reflects the adjustment when the force field is removed. Therefore, it should possible to reverse-engineer the problem and design force fields that will ultimately result in prespecified, "desired" after-effects.

A number of potential solutions may solve this force field design problem. An earlier investigation demonstrated the use of models for force field design, which required a complex regression technique and numerous assumptions [8, 9]. In this investigation we explore what we believe to be the simplest possible approach -- a model-free technique. Specifically, we record the forces necessary to shift the subjects to a “desired” trajectory, and then train them on their vector opposite so that the after effect resembles the desired movement. In the following sections we present a general framework and then test it using a two-joint planar robot.

2. Methods

2.1 Robotic training algorithm

The goal of adaptive training is to determine robotic training forces that will lead to the execution of the desired movement $\mathbf{x_D}(t)$ as an after-effect of adaptation. Here, we test the idea using the simplest possible method of adaptive training. We assume that adapted torques are an alteration in the feedforward plan that cancels out externally applied forces from the robot, t+Dt. When the robot forces are suddenly removed, the adaptation Dt causes the arm to move along the new after-effect trajectory. The adapted torques Dt must be equivalent to the forces required to shift the trajectory to the desired trajectory.

We used a simple, iterative algorithm determined the feedforward forces $\mathbf{F_{Di}}(t)$ required to shift the unsuspecting subject's trajectory to the desired trajectory $\mathbf{x_{Di}}(t)$ during the first 200 ms of the movement. (Subscript *i* represents the three directions of motion.) Forces were presented intermittently (1 in every 4 movements, randomly presented) to prevent any expectation. Once these forces $\mathbf{F_{Di}}(t)$ had been determined, their vector inverse was applied in a training session to cause the desired adaptation.

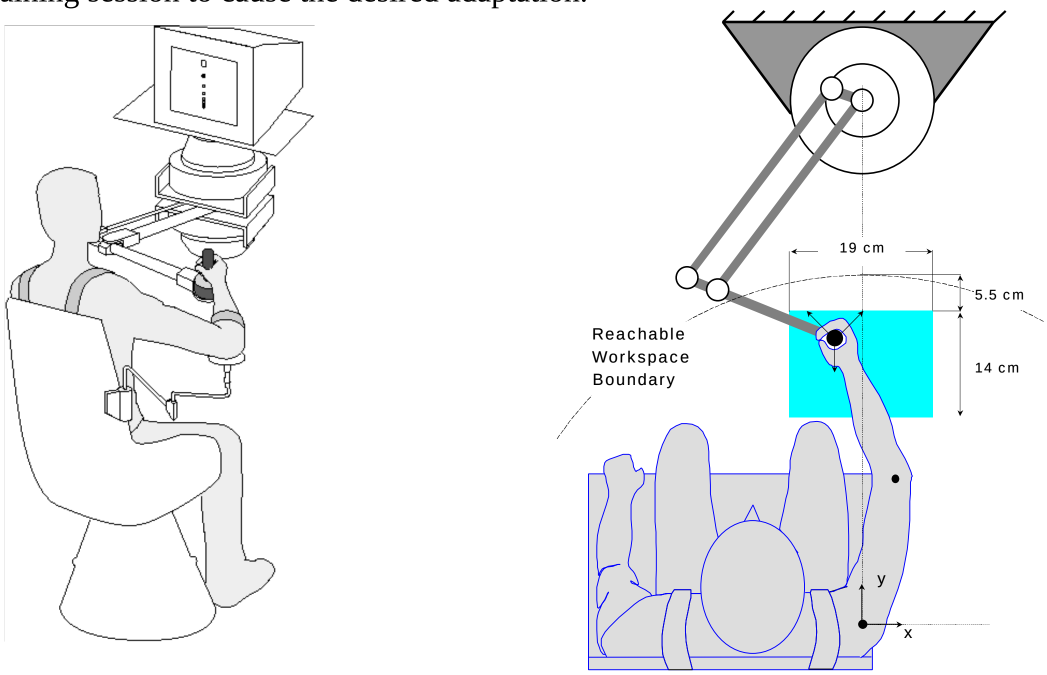

Figure 1. The subject seated at the robot. The shaded area on the right figure indicates the rectangular region in which movement targets were presented.

2.2 Experiments

Eight healthy right-handed adults with no history of orthopedic or neurological disorders volunteered to participate. Before beginning the experiments, each subject signed a consent form that conformed to federal and university guidelines. Subjects held a two-degree-of-freedom manipulandum (Figure 1) described elsewhere [10]. The manipulandum consisted of two brushed DC torque motors (Kolmorgen Motion Technologies PMI model JR24M4CH) that control forces at a handle via a 4 bar linkage (Figure 1). Rotational digital encoders (Teledyne-Gurley model 25/045-NB17-TA-PPA-QAR1S) report the angular position, and a 6-axis force/torque sensor (ATI Gamma 30/100) reports the interface kinetics. Data were collected at 100 Hz.

Subjects were seated so that the center of the range of targets was anterior to the shoulder approximately in the center of their reachable workspace (see inset of Figure 1). 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. Each movement was 10 cm in one of 3 randomly chosen directions spaced 120 degrees apart: anterior-right, anterior-left, and posterior-center (towards the chest). To avoid fatigue, subjects could choose to rest before initiating any movement, though they rarely did. All subjects performed a total of 873 movements, broken down into the following experimental phases:

- Unperturbed familiarization. 15 movements to become familiar with the system.
- Unperturbed baseline. 15 movements to establish a baseline pattern.
- Machine learning. 298 movements, with random, intermittent perturbations presented 1in 4 movements. The computer learns the forces required to push the subject over to the "desired" trajectory.
- Unperturbed baseline. 18 movements to determine if the baseline pattern changed.
- Learning. 330 movements of constant exposure to the forces.
- After-effects. 120 movements, with random, intermittent removal of the force field for 1 in 8 of the movements (*catch trials*) to determine the after-effects.
- Washout. 75 movements, all without forces. The subject de-adapts.

The number of movements in each direction was the same for each phase.

The desired trajectory $\mathbf{x_D}(t)$ that we chose for all 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. Note that the learning of this new trajectory was *implicit* -- subjects were never given any knowledge of the desired trajectory.

We determined 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 $a = 0.05$.

3. Results

As reported previously, when unperturbed, subjects performed straight-line movements with approximate bell-shaped velocity profiles (Figure 2, left). Subjects recovered their kinematics similar to the unperturbed movements (not shown), occurred when the robot forces are suddenly removed (Figure 2, right). These after-effects washed out in the final 75 movements. There was a significant reduction in all error measures between baseline and after-effects catch trials, indicating their trajectories shifted closer to the desired trajectory (Figure 3). However, though the shift was present, it was not perfect, indicated by nonzero error in the after-effects. Finally, the after-effect of adaptation gradually “washed out” after 75 movements, with the final trajectories being very similar to the baseline (Figure 4; compare to Figure 3).

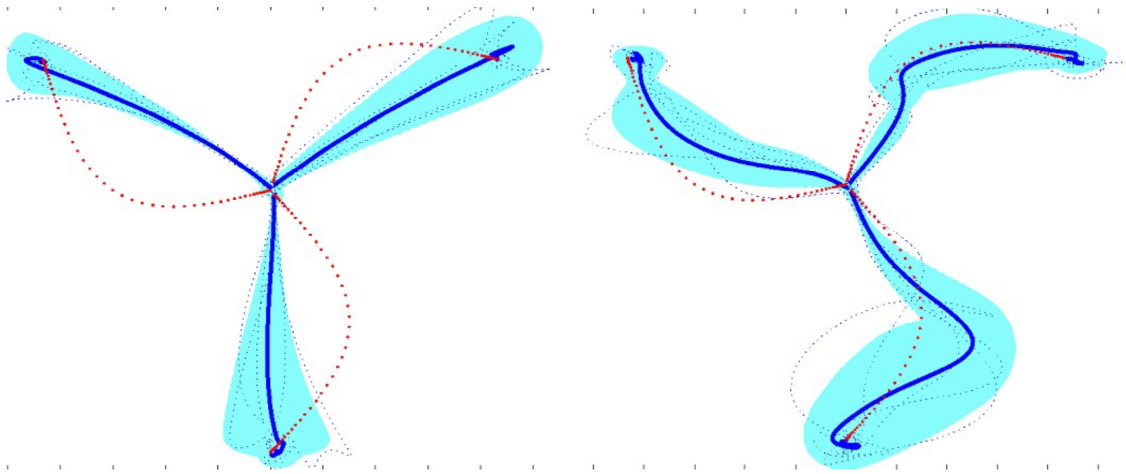

Figure 2. Movements before (left) and after (right) training for a typical subject. Desired trajectories are the bold dotted lines, the average trajectory are the bold solid lines, individual trajectories are thin dashed lines, and shaded areas indicate 95% confidence.

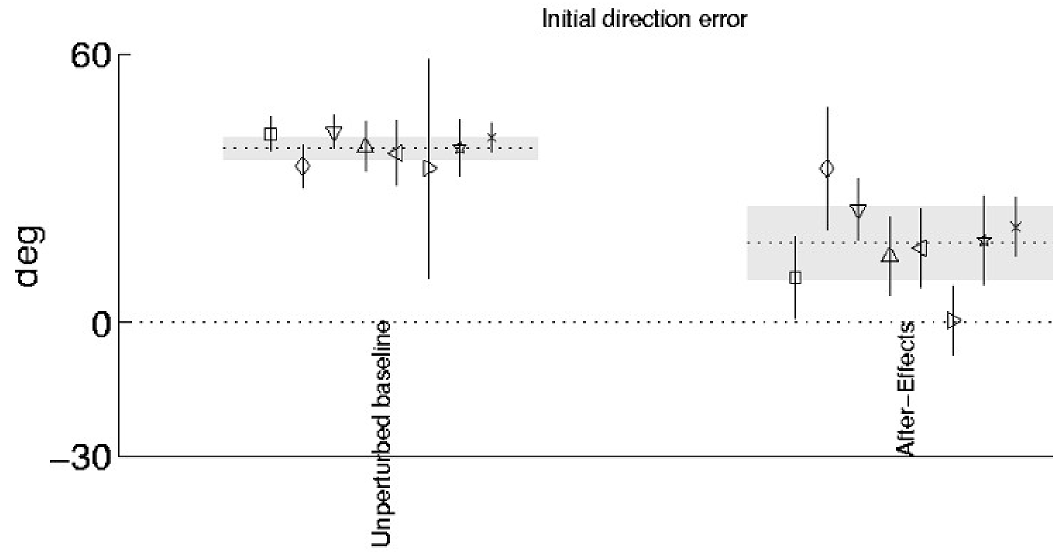

Figure 3. Group errors from the desired trajectory before and after training. Each symbol is a subject; each bar indicates the 95% confidence interval. Dotted lines are group means; shaded areas indicate group 95% confidence interval.

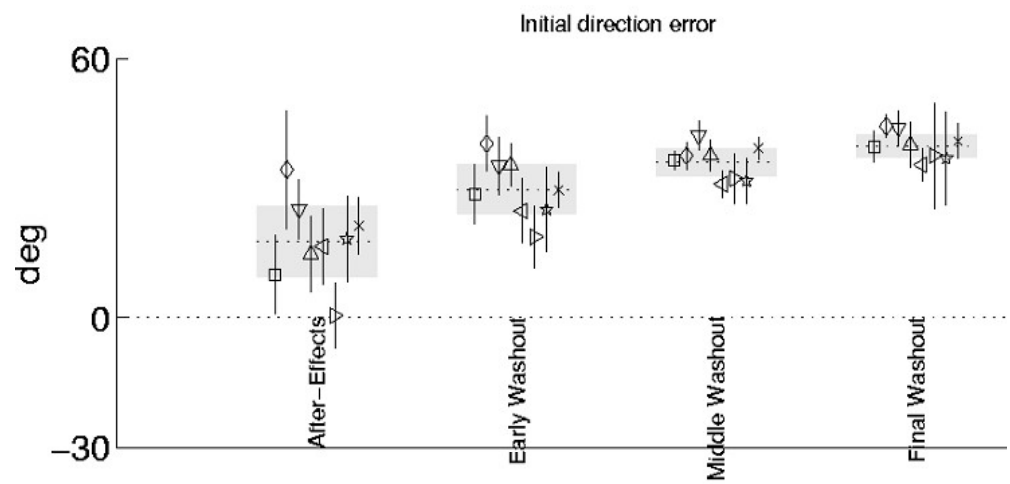

Figure 4. Washout of the after-effect. The movements were subdivided into first 15 (Early), middle 45 (Middle), and final 15 (Final).

4. Summary & conclusions

This study tested a new approach to robotic learning: the implicit teaching via training and after-effects. 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 a significant shift of their trajectories towards the desired trajectory, even though they were never given any knowledge of what it was. Essentially, this method "tricks" the nervous system into making a different movement pattern. Although the study was not exhaustive by any means, it provides preliminary evidence that encourages us to believe that this type of approach can be used to implicitly teach new movements.

This system is reasonably successful although it neglects to take into account musculoskeletal impedance and spinal reflex properties. Although we only evaluate the first 200 ms of the movement, this interval is long enough for spinal reflexes to play a role, as well as for the force-length and force velocity relationship of muscle to provide additional torque. If these contributions were more than negligible, the strength of the approach would have been degraded. For this reason, a more sophisticated approach may be to model these contributions and factor them in to the estimate [9]. Such a modeling approach has proved less successful up to this point [11], but as more sophisticated models are developed, the modeling approach may prove more effective.

Our approach makes the assumption that the forces that push the subject over to the desired trajectory $\mathbf{x_D}(t)$ can be learned correctly though they are learned along a different trajectory (near the subjects expected trajectory $\mathbf{x_E}(t)$). However, our results show that if the desired and expected trajectories are both within a "domain of proper generalization," [9] the resulting after effects may be satisfactory. One can consider repeating this type of training over many days to get ever closer to the desired outcome.

What is not clear is whether the washout seen in these healthy subjects (Figure 4) will also exist in pathological situations where the result of training is a more normal movement. The washout we observed is not surprising because the subject recognizes that the after-effect as an error and attempts to correct it in subsequent movements. A brain-injured patient should perceive the after-effect as an improvement and attempt to keep it. Preliminary studies in our laboratory on stroke subjects have revealed that after-effects can persist for many movements when the after-effects resembled healthy movements [12]. However, only patients that retain the ability to adapt should benefit from this type of procedure.

Other studies using robotics for rehabilitation have also provided tools for assessment and training [13-16]. Training typically requires a balance of repetitive practice, strengthening, and expert guidance, we believe that this implicit approach may provide a form of guidance that allows the realization of enhanced performance. This implicit teaching technique may become a valuable tool in the arsenal of robotic techniques for therapy and training.

Acknowledgements

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