Prespecified After-effects Elicited from Robotic Force Fields

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63.16
Neuroscience, New Orleans, 2000
Board Number: JJ-64

INTRODUCTION

Robots have a promising future in the area of training, particularly in neuro-rehabilitation. However, the most effective training algorithm has yet to be determined.

Here we capitalize what is known about implicit learning in *motor adaptation* :

- Repeated exposure to a force field leads the original movement being recovered.
- Subjects do this by canceling the forces of the field.
- When the disturbing force field is unexpectedly removed, subjects exhibit *after-effects.* (Shadmehr & Mussa-Ivaldi, 1994).
- Subjects learn an *internal model* of the robot field that approximates the perturbing field's equation. (Conditt & Mussa-Ivaldi, 1997).
- Subjects can also generalize to new movements in a region near where the training occurred. (Gandolfo et al 1996).
- Neuromechanical models can predict after-effects (Shadmehr & Mussa-Ivaldi, 1994).

Therefore, it should possible to design force fields that induce desired after-effects.

In this initial study, we address 1) whether it is possible and 2) we compare two possible approaches.

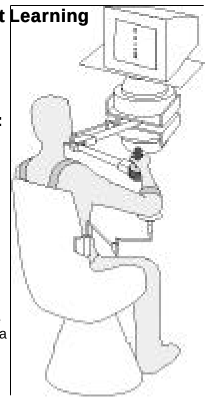
METHODS

Goal: For at least the initial part of the movement (first 200 ms), cause the subjects to move along a ***desired trajectory*** unbeknownst to them, x_D, as an after-effect.

1 Robot Learning

2-degree-of-freedom manipulandum:

- 4 bar linkage
- 2 brushed DC torque motors (Kolmorgen Motion Technologies PMI model JR24M4CH)
- 2 Rotational digital encoders (Teledyne-Gurley model 25/045-NB17-TA-PPA-QAR1S)
- 6-axis force/torque sensor (ATI Gamma 30/100) reports the interface kinetics.
- Collected & controlled 100 Hz



Two "field design" approaches:

1. "Direct" Approach (8 subjects):

A. The robot learns the forces necessary to move the subject along the desired trajectory, $F_D(t)$ intermittently adjusting $F_D(t)$, following the online learning rule:

$$F(t)=F(t)+m(x(t)-x_D(t))$$

B. The robot applies the opposite forces for training.

2. Modeling Approach: (4 subjects)

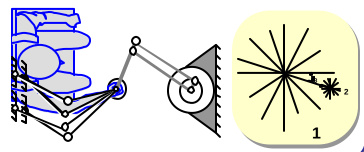
A. The robot perturbs the subject

B. System Identification: Fit a model like (Shadmehr & Mussa-Ivaldi, 1994), but consisting of a linear combination of many slightly different arm-and-controller models (Patton & Mussa-Ivaldi, submitted) (Figure 2).

C. The model calculates the forces necessary to move the subject along the desired trajectory, reverses them (in torque space), and then fits them to an array of regional force fields.

- Subjects were not told about or shown the desired movement

2 Modeling approach uses a linear combination of many different estimates of the subject's arm & controller:



HYPOTHESES:

Do we get desired after-effects?

$H_{\emptyset 1}$: After effect trajectories are no different than baseline movements. Rejected.

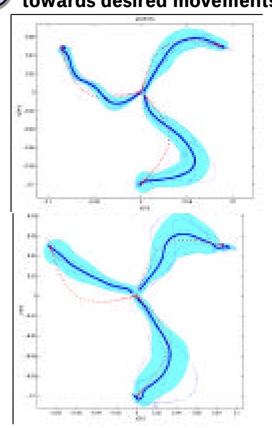
H_2: Aftereffect trajectories are no different than desired trajectories. No.

Comparing approaches:

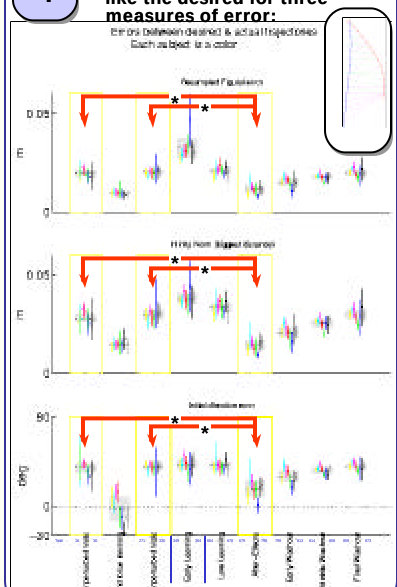
$H_{\emptyset 1}$: After-effect trajectories are closer to desired when the modeling approach is used. No.

RESULTS

3 After-effects from the direct approach show a clear shift towards desired movements

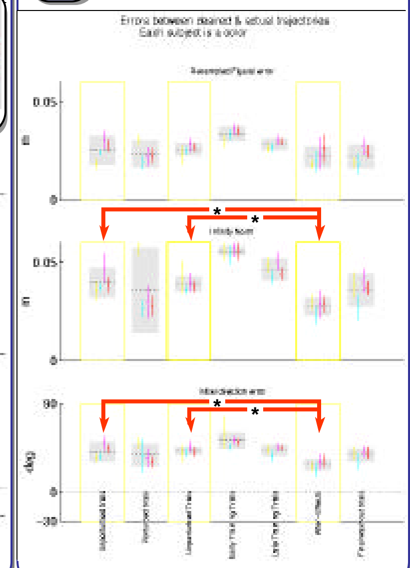


4 Direct approach: Trajectories became significantly more like the desired for three measures of error:



* $p<0.05$

5 Modeling Approach: Not as good



SUMMARY & CONCLUSIONS

- It is possible to design force fields that shift trajectories towards desired movements. Hence these approaches show great promise for the rehabilitation of movement deficits in patients.
- Surprisingly, the direct approach is best -- a model that simply considers feedforward and LTI neuromechanical impedance (as in Shadmehr & Mussa-Ivaldi, 1994) is not enough.
- This "implicit learning" approach is an alternative to training methods based on the explicit specification of the desired movement to the learner.

References

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- Gandolfo, F, Mussa-Ivaldi, FA and Bizzi, E (1996) Motor learning by field approximation. Proceedings of the National Academy of Sciences of the United States of America 93: 3843-6.
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See http://manip.smpp.nwu.edu for more.

Suppoorted by NIH 5 T32 HD07418, NIH 5 RO1 NS 35673, NIH F32HD08658 and NIH R24 HD39627