Adaption of Reaching Movements to Assistive Forces

Vladimir Novakovic, Maura Casadio, Vittorio Sanguineti, Pietro Morasso

Abstract - **When learning to move within an unfamiliar environment (force field), the dynamics of adaptation has been often described by a linear model, which accounts for the temporal evolution of an internally stored 'motor command' that would anticipate force perturbations. In this study, we focus on reaching movements within a particular type of dynamic environment: a force of constant magnitude, always directed toward the target.**

Here we model the adaptation process as a linear dynamical system. We show that, when exposed to this type of environment, subjects gradually adapt to the force, by reducing their degree of voluntary control.

I. INTRODUCTION

DURING the last 20 years, robots have been widely used to investigate the mechanisms underlying the neural control of movements. A robot may apply controlled perturbations during movements, and the observed response may unveil the underlying control modalities. The adaptive properties of the motor system have been studied in experiments in which robots deliver forces that may be made dependent on position, speed and/or acceleration, thus emulating specific dynamic environments ('force fields')[1]. When subjects are exposed to a force field that systematically perturbs arm motion, they gradually recover their original movements by learning to predict the disturbance. This feed-forward control modality is revealed by the sudden removal of these forces: in this case, subjects make errors in opposite directions (after-effects). Adaptation studies have provided a large body of knowledge on the mechanisms underlying the way the brain reacts to novel dynamic environments, and may provide insights on the way the nervous system represents information about the body and the environment. Recently, it has been suggested that sensorimotor adaptation is better characterized in terms of its temporal evolution rather than its final outcome[2]. For instance, in force field adaptation the errors experienced in a movement can be related to the previous history of movements. It has been suggested that, over trials, adaptation dynamics may be described by a dynamical model, which accounts for the temporal evolution of an internally stored 'motor command' that would predict, and therefore compensate, the robot-generated perturbation. Such evolution is driven by the movement error, which, on its hand, is determined by both perturbation and the actual motor command. Both movement error and the motor command are affected by noise.

Variants of this model have been used to infer a number of features of learning dynamics [3, 4].

In this study, we focus on a particular type of perturbation: a force of constant magnitude, directed toward the movement target. This situation typically occurs in robot-aided rehabilitation, in which a robot assists impaired subjects in performing a task which they would be otherwise unable to complete without help. When exposed to these forces, subjects may gradually reduce their degree of voluntary control[5]. This is still an adaptation process, which can be described by a linear dynamical model.

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II. METHODS

A. *Experimental Procedure*

Five healthy, right-handed subjects, of age 21-29 participated in this experiment. Subjects sat on a chair, with their torso and wrist restrained by means of suitable holders, and grasped the handle of the manipulandum with their dominant hand. A light support was connected to the forearm to allow low-friction sliding on the horizontal surface of the table. Movements were restricted to the horizontal plane, with no influence of gravity. The position of the seat was also adjusted in such a way that, with the cursor pointing at the centre of the workspace, the elbow and the shoulder joints were flexed about 90° and 45°, respectively and the arm was kept approximately horizontal, at shoulder level. A 19" LCD computer screen was placed in front of the subjects, about 1 m away, at eye level. The current position of the hand was continuously displayed, as a yellow circle. The target was also displayed, as a green round circle (diameter 2 cm). The visual scale factor was 1:1. Subjects had to perform center-out reaching movements, under visual control, starting from the same central position and moving toward four randomly selected directions (45°, 135°, 225° and 315°). Target distance was 0.1 m.

The experimental protocol was organized into target sets, each consisting of six repetitions of each of the four directions (a total of 6×4 = 24 movements). The experiment consisted of 240 movements, divided into three phases: base line (the robot generates no force; 4 target sets, i.e. 4×24=96 movements), force (the robot generates a constant force, see below; 4 target sets, i.e. 96 movements) and wash-out (no force, 2 target sets, i.e. 48 movements). During force trials, the robot generated assistive forces of constant magnitude, directed toward the target. Force started when the cursor was at least 1 cm away from the start position, and ended at 9 cm from the same position. Therefore, subjects had to start the movement in order to get assistance; in addition, assistance did not interfere with completion of the movement. Force magnitude was kept constant within the same target set, but varied in the different target sets. In particular, we used four different levels of force (F = 3 N, 5 N, 7 N and 9 N). During every target set in the force phase, in 1/6 of the movements force was unexpectedly turned off (catch trials).

Trajectories were sampled at 100 Hz, and smoothed by using a 4th order Savitzky-Golay filter, with a 270 ms time window (equivalent cut-off frequency: 7.5 Hz). We used the same filter to estimate the velocity as the first derivative of the trajectory. For each trajectory, we then computed the peak speed and the endpoint error (distance between the target and the first stop of the movement).

B. *Modeling*

If subjects can move without assistance, the observed movement performance can be taken as a measure of voluntary control. But, what to do if subjects are so severely impaired that, at least in the early phases of rehabilitation, they cannot move without assistance? In this case, the degree of voluntary control would be a 'hidden' variable. How to estimate it? One possibility is to treat recovery as an adaptation process, by using the dynamical systems framework that has been shown effective to characterize force field adaptation experiments [2, 3]. In other words, we propose to model the process of motor learning and adaption as a dynamical system, in which performance (system output, y_i) is determined by the degree of voluntary control (system state, x_i) and by the degree of assistance (system input, w_i). The evolution of voluntary control is described by a dynamic equation, which is driven by a measure of performance and/or performance error, u_i.

$$\begin{aligned} y_i &= x_i + Dw_i + r_i \\ x_{i+1} &= Ax_i + Bu_i + q_i \end{aligned} \qquad (1)$$

Model parameters A and B denote, respectively, the rates of forgetting and learning of the degree of voluntary control. Parameter D accounts for the dependence of performance on the degree of assistance. More specifically, if the degree of assistance can be interpreted as a force level and performance is a kinematic measurement, D can be interpreted as a compliance measure; low D would indicate that performance is little sensitive on assistive force. Moreover, the degree of voluntary control may be interpreted as the performance expected when assistance is zero.

The quantities r_i and q_i are noise terms that denote, respectively, the portion of performance that is not accounted for by voluntary control and the degree of assistance (performance or execution noise, r_i) and the portion of voluntary control that is not accounted for either learning or forgetting (adaptation or recovery noise, q_i).

The quantity y_i should be a task-relevant measure of performance. In the present experiment, we took the peak velocity during the movement as a measure of performance, y_i. Since the force we used in the experiment is always directed towards the target and does not change throughout the movement, a logical choice for the degree of assistance w_i would be force magnitude. Finally, for the 'error signal', u_i, that drives adaptation/recovery, we took the endpoint reaching error. Endpoint error is defined, as the distance of the end position of the movement from the center of the target End position is the position of the cursor when the smooth movement has come to an end, i.e. when velocity is below a certain threshold. Reaching error can be positive or negative. It is positive if the target is closer to the start position then the end position. In other words if the distance from the center of the screen to the target is 10cm, the endpoint error is negative if the end position of the cursor is closer then 10cm to the center and positive if it is further. Parameter x_i is, as mentioned before, state of the system, and can be interpreted as the peak velocity displayed when assistance is removed.

III. RESULTS

Figure 1 depicts, for a typical subject, the trajectories observed with the different degrees of assistance. It can be seen that trajectories differ for different levels of assistance. If we compare only movements when the force is applied, it can be seen that trajectories are more curved with the higher degree of assistance. To prove this assumption, in the Figure 2 we depicted the curvature as a function of assistance and it can be seen that there is a positive correlation between these two parameters. Figure 3 shows the corresponding speed profiles (averaged over directions (a) and averaged over assistance levels (b)). The figure clearly indicates that peak

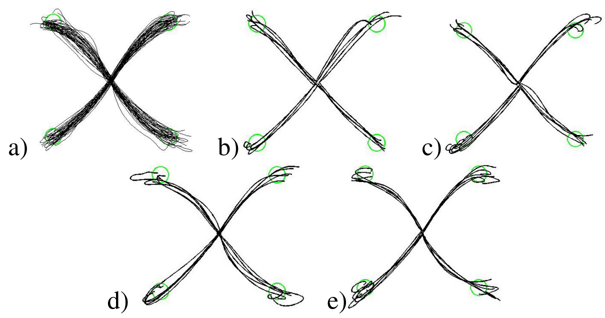

Figure 1: Trajectories for different levels of assistance:
(a) No assistance (b) F = 3N (c) F = 5N (d) F = 7N (e) F = 9N

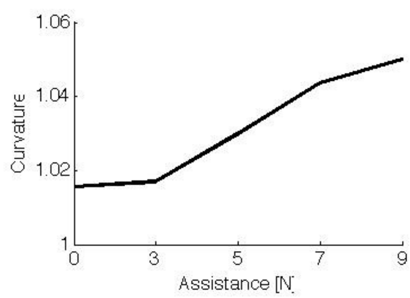

Figure 2: Curvature as a function of force applied

a)

b)

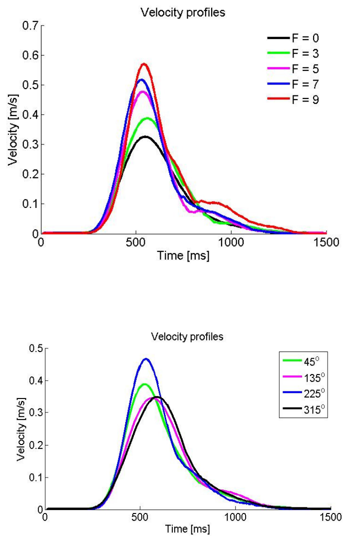

Figure 3: Velocity profiles: (a) For different level of assistance (b) For different directions

a)

b)

c)

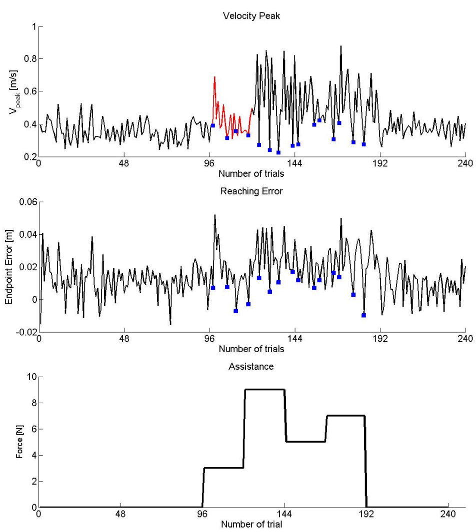

Figure 4: Time course of: (a) Peak velocity (b) Endpoint error (c) Assistance (squares represent catch trials)

speed increases with the degree of assistance.

As regards the endpoint error, it ranges from 6.3 mm (no assistance) to 21.2 mm (9N assistance). The endpoint error also varies with direction; it is smaller (8 and 8.9 mm) in the directions 135° and 225° and greater in directions 45° and 315° (10.9 and 10.2 mm).

This result is important, because it shows that every direction has its own peculiarities. That was also already reported by [3]. This also suggests that model coefficients A, B, and D may depend on direction of the movement, and we can denote them as $A_{45}{}^{o}$, $A_{135}{}^{o}$, $A_{225}{}^{o}$ and $A_{315}{}^{o}$ and for B and D following the same rule ($B_{45}{}^{o}$, …, $D_{225}{}^{o}$).

To understand in more detail how movements are affected by assistance, we then looked at the time course of movement performance over the changing degree of assistance. Figure 4 shows the time course of movement speed during the entire

a)

b)

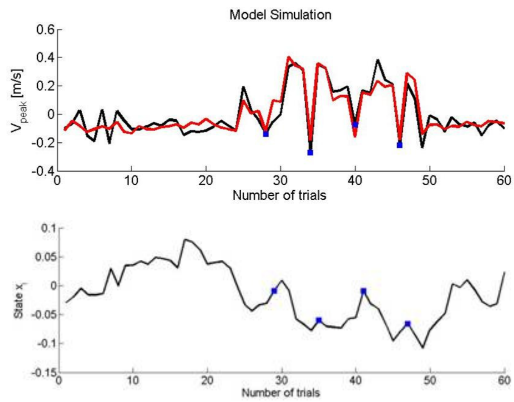

Figure 5: Model results for one direction (225°)
(a) Peak velocity: black line is experimental data and red line is the result from the model
(b) Development of the state variable throughout the experiment

experiment for one subject. The emphasized part (red colored part) in figure clearly shows that peak speed tends to adapt (it decreases to the baseline level) when assistance is present.

We then used the time course of performance to identify the model of Eq. (1). Model coefficients were estimated using the identification algorithm described by [2]. Figure 5 depicts the results for direction 225° (other directions display similar results). It can be seen that the model satisfactorily matches the experimental data (peak velocity) (Figure 5a). Markers in Figure 5a represent catch trials. The quality of the fit was checked using r^2 method:

$$r^2_{45^o} = 0.87,\ r^2_{135^o} = 0.73,\ r^2_{225^o} = 0.88 \text{ and } r^2_{315^o} = 0.83.$$

Figure 5b shows all the trends mentioned. At the beginning voluntary control is low, then while there is no force (first 24 trials) it increases until a certain level. Maintaining the force at the same level, after some time, voluntary control should decrease. This can be seen after 18th trial in Figure 5b. Then there is an obvious decrease when the force is introduced. The higher the force, the lower the voluntary control. It can be seen that immediately after the catch trials (blue markers, Figure 5b) there is a temporary increase in voluntary control, which also confirms our assumptions.

Until now, we have shown the experimental results and how does our model fit them. Let us consider the model itself, i.e. model coefficients. As mentioned in the modelling part, there are 3 coefficients in the model: A, B and D. In the Figure 6 the average values of the coefficients (A_i, B_i and D_i, where i=45°, 135°, 225°, 315°) are shown. D_i was multiplied by 10 for visibility.

Parameter A is a forgetting term, and should range from 0 (no retention at all) to 1 (no forgetting). An intermediate value indicates that voluntary control, and therefore performance, decreases over time if assistance or endpoint error are equal to zero.

Parameter B reflects the extent to which the degree of voluntary control is modified by the observed endpoint error. It can be interpreted as trial-by-trial learning rate. A negative

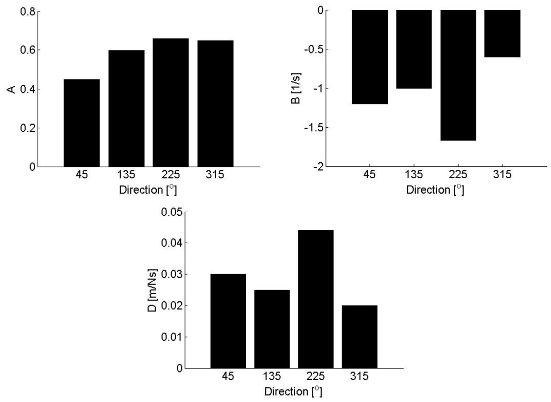

Figure 6: Model Coefficients

B indicates that if the subject overshoots in one trial, he will tend to involve less effort in the next in order to reach the target and vice-versa, in case of undershoot the subject will add some more force in his movement. The higher the absolute value of B, the higher the learning rate of the subject. We can see from Figure 6 that for direction 45^o and 315^o parameters A and B show that learning rate is lower and combined with forgetting rate shows us that in these directions performance should be worse. As it was mentioned in these directions the reaching error is higher which concurs with our model.

Finally, parameter D scales the influence of assistance (external force) on performance (y_i). It shows the ratio of our involvement in the movement and to what extent the assistance is incorporated in our movement. It can be seen (Figure 3b and Figure 6) that for directions where peek speed is higher also value of parameter D is higher.

DISCUSSION

Recent studies [6] have suggested that the purpose of human movements is to acquire rewarding states at a minimum cost. In our results, we have seen that the movement changes with the magnitude of the force applied. An explanation for the “curvature” of the movement might be based on the phenomenon mentioned in [5]: when moving under the effect of assistive forces, provided by a robot agent, humans tend to quickly incorporate these forces in their motor plan. More specifically, the motor system appears to behave as a ‘greedy’ optimizer, which exploits assistive forces in order to reduce the amount of voluntary control (and therefore muscle activation), while keeping the position error small. This strategy would minimize effort while maintaining the required performance.

The goal of this paper was to somehow quantify this phenomenon, and provide a quantitative description for it. In other words, the idea was to identify a suitable indicator that would quantify the degree of voluntary control, and its dependence on the level of assistance.

Our model is based on two types of signals. One quantity, the motor ‘output’, is movement ‘performance’, represented by speed. Another signal is the reaching error, which is responsible for the adaptation of the degree of voluntary control. It is necessary to have these two inputs, because only speed or only reaching error are not able to represent voluntary control. This is a consequence of the ‘greedy’ optimizer notion. If we take only one parameter (for example reaching error), subject will tend to improve his performance only in terms of reaching error, and he would neglect the speed. Therefore, both parameters (one performance and one performance indicator parameter) have to be taken into consideration in order to have a model as realistic as possible.

This result is potentially important, because we are able to extract and describe the modalities of adaptation. By identifying the learning process, we may be able to design an ‘optimal’ controller for assistance, based on the estimated degree of voluntary control. This would potentially allow to make motor adaptation much faster and much more efficient. Furthermore, a model of adaptation would give us the opportunity to determine an optimal pattern of variation for assistive force for patients with different disorders or different degrees of impairment.

Finally, now that an estimate of the level of voluntary control is available, it should be feasible to extract this information also from EEG or other physiological signals.

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