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Change of desired trajectory caused by training in a novel motor task

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Abstract—**When the human motor system adapts to novel dynamics of the arm during reaching, hand trajectories tends to converge toward a roughly straight line. This straight line is thought to be the desired trajectory of the system. Trial-to-trial changes in performance are well described by a first order state-space model: errors in a given trial affect performance on the subsequent trial as a function of the distance in state space between the two trials. This function describes the generalization patterns that govern adaptation. Whereas the desired trajectory and the generalization function have been quantified for short-term adaptation, little is known about their behavior with long-term training. We report that when subjects are trained to reach in novel force fields over multiple days, the state-space model suggests that the desired trajectory undergoes systematic changes. In a constant field, the desired trajectory becomes curved. The direction of change of the desired trajectory is affected by the training protocol, such that occasional unperturbed trials (catch trials) caused subject to increasingly under-compensate for the perturbations whereas a lack of such trials caused subjects to increasingly over-compensate for the perturbations. We suggest that the desired trajectory is not constant, but is a result of an optimization that considers the success rate. In this optimization process, subjects weigh more heavily the importance of certain trials: either those that are infrequent or those that cause large errors.**

Keywords—**reaching movement, motor control, motor learning, state-space model, adaptation**

I. Introduction

Many studies of motor learning focus on the process of adapting to a novel condition, for example, examining effects that develop over a tens of minutes. We have recently demonstrated that when reaching movements are performed in novel force fields, the adaptation process can be effectively modeled using a first order state-space model [1,2] in which the expected perturbation is adjusted after each movement as a result of the error experienced on that movement:

$$\begin{cases} \boldsymbol{y}^{(n)} = D\,\boldsymbol{F}^{(n)} - \boldsymbol{z}_{k^{(n)}}^{(n)} \\ \boldsymbol{z}_l^{(n+1)} = \boldsymbol{z}_l^{(n)} + B_{l,k^{(n)}}\,\boldsymbol{y}^{(n)} \end{cases} . \quad \textbf{(1)}$$

Here, $\boldsymbol{y}^{(n)}$ is the error on movement n (bold font indicates a 2x1 vector), $\boldsymbol{F}^{(n)}$ is the perturbing force on that movement, and $\boldsymbol{z}_{k^{(n)}}^{(n)}$ is the amount of perturbation expected on that movement for a movement in direction k. The expectation is updated after each movement by some amount proportional to the error, with the gain, $B_{l,k}$, set by the relationship between the direction the subject moved and the direction in which the expectation is being updated. This is a measure of plasticity and is called a generalization function. A model of this sort is able to explain in excess of 90% of the variance in a series of perturbed reaching movements made in different directions.

We used this model to better understand behavior of subjects as they continued to practice in a given force field for several days. Our naïve prediction was that subjects would respond to extended training by becoming more resistant to errors, i.e., the generalization function might become smaller. Instead, we found that the generalization function, our measure of sensitivity to error, was essentially unchanged throughout training. Instead, the desired trajectory of subjects changed . Formation of a new desired trajectory indicates a change in motor planning: the motor system tries to find a movement that will optimize performance. However, by comparing the effects of training with and without catch trials, we demonstrate that subjects are overestimating the effects of the catch trials, and that their planning may not be optimal.

II. Methodology

A. Behavioral paradigm

Each subject in this study performed three consecutive days of training on a perturbed reaching task. The task has been described elsewhere [3]. Briefly, subjects held a light weight planar manipulandum with two degrees of freedom in a horizontal plane and made 10 cm reaching movements to 0.5 cm targets. During movements, motors in the base of the manipulandum applied force to the hand according to the following rule:

$$\boldsymbol{F}(t) = \begin{bmatrix} 0 & c \\ -c & 0 \end{bmatrix} \dot{\boldsymbol{x}}(t) . \quad \textbf{(2)}$$

This is called a curl field. The parameter c took on one of three values: 0 N·s/m, a null field; 13 N·s/m , a clockwise curl field; and -13 N·s/m, a counterclockwise curl field. Sensors in the manipulandum provided data on position, velocity, and force at the handle. Subjects were rewarded with a successful trial when they came to a stop inside the target within 460-540 ms of movement onset.

Subjects trained in six directions of movement and performed sets of 150 movements. Each day began with a null field. This was followed by four training sets. Subjects were divided into four groups in a 2x2 design. The training was either in a clockwise or counterclockwise field and training was either with catch trials (probability of 1/6) or

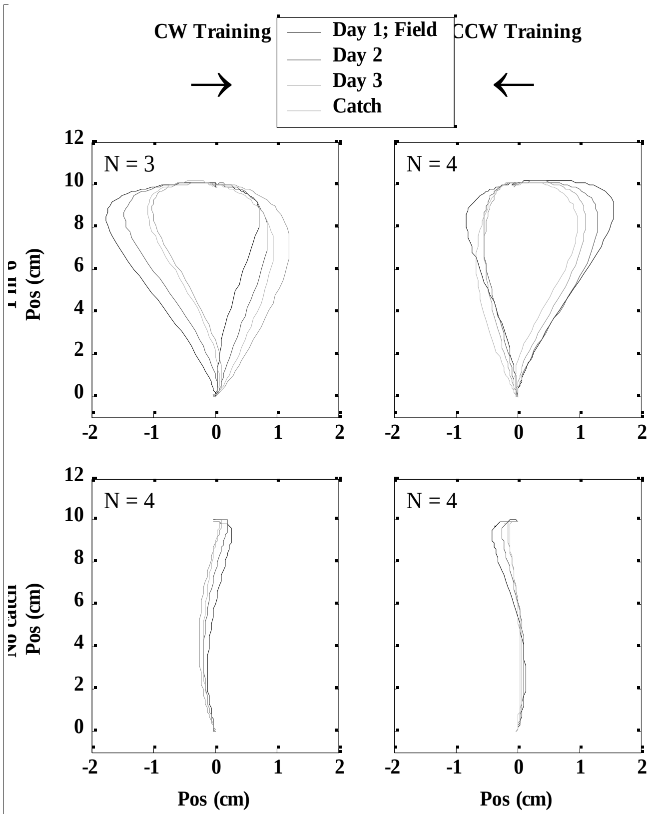

Fig. 1 Average trajectories during the last training set in each day. Movements in different directions have been rotated so they are aligned to the target (target is at top, start position is at bottom). CW: clockwise; CCW: counterclockwise. Arrows above plot indicate direction of force.

without catch trials (all movements were in the curl field). Fig. 1 shows the number of subjects in each group.

B. Data analysis

Data analysis included examination of the trajectories and the deviation from a straight trajectory. This led to a hypothesis that the desired trajectory was changing as a result of training. To test this hypothesis, we updated the model in (1) To include the desired trajectory as an extra parameter:

$$\begin{cases} \boldsymbol{y}^{(n)} - \boldsymbol{y}^*_{k^{(n)}} = D\,\boldsymbol{F}^{(n)} - \boldsymbol{z}^{(n)}_{k^{(n)}} \\ \boldsymbol{z}^{(n+1)}_l = \boldsymbol{z}^{(n)}_l + B_{l,k^{(n)}}\left(\boldsymbol{y}^{(n)} - \boldsymbol{y}^*_{k^{(n)}}\right) \end{cases} . \qquad \textbf{(3)}$$

Here, $\boldsymbol{y}^*_{k^{(n)}}$ is the point through which the desired trajectory passes at maximum velocity during movements in direction $k^{(n)}$, the direction of the *n*th movement. By fitting this revised model to the data on successive days, it was possible to generate an measure of the desired trajectory as the reference point for error.

III. Results

A. Catch trials affect the desired trajectory

Subjects trained for three consecutive days. Fig. 1 shows the average trajectories during the last set of movements on each day. Subjects that training with catch

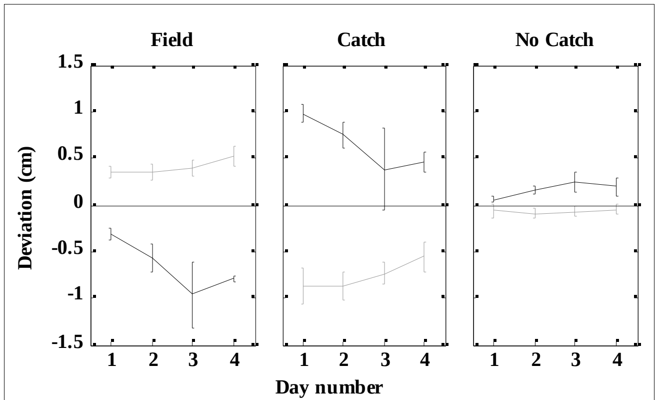

Fig. 2 The deviation from a straight trajectory, averaged across trials in the last training set in each day. In each column, the black line is for subjects who trained with a clockwise curl field, and the gray line is for subjects who trained with a counter clockwise curl field. The left two columns plot characteristics of field and catch trials in the group that experienced catch trials at probability of 1/6. The right column plots characteristics of field trials in the no-catch group. Error bars show +/- 1 S.E.M.

trials under compensated for the effects of the field, and this under compensation became more pronounced with each successive day of training (Fig 2). The trend is also clear in the catch trials of these subjects: with more training, the deviation from a straight trajectory becomes smaller. In contrast, subjects who trained without catch trials tended to over compensate for the effect of the field: with more training, the over compensation became larger.

B. State-space model indicates change in desired trajectory

We fitted the model in (3) to the trial-by-trial sequence of trajetories recorded from subjects in all the training sets. Fig. 3 shows the development of $\boldsymbol{y}^*_{k^{(n)}}$ across days. We only show the component of $\boldsymbol{y}^*_{k^{(n)}}$ perpendicular to the target direction. In effect, this represents the deviation of the estimated desired trajectory from a straight line. Fig. 3 shows that training with and without catch trials have opposite effects on this parameter. For both the clockwise and counterclockwise field, training with catch trials moves the reference point for the error more in the direction that the field pushes. This means that, on average, these subjects correct less for movements that are deviated in the direction of the field and more for movements deviated in the opposite direction. As a result, their desired trajectory will move more in the direction of the force field, producing an apparent under compensation. This is consistent with the result in the movement trajectories in Fig. 1. Subjects who train without catch trials have an opposite trend: the reference point for the error is moved so that they have an increased tendency to overcompensate for the field. This is especially true for the subjects training in the clockwise curl field.

C. Null sets at the beginning of each day reflect change in desired trajectory

If the desired trajectory really changes, then this change may be reflected in the null set performed by subjects at the

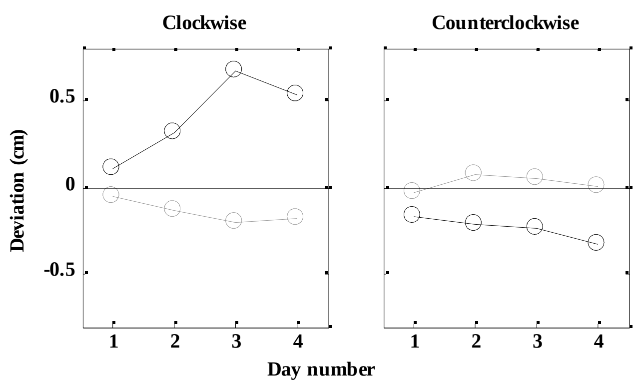

Fig. 3 With training, the reference point for error as measured by the model in (3), i.e., the desire trajectory, changes. Black line is for subjects trained with catch trials and gray is for subjects training without catch trials. The clockwise curl field pushes towards positive numbers.

beginning of each day. At the beginning of these null sets, subjects showed after-effects from the previous day's training and deviation from a straight trajectory was opposite to the direction of the field. By the end of the null set on the first day, no real difference existed between the groups. However, as shown in Fig. 5, trajectories at the end of the null set on subsequent days were deviated in the same direction as movements in the field. For subjects who trained with catch trials, this is the direction in which the field pushed the hand. For subjects who trained without catch trials, this is opposite to the direction in which the field pushed the hand. The consistency between deviation in the field and deviation at the end of the null set suggests that subjects who trained with catch trials changed their desired trajectory so they under compensated the field while those who trained without catch trials changed their desired trajectory to overcompensate the field.

D. Success rates increase for all subjects

One reason the desired trajectory may be changing may be an effort to improve performance. Indeed, Fig. 4 shows that performance in the task improved as a result of training. However, it is not possible that both kinds of training led to movements that were optimal for the field because the desired trajectories changed in opposite directions. It is possible that the trajectory planned by the subjects training without catch trials is close to the optimal trajectory for movements in the field. Along these lines, Fig. 4 shows that the success rate for subjects training without catch trials improved more quickly than the success rates for subjects training with catch trials.

IV. DISCUSSION

Our results indicate that subjects change their desired trajectory as a result of training and that this change can depend on the details of the training regimen, such as the frequency of catch trials. We arrived at this interpretation through a number of independent approaches to the data. We first demonstrated that the trajectories at the end of

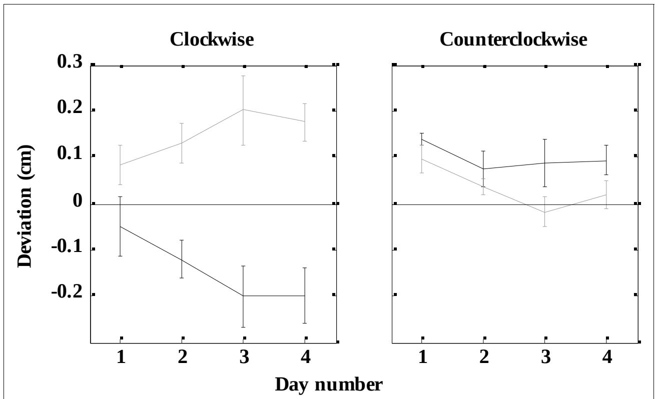

Fig. 5 Deviation at the end of the null set. The amount of deviation at the end (last 30 movements) of the null sets that were performed at the beginning of every day. Black line indicates performance of subjects who trained in clockwise curl field and gray is subjects who trained in counterclockwise curl field. Error bars are +/- 1 S.E.M.

training in each day depended on the probability of catch trials. Second, the change in the trajectory was quantified by the trial-to-trial effect of error. By finding the reference point for the error that best fits the data, we found that the reference point for error changed with training in a direction which was consistent with the change in the average trajectory. Subjects who trained with catch trials had a zero-point for error that was deviated in the direction of the field while subjects who train without catch trials had a zero-point for error that was deviated opposite to the direction of the field. Third, we tested whether there was a change in the performance of the null sets at the beginning of every day. Movements at the beginning of the null sets were not changed as a result of training: they always reflected an after-effect of training and were deviated against the direction of the field. By the end of the null sets, differences caused by training emerged and these differences grew more pronounced with increased training. Deviation of the null movements at the end of the set were consistent with the effect seen during training.

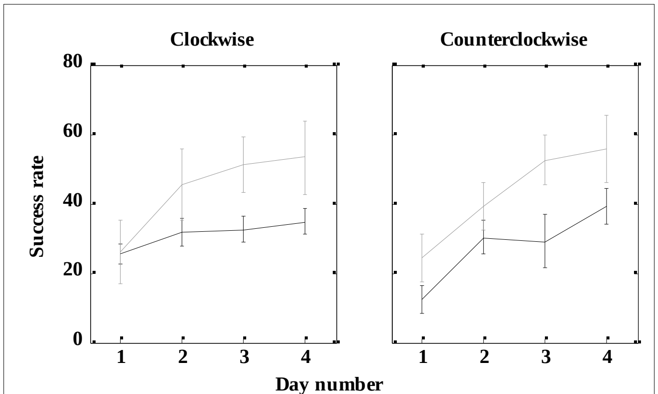

Fig. 4 Success rates during training. Percentage of succesful trials during the last set on each day averaged across subjects for clockwise and counterclockwise training. Black line represents performance of the group that trained with catch trials, gray line is for no-catch group.

One might reasonably ask why the desired trajectory is changing. We suggest that the desired trajectories change in order to improve performance on the task. Initially, it appears that our results are consistent with this hypothesis, as performance improves for all subjects. However, this does not explain why movements in the field are increasingly under compensated when training with catch trials and increasingly over compensated when training without. If a slight over compensation is optimal, why should subjects training with catch trials change their desired trajectory in the opposite direction? This is probably because subjects training with catch trials are optimizing success during movements in the field and during catch trials. The optimization process seems to weigh the catch trials more heavily, either because they are rare or because they cause a greater amount of error. As a result, the relatively small proportion of catch trials has a large effect on the desired trajectory.

The idea that the desired trajectory can change as a result of training has important implications for our understanding of motor control. For instance, there is a long history of efforts to determine the parameter being optimized by the motor system, especially focusing on the minimum jerk [4] and minimum torque change [5] hypotheses. Recently, some authors have suggested that no single optimization is used and that the motor system simply optimizes its success in each task [6,7]. Our results are consistent with the second hypothesis. However, our approach goes beyond the earlier work in exploring the actual dynamics of the systems adaptation to a novel task. A model of these dynamics would reveal much about how the motor system attempts to optimize its success in the face of an unpredictable and changing environment.

V. Conclusion

Our results show that the desired trajectory for reaching movements can change as a result of training in a perturbing force field. The change in the desired trajectory depends on details of the task so that changing the fraction of catch trials (trials in which the perturbing force is not applied) affects the direction in which the desired trajectory changes. These results are not consistent with the idea that the motor system is optimized for any specific kinematic or dynamic parameter of movement. Instead, they seem to support the idea that the motor system adapts in an effort to achieve optimal performance in each task.

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