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Simultaneous coordinate representations are influenced by visual feedback in a motor learning task

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Abstract— **It has been widely accepted that the CNS develops a representation (model) of the environment, but what is not entirely clear is the coordinate reference frame used. We explored how visual feedback influenced the coordinate frame in which the CNS stores and recalls these memories of learned skills in a reaching-generalization task. Four groups of subjects trained to perform reaching movements in a perturbing force field, two with aligned (first person) visual feedback and two with non-aligned (vertical screen). After 170 trials of practice, we asked subjects to extrapolate (generalize) what they learned to a new part of the workspace in novel force environments (endpoint-based versus joint-based extrapolated force fields). Regardless of the test condition, all subjects improved their ability to generalize skills to the new workspace. There was evidence that the extrapolation of their learned skills was based on both object-centered and joint-based coordinates. Consistent with previous studies, subjects performed significantly better in joint-extrapolated force field, but only if the visual feedback was vertical. Subjects performed equivalently in both force fields with aligned (first person) feedback. These findings suggest that the type of visual feedback biases the way subjects perform, and that learning results can be significantly influenced by feedback.**

I. Introduction

Recent studies have shown evidence of how the nervous system employs internal models to anticipate and compensate for the dynamics of an environment. The nervous system has the remarkable ability to adapt to its surroundings, and one of the most common approaches is by distorting the mechanical environment and observing the subject's adaptation of control [1, 2]. An interesting prospect of this work is to evaluate the success of extrapolation to untrained regions of the workspace. Such tests can determine the coordinate reference frame used by the motor system [1, 2].

In such studies, researchers have found evidence that the nervous system employs intrinsic coordinates to store and recall learned motor skills [1-5]. In other words, the internal model generates torques to control the arm based on shoulder and elbow kinematics rather than Cartesian endpoint kinematics. In contrast, other studies have demonstrated evidence for learning in extrinsic coordinates. For example, for a simpler external dynamic environment, the internal model encodes in object-centered or extrinsic coordinate system [6].

Additionally, distorting visual feedback can also dramatically influence adaptation [7-10], so it is plausible that even a simple manipulation of visual feedback can impact learning. In this study, we were interested in how display alignment affects the coordinate frame representation used within the internal model. Veilleux and Proteau have shown that performance is less variable with an aligned (first person) versus a non-aligned (vertical) display [11]. While this study highlights the impact of visual alignment on online control, it is unknown how this experiment factor influences learning generalization.

In this study, we explored the properties of the internal model considering both display approaches for the adaptation. Here we present an experiment that evaluates the coordinate reference frame for representing the environment when the visual feedback is provided in the aligned and the non-aligned feedback conditions. Our results suggest multiple coordinate representations employed by internal model and the reaching performance influenced by the type of visual feedback presented during training.

II. Materials and Methods

A. Experimental Setup

The purpose of our experiment was to understand adaptation to changed dynamics of a reaching task under different visual feedback conditions. A robot manipulandum was used for generation of different dynamical environments within which human subjects performed reaching task by grasping robot's handle.

The measurement apparatus, the manipulandum, used in this study is a light weight, low friction, and two degree of freedom robot [12]. The robot produced forces at its end-effector, the handle, using two low-inertia DC torque motors (PMI Corp. model JR16M4CH) that are mounted on its base and are independently connected to each joint using a parallelogram arrangement. Position and velocity measurements were made using two optical encoders (Teledyne Gurley) and two tachometers (PMI), respectively, which are mounted on the joint axes.

The visual feedback regarding location of a target and position of a subject's hand (in form of a cursor) was provided using either of two display screens shown in Fig. 1(a). The aligned display was an opaque, rectangular, and

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white platform mounted horizontally and directly above the handle of the robot. Video was projected on the aligned screen using a projector mounted on the ceiling. The non-aligned display was a LCD monitor mounted directly above the base of the robot at approximate eye level of a subject.

B. Subjects

Twenty right handed human subjects participated in this study. They had no past history of neurological, shoulder or elbow disorders and were within the age range of 21 to 40 years. The Subjects with ambidexterity were excluded from this study.

C. Experimental Procedures

Each subject participated in this study were given a reaching task where they had to move the handle of the manipulandum to bring a cursor on the screen into a target circle. The cursor indicated position of the handle. In particular, the reaching task included moving a cursor from the center of a workspace to a target and back to the center of a workspace which represented center-out reaching movements. A target was randomly chosen from the set of four targets which were 10 cm away from the center of a workspace at 24, 114, 204, and 294 degrees from the x-axis. A positive reinforcement feedback in form of yellow to red target color change was given to subjects if completed movements were within the range of 0.4 to 0.6 seconds.

The reaching task was specified in two regions: the training and test workspaces. Each workspace was of the size 20 x 20 cm^2, and its location with respect to a subject is shown schematically in Fig. 1(b). In order to prevent inertial artifacts of the manipulandum associated with changing the operating configuration, the training and test workspaces were selected by moving the subject with respect to the robot.

During certain phases of the experiment, the manipulandum was programmed to produce forces on the handle, hence on the hand of the subject during reaching task. These forces were velocity dependent and indicated by the vector f in the following equation:

$$f = B\dot{x}, \qquad (1)$$

where $\dot{x}$ is the velocity vector for subject's hand, and B is a viscosity matrix in the extrinsic coordinates:

$$B = \begin{bmatrix} -15.69 & 9.80 \\ 9.80 & 15.69 \end{bmatrix} N \cdot sec/m. \qquad (2)$$

The force field defined by (1) is translation invariant in end-point coordinates, and produced forces are identical in the training and the test workspace (Fig. 1b). Hereafter this force field is termed the "end-point field".

During certain phases of the experiment, a different force field was imposed on the handle. This field was depended upon the angular velocities of subject's elbow and shoulder joints:

$$\tau = W\dot{q}, \qquad (3)$$

where τ is the torque vector acting on the subject's shoulder and elbow joints, $\dot{q}$ is the subject's joint angular velocity, and W is a viscosity matrix in the subject's joint coordinates. The field described by (3) is translation invariant in joint coordinates. In fact, it is equivalent to following:

$$f = (J(q)^T)^{-1}\, W\dot{q}, \qquad (4)$$

where $J(q) = \partial x / \partial q$ is the configuration dependent Jacobian which maps the configuration from q to x, and the superscript T suggests the transpose operation. Since the Jacobian used is a function of the angular configuration of a limb, the force field define by (4) depends on workspace location. Thus, the produced forces are not identical in the training and the test workspace (Fig. 1b). Furthermore, we chose W such that the forces field produced by (4) was identical to the force field produced by (1) at the training workspace. For each subject, the matrix W was calculated as following:

$$W_R = J_{o,R}^T\, B\, J_{o,R}, \qquad (5)$$

where W_R is the joint-viscosity matrix, and $J_{o,R}$ is the Jacobians evaluated at the center of the training workspace for the subject's right arm. Hereafter this force field is termed the "right-joint field".

The end-point field and the right-joint field were identical at the training workspace with correlation coefficient of 0.99 and were almost orthogonal to each other with correlation coefficient of -0.25. Furthermore, the forces produced by both fields were equivalent in magnitude at both workspaces.

The experiment consisted of baseline, initial exposure, training, aftereffect and final performance phases. The subjects were randomly divided into four groups of five. All subjects were trained to make reaching movements with their right arm in the end-point field at the training workspace. Their performance was tested before and after the training with either the end-point or the right-joint field at the test workspace. The procedure is summarized in Fig. 2. The visual feedback of the hand position was removed during the specified trials by blanking the cursor.

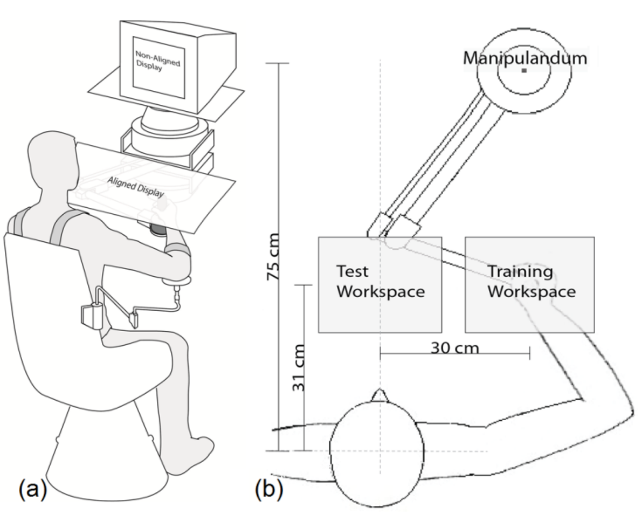

Fig. 1. Sketch of the manipulandum and the experimental setup: (a): Human subjects sat in front of the manipulandum robot and grasped the handle in order to perform reaching tasks while targets were presented using either the aligned or the non-aligned display. The aligned display is shown transparent here only for illustration purpose. (b): location of the training and the test workspace respect to a subject.

Phase No.	Phase Type	No. of Trials	Cursor displayed?	Environmental Field	Workspace
1	Familiarization	40	Yes	Null	Training
2	Baseline	20	No		
3	Familiarization	40	Yes		Test
4	Baseline	20	No		
5	Intermittant Initial Exposures	120, 20	Yes, No	Group 1&3: NULL, end-point field Group 2&4: NULL, right-joint field	
6		120, 20	Yes, No	NULL, end-point field	Training
7	Training	150	Yes	end-point field	
8	Final Training	20	No		
9	Aftereffects	20, 120	No, Yes	NULL, end-point field	
10	Training Refresher	20	Yes	end-point field	
11	Final Performance	20	No	Group 1&3: end-point field Group 2&4: right-joint field	Test

Fig. 2. Summary of experimental procedure: Group 1 and 2 received visual feedback with the aligned display, whereas group 3 and 4 received visual feedback with the non-aligned display.

D. Data Analysis

The position and velocity data of the subjects' hand were acquired from the manipulandum at 400 Hz. The trajectories were compared using the correlation coefficient which was previously developed by Shadmehr and Mussa-Ivaldi [1]:

$$\rho = \frac{Cov(U,Y)}{\sigma(U)\sigma(Y)}, \tag{6}$$

where ρ is the correlation coefficient comparing U (u_1, u_2, …, u_n) and Y (y_1, y_2, …, y_n) velocity vectors. The covariance and standard deviations are described as:

$$Cov(U,Y) = \epsilon(\langle U - \epsilon(U), Y - \epsilon(Y)\rangle) \tag{7}$$

$$\text{where } \langle U,Y\rangle = \sum_{i=1}^{n} u_i \cdot y_i \text{ and } \epsilon(\langle U,Y\rangle) = \frac{1}{n}\langle U,Y\rangle, \tag{8}$$

$$\sigma(U) = \sqrt{\epsilon(\langle U - \epsilon(U), U - \epsilon(U)\rangle)}. \tag{9}$$

The ϵ operator represents the expected value of the argument and the symbol · in (8) indicates the dot product operation between two vectors.

The correlation coefficient compares reference hand velocity vectors to that of average baseline. This is also referred to as the performance measure since it determines the closeness to the best performed trajectories: baselines.

The measure used in this paper was statistically analyzed using repeated measure analysis of variance with factors: evaluation, display, and time. Normalized pre to post change was analyzed using two-way analysis of variance with factors: evaluation and display. Post hoc comparisons between four paired group means were done using Bonferoni-Holm method. These four pairs were chosen such that one of the factors in a pair was always common.

III. Results

The subjects performed reaching task in artificially created force environment. The manipulandum robot was programmed to produce different types of force field which acted on the subject's hand, hence changing the arm dynamics. The subject's movement patterns were assessed during the different conditions to understand the reference coordinates used by the internal model.

First, the baselines were collected in the unperturbed force environment. The baseline trajectories were essentially in the straight line path regardless of different workspace and display. The correlation coefficient for baselines was 0.9434 ± 0.0116 (mean ± 95% confidence interval). Furthermore, these baselines had almost symmetric bell shaped velocity curves [13, 14].

Next, the initial performance was measured at the test workspace when subjects were intermittently exposed to the force field assigned to their group. The group average of hand trajectories during the initial exposure is shown in Fig. 3. Notice that the effect of the field on hand movements was quite significant which drove the hand to an undesired position, away from the target. Since the cursor position was blanked throughout these movements, corrective actions that we observe must have been due to proprioceptive feedback. In pictorial manner, the initial burst of movements followed by corrective actions produced "hooks" in trajectories [1].

Next, all subjects were trained to make reaching movements in the end-point field at the training workspace. At the beginning of the training, the perturbation affected their movements which were significantly different than baselines. However, the hooks that were observed initially vanished as the subjects practiced, and their hand movement started to resemble baselines. Finally aftereffects were observed in their movements when the force field was removed. It must be noted here that the groups who were trained using the aligned display had statistically identical results to those who were trained using the non-aligned display during the training. The results of this adaptation were consistent with previous studies [1-3, 15].

Finally, our subjects performed reaching movements in the test workspace and in the presence of the force field assigned to their group. The group average of hand trajectories during the final performance is shown in Fig. 3. Note the improvement in the group's final performance in novel fields when compared to initial exposure.

The initial exposure and the final performance trajectories at the test workspace were compared using correlation coefficient and are summarized in Fig. 4(a) and (b). Based on repeated measure ANOVA, groups' performance in the right-joint field was significantly better than in the end-point field regardless of training and different displays ($p = 6.03e-5$). Furthermore, the effect of the training itself improved all group's performance regardless of different displays and field exposures ($*^1$; $p = 3.07e-4$). There was an interaction detected between different displays and the field exposures ($p = 4.78e-3$). This interaction effect was further analyzed using Bonferoni-Holm post hoc method after taking out the factor of time from the model. When the non-aligned display was used, subjects' performance in the end-point field was significantly lower when compared to their performance in the same field but with the aligned display ($*^2$; $p = 1.29e-2$) and in the right-joint field with the non-aligned display ($*^3$; $p = 5.03e-3$). Also note that the initial exposures for all groups were significantly worse than baseline, and total recovery in their performance was not observed at the test workspace even after the improvement due to the training.

Finally, the difference between the final performance and the initial exposure at the test workspace was computed. Fig. 4(c) shows normalized pre to post change. Based on two

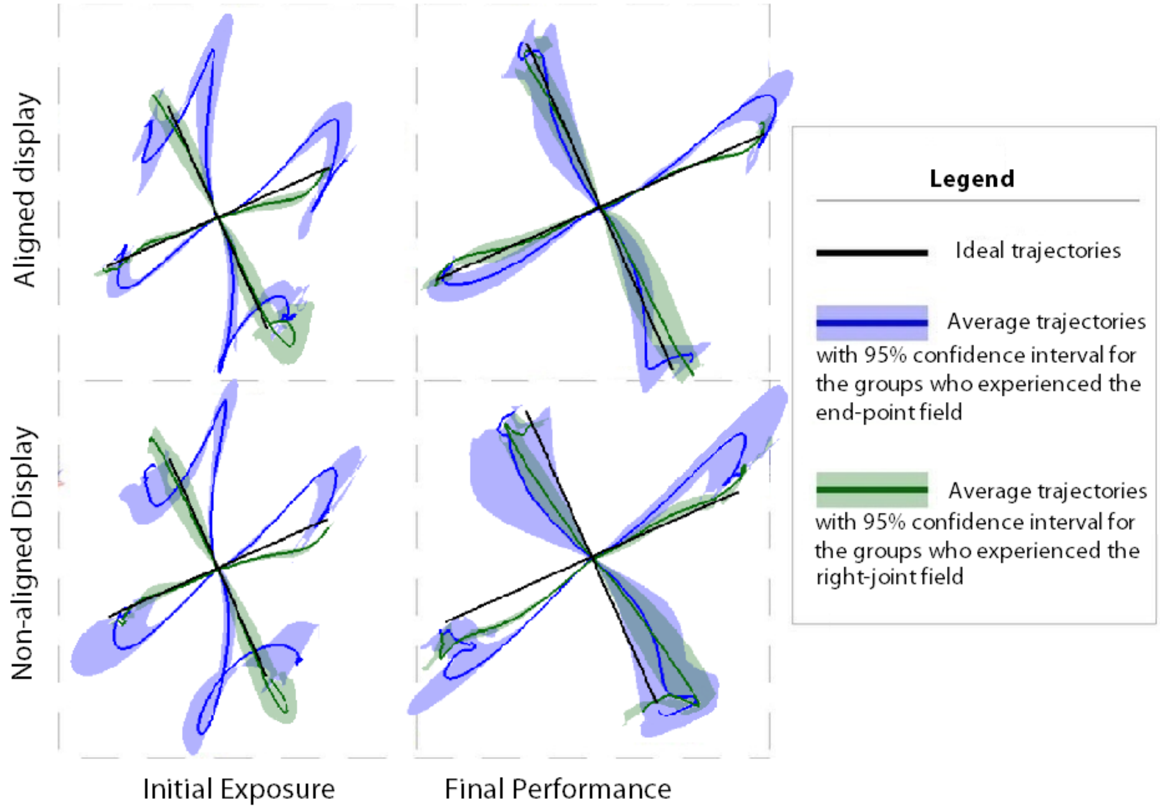

Fig. 3. Average hand trajectories with 95% confidence interval for different groups during the initial exposure and the final performance phase at the test workspace.

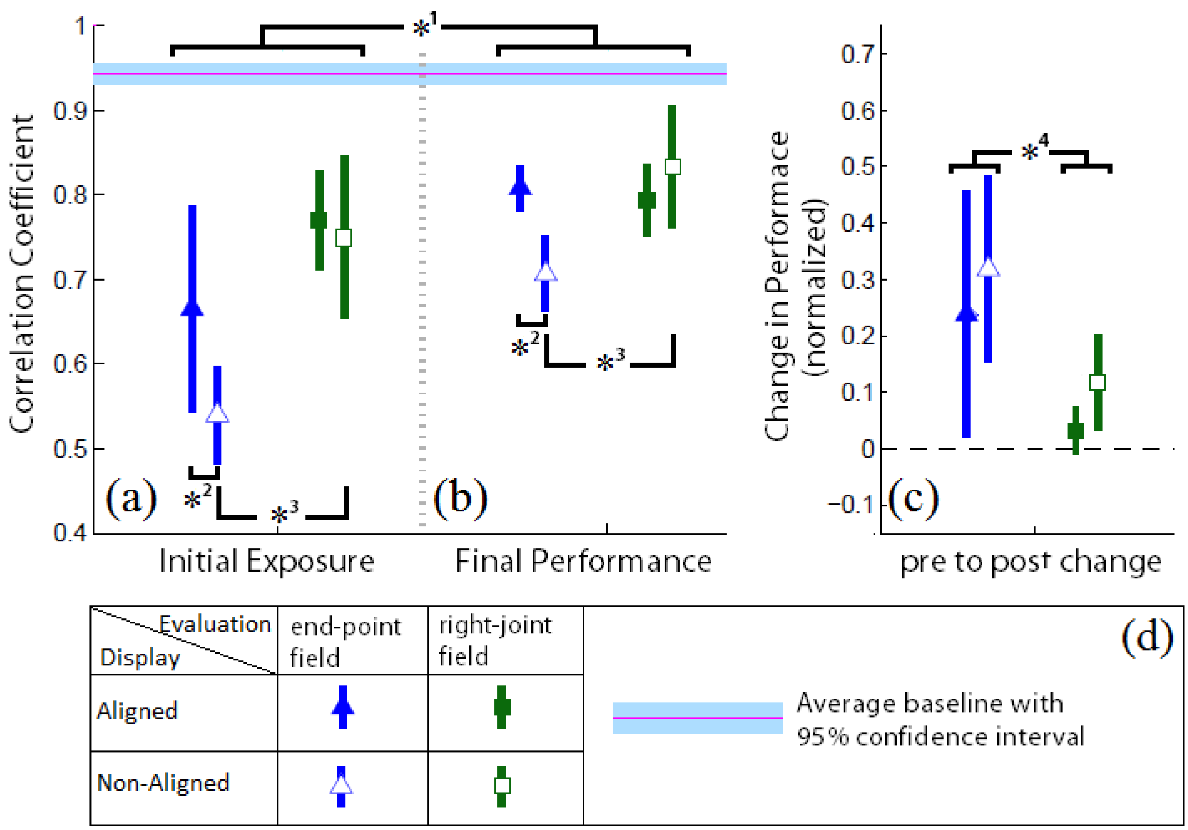

Fig. 4. Average group correlation coefficient with ± 95% confidence interval during different conditions at the test workspace: a) the initial exposure, b) the final performance, c) normalized change from the initial exposure to the final performance, d) legend. Significant difference between groups ($p<0.05$) is displayed as a dark horizontal bracket with an asterisk. Significant differences for the same post hoc test by combining group means in time are shown by asterisk hat ($*^2$,$*^3$) since the effect of training does not seem to alter displayed trends. For more information about $*^i$, refer to the results section.

factor ANOVA, there was no significant difference between groups who experienced same force environment but trained using different visual displays. Thus neglecting the effect of different displays, the pre to post change for all groups was significantly greater than zero (p = 4.26e-5 and 3.84e-3 for groups who experienced the end-point field and the right-joint field, respectively). Note that this improvement for all groups was also detected by repeated measure ANOVA. The change was significantly higher for the groups who experienced the end-point field compared to the groups who experienced the right-joint field ($*^4$; p = 2.44e-3).

IV. Discussion

This study investigated the possible coordinate representations of the internal model under different visual feedback conditions as someone recalls and extrapolates recently-learned reaching skills. As evidenced by pre to post change (Fig. 4c), training improved performance in both endpoint-based and joint-based force fields in the test workspace, regardless of different visual feedback conditions. Furthermore, the subjects who received visual feedback with the non-aligned (vertical screen) display had the lowest performance in the end-point field in spite of the improvement due to training (Fig. 4b). There is clear positive influence caused by first-person feedback in these learning tasks.

Generalization has been studied quite extensively for deducing coordinate reference frames of neuromotor learning, whether it is new hand positions [1, 2], tasks [16], movement directions [3], dynamics [17], speeds [4], or visuomotor environments [18]. These have revealed evidence for imperfect generalization, that is, despite evident improvement through training in the novel environments, the motor system is not able to reproduce baseline performance [3, 4, 8, 16, 19-21]. It is through these imperfections that we gain insights into the manner in which the nervous system represents what it has learned.

Our results are consistent with the hypothesis that multiple, simultaneous internal representations of extrinsic and intrinsic coordinate systems mediate learning and control of novel environments. The evident performance improvement in the region outside the training workspace demonstrates at least some compatibility of subject learning with both evaluation force fields. If subjects had, for example, developed the internal model based on only the intrinsic space, we would not have observed performance improvements when evaluated in the end-point field. However, improvements in both the end-point and the right-joint fields provide evidence of simultaneous extrinsic and intrinsic representations of the environment.

Multiple representations may simply be because of multiple modes of feedback. Krakauer et al. (1999) showed that hand kinematics were learned from visual errors in extrinsic coordinates and dynamics were learned from proprioceptive errors in intrinsic coordinates [22]. In our study, we let our subjects simultaneously observe visual error (as a cursor) while they trained with a dynamic force field. If so, one might expect better performance when visual feedbacks are closer to first person feedback in the end-point field condition, which was found to be the case. Also one might predict that this difference due to vision would not influence the performance observed in the joint based field condition, which we also found to be the case.

Wolpert and Kawato (1998) proposed a possible mechanism for multiple paired forward and inverse models explaining partial generalization [23]. It was postulated based on the assumption that a single neuron cannot learn to cope with all different types of dynamics and kinematics of the environment and objects. Based on this modular structure hypothesis, different modules can learn a task at the same time and build different internal models while training which can be called upon independently or simultaneously during generalization depending on feedback cues. Simulation and behavioral studies show that multiple internal models can be learned [24-26]. Furthermore, these internal models can also have interference or combinatory effect during adaptation [17, 23-28]. We suspect that separate neural networks are responsible for encoding the inverse dynamics of the environment, based on both extrinsic versus intrinsic coordinates.

Similar evidence for simultaneous representation of internal models using different coordinate systems has been provided by studies of interference [17, 22, 29, 30]. These studies suggested that tasks with opposing forces, each learned independently in extrinsic and intrinsic coordinates, would not show any interference, since they would not compete for same memory resources [22, 31]. For example, visual rotations are known to be learned in extrinsic coordinates [10], and inertial perturbations which are speculated to be learned in intrinsic coordinates do not interfere with learning visual rotations [22]. Furthermore, the retrograde and anterograde interference has been reported when learning velocity dependent and position dependent inertial loads [32]. In contrast, Davidson et al. (2005) evidenced that loads applied to hand and arm are learned, but not represented separately, which hints for common coding [33]. They further showed that joint based and hand based forces can be learned equally well, which is independent of coordinate system in which load is represented and exposed to the subjects (on hand versus on arm). The interference behavior in these studies could be explained by our assertion of multiple simultaneous extrinsic and intrinsic representations. Our result that feedback influences the amount of each type of representation may also explain why some studies show interference and some do not.

The complexity of visual feedback could affect the degree of computational processing by the nervous system. Similar to Ahmed et al. (2008) interpretation, we believe that the non-aligned screen may have introduced an additional step of neural computation (task complexity) to map movements in the horizontal plane to the visual feedback in the vertical plane [6]. The effect of different visual presentation on online control processes has been shown by Veilleux and Proteau (2010) [11]. Thus, we suspect the additional step of online computation might have interfered with the internal model that predicts the dynamics of the environment based on extrinsic coordinates but not with one that predicts the environment based on intrinsic coordinates. This further supports the previous claim that the joint coordinate based environment is easier and manageable regardless of different visual feedback conditions and even before training.

Our results complement and extend previous studies concerning the coordinate representations. Many studies have reported evidence that information about dynamics is represented in muscle or joint-based coordinates for the training arm [1, 2, 15, 20, 34, 35]. In contrast, there has been evidence for extrinsic coordinate space generalization for learning kinematic transformations [36]. Although our method of probing the structure of internal model is similar to Shadmehr and Mussa-Ivaldi (1994), we introduce some new analysis and conclusions. It should be noted that Shadmehr and Mussa-Ivaldi (1994) based their analysis on final performance [1]. They suggested intrinsic coordinate representation for the learned dynamics since the subjects' performance after training was better in the right joint field (correlation coefficient = 0.91) versus the end-point field (correlation coefficient = 0.62). However, with analysis of both initial exposure and final performance, we examined learning compatibility from each group, and can now infer the existence of simultaneous coordinate representations. Beyond the impact of training, force fields based in different coordinate systems may simply differ in overall difficulty. One striking finding from our experiment was that subjects' performance in the right-joint field during the initial exposure was significantly better than those who experienced the end-point field (Fig. 4a) even though force magnitude experienced in both fields were similar. This suggests that the right-joint field is intrinsically easier for the subjects to handle even before training had begun. Thus the subjects had an intrinsic advantage of performing better in the joint space force field.

This study provides new understanding of how internal models are affected by different visual presentation. Our findings have potential impact on motor control investigation in general, since the presentation of visual feedback is typical for a majority of training paradigms. The results from this study can help develop robotic neurorehabilitative treatments for patients who have impaired ability to control reaching activities. The future training scenarios that incorporate the both intrinsic and extrinsic coordinate reference frame should best optimize robotic training programs. Furthermore, the presentation of visual feedback during training must be kept in mind when designing future experiments and patient treatments since it has greater impact on the reaching movement performance.

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