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Reversal Phenomenon in a Simple Motor Task: Evidence for an Indirect Model

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***Abstract* - When we first learn to control a cursor on the screen by means of a computer mouse the brain can either learn the mapping from the brain to the cursor as a whole (direct model) or count on knowledge of the mapping from the brain to hand and augment it with a learned mapping from the hand to the cursor (Indirect model). While the complete direct mapping involves complex nonlinear components arising from the body dynamics, we can set the hand to cursor mapping to be a simple linear transformation. We describe a simple cursor movement task carefully designed to reveal a clear reversal phenomenon in which trials that are a reversal of their predecessor, score higher than non reversal perpendicular trials. We suggest that this phenomenon is evidence of representation and learning of the hand to cursor mapping during the initial stage of learning the task, and discuss implications to brain machine interfaces.**

I. Introduction

Research of brain machine interfaces is increasingly taking into account the plasticity of the brain and its adaptation to the environment. Several studies suggest that the central nervous system constructs internal models of the arm dynamics and the external environment to generate the motor commands needed to drive the hand along a planned trajectory [1-7]. By imposing position or force perturbations on the hand, the formation of the internal model can be measured. Ref. [8] altered the cursor-mouse mapping during various reaching movement tasks in order to elucidate the properties of the internal model being acquired. They showed that directional generalization is only partial when practicing on four directions, and is complete when practicing on eight. Ref. [9] used a similar paradigm to show that directional control is local to the area in which it is practiced, deriving a possible representation of an internal model. Others have used this method to infer the coordinate system used by the internal model [8-10] and it seems that the coordinates of the hand are taken into consideration by the brain during adaptation to visuomotor transformations.

In order to further explore the structure of the internal representation we introduce a dichotomy between direct and indirect internal representation (Figure 1) and demonstrate an experimental result supporting the indirect model.

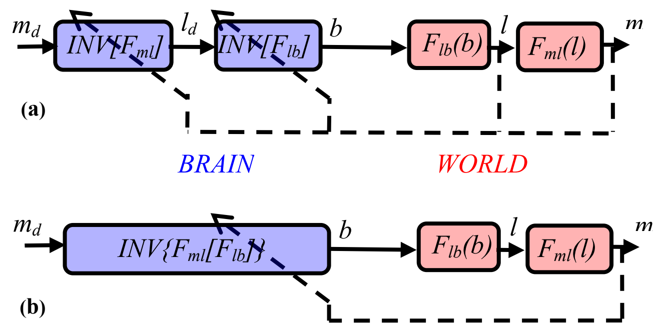

Figure 1: Direct Vs. Indirect internal model. m_d is the desired cursor location (m for machine), l is the hand coordinate (l for limb) and b the output signal from the brain. (a) The indirect model in which the controller explicitly represents the inverse of the limb machine mapping. (b) Direct model in which the controller learns and represents the brain machine mapping as a whole without an explicit representation of the limb machine mapping. The dashed line represents an unknown learning algorithm that is not discussed in this paper.

We use a cursor moving task, differing from traditional such experimental procedures in two main details: First, we eliminate visual feedback during initial phase of cursor movement by using a masking circle, rather than rely on subject's adherence to the instruction to execute sharp uncorrected reaching movements. Second, our task executes across the whole workspace, rather than repeating center out reaching movements from same focal point. The purpose of our experiments is to reveal a reversal phenomenon. The 180 degrees visuomotor transformation was found to be the easiest to learn [11][12][13]. However the clear preference of opposing directions during task learning of a specific visuomotor transformation has not been sufficiently explained. We believe this property of the task learning constrains the type of internal model that is being used. We analyze this property in terms of a distinction between direct and indirect internal models and show that the reversal phenomenon supports the indirect model. The rest of this paper is organized as follows: We first formally describe the two alternative models and their predictions, then we specify the experimental procedure in the methods section followed by the experimental results and the discussion of its implications to brain machine interfaces and the required future research.

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II. DIRECT VS INDICRECT MODEL

The concept of internal model can be described in terms of a controller that adapts and learns the environment. Applied to learning the control of positioning the arm, the system is composed of the brain command, the limb dynamics, the resulting limb location, and the controller. The internal model is the controller's formation and representation of the inverse of limb's dynamics, in other words the acquisition of the inverse mapping from desired limb position to the required brain command. When considering the process of learning to control an external object, referred to as the machine, the system is extended to contain a further mapping from limb response to the resulting response of the machine (for instance its location). The external system previously consisting of the arm dynamics transforming brain commands to limb position, now consists of two successive mappings, the limb dynamics, and the machine dynamics that transforms limb movement to machine location. For such a system we propose two different representations of an internal model (see Figure 1). A direct model in which the controller learns the inverse of the superposition of the two mappings as a whole, representing an inverse mapping directly from desired machine response to required brain command. Alternatively, an indirect model in which controller learns and represents the inverse of the limb machine mapping separately and chains it to the inverse of the brain command to limb mapping which is assumed to be previously known.

The structure of the internal model could be either direct or indirect and it could also evolve from indirect to direct with learning and adaptation. As a first step we consider here a simple linear transformation between the limb and the machine. The brain machine mapping as a whole is a complex nonlinear transformation, which includes the nonlinear transformation of the excitation of the motor neurons to muscle flexion and extension and the transformation from the muscle activity to joint angles and location of hand. In contrast, the limb machine mapping can be chosen as a simple linear transformation. We reason that if the controller is forming an internal model of the hand cursor transformation, we should observe properties that arise from the linear representation of the hand to cursor mapping, which are not likely to occur in learning the representation of the complex nonlinear direct transformation from brain to cursor. We imposed a 90 degree rotation on the common mapping between hand and cursor movement and observed if opposing directions are learned as a whole or each learned separately. During the initial phase of the task, the controller uses an incorrect internal model. However, although incorrect, because of its linearity, an internal model of the hand to cursor mapping under the indirect model that solves one direction will also solve the opposing direction. The following experiment was devised to test for this effect. We now describe the experimental methodology and the results and then tie the specific results to the predictions of the indirect model in the discussion section.

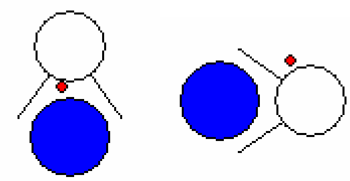

Figure 2: demonstration of a successful iteration in which the red cursor exits the masking circle within the rays and is on way to contact the blue target (left), and a failed iteration in which the cursor exits the masking circle inaccurately, generating an error sound (right).

III. METHODS

Subjects: Seven subjects (male, aged 25-38 years, right handed) participated in this study after giving their informed consent as confirmed by the Ben-Gurion University Helsinki committee.

System: An Ascension 5mm MiniBird system was used to measure hand position. Subjects were instructed to hold the sensor between thumb and index finger and move it on top of a horizontal table in order to control a cursor displayed as a small red circle on the monitor. The cursor was programmed to respond to sensor position so as to induce a 90 degrees clockwise rotation on the standard mouse-cursor correspondence. The whole system (sensor position measurements, display refresh rate etc.) was sampled at 100 Hz.

Task: A large blue target circle is initially placed in center of screen and the task is to move the cursor along the imaginary straight line from the cursor's onset position to target position (see Figure 2). When target is contacted, it moves a fixed magnitude in a direction randomly chosen from the four main axis directions, and a new trial begins from the current position of cursor. In order to measure the formation of an internal model rather than feedback corrections, the area around the initial cursor position of each trial is masked by a white circle, thus forcing the subject to perform the initial phase of the reaching movement in absence of visual feedback of cursor, revealing the current status of the internal model. To promote precision, the path from cursor onset to target is delineated by two rays extending from the border of the masking circle towards the target (see Figure 2). A trial is successful if cursor exits the masking circle within these rays, otherwise, a beep is sounded to mark failure. Subjects are instructed to contact the target as precisely as possible so as to minimize the error beeps, and are told that "speed is not an issue".

Protocol: Subjects begin with a 50-iteration familiarization session without the rotation, (i.e. the cursor responds as to an ordinary mouse) acquainting them with the purpose of the task and the required precision. After a one minute rest period subjects are informed that the actual experiment begins in which the cursor responds differently, and a 200 iteration session is performed under a 90 degrees CW rotation.

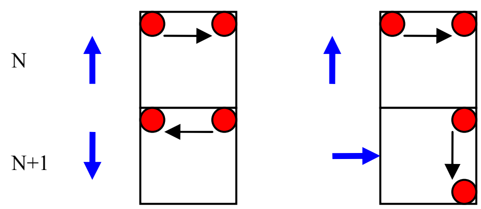

Figure 3: The blue arrow represents hand movement and the red is the corresponding cursor movement. A reversal sequence is shown on the left (first hand movement is up and the next movement down) and a perpendicular on the right (first movement is up and the second to the right).

Measurements: Two main values are collected from each trial: the success (i.e. cursor is within the bounding rays upon exit from masking circle), and the time elapsed from onset until cursor crosses the border of the masking circle. We refer to these values as success rate and time-to-crossing respectively.

The seventh subject performed a bimanual version of the experiment. Subject held a sensor in each hand, and the control of the cursor alternated on each iteration between the right and left hands. We describe the significance of this modification in the discussion section.

IV. Results

In order to test for a reversal phenomenon we focus only on those iterations that are preceded by a successful iteration, and further separate these iterations into three categories according to the direction of movement of the target in relation to the preceding iteration (see Figure 3):

- Repeat - target moves in same direction as preceding iteration.
- Reversal - target moves 180 degrees to the direction of preceding iteration.
- Perpendicular- target moves 90 degrees to the direction of preceding iteration.

In this report we concentrate only on the comparison between the reversal and perpendicular categories. Figure 4 depicts results from one of the subjects which are characteristic of results observed for all six subjects.

All six subjects show a success rate significantly higher for reversal iterations compared with the perpendicular iterations (chi-square test, $p<0.01$ for each and every subject). In addition, all six subjects performed the reverse iterations significantly faster than the perpendicular iterations (t test, $p<0.01$ for each and every subject).

V. Discussion

Our experiment reveals a clear reversal phenomenon during the initial stage of task acquisition, in which subjects perform better in terms of both accuracy and speed, for a trial that reverses the direction of its previously successful trial than for a trial perpendicular to its predecessor. A successful trial enhances performance on the following trial only if it is a

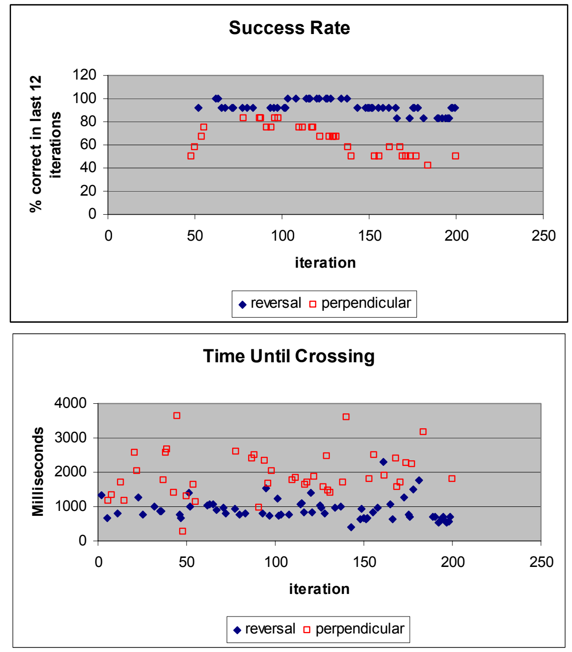

Figure 4: Typical comparison between the reversal (filled) and perpendicular (empty) categories with respect to success rate (top) and speed (bottom), observed in one of the subjects. The speed is shown as the milliseconds elapsed between the trial onset and the time when the cursor exited the masking circle so the higher graph indicates slower performance. For clarity of the graphical representation the success rate is shown as a moving average - the percentage of successful iterations out of the preceding 12 iterations in that category.

reversal while it does not assist a perpendicular trial. It is precisely this preference of opposing directions over perpendicular directions that requires explanation. The persistence of this phenomenon in the bimanual version of the experiment rules out the possibility that the preference of reversing directions is a physiological constraint of the hands' musculoskeletal dynamics and kinematics.

Under the indirect model the controller is attempting to learn the linear inverse transformation from target to hand direction. We describe a simple control strategy for which a reversal effect arises if the controller represents both hand and cursor direction using Cartesian coordinate system. Specifically, let us consider the two dimensional movement of constant magnitude in the experiment. The four directions are:

$$d_{right} = \begin{bmatrix} 1 \\ 0 \end{bmatrix} \quad d_{left} = \begin{bmatrix} -1 \\ 0 \end{bmatrix} \quad d_{up} = \begin{bmatrix} 0 \\ 1 \end{bmatrix} \quad d_{down} = \begin{bmatrix} 0 \\ -1 \end{bmatrix}$$

and one should note that the opposing direction have the same representation with an opposing sign.

$$d_{right} = -d_{left} \quad d_{up} = -d_{down}$$

Due to the linearity we expect that the controller will learn two opposing directions as a whole: Initially controller is using an incorrect internal model represented by an inaccurate rotation matrix. However, by linearity, the reversal phenomenon is expected even with an incorrect internal model, since the following holds for any pair of target and hand directions:

$$IM_{incorrect} d_{target} = d_{hand} \Leftrightarrow IM_{incorrect}\left(-d_{target}\right) = -d_{hand}$$

Consider, for example, the sequence described in figure 3. The controller is assumed to use a general learning strategy in which initially it chooses an internal model; if it is successful on a trial, it is used again for the following trial, otherwise it is updated through an unknown learning algorithm. At iteration N (see figure 3), the controller has successfully applied its current inverse transformation to generate an up hand movement in order to move the cursor to the right:

$$\begin{bmatrix} a & b \\ c & d \end{bmatrix} * \begin{bmatrix} 1 \\ 0 \end{bmatrix} = \begin{bmatrix} 0 \\ 1 \end{bmatrix} \Rightarrow a = 0;\ c = 1.$$

Therefore the state of the internal model at iteration N must have had the form

$$\begin{bmatrix} 0 & b \\ 1 & d \end{bmatrix}$$

If the next trial is a reversal trial and the same internal model is used at iteration N+1 then the outcome is

$$\begin{bmatrix} 0 & b \\ 1 & d \end{bmatrix} * \begin{bmatrix} -1 \\ 0 \end{bmatrix} = \begin{bmatrix} 0 \\ -1 \end{bmatrix}$$

Resulting in a successful trial for any values of b and d. In other words, the internal model of iteration N assists a reversal iteration N+1 even if it maps incorrectly the right and left directions. In contrast, the internal model of iteration N will solve a perpendicular iteration N+1 only for b = -1 and d = 0, in other words only if the internal model at iteration N was completely accurate.

Let us also consider the alternative model, i.e. the direct model (see Figure 1). Without building a complete model of the spinal cord muscles and arm dynamic model we can safely state that since muscles can only be shortened actively, even at the single joint level different muscles (and hence different motor neurons) are activated at opposite directions and a reversal phenomenon is not expected, unless of course the structure of the hand is taken into account in higher brain areas, an additional assumption that is consistent with the indirect model but not with the direct model.

This report concentrates on the early stage of task acquisitions, however it is known that such visuomotor transformations could be learned [e.g., 8, 11, 14] and the possible transition between indirect to direct internal representation is one of the open questions for future research.

We can further hypothesize that the brain employs visual and proprioceptive information about the position of the hand in order to build the internal model of the hand machine mapping. This hypothesis can be put to test by experimenting with subjects lacking sensory information from hand, such as nerve blocked patients or pathologically deafferented patients. This second hypothesis predicts that when learning such tasks, deafferented subjects would employ the direct approach to learn the brain cursor mapping and will not show any preference for opposing directions over perpendicular directions, and a reversal phenomenon will not be observed. In other words, the intuitive concept of reversing directions could be lost under certain conditions or after some certain training procedure.

Task learning under the direct model is of special interest for brain machine interfaces due to the direct link between brain commands and the machine that bypasses the subject's own limbs. Generalizing the analysis of the reversal effect within the framework of the direct and indirect models, provides insight to the characteristics and limitations of learning under the direct model: By splitting the brain machine mapping and representing separately the limb machine component, the indirect model can exploit relationships within the limb machine mapping to enhance the learning process, relationships that are not available to a controller that directly maps brain commands to machine response.

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