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Lateralization and Model Transference in a Bilateral Cursor Task*

Martin K. Burns, *Student Member, IEEE*, Julia Stika, Vrajeshri Patel, Dingyi Pei, *Student Member, IEEE,* Raviraj Nataraj, *Senior Member, IEEE,* and Ramana Vinjamuri, *Senior Member, IEEE*

***Abstract*—Post-stroke rehabilitation, occupational and physical therapy, and training for use of assistive prosthetics leverages our current understanding of bilateral motor control to better train individuals. In this study, we examine upper limb lateralization and model transference using a bimanual joystick cursor task with orthogonal controls. Two groups of healthy subjects are recruited into a 2-session study spaced seven days apart. One group uses their left and right hands to control cursor position and rotation respectively, while the other uses their right and left hands. The groups switch control methods in the second session, and a rotational perturbation is applied to the positional controls in the latter half of each session. We find agreement with current lateralization theories when comparing robustness to feedforward perturbations in feedback and feedforward measures. We find no evidence of a transferable model after seven days, and evidence that the brain does not synchronize task completion between the hands.**

***Clinical Relevance*— This work has implications in clinical motor rehabilitation, with relevance to restoring function in individuals with hand paralysis and learning to use assistive devices. Mirror therapy, model transference, and handedness hold particular relevance to these results.**

I. Introduction

The scientific view of handedness has evolved over recent years. The dominant hand was once viewed as the strong or skilled hand while the nondominant hand was seen as weak and unskilled. This view has evolved away from interpreting one hand as superior, and instead to viewing each hand as having distinct strengths in normal task execution. A more recent view is that the nondominant hand exhibits stabilizing control which integrates sensor feedback to maintain a positional setpoint in the environment, thus being the feedback hand. The dominant hand, alternatively, utilizes feedforward behavior to accurately execute tasks before sensor feedback is reliably available, and so complete the tasks quicker without compromising accuracy [1]–[3]. However, the latest perspective on handedness implies that the dominant and nondominant hands are specialized for dynamically predictive and impedance stabilization, respectively [4]. This framework has been demonstrated in numerous studies in healthy subjects and with individuals with stroke [5]–[7], although they were demonstrated for unilateral arm reaching tasks.

Inter-hemispheric coordination to execute hand and arm-based tasks may not only apply to the control modes used, but also to the learned model itself. Daily hand grasping tasks require a degree of bimanual coordination, the execution of which is hypothesized to rely on visual and proprioceptive feedback along with an internal visuomotor map [8]. The visuomotor map is an internal representation of movement kinematics and dynamics which is updated and refined as an individual is repeatedly exposed to a task [9]. Several groups have shown that unimanual task performance improves by way of learning a model of task dynamics [10]. These groups have gone further to suggest that this model is accessible to the untrained contralateral arm/hemisphere system [9], [11]. The untrained arm, therefore, can exhibit improved performance if the contralateral arm is trained on the task. However, these studies examined this effect within short-term experiments and so no evidence has suggested that this effect may be persistent.

In this study, healthy subjects are recruited to play a bimanual game involving two joysticks. The objective is to simultaneously move and orient a cursor onto a target cursor with predetermined but randomized positions. Dominant versus nondominant control strengths will be quantified using several feedforward and feedback performance measures. Based on prior literature, a higher performance is expected in the dominant hand for feedforward aspects of the tasks while the non-dominant hand is expected to show greater performance on feedback measures. A perturbation is introduced in a task set, eliciting a remapping of bimanual control to compensate for the modified controls. The effect of this perturbation on feedforward and feedback measures for both the dominant and nondominant hands is analyzed. Additionally, we analyze the effect of an inter-session washout period on motor learning and remapping by having the subjects repeat the experiment after seven days with swapped controls. The parameters and metrics examined here are similar to those studied in previous unimanual tasks, however this is the first study to examine these metrics in a bimanual task where each hand operates an orthogonal control (translation versus rotation). This study is also the first to examine if task models learned on one hand are accessible to the opposite hand after a period without practice.

II. Materials and Methods

A. Subjects

This study recruited ten healthy subjects from 20 to 23 years of age, with two females and eight males enrolled. All subjects are self-reported as right handed, and had normal or corrected-to-normal eyesight. This study was executed under an IRB-approved protocol after each subject signed informed consent documents.

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M. Burns, J. Stika, V. Patel, D. Pei, R. Nataraj, and R. Vinjamuri are with the Department of Biomedical Engineering, Stevens Institute of Technology, Hoboken, NJ, 07030, USA (e-mail: ramana.vinjamuri@stevens.edu).

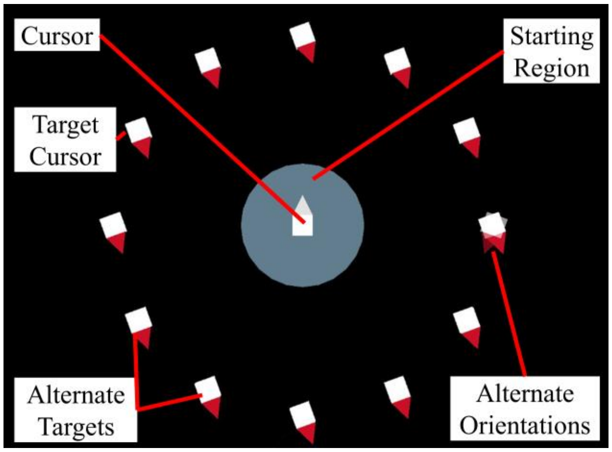

Figure 1. Joystick cursor task layout. The subject's cursor starts at the center of a 5-unit starting circle. All 12 possible target positions are shown, along with one location showing the two possible target orientations.

B. Joystick Task

Two joysticks (Logitech, Neward CA, USA) are firmly affixed to a table in front of a computer screen. A cursor at the center of a 5-unit starting region is controlled by the subject using one joystick for x and y position and one joystick for orientation (Fig. 1). The objective is to reach a target cursor, at one of twelve positions and one of two orientations, shown at a randomized but consistent order across subjects. The targets are evenly spaced around a 14-unit radius circle centered at the starting cursor position, and at either ±160° from vertical. The x and y axes of the position joystick is linearly mapped to the ±20-unit range and the axial twist of the orientation joystick is linearly mapped to ±180°. The subject is instructed to reach the displayed target cursor as fast as possible, while simultaneously controlling the three DoF of the cursor. A successful task is counted when the cursor's x and y positions and orientation are within 0.4 units and 10° of the target's x and y position and orientation, respectively.

Each session is organized into three trials, and lasts aproximately 45 minutes. The first trial is a familiarization set where subjects are acquanted with the game interface, task timing, and success criteria. This trial lasts until 24 tasks are successfully completed. The second trial is a baseline set of 48 successful trials, in which no control perturbation is added. The third trail is a perturbation set of 48 trials, where a clockwise rotation of $\theta = 45$ degrees is applied to the positional controls, $\vec{x}$, to get rotated coordinates, $\vec{x}_{rot}$.

$$\vec{x}_{rot} = R\vec{x}_j = \begin{bmatrix} \cos(\theta) & -\sin(\theta) \\ \sin(\theta) & \cos(\theta) \end{bmatrix} \begin{bmatrix} x_j \\ y_j \end{bmatrix}, \theta = -45° \quad (1)$$

Subjects were instructed that there will be a change made to the controls but were not instructed on the nature of the change. This perturbation is classified as a feedforward perturbation, since it is a static modification made to the cursor kinematics.

Subjects were divided into two groups, and each group participated in two sessions spaced seven days apart. Group A used their left and right hands to control cursor position and orientation, respectively during session 1, and Group B used their right and left hands for position and orientation. During the second session, the groups swapped controls.

C. Tracked Measurements

The cursor's x and y position and orientation are recorded at 60 Hz and filtered using a 10-sample moving average filter. The number of successes and misses is tracked, with misses being counted as tasks taking longer than 10 seconds or those which the subject fails to control the cursor simultaneously across all DoF. In addition, several other metrics are tracked which are classified as feedforward or feedback measurements.

The feedforward measurements are derived from phenomenon that do not involve compensation based on sensory feedback. Movement onset time is computed as the time from the task start cue to the first instance that the cursor's tangential velocity exceeds 10% of the task's maximum velocity. Translational directional error (TDE, θ_{TDE}) is measured as the angular difference between the line of best fit of the trajectory within the starting area and the straight-line path to the target position.

$$\theta_{TDE} = \tan^{-1}(\mathrm{p}_1) - \tan^{-1}(\mathrm{y_t}/\mathrm{x_t}) \quad (2)$$

p_1 is the slope of the best-fit line to the initial trajectory, found using the least-squares method, and $\mathrm{x_t}, \mathrm{y_t}$ are the target x and y positions.

The primary feedback measurement is path length ratio, η. This value is calculated as the ratio of the length of the shortest path to the target to the length of the path taken by the subject. The measured path length is computed by numerically summing the hypotenuses connecting each data point. For simplification, we approximate the 0.8-unit square target region as a 0.4-unit radius circle, so the shortest path length to the target is 13.6 units. Since achieving the shortest path would require subjects to adjust their controls in response to the movement of the cursor, η is regarded as a feedback measurement.

In addition to the feedforward and feedback measures, two timing metrics are tracked named the task completion time and completion synchrony time. The instant that the cursor's x and y positions are within 0.4 units of the target cursor is measured, along with the instant that the cursor's orientation is within 10° of the target orientation. The task completion time is defined as the time that both criteria are met simultaneously. The completion synchrony time is calculated as the difference between the positional completion time and rotational completion time.

III. Results

Fig. 2 shows the TDE averaged across subjects for each task for group A (black triangles) and group B (red circles), with a line fit to the plotted data for baseline (left) and perturbation (right). For statistical analysis a linear fit was computed for each subject individually and compared between groups using a t-test for each trial with corrected $\alpha = 0.025$. No significant difference was found between the slopes of the baseline trial ($p = 0.583$), indicating that any baseline learning rates were consistent on dominant and nondominant hands. It is worth noting that group A appears to trend away from zero towards a larger TDE, while group B appears to

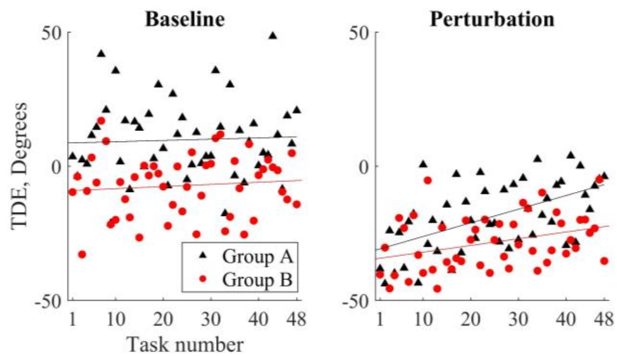

Figure 2. Translational Directional Error (TDE) during baseline and perturbed trials in Session 1. The average TDE across subjects for each task is plotted, with the line of best fit to all tasks and subjects overlaid. No significant difference is found in group A and B slope in baseline trial ($p = 0.583$), but significant differences are present during perturbation trials ($p = 0.0062$).

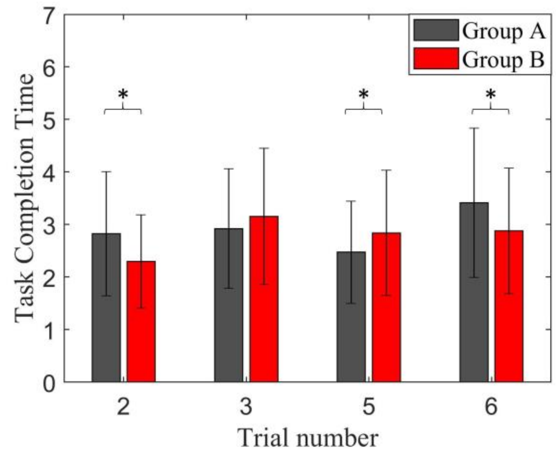

Figure 3. Task completion time for baseline (Trial 2 and 5) and perturbation (trial 3 and 6) trials of session 1 (Trial 2 and 3) and session 2 (5 and 6).

trend towards a lower TDE, towards zero. These slopes, however, were not statistically different from a mean of zero by t-test with $\alpha = 0.0125$ ($p_A = 0.287$, $p_B = 0.115$). Both groups began the perturbation trial near the same TDE and showed improvement towards zero. A significant difference was found between slope for group A, 0.509 ± 0.078°/task, and group B, 0.251 ± 0.136°/task ($p = 0.0062$), indicating that the nondominant feedback hand recovered from the perturbation faster than the dominant feedforward hand. The difference in TDE between baseline and perturbation trials was larger in group A (-28.62 ± 3.41°) than in group B (-21.19 ± 4.31°), indicating that the feedforward hand was more robust to the feedforward perturbation ($p = 0.0163$).

Fig. 3 examines the path ratio across subjects for each group in the baseline trial (left) and perturbation trial (right). Path ratio is averaged across subjects for each task with group A in black triangles and group B in red circles. The fit line is computed for the data points averaged across subjects, however for statistical comparisons it was calculated for each subject individually. The statistical similarity of the slope of the best-fit line suggests that each hand performs equivalently in baseline path ratio ($p = 0.869$). The perturbation trial shows the statistical difference in performance ($p = 0.0026$), but the slopes of group A (2.6·10-3 ± 0.68·10-3) and group B (2.1·10-3 ± 1.5·10-3) remain equal ($p = 0.483$). This implies that the two hands have equal learning rates in response to the perturbation for the feedback measurement.

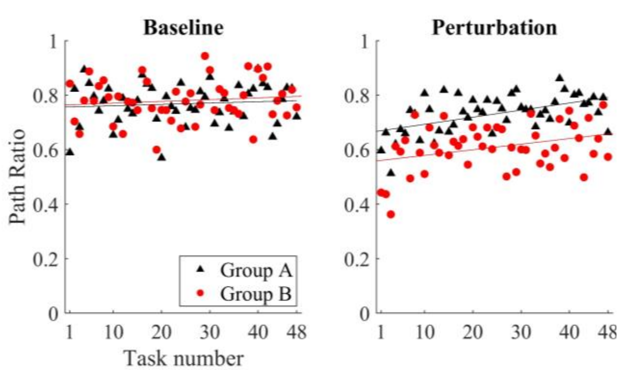

Figure 4. Path ratio during baseline and perturbation trials in session 1. Baseline performance was identical between groups ($p = 0.869$), but Group B was significantly more impacted by the perturbation than Group A ($p = 0.0026$).

Task completion time for the baseline (trials 2 and 5) and perturbation (trials 3 and 6) trials of session 1 and 2 are shown in Fig. 4 for group A (gray) and group B (red). Significant differences between groups for each trial are marked, and were found using two-sample t-tests with Bonferroni-corrected $\alpha = 0.0165$. In session 1, group B's completion time of 2.30 ± 0.89s was significantly faster than that of group A, 2.82 ± 1.19s ($p \ll 0.0165$). Group A was faster than group B in the perturbation trial of session 1 with completion times of 2.92 ± 1.14s and 3.15 ± 1.29s, respectively, although this difference did not reach statistical significance ($p = 0.04$). Based on these results, the subjects performing the baseline tasks with their dominant, feedforward hand (group B) were faster than those using their nondominant, feedback hand. Group A yielded a statistically lower baseline completion time of 2.47 ± 0.97s compared to the completion time of group B of 2.84 ± 1.19s ($p \ll 0.0165$). This relationship was reversed in the perturbation trial, where group B's completion time of 2.88 ± 1.19s was significantly lower than that of group A, 3.41 ± 1.42s ($p \ll 0.0165$). This is in accordance with our hypothesis, which predicted that subjects controlling cursor translation with their dominant feedforward hand would be able to complete tasks faster than those using their nondominant hand.

IV. Discussion

In this study, we analyze the TDE and path ratio for subjects using the dominant and nondominant hands in perturbed and unperturbed tasks. We determined that the dominant hand was more robust to the perturbation than the nondominant hand in TDE, while the nondominant hand was stronger than the dominant hand in path ratio. Both the feedback/feedforward and stabilizing/predictive models agree that TDE would classify as a feedforward or predictive measure, and accurately predict that the dominant hand was more robust to the perturbation than the nondominant hand. However, the stabilizing/predictive model could view path ratio as a measure of trajectory shape rather than a measure of stability, and so predict that the dominant hand should outperform the nondominant hand under perturbation. Our results show that the nondominant hand was more robust to perturbation than the dominant hand in path ratio, which aligns with the predictions of the feedback/feedforward framework. However, prior work with individuals with stroke performing unimanual reaching motions has demonstrated this trajectory shaping effect in equivalent trajectory measures [6], [7], and has demonstrated the framework as a whole in additional studies [5], [12], [13]. This experiment primarily focuses on a hand-based task, while prior work on the stabilizing/predictive model has been applied to arm reaching. We also studied a bimanual task that requires simultaneous coordination between both limbs, and therefore both hemispheres. Extensive research has demonstrated that activation patterns in the motor system differ between unimanual and bimanual tasks [14] in fMRI [15]–[17] and EEG [18]. The central motor system, therefore, may alter its control paradigm for bimanual movements. The effects of this study, however, must first be tested on a larger subject population.

Prior work covered in the introduction demonstrated that task models learned on one hand can be accessible to the opposite hand. These studies were within one experimental session, so there was no data on whether this was a temporary or lasting effect. Our results determine that no transferable model of the bimanual joystick task is available to the opposite limb after seven days without practice. This raises the question of how long a transferable model is present after practicing, and if that time can be extended or the effect amplified by repetitive practice. An fMRI study has found activations of fast learning patterns of habituation and enhancement within the first session, with slow learning patterns dominating by week 3 of practice [19]. Our experiment design, therefore, may not have given sufficient practice to stimulate slower, more persistent learning patterns. This can be studied by giving subjects several sessions of practice before the break period, or by shortening the break period until learning effects are present.

Model transference of learned dynamics can have several applications in rehabilitation and assistive robotics. Mirror therapy and other contralateral rehabilitation techniques leverage similar effects to stimulate functional recovery in an affected limb by exercising the unaffected limb [20], [21]. Interlimb transference has been evaluated in prosthetics users with negative results [22], however these methods may be improved by integrating some of the considerations outlined above. Future training paradigms for prosthetic or assistive exoskeleton systems may benefit from knowledge of model transfer, leading to more fluid lifelike control of these devices.

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