Evolution of Human Upper-Limb Manipulability During Spiral Drawing: A Comparative Study of Dominant and Non-Dominant Hands

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***Abstract*—This paper investigates the evolution of human upper-limb manipulability during the acquisition of a novel spiral drawing task. By comparing performance between the dominant and non-dominant hands across multiple trials, the study aims to reveal insights into differential motor learning dynamics. Manipulability indices are computed using a Jacobian-based analysis of joint angles, and learning behaviors are modeled through exponential fitting. The findings hold potential significance for advancing the design of human-robot collaborative systems.**

I. Introduction and Literature Survey

II. Introduction and Literature Survey

Understanding human motor adaptation is critical for designing intuitive and efficient human-robot collaboration systems. When humans interact with complex tasks or external constraints, they modify their movement strategies dynamically, adjusting factors such as muscle activation patterns, limb impedance, and trajectory planning. A key quantity to characterize upper-limb capability during such tasks is *manipulability*, which represents the ease with which the end-effector (e.g., the hand) can move in various directions [1].

Manipulability analysis, initially developed for robotic manipulators, has been extended to study human biomechanics, providing insights into reachable workspaces, movement efficiency, and adaptability. Investigating how manipulability evolves during task learning reveals information about neuromotor control strategies and the plasticity of the musculoskeletal system.

Hand dominance plays a crucial role in motor control performance. Several studies have shown that the dominant limb generally exhibits superior coordination and movement smoothness compared to the non-dominant limb [2]. However, with repeated practice, non-dominant limbs can adapt and reduce performance gaps, demonstrating the remarkable plasticity of motor learning systems.

Motor learning, particularly during the acquisition of complex tasks, often follows an exponential improvement curve characterized by rapid initial gains and slower refinements [3]. Quantifying learning through manipulability indices, rather than simple error metrics, offers a richer view of skill acquisition.

These observations have significant implications for human-robot interaction (HRI). Robotic partners designed to work closely with humans must account for the evolving capabilities of human users, adapting assistance levels as motor skills develop.

In this project, we investigate the evolution of upper-limb manipulability during a novel spiral drawing task, comparing dominant (right) and non-dominant (left) hand performance across multiple trials. This analysis aims to shed light on differential learning dynamics and adaptability across limbs, and its implications for future human-robot collaborative designs.

III. Problem Statement and Objectives

Humans possess an extraordinary ability to adapt their motor control strategies when faced with novel tasks or external constraints. One fundamental aspect of this adaptation is the modulation of upper-limb *manipulability*, which characterizes the ease of movement in various directions and reflects the underlying coordination between different joints.

In this project, we seek to investigate how upper-limb manipulability evolves during the acquisition of a novel and complex motor task: *spiral drawing*. Furthermore, we aim to compare this evolution between the dominant (right) and non-dominant (left) hands, thereby exploring asymmetries in motor learning and control between limbs.

The specific problem we address is:

> *How does the manipulability of the human upper limb change across repeated practice of a spiral drawing task, and how does this change differ between the dominant and non-dominant hands?*

Through systematic experimentation involving multiple trials for each arm, we intend to quantify learning curves based on manipulability indices. The manipulability at each time instance will be computed via Jacobian-based analysis of shoulder and elbow joint angles, and its evolution over trials will be modeled using exponential learning functions.

The primary objectives of the study are as follows:

1) To measure and analyze the manipulability of the human upper limb during spiral drawing tasks across successive trials.
2) To model the learning process by fitting exponential curves to the manipulability data.
3) To compare learning dynamics between the dominant and non-dominant hands in terms of learning rates and final performance levels.
4) To draw insights into the implications of limb-specific motor adaptation for human-robot collaborative system design.

By accomplishing these objectives, the project aims to contribute to a deeper understanding of motor learning phenomena and their applications in developing safer and more adaptive human-robot interaction frameworks.

IV. Experimental Methodology

A. Participant and Experimental Setup

Due to time constraints, the study was conducted with a single right-handed participant. The participant was instructed to perform a spiral drawing task while maintaining strict planar arm motion. To minimize the influence of wrist joints and ensure that movements were predominantly driven by the shoulder and elbow, the wrist was locked using a supportive brace.

Motion capture data was collected using a Vicon system equipped with an upper-limb Plug-in Gait model. Reflective markers were placed at anatomical landmarks following the standard Plug-in Gait protocol, including the thorax, upper arm, forearm, and hand segments. The system recorded three-dimensional marker trajectories and calculated segment orientations at a sampling frequency of 200 Hz.

B. Data Acquisition and Preprocessing

The raw data exported from Vicon included segmental Euler angles for each upper-limb joint, represented relative to their parent segments. Specifically, the thorax-to-upper-arm and upper-arm-to-forearm rotations were extracted. Vicon reported these rotations following a YXZ Euler sequence.

For the purposes of this study, only the Z-axis rotations were considered, corresponding to planar flexion/extension motions required for spiral drawing. This assumption was valid given the wrist immobilization and planar movement constraint imposed during trials.

Each side (dominant and non-dominant) was tested across ten repeated trials.

To obtain smooth and reliable joint angle trajectories, the following preprocessing steps were applied:

1) Smoothing of Joint Angles: Raw shoulder and elbow Z-axis angles often contained high-frequency noise inherent to optical motion capture systems. To mitigate this, a Savitzky-Golay filter was applied to each trajectory. The filter preserves important features such as peak amplitudes and phase relationships while reducing noise.

Mathematically, given a discrete signal $x[n]$, the Savitzky-Golay filter fits a low-degree polynomial (typically third-order) over a moving window of fixed size and evaluates the smoothed value at the center point. For this study:

- Window size: 51 samples (equivalent to approximately 0.25 seconds)
- Polynomial order: 3

This smoothing step ensured that the joint angle time-series remained faithful to the underlying movement patterns while suppressing measurement noise.

C. Computation of Manipulability

Using the smoothed shoulder and elbow Z-axis angles $\theta_1(t)$ and $\theta_2(t)$ at each time step, a two-link planar arm model was assumed. Forward kinematics were computed based on nominal link lengths ($L_1 = 0.26$ unit and $L_2 = 0.31$ unit). The position of the end-effector (hand) was calculated as:

$$x(t) = L_1 \cos(\theta_1(t)) + L_2 \cos(\theta_1(t) + \theta_2(t)) \tag{1}$$

$$y(t) = L_1 \sin(\theta_1(t)) + L_2 \sin(\theta_1(t) + \theta_2(t)) \tag{2}$$

The Jacobian matrix $J(t)$ at each time step was constructed as:

$$J(t) = \begin{bmatrix} -L_1 \sin(\theta_1(t)) - L_2 \sin(\theta_1(t) + \theta_2(t)) & -L_2 \sin(\theta_1(t) + \theta_2(t)) \\ L_1 \cos(\theta_1(t)) + L_2 \cos(\theta_1(t) + \theta_2(t)) & L_2 \cos(\theta_1(t) + \theta_2(t)) \end{bmatrix} \tag{3}$$

The manipulability index $w(t)$, representing the instantaneous ability of the arm to generate end-effector velocities in arbitrary planar directions, was computed as:

$$w(t) = \sqrt{\det(J(t)J^T(t))} \tag{4}$$

Thus, for each trial, a time-series of manipulability indices was obtained, forming the basis for learning curve analysis and dominant vs non-dominant arm comparison.

V. Results

This section presents the experimental results obtained from the spiral drawing task. All figures have been placed toward the end of the document to maintain formatting consistency.

A. Hand Trajectory during Spiral Drawing

Figure 1 shows a sample hand trajectory captured during a right-hand trial (Trial 9). Although the participant was instructed to maintain strict planar motion with the wrist locked, minimal out-of-plane movements occurred, resulting in slight distortions in the trajectory. Despite this, the overall spiral pattern is clearly evident in the recorded endpoint path.

The observed deviations are common in human motor control tasks, especially when constraining joint degrees of freedom voluntarily rather than mechanically. Nevertheless, the gross spiral shape was successfully traced, allowing meaningful analysis of joint behavior and manipulability evolution.

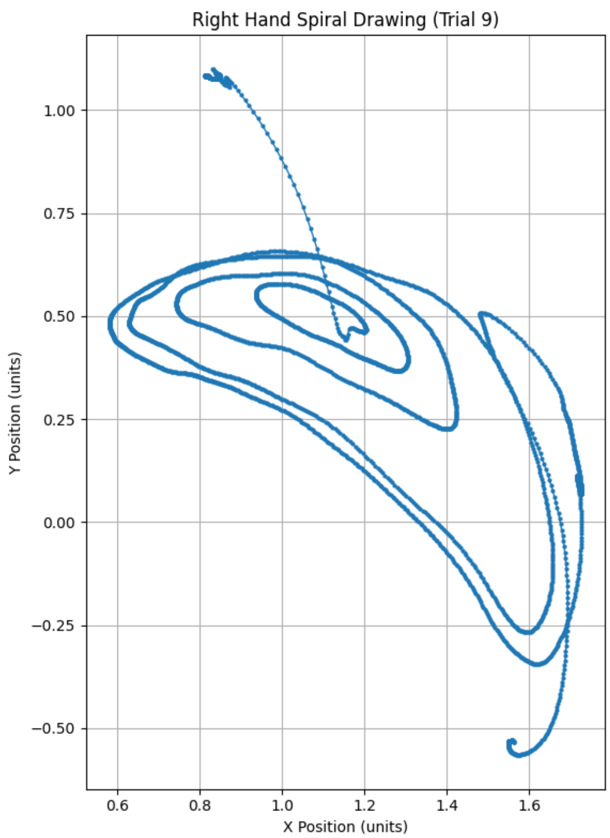

Fig. 1. Hand trajectory during right-hand spiral drawing task (Trial 9). Minor deviations from the ideal planar motion are observed, but the overall spiral structure is maintained.

B. Manipulability Evolution during Trials

Figure 2 and Figure 3 illustrate the evolution of manipulability index over time across different trials for the dominant (right) and non-dominant (left) hands, respectively. Early trials and late trials are compared to observe adaptation effects.

In the right-hand trials (Figure 2), a relatively consistent manipulability profile is maintained across trials, with fluctuations reducing toward later stages. In the left-hand trials (Figure 3), greater fluctuations are observed during initial trials, which slightly stabilize by the final trials, indicating gradual motor adaptation.

Furthermore, Figure 4 and Figure 5 compare manipulability evolution between the dominant and non-dominant hands for early and late trials respectively. Initially, the dominant hand exhibits higher and more stable manipulability values compared to the non-dominant hand (Figure 4). However, by the final trials (Figure 5), the gap between the two hands reduces, suggesting significant motor learning and adaptation by the non-dominant hand over practice sessions. We can also see that across trials the dominant hand has started optimizing for time, while the non-dominant hand is still trying to learn the pattern.

Overall, these results are consistent with expected motor learning behavior, where the dominant hand starts at an advantage but the non-dominant hand improves substantially with repetition.

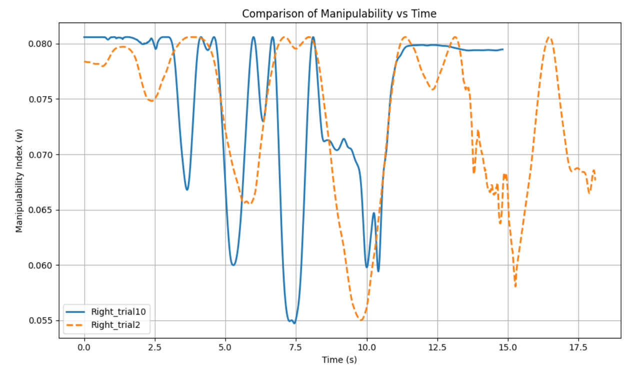

Fig. 2. Comparison of manipulability index over time for Right_trial2 and Right_trial10. Minor reduction in fluctuations suggests increased control with practice.

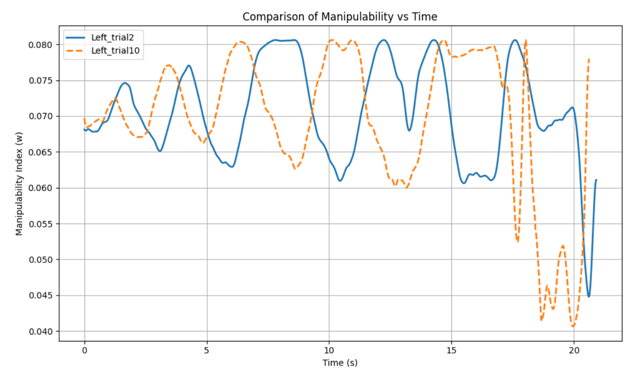

Fig. 3. Comparison of manipulability index over time for Left_trial2 and Left_trial10. Gradual stabilization observed with practice.

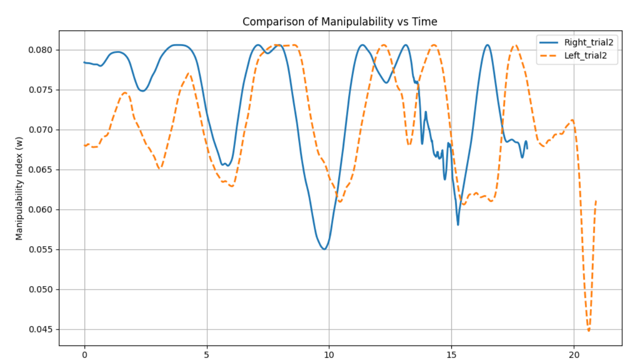

Fig. 4. Comparison of manipulability index over time between Right_trial2 and Left_trial2. Dominant hand shows higher manipulability and lower fluctuations.

C. Manipulability Ellipsoids Analysis

To further understand the directional movement capabilities of the arm during the task, velocity manipulability ellipsoids

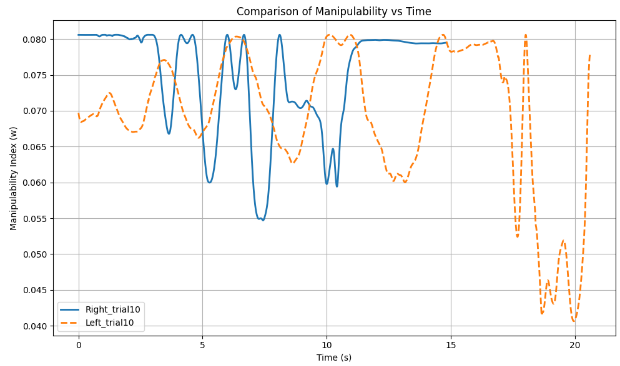

Fig. 5. Comparison of manipulability index over time between Right_trial10 and Left_trial10. The gap between hands reduces, showing adaptation by the non-dominant hand.

were plotted at selected points during representative trials for the dominant and non-dominant hands.

Figure 6 shows the manipulability ellipsoids for the right hand (dominant) during Trial 4, while Figure 7 shows the ellipsoids for the left hand (non-dominant) during Trial 7. The ellipsoids represent the reachable end-effector velocities when a unit norm joint velocity vector is applied, indicating the ease of motion in different directions.

In both hands, the ellipsoids exhibit clear anisotropy, indicating directional preferences in movement ability at various points in the task. The dominant hand ellipsoids (Figure 6) tend to maintain more consistent shapes and sizes across samples, suggesting greater stability and more isotropic control. Conversely, the non-dominant hand ellipsoids (Figure 7) show greater variability, with some ellipsoids becoming more elongated, reflecting less uniform movement capabilities.

These observations are consistent with the manipulability time-series and learning curve analyses, where the dominant hand achieved faster stabilization and better isotropy, while the non-dominant hand exhibited ongoing adaptations across trials.

D. Animated Visualization of Arm Motion and Manipulability Evolution

To better visualize the dynamic behavior of the upper limb during the spiral drawing task, an animated simulation was created. The animation simultaneously illustrates the 2R planar arm movement and the evolution of the velocity manipulability ellipsoid at the hand (end-effector) position.

At each timestep, the joint angles (shoulder and elbow) were used to reconstruct the limb configuration. The corresponding velocity manipulability ellipsoid was computed from the Jacobian matrix, capturing how the arm's capability to generate end-effector velocities varied throughout the task.

The animation reveals several important aspects of motor behavior:

- The shape and orientation of the manipulability ellipsoid change dynamically as the arm moves through different postures.

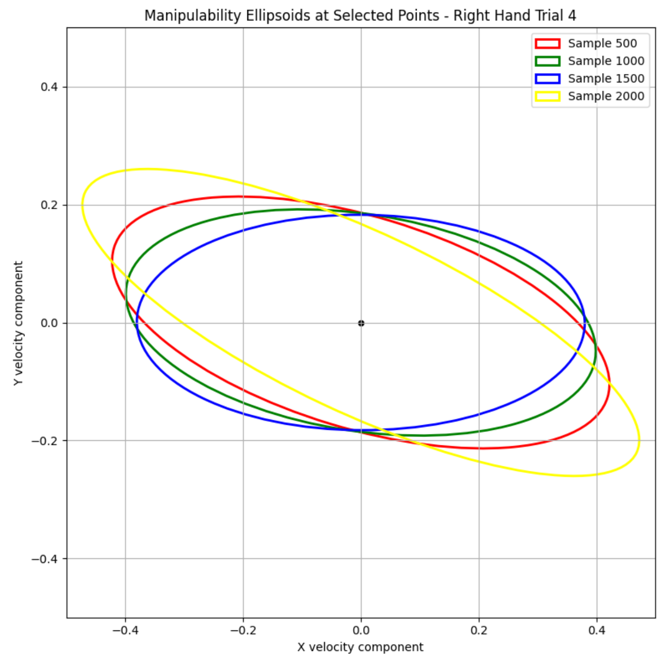

Fig. 6. Velocity manipulability ellipsoids at selected points during Right Hand Trial 4. Consistent ellipsoid shapes indicate stable, isotropic control.

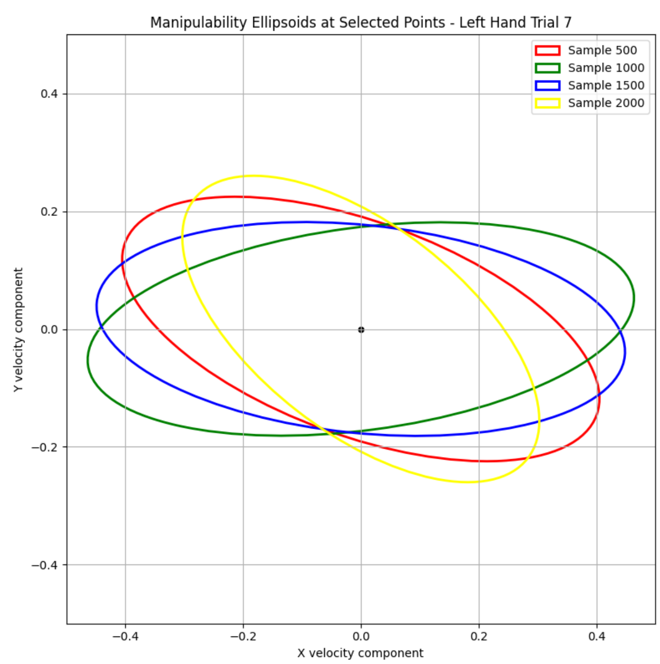

Fig. 7. Velocity manipulability ellipsoids at selected points during Left Hand Trial 7. Greater variability indicates ongoing adaptation and directional preferences.

- Ellipsoids that are more circular represent configurations with isotropic movement capability, whereas elongated ellipsoids indicate directional biases.
- Over the course of the task, the dominant hand tends to maintain more consistently shaped ellipsoids, reflecting greater control stability, while the non-dominant hand

shows more variability.

This dynamic visualization complements the static analyses presented earlier by offering an intuitive, time-resolved view of how manipulability evolves during complex motor learning tasks.

The generated animations are included as supplementary materials[1].

E. Learning Curves and Exponential Fitting

To quantify motor learning during the spiral drawing task, we analyzed the evolution of the mean manipulability index across successive trials. For each trial, the average manipulability value was computed by taking the mean of the manipulability time-series obtained during that trial.

Manipulability is an important metric because it reflects the ease with which the hand can be moved in different planar directions. A higher manipulability index indicates a more isotropic and efficient configuration for producing endpoint motions. As the participant adapts and improves control strategies, we expect the manipulability to increase and stabilize across trials.

It is important to note that while the general trend indicates improvement, occasional decreases in mean manipulability across certain trials were observed. This phenomenon may be attributed to the participant's parallel focus on minimizing task completion time, which was also recorded during the experiments.

As movement speed increases, humans often prioritize task efficiency over maintaining optimal limb configurations, leading to potential sacrifices in manipulability. Such trade-offs between speed and movement quality are well-documented in motor control literature and are characteristic of natural learning strategies where multiple objectives (accuracy, effort, speed) are being optimized simultaneously.

The trial-wise mean manipulability values were first visualized without fitting (Figure 8). This raw data shows the general trend of improvement over trials for both hands.

To capture the underlying learning behavior quantitatively, the mean manipulability values were fitted with an exponential learning curve model:

$$y(t) = a(1 - e^{-bt}) \tag{5}$$

where:

- $y(t)$ is the mean manipulability at trial number t,
- a is the asymptotic final performance (maximum achievable manipulability),
- b is the learning rate (higher b indicates faster learning).

This model was chosen because it reflects the typical learning dynamics observed in human motor learning studies [3].

Figure 9 shows the raw points along with the fitted exponential curves for both the dominant (right) and non-dominant (left) hands.

The fitted parameters are summarized in Table I.

[1]Animations available at https://github.com/Dkthestoryteller/HRI_Project2/blob/main/RightHand_Animation.gif

TABLE I
FITTED EXPONENTIAL LEARNING CURVE PARAMETERS

Hand	Final Performance (a)	Learning Rate (b)
Left (Non-dominant)	0.072	3.275
Right (Dominant)	0.075	18.152

As observed, the dominant (right) hand achieves slightly higher final manipulability (a = 0.075 vs 0.072) and exhibits a significantly higher learning rate (b = 18.152 vs 3.275). This indicates that the dominant hand learned the task much faster, reaching its stable performance level within fewer trials.

The non-dominant hand, while slower to adapt (lower b), nonetheless shows clear evidence of learning, reducing the initial performance gap over repeated practice.

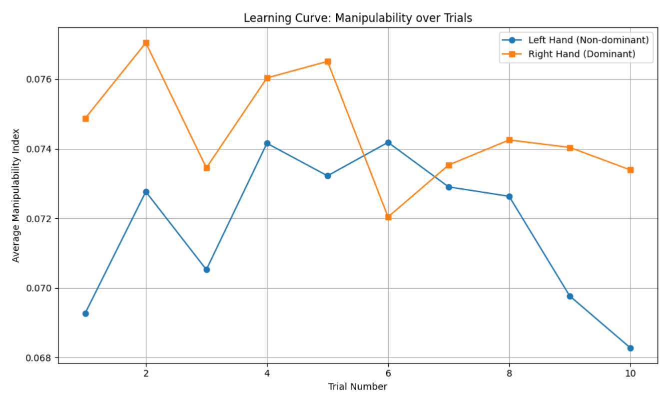

Fig. 8. Learning curve: Trial-wise average manipulability values for dominant and non-dominant hands (raw).

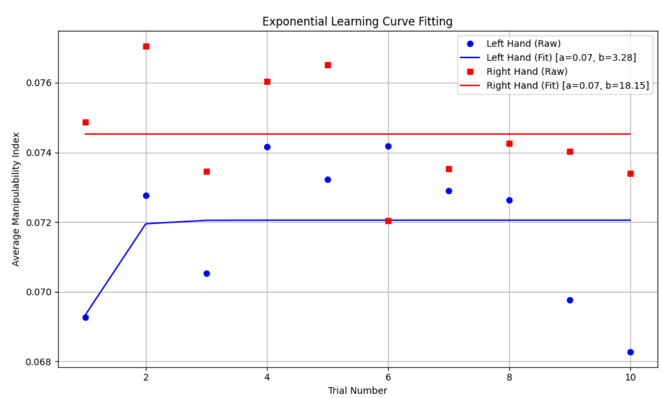

Fig. 9. Exponential curve fitting of learning behavior: Raw mean points and fitted curves for dominant and non-dominant hands.

VI. DISCUSSION

This study investigated the evolution of upper-limb manipulability during the acquisition of a novel spiral drawing task, comparing dominant and non-dominant hands. Several key observations emerged from the experimental results.

Firstly, as expected, the dominant (right) hand initially demonstrated superior performance in terms of higher mean manipulability values and faster learning rates. The fitted learning curves showed that the dominant hand reached a stable manipulability value within fewer trials (higher b parameter), consistent with previous findings on handedness asymmetries in motor control. This advantage likely stems from habitual usage patterns, better-developed neuromuscular control, and greater movement experience with the dominant arm.

Secondly, although the non-dominant (left) hand started with lower initial manipulability, it exhibited clear improvements across trials, as reflected in the upward trend of mean manipulability and the exponential learning behavior. This demonstrates the inherent plasticity of the human motor system, where even less-practiced limbs can adapt effectively to novel task demands with sufficient repetition.

An important observation was that the mean manipulability did not monotonically increase across trials. Instead, occasional decreases were recorded. One plausible explanation for this phenomenon is the participant's concurrent focus on minimizing task completion time, as time was being recorded during the trials. When participants attempt to move faster, they often sacrifice optimal joint configurations in favor of task speed, resulting in lower manipulability. Such behavior reflects well-documented trade-offs between speed, accuracy, and movement quality in motor learning literature [4].

These findings suggest that while manipulability is a valuable proxy for movement efficiency, it is only one aspect of motor control. Real-world motor learning involves balancing multiple, sometimes competing objectives, including minimizing effort, maximizing speed, and maintaining accuracy.

It is also important to recognize limitations of the current study. Due to project time constraints, only a single participant was tested. Thus, the results cannot be generalized without further validation across a larger subject pool. Furthermore, while planar movement was encouraged by wrist immobilization, minor out-of-plane movements may have introduced some variability in the results.

Future work could extend this study by incorporating explicit speed-accuracy measurements, using external perturbations to challenge stability further, or exploring muscle activation strategies via electromyography (EMG). Such extensions would provide a more comprehensive understanding of how manipulability, speed, and effort co-evolve during skill acquisition, and would contribute valuable insights for the design of adaptive human-robot collaboration systems.

VII. Conclusion

This project explored the evolution of upper-limb manipulability during the learning of a spiral drawing task, with a comparative analysis between dominant and non-dominant hands.

We measured and analyzed the manipulability index over successive trials using joint angle data derived from motion capture recordings. The learning process was quantitatively modeled by fitting exponential curves to the mean manipulability values across trials, capturing the rapid initial improvements and slower later refinements characteristic of motor learning.

A clear comparison between the dominant and non-dominant hands revealed expected asymmetries: the dominant hand exhibited faster learning rates and achieved higher final manipulability values. Nevertheless, the non-dominant hand demonstrated significant adaptation over time, reducing the initial performance gap.

Interestingly, across trials, the dominant hand appeared to transition toward optimizing task completion time — suggesting a shift to higher-level performance criteria — whereas the non-dominant hand was still primarily engaged in refining its basic movement kinematics. This observation highlights the sequential nature of motor learning, where mastering efficient motion precedes optimization for secondary objectives such as speed.

Finally, the study offered insights into human motor adaptation strategies relevant for human-robot collaboration system design. Understanding how manipulability evolves under self-imposed complexity and practice can guide the development of robotic partners that adaptively assist human users based on their motor learning stages.

Future work can expand these findings by incorporating larger participant groups, exploring multi-objective learning trade-offs explicitly, and integrating muscle activity measurements to further deepen our understanding of human movement adaptation.

VIII. Data and Code Availability

All datasets, processing scripts, and animation codes used in this study have been made publicly available in the following GitHub repository:

https://github.com/Dkthestoryteller/HRI_Project2

This repository contains:

- Processed joint angle datasets (CSV format)
- Python scripts for data preprocessing, manipulability analysis, and visualization
- Animation scripts for dynamic 2R arm and manipulability ellipsoid generation

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