HRI Project 2

Limb Impedance Estimation During a Constrained Haptic Tracking Task with Force Perturbation

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1 Introduction and Literature Survey

Studying human limb impedance through perturbation experiments is a pivotal pursuit in biomechanics and human movement analysis. Human limb impedance, which characterizes its resistance to external forces and dynamic responses to applied perturbations, is influenced by multifarious factors such as musculoskeletal structure, neural control, and the mechanical properties of soft tissues. The Central Nervous System (CNS) intricately regulates the mechanical impedance of the musculoskeletal system to manage joints with redundant muscles, including agonists and antagonists. Hogan and Hondori et. al.[3]. demonstrated that co-activation of antagonist muscles is pivotal in generating mechanical impedance, essential for executing both manual and bimanual tasks. Notably, optimizing mechanical impedance becomes imperative in scenarios of dynamically unstable tasks, as highlighted by Burdet et. al.[2] .This project focuses on quantifying the apparent mechanical impedance (stiffness, damping, inertia) of a human upper limb during a path-following task while subjected to externally applied random force perturbations. This specific problem statement draws from existing work on quantifying human limb impedance and compensation for imposed dynamics, aiming to characterize the human's dynamic response in a collaborative-like scenario where external forces are actively applied.

2 Methodology

2.1 Mechanical Impedance

Mechanical impedance is a fundamental concept in biomechanics that quantifies a system's resistance to motion when subjected to external forces. In the context of human motor control, limb impedance specifically characterizes the dynamic relationship between applied forces and resulting motion at a limb endpoint, such as the hand holding a haptic device. This impedance arises from a combination of passive musculoskeletal properties (like the elasticity of muscles and connective tissues, and joint viscosity) and active neural control (muscle activation levels, including co-contraction of antagonist muscles).

The mechanical impedance of a limb is often modeled as a combination of three primary components:

- **Stiffness (K):** Represents the resistance to displacement. A stiffer limb requires a larger force to achieve a given displacement.
- **Damping (D):** Represents the resistance to velocity. A more damped limb dissipates energy more quickly and resists faster movements.
- **Inertia (M):** Represents the resistance to acceleration, primarily due to the mass distribution of the limb segments.

A common linear, time-invariant model used to represent this relationship in 3D space is:

$$F = Kx + Dv + Ma + \text{bias}$$

where F is the force vector applied to or by the limb endpoint, x, v, and a are the 3D position, velocity, and acceleration vectors of the endpoint, respectively. K, D, and M are 3x3 matrices that describe the directional properties of stiffness, damping, and inertia, and bias is a constant force vector that might represent gravity or a tonic muscle activation.

Measuring human limb impedance accurately presents several challenges. These include the non-linear and time-varying nature of biological tissues, the influence of active neural control which can adapt rapidly, the difficulty in isolating the limb's response from external forces (like device dynamics), and the need for precise measurement of both forces and motion.

2.2 Experiment Design

The experimental setup involves a human participant interacting with a haptic device while viewing a visual interface on a computer screen. The haptic device used is assumed to be capable of measuring 3D position and applying 3D forces. The visual interface displays a simple, straight-line path from a designated start point to an end point. The participant's primary task is to move the haptic device's end-effector, represented by a cursor on the screen, accurately along this straight path from start to finish.

Figure 1: Geomagic Touch Haptic Device

To investigate the user's impedance characteristics, the experiment incorporates force perturbations applied through the haptic device during specific trials. This experiment employs **random force perturbations**. These perturbations are generated as a 3D force vector with components (Fx, Fy, Fz) that change randomly at a specified frequency within a defined magnitude range. This broadband excitation is intended to probe the user's dynamic response across a wider range of frequencies and motion states, which is more suitable for system identification.

The experiment is structured into multiple batches of trials to compare performance and analyze impedance under different conditions. The typical experimental conditions include:

- **Baseline (No Perturbation):** Trials where no active force feedback is applied by the experiment software (other than potential implicit forces from the path guidance if implemented). 10 trials with no perturbation, participant just performs ordinary path tracking with the haptic device stylus.
- **Perturbation (Random Force):** Trials where random force perturbations are applied for a specified duration within the trial. The force is random in magnitude and direction and is applied for 5 seconds after the trial is started. Participant has to complete the path tracking with minimum deviation from the path. There are 30 such trials.

The forces applied during the perturbation are randomly chosen from within 0.5N to 2N range and the values are stored in an array for the Regression analysis.

2.3 Data Acquisition

Data acquisition is performed synchronously with the experiment's visual display update rate, which is set by the Pygame frame rate (FPS = 100). This rate also dictates the data logging frequency. During each trial, the following key variables are recorded at every time step:

- **Device Position:** The 3D position (x, y, z) of the haptic device's end-effector in the device's coordinate system. This is directly measured by the haptic device hardware.
- **Device Velocity:** The 3D velocity vector (v_x, v_y, v_z) of the device's end-effector. While some haptic devices provide velocity measurements, in this setup, velocity is calculated offline from the recorded position data using numerical differentiation.
- **Commanded Force:** The 3D force vector $(F_{commanded,x}, F_{commanded,y}, F_{commanded,z})$ that the experiment software commands the haptic device to exert on the user.

- **Assumed User Force: Based on the simplifying assumption ($F_{\text{user}} = -F_{\text{commanded}}$),** this variable represents the estimated force exerted by the user. It is calculated offline as the negative of the commanded force.
- **Cursor Position:** The 2D position of the cursor on the screen, mapped from the 3D device position using defined scaling and offset parameters.
- **Path Following Errors:** Metrics such as tracking error (distance from the cursor to the closest point on the path) to compare the before and after differences between participant response.
- **Perturbation Status:** A boolean flag indicating whether the random force perturbation is currently active.

All recorded and calculated data for each trial within a batch are saved into a single CSV file. These CSV files are organized into subfolders named after the corresponding experimental batch within a base logging directory.

2.4 Data Analysis

The collected data undergoes offline analysis using Python scripts. The initial steps involve loading the data from the CSV files for each batch into data structures suitable for processing (e.g., pandas DataFrames).

Performance metrics are calculated for each trial and averaged across trials within a batch. These include the average tracking error, average absolute cross error, and average device velocity magnitude, typically computed within a defined analysis window that excludes the start and end phases of the trial.

For the impedance analysis, accurate velocity and acceleration data are crucial. Velocity is calculated from the raw position data using the difference between consecutive position samples divided by the time step. Acceleration is then calculated from the velocity data using a similar numerical differentiation approach. To minimize the amplification of noise inherent in numerical differentiation, a moving average smoothing filter is applied to the velocity components before calculating acceleration.

The core of the simplified impedance analysis relies on estimating the parameters (K, D, M, and bias) of the linear impedance model using Ordinary Least Squares (OLS) multivariate linear regression. The dependent variables for the regression are the components of the assumed user force ($F_{\text{user},x}, F_{\text{user},y}, F_{\text{user},z}$), which are taken as the negative of the commanded forces. The independent variables are the corresponding components of device position (x_i), velocity (v_i), and acceleration (a_i), along with a constant term to estimate the bias vector. The regression is performed separately for each force component. The coefficients obtained from the regression for $F_{\text{user},x}$ form the first row of the K, D, and M matrices (and the first element of the bias vector), and similarly for $F_{\text{user},y}$ and $F_{\text{user},z}$.

It is important to acknowledge the significant limitation of this method: the assumption $F_{\text{user}} = -F_{\text{commanded}}$. This assumption ignores the passive dynamics (stiffness, damping, and inertia) of the haptic device itself, as well as the complex, non-linear, and adaptive nature of human motor control. Therefore, the resulting K, D, and M matrices represent the *apparent* impedance of the combined human-device system under the commanded force, rather than the isolated biological impedance of the human limb.

Finally, the estimated K, D, and M matrices are visualized as 3D ellipsoids and their 2D projections onto the principal planes (XY, XZ, YZ). While a true impedance ellipsoid requires a positive definite matrix, the visualization uses the square root of the absolute eigenvalues to represent the directional "strength" of the estimated linear relationship, providing a qualitative understanding of how the apparent impedance varies with direction.

2.5 Experiment Design and Protocol

The experimental setup involves a human participant interacting with a haptic device while viewing a visual interface on a computer screen. The haptic device used is assumed to be capable of measuring 3D position and applying 3D forces. The visual interface displays a simple, straight-line path from a designated start point to an end point. The participant's primary task is to move the haptic device's end-effector, represented by a cursor on the screen, accurately along this straight path from start to finish.

To investigate the user's impedance characteristics, the experiment incorporates force perturbations applied through the haptic device during specific trials. This experiment employs **random force perturbations**. These perturbations are generated as a 3D force vector with components (Fx, Fy, Fz) that change randomly at a specified frequency within a defined magnitude range. This broadband excitation is intended to probe the user's dynamic response across a wider range of frequencies and motion states, which is more suitable for system identification.

The experiment is structured into multiple batches of trials to compare performance and analyze impedance under different conditions. The typical experimental conditions include:

- **Baseline (No Perturbation):** Trials where no active force feedback is applied by the experiment software (other than potential implicit forces from the path guidance if implemented). These batches help establish a baseline for performance without external dynamic influences.
- **Perturbation (Random Force):** Trials where random force perturbations are applied for a specified duration within the trial. These batches are the primary focus for analyzing the human's dynamic response and estimating apparent impedance.

Each batch consists of a set number of trials under a single condition, and participants complete these batches sequentially. The experimental protocol involves:

1. **Participant Onboarding:** Participants are informed about the experiment's purpose and procedure, provide informed consent, and are seated comfortably at the experimental setup.
2. **Device Setup:** The haptic device is initialized and calibrated. The mapping between device space and screen space is confirmed.
3. **Instructions:** Participants receive clear instructions to follow the path as accurately as possible. They are informed about the different trial conditions (though not necessarily the exact nature or timing of the random forces) and the importance of maintaining a consistent grip.
4. **Batch Execution:** Participants complete the trials batch by batch. Before each trial, they position the cursor at the start point.
5. **Trial Execution:** During each trial, participants move along the path. In perturbation trials, random forces are applied during a predetermined time window. Trials end when the participant reaches the end point or if they choose to skip using a designated key.
6. **Breaks:** Appropriate breaks are provided between trials and batches to mitigate fatigue.

3 Experimentation

3.1 Participants

The experiment involves human participants.The number of participants would depend on the study's design and statistical power requirements. Ethical considerations, including informed consent and the right to withdraw, are addressed as in a formal experimental protocol.

Figure 2: Participant Trials

3.2 Procedure

The experimental procedure is structured around completing a series of trials organized into distinct batches. Participants are guided through the experiment batch by batch. Within each batch, participants perform multiple trials of the path-following task. The sequence of batches is predetermined, allowing for the comparison of performance and impedance characteristics under different experimental conditions (e.g., baseline vs. random perturbation). Each trial begins with the participant positioning the haptic device end-effector at a designated starting location on the screen. Upon initiation of the trial, the participant attempts to move the cursor along the straight-line path to the end point. Force perturbations, when applicable to the current batch, are applied during a specific time window within the trial duration.

3.3 Setup Process

Prior to the commencement of experimental trials, a standardized setup process is followed for each participant. This process includes the initialization of the haptic device hardware and software. The participant is comfortably seated in front of the computer screen, and the haptic device is positioned within easy reach. The shoulder joint of the participant is also securely held in the chair armrest to **lock it in** place. To reduce multijoint influence. The mapping between the haptic device's workspace and the screen coordinates is verified to ensure accurate visual feedback (200 pixels = 5cm). The participant is guided to the starting position for the first trial, and the experiment software is initiated to begin data acquisition and force rendering according to the defined batch sequence.

3.4 Challenges

Several challenges can be encountered during the execution of such a haptic experiment. Participant fatigue can also become a factor, potentially affecting performance and impedance characteristics, especially in longer experimental sessions. Ensuring a consistent grip on the haptic device is important for reliable force transmission and measurement, but can be challenging for participants to maintain perfectly. Technical challenges may include haptic device calibration drift, potential software glitches, or synchronization issues between the visual display, haptic rendering, and data acquisition systems. These factors can introduce variability and noise into the collected data.

4 Results

The data collected from the experiment was analyzed to assess participant performance under different perturbation conditions and to estimate the apparent mechanical impedance. The analysis focused on performance metrics such as tracking error, cross-track error, and device velocity, as well as estimating the stiffness (K), damping (D), and inertia (M) matrices from the perturbation trials.

4.1 Performance Analysis

The performance analysis revealed distinct differences between the baseline trials (without random perturbation) and the perturbation trials (with random force). Table 1 summarizes the overall average performance metrics within the defined analysis window for each experimental batch:

Table 1: Overall Batch Averages (within analysis window)

Batch	Avg Tracking Error (pixels)	Avg Abs Cross Error (pixels)	Avg Velocity Magnitude (m/s)	Avg Commanded Force Mag (N)	Avg Assumed User Force Mag (N)
NoDrift_Batch1	3.3211	1.6090	17.6198	0.0000	0.0000
RandomPerturbation_Batch	12.0871	11.0945	46.9936	1.1160	1.1160
NoDrift_Batch2	6.5073	5.2887	35.6115	0.0000	0.0000

As expected, the `RandomPerturbation_Batch` showed significantly higher average tracking error compared to the baseline batches (`NoDrift_Batch1` and `NoDrift_Batch2`). This indicates that the random force perturbations effectively challenged the participants' ability to maintain accurate path following.

Also the Avg. Tracking error in NoDrift_Batch2 is higher than in NoDrift_Batch1 before the Perturbation batch, this suggests that the impedance of the limb increases momentarily after the doing the perturbed trials. The average device velocity magnitude was also different across batches, potentially reflecting varying strategies or difficulty levels.

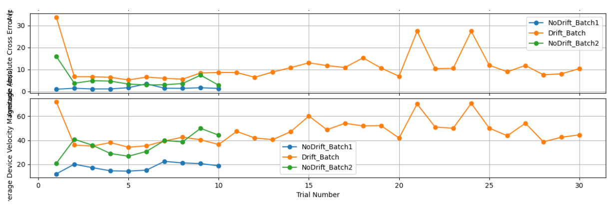

Figure 3: Tracking Cross error and Velocity with time

Figure above illustrates how these average metrics evolved over the course of trials within each batch, potentially showing learning effects or adaptation to the perturbation.

Figure below shows the force applied by the participant with time.

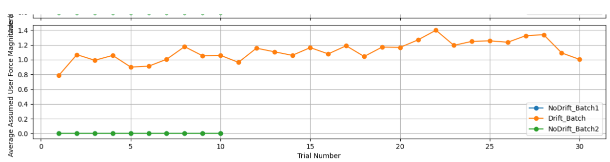

Figure 4: Average force applied by the participant

4.2 Simplified Impedance Analysis

The simplified impedance analysis, based on the assumption $F_{\mathbf{user}} = -F_{\mathbf{commanded}}$, was performed for the `RandomPerturbation_Batch` where active forces were applied. Ordinary Least Squares (OLS) regression was used to estimate the parameters of the linear impedance model (K, D, M, and bias).

The R-squared values for the regression models were 0.2760 for Fx, 0.2088 for Fy, and 0 for Fz.

These values indicate that the linear impedance model explains a **portion** of the variance in the assumed user force, particularly in the X and Y directions, which were primarily perturbed. However, the relatively low R-squared values suggest that a significant amount of variance in the assumed user force is not captured by this simple linear model, likely due to the limitations of the $F_{\text{user}} = -F_{\text{commanded}}$ assumption, device dynamics, and the complex nature of human motor control.

The condition number of the regression (1.89e+04) was high, indicating multicollinearity among the independent variables (position, velocity, and acceleration). This suggests that the estimated coefficients may be sensitive to noise and highly correlated, making their precise interpretation challenging.

The estimated apparent impedance matrices and bias vector for the **Random Perturbation Batch** are:

$$K = \begin{pmatrix} 5.3 \times 10^{-4} & 8.63 \times 10^{-3} & 6.97 \times 10^{-3} \\ 1.034 \times 10^{-3} & 1.855 \times 10^{-2} & -1.40 \times 10^{-2} \\ 3.98 \times 10^{-5} & 2.26 \times 10^{-4} & 4.43 \times 10^{-4} \end{pmatrix}$$

$$D = \begin{pmatrix} 1.10 \times 10^{-2} & 1.71 \times 10^{-3} & 8.42 \times 10^{-4} \\ 1.33 \times 10^{-3} & -1.05 \times 10^{-2} & 1.38 \times 10^{-3} \\ -7.26 \times 10^{-6} & -3.68 \times 10^{-5} & 1.28 \times 10^{-3} \end{pmatrix}$$

$$M = \begin{pmatrix} 2.73 \times 10^{-4} & -1.42 \times 10^{-4} & 3.05 \times 10^{-4} \\ -1.56 \times 10^{-4} & 4.33 \times 10^{-4} & -8.44 \times 10^{-5} \\ 3.97 \times 10^{-6} & 8.49 \times 10^{-5} & 1.53 \times 10^{-5} \end{pmatrix}$$

$$\text{bias} = \begin{pmatrix} 1.2494 \\ -2.3444 \\ -0.0047 \end{pmatrix}$$

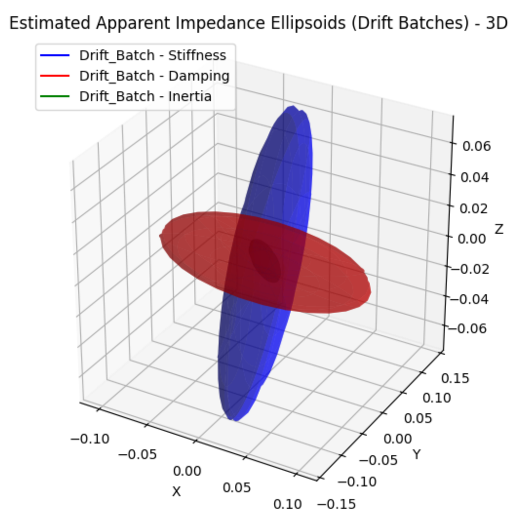

Figure 5: 3D Impedance Ellipsoids of the arm

2D projected Ellipse :-

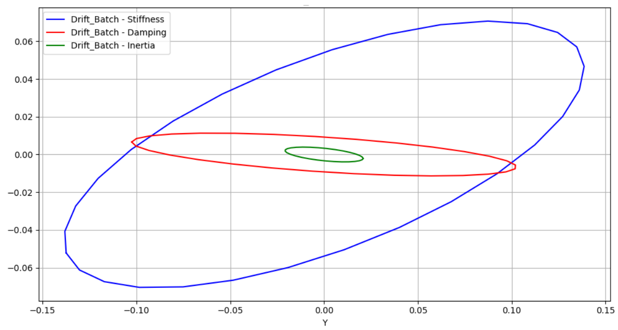

Figure 6: 2D projection YZ plane

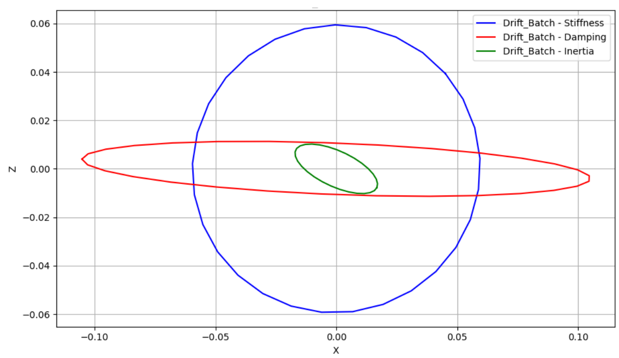

Figure 7: 2D Projection XZ plane

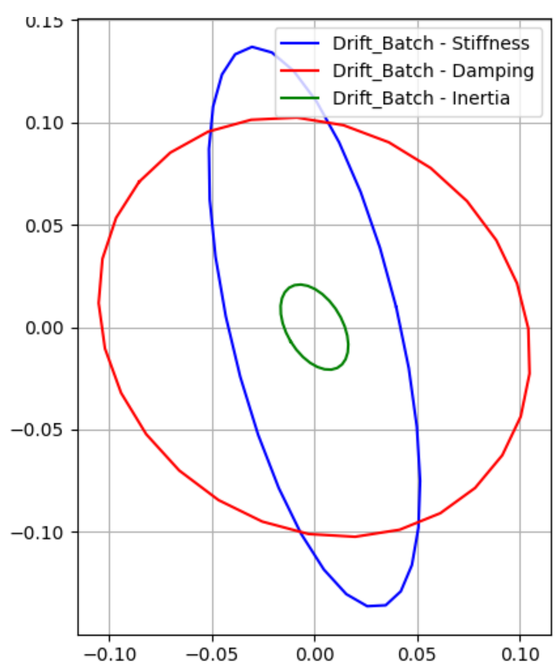

Figure 8: 2D Projection XY Plane

Figure 4, 5 and 6 helps us visualize the directional properties of these estimated Impedance (K,D,M) matrices. It can be seen that some of the estimated matrices are not positive definite, indicating that they do not represent physically passive stiffness, damping, or inertia. The ellipsoid plots were generated using the square root of the absolute eigenvalues for scaling to illustrate the directional scaling of the estimated linear model.

The results of the impedance analysis, particularly the low R-squared values and non-positive definite matrices, highlight the limitations of estimating isolated human impedance using this simplified method and setup. Negative values in the impedence matrices suggest that the assumption of $F_{\text{user}} = -F_{\text{commanded}}$ couples a lot of system(device) dynamics in the analysis of limb dynamics.

5 Discussion

The results of this experiment provide insights into human motor control strategies when performing a haptic path-following task under random force perturbations and highlight the challenges of estimating human limb impedance with a simplified setup. The significant increase in tracking error during the random perturbation batch, compared to baseline, clearly demonstrates that the applied forces effectively disrupted path adherence. This suggests that participants had to actively engage their motor control systems to counteract the unpredictable forces, likely involving increased muscle activation and potentially altered control strategies to maintain stability and minimize deviation from the path.

The simplified impedance analysis, while subject to significant limitations, provides a preliminary look at the apparent mechanical properties of the human-device system during the perturbed task. The estimated K, D, and M matrices, and their corresponding ellipsoid visualizations, suggest directional dependencies in the system's response to position, velocity, and acceleration. Qualitatively, the concept of directional impedance aligns with findings from previous studies on human limb impedance, such as those demonstrating impedance ellipses during planar movements (Hondori et al., 2012; Singh et al., 2023). These studies have shown that limb impedance is not uniform in all directions and can vary with posture and task demands. However, a direct quantitative comparison of the estimated matrix values to typical human impedance parameters from the literature is difficult due to the significant assumptions and limitations of the current analysis method. The low R-squared values indicate that the linear impedance model, based on the $F_{\text{user}} = -F_{\text{commanded}}$ assumption, **does not fully capture** the complexity of the force-motion relationship in this task. This could be attributed to the inherent **non-linearities** of human impedance, the influence of the haptic device's own dynamics, and the adaptive nature of the user's active control. The high condition number further suggests that the estimated coefficients are sensitive to noise and potentially unreliable due to multicollinearity among the kinematic variables. The observation that some estimated matrices are not positive definite underscores that these are estimates of the *apparent* system impedance under the specific commanded forces, rather than true, isolated human impedance which is typically modeled with positive definite components.

The primary limitation of this experimental design and analysis method is the reliance on the assumption that $F_{\text{user}} = -F_{\text{commanded}}$. This assumption neglects the passive mechanical impedance of the haptic device itself, which contributes to the overall force experienced by the user and the resulting motion. Without directly measuring the interaction force between the user's hand and the haptic device, it is impossible to accurately isolate the human user's impedance from that of the device. Furthermore, the analysis employs a simple linear, time-invariant model, which may not fully represent the complex, non-linear, and time-varying dynamics of the human neuromuscular system.

6 Video Demonstration

A video demonstrating the experimental setup and procedure is available at the following link: Video

7 Conclusion

In conclusion, this project successfully implemented a haptic path-following experiment with random force perturbations to investigate human motor control and apparent limb impedance. The performance analysis clearly demonstrated that random force perturbations significantly increased tracking and cross errors, highlighting the challenge posed to participants in maintaining path accuracy. While the objective of estimating human limb impedance was pursued, the simplified analysis method, based on the assumption of $F_{\text{user}} = -F_{\text{commanded}}$ and a linear model, yielded apparent impedance matrices that are likely influenced by device dynamics and do not fully capture the complexity of human impedance. The work serves as a valuable step in exploring human-robot interaction and the challenges inherent in characterizing human motor dynamics in such systems.

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