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Human Variability in Human-Robot Locomotion

Sean Kille * **Adina M. Panchea** ** **Sören Hohmann** *

* *Institute of Control Systems, Karlsruhe Institute of Technology, 76131 Karlsruhe, Germany (e-mail: sean.kille@kit.edu).*
** *Department of Electrical Engineering and Computer Engineering, Interdisciplinary Institute for Technological Innovation (3IT), Université de Sherbrooke, 3000 Bd de l'Université, Sherbrooke, J1N 3C6, QC, Canada (e-mail: adina.panchea@USherbrooke.ca).*

Abstract: Understanding natural human behavior is essential for designing effective and well-perceived automation in physical human–robot interaction (pHRI). While model-based control strategies are increasingly applied in assistive systems, most current approaches assume humans behave deterministically, which is contradicting evidence from neuroscience that highlights the stochastic nature of human motor control. This paper presents a user study with 21 participants performing goal-directed locomotion while physically pushing a smart wheelchair. By analyzing unconstrained human-only trials, we focus on characterizing human inherent variability in the context of physical coupling. Our results reveal structured patterns of task-relevant and task-irrelevant variability across repetitions, suggesting that variability is not random but systematically shaped by the task. These findings offer important insights for future shared control systems that aim to accommodate, rather than disregard, human movement variability.

Keywords: Design Methodology for HMS, Human Centred Automation, Stochastic System Identification, Cooperative Control, Modeling of Human Performance, Engineering Methods for HMS

1. INTRODUCTION

Understanding natural human locomotion behavior is essential for designing interactive and assistive systems that respect and adapt to human motor capabilities. While much research in physical human-robot interaction (pHRI) has focused on automation strategies and performance optimization, fewer studies have systematically analyzed inherent human variability in unconstrained movement scenarios. Investigating how variability emerges during goal-directed locomotion can inform the development of shared control systems that better align with human tendencies and promote user autonomy.

This study focuses on the analysis of natural human movement behavior during a wheelchair navigation task, without the influence of any automation assistance. By quantifying movement patterns and variability across multiple task repetitions, we aim to characterize task-relevant and task-irrelevant movement features and explore the implications for the design of user-centric assistive technologies.

2. MATERIALS AND METHODS

2.1 Related works

Human motor behavior is inherently variable. Repetitive movements, even under identical task conditions, result in non-identical trajectories assumed due to internal noise and sensorimotor uncertainty (Bernstein, 1967). Early work by Abend et al. (1982) and Harris and Wolpert (1998) highlighted the stochastic nature of human motion, showing that motor output is shaped by signal-dependent noise. This has led to a shift away from deterministic models toward probabilistic or noise-informed frameworks for understanding human control.

More recent models, such as the linear-quadratic sensorimotor framework proposed by Todorov (Todorov and Jordan, 2002), formally characterize how humans optimize movement trajectories in the presence of signal-dependent noise. Recent works allow the identification of these model parameters, including multiplicative noise (Karg et al., 2023, 2024), serving as a foundation for novel shared control designs (Kille et al., 2024), potentially elevating human experience (Kille et al., (in press)).

In the context of physical interaction with coupled systems, human variability becomes particularly relevant. Studies on physical human-human or human-robot collaboration often interpret variability as a source of uncertainty that should be compensated for (Medina et al., 2012; Gribovskaya et al., 2011). Even recent cooperative control approaches (Wu, 2022; Varga, 2024; Varga and Poncelet, 2025) overlook the potential functional role of variability as an expression of confidence, flexibility, or exploration.

A prominent explanation for structured variability in movement comes from the theory of task-relevant variability (Todorov and Jordan, 2002), which proposes that variability is minimized in task-critical dimensions (e.g.,

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Fig. 1. Intelligent powered wheelchair being pushed by a human user, with force sensors mounted on the rear handles to measure input forces.

endpoint accuracy) while being tolerated or even exploited in task-irrelevant dimensions. This theory aligns with empirical findings in reaching, locomotion, and object manipulation, where humans exhibit consistent behavior at key goal points while allowing for flexibility between them (e.g., Miossec and Kheddar (2009)).

The study of locomotion in the context of physically coupled assistive systems—such as wheelchairs and walking aids—provides further evidence of the structured nature of human movement. While research on joined walking between human and robot is quite active (e.g. Schneider et al. (2024)), variability analysis is rare. Research on manual wheelchair propulsion (Chaikhot et al., 2023) and gait with rollators or walkers (Mundt et al., 2019) has shown that users naturally modulate their stride, force application, and trajectory depending on task demands, environmental layout, and personal comfort. Variability in these systems is not random but often reflects adaptive responses to mechanical constraints or individual strategies for maintaining balance and control.

In particular, pushing a wheelchair introduces a unique form of coupled locomotion, where the user's upper-body input determines the path and velocity of a larger, external system. Studies have highlighted that users adopt distinct movement profiles when maneuvering such devices, especially in constrained spaces (Jung and Kim, 2023). These insights support the need for more detailed analysis of how variability emerges in such interaction settings.

The present study contributes to this body of work by empirically characterizing natural human variability in a physical task setting while pushing a wheelchair. By quantifying variability across task regions and subjects, it provides a descriptive foundation for understanding how movement flexibility emerges in natural interaction with physically coupled systems.

2.2 System design

To investigate natural movement patterns, we employed an intelligent powered wheelchair (IPW) described in Panchea et al. (2022) and depicted in Fig. 1. The wheelchair is actuated by two independent electric motors that are driven by on-board controllers that aim to follow translational and rotational set-velocities: u_{trans} and u_{rot}. For the purpose of this study, the behavior of a conventional, non-powered wheelchair that is pushed by a human, was to be imitated. To do so, 1-dimensional force sensors were attached to the handles of the wheelchair, measuring the push- and pull-forces exerted by a human on the left and right wheelchair handles: F_{L} and F_{R}. Based on these forces, IPW set-velocities are calculated using scaling factors a_{trans} and a_{rot}:

Fig. 2. Map of the experimental environment generated by RTAB-Map. The start and end positions are located in the upper left corner (green circle) and on the right side (red cross), respectively.

$$u_{\text{H,trans}} = a_{\text{trans}}(F_{\text{L}} + F_{\text{R}}), \tag{1}$$
$$u_{\text{H,rot}} = a_{\text{rot}}(F_{\text{L}} - F_{\text{R}}). \tag{2}$$

Localization of the IPW's position and orientation was achieved using a SLAM approach based on the RTAB-Map library (Labbé and Michaud, 2019), combining LIDAR and odometry information for robust state estimation.

3. SUBJECT STUDY

3.1 Study design

Task The task required participants to push the IPW from a defined start position (inside a doorframe) to an end position (across an opening into an adjacent laboratory room). Participants were instructed to perform the movement smoothly and swiftly. After having reached the endpoint, they were asked to pull the IPW back to the start position. The environment layout is shown in Fig. 2. The overall travel distance per movement is approximately 4.5 m.

Ethical approval The study was approved by the Research Ethics Board of the Université de Sherbrooke (CÉR Lettres et sciences humaines). All participants provided written consent and were informed about the data privacy regulations, and their right to withdraw at any time without consequences.

Procedure Initially, participants were introduced to the system and received information regarding the general objective, data privacy regulations and an explanation of the task. Participants then underwent a familiarization phase with five trial runs, followed by 15 repetitions of the task. After the successful completion of these repetitions, the participants completed a questionnaire which assesses their interaction experience. The overall procedure time for these steps was approximately 20 mins.

3.2 Data processing

Before analysis, the recorded trajectories were cropped at spatial boundaries ($p_x > 2.85\,\mathrm{m}$ or $p_y > 2.35\,\mathrm{m}$) to ensure consistency. Each trajectory was resampled to 300 equally spaced points using spline interpolation to normalize the spatial and temporal representation across trials.

A mean trajectory was computed for each participant by averaging their repetitions of one direction. Variability in form of variance $\mathrm{cov}(e_k)$ was quantified by calculating the Euclidean distance e_k between each individual trajectory (consisting of x- and y-positions $p_{x,k}$ and $p_{y,k}$) and the participant's mean trajectory $\bar{p}_{\square,k}$, which was computed as the mean of all repetitions c at each sample index k:

$$e_k = \sqrt{(p_{x,k} - \bar{p}_{x,k})^2 + (p_{y,k} - \bar{p}_{y,k})^2}, \tag{3}$$

$$\mathrm{cov}(e_k) = \frac{1}{c-1} \sum_{i=1}^{c} |e_k|^2. \tag{4}$$

3.3 Subjective measures

Participants' subjective experiences during the task were evaluated using three standardized self-report instruments:

- **Sense of Agency (SoA):** Participants' perceived control over their actions and outcomes was assessed using the 13-item short form of the Sense of Agency Scale (Tapal et al., 2017).
- **Questionnaire for the Evaluation of Physically Assistive Devices (QUEAD2):** User experience related to physically assistive devices was captured using the 16-item short version of the QUEAD (Schmidtler et al., 2017). This instrument evaluates several subdimensions, including perceived usefulness (PU), perceived ease of use (PEU), emotional response (E), attitude (A), and physical comfort (C).
- **User Experience Questionnaire (UEQ):** Overall user impressions, including system usability and satisfaction, were measured using the 8-item short version of the UEQ (Laugwitz et al., 2008).

This combination of measures provided a comprehensive assessment of participants' perceived control, system acceptance, emotional engagement, and overall satisfaction during task execution.

4. RESULTS

In the presented study, 21 participants took part, of which 5 were female. The participants' age spread from the 20s (17 participants) over 30s (3 participants) to one participant in their 40s.

4.1 Objective

The observed behavior and position variance for an individual participant are shown in the left column of Fig. 4. The trajectories of this subject demonstrate low variability

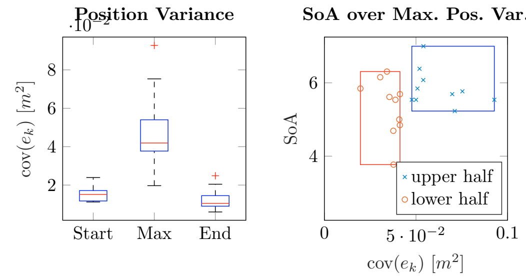

Fig. 3. Left: Position variance at startpoint and endpoint as well as maximum variance. Right: Participants grouped by maximum position variance and analyzed for Sense of Agency (SoA).

at both the starting and ending positions, while increased deviation is evident in the midsection of the path. This is particularly visible in the computed position variance $\mathrm{cov}(e_k)$, which remains low throughout the first quarter of the trajectory, rises to a peak around one-third of the path, and then gradually decreases toward the endpoint.

The participant's velocity profile follows a consistent acceleration phase, with minor variability in peak velocity. In contrast, the rotational input displays no clear pattern but shows a slight positive bias, which corresponds to the slight leftward curvature observed in the participant's overall path from start to end.

Comparable patterns emerge in the aggregated data across all 21 participants, shown in the right column of Fig. 4. While both the starting and ending regions consistently show low positional variance, a clear peak in variability appears in the center of the trajectory, approximately at sample index $k = 125$. A quantitative breakdown of the variability in different spatial regions is presented in Fig. 3. On average, the start and endpoint variances were approximately $0.015\,\mathrm{m}^2$ and $0.01\,\mathrm{m}^2$, respectively, while the midpoint region showed significantly higher variability, with an average of approximately $0.04\,\mathrm{m}^2$.

Although the general variability pattern was consistent across participants, inter-subject differences were observed in the magnitude and spatial extent of the variability peak. Notably, the variance at the start and endpoint remained low across all participants, indicating task-relevant consistency.

Regarding velocity trajectories, a modest increase in variability was observed around the point of peak velocity (approximately $k = 125$) and again shortly before stopping (around $k = 275$). For most participants, the variance in velocity remained low up to approximately one meter before the endpoint.

The mean rotational input exhibited a moderate peak early in the trajectory, particularly between $k = 50$ and $k = 150$, which may reflect individual differences in alignment correction or initial trajectory shaping.

4.2 Subjective results

Subjective experience was assessed using standardized questionnaires covering dimensions of perceived agency, usability, emotional response, and overall user satisfaction, as introduced in Sec. 3.3.

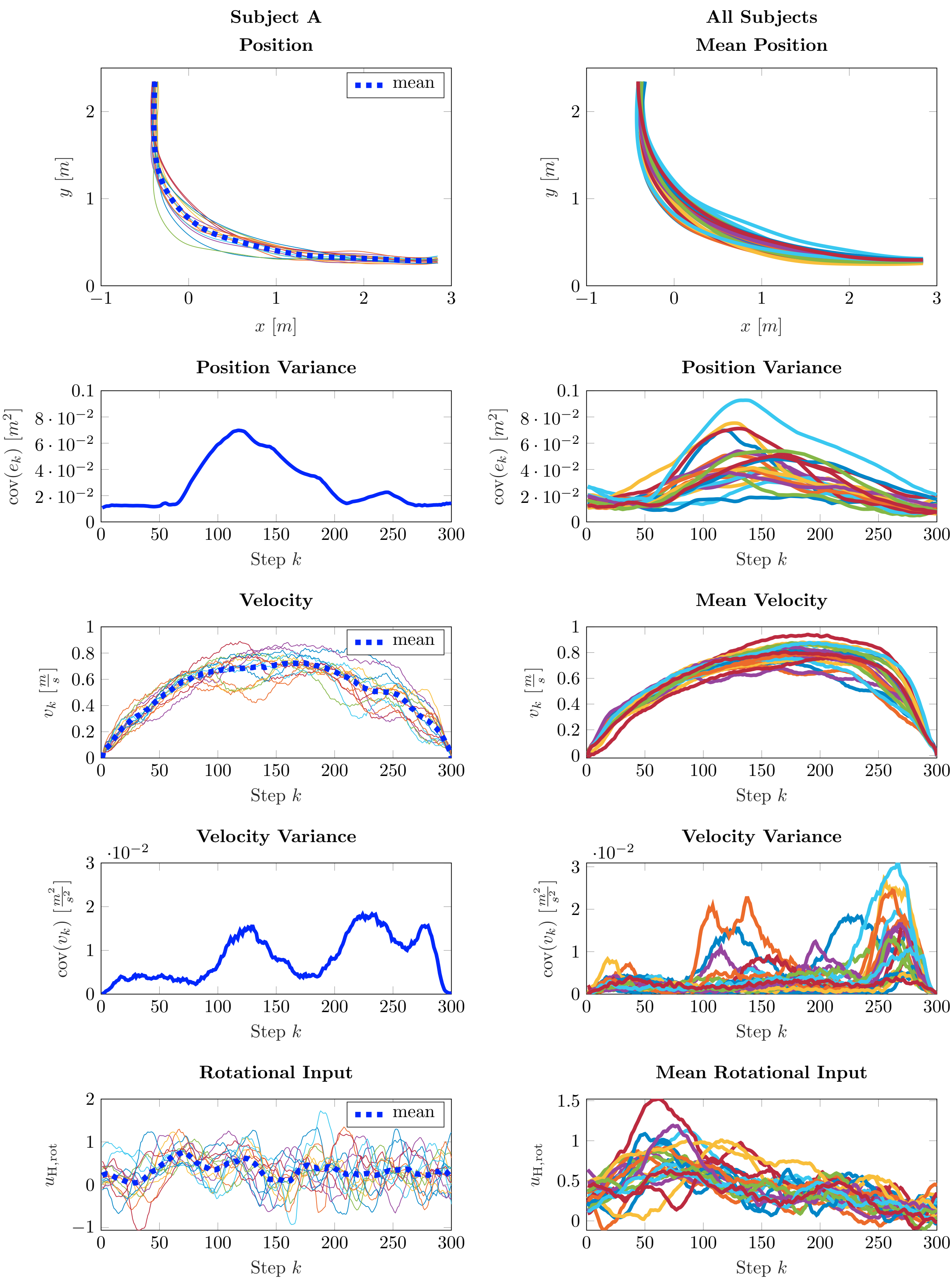

Fig. 4. Observed position and velocity as well as their variance and rotational input. Left column: Behavior of one example participant. Right column: Mean behavior of each of the 21 participants.

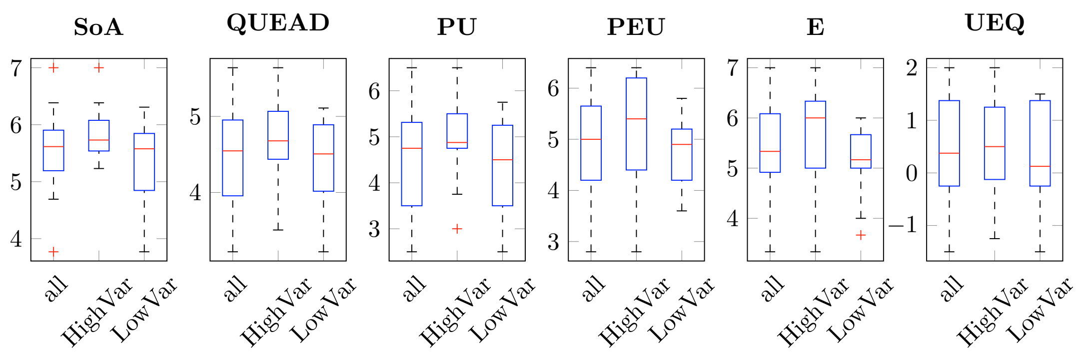

Fig. 5. Subjective evaluation of the interaction by all participants as well as filtered by two subgroups: Participants were divided based on maximum positional variability into LowVar (lower two quartiles) and HighVar (upper two quartiles). Depicted is the response regarding Sense of Agency (SoA), overall usability (QUEAD), perceived usefulness (PU), perceived ease of use (PEU), emotional response (E) as well as user experience (UEQ).

To explore potential relationships between subjective experience and natural movement variability, participants were divided into two subgroups based on their individual maximum positional variability during the task. The lower-variability subgroup comprised participants whose peak variability values fell within the lower two quartiles, while the higher-variability subgroup included those within the upper two quartiles. This stratification enabled a comparative analysis of subjective measures across distinct variability profiles. Figure 5 summarizes the responses across all participants as well as the two subgroups stratified by maximum positional variability (LowVar and HighVar).

Participants in the HighVar group (those who exhibited greater natural movement variability) tended to report slightly higher values in the SoA scale.

A similar trend was observed in the QUEAD responses, where the HighVar group showed marginally higher scores in perceived usefulness (PU), perceived ease of use (PEU), and emotional response (E). However, the absolute differences were small and did not reach statistical significance.

Overall user experience ratings as captured by the UEQ scale were more mixed. Although all groups reported moderately positive impressions, the difference between LowVar and HighVar groups was less pronounced, and no systematic pattern emerged.

5. DISCUSSION

The observed distribution of movement variability aligns with the theory of task-relevant variability (Todorov and Jordan, 2002), which posits that humans reduce variability at task-critical points and allow for greater flexibility where precision is less essential. In our study, participants consistently exhibited low positional variability at the start and endpoint regions (both clearly defined spatial goals) while allowing for significantly greater variability during the midsection of the task. This structured pattern reinforces the idea that human motor behavior is not merely stochastic noise, but a goal-oriented optimization strategy that balances effort and control.

These insights have direct implications for the design of shared control and assistive systems. Recognizing that humans naturally tolerate and may benefit from variability during specific task phases suggests that assistive algorithms should avoid over-constraining user motion in task-irrelevant areas. Instead, selectively applying support only in high-precision zones may preserve the user's natural movement patterns and improve system transparency.

Interestingly, despite the increased variability observed in the midpoint region, task performance remained stable, particularly in terms of endpoint accuracy. This finding highlights that variability during the task execution does not necessarily degrade performance - rather, it may reflect adaptive and energy-efficient motor strategies.

When participants were grouped according to their maximum positional variability, those in the HighVar group reported slightly higher levels of perceived agency and ease of use. While these trends were not statistically significant, they suggest that greater variability may reflect a more self-directed and confident interaction style. Conversely, participants in the LowVar group - who demonstrated more constrained movement - may have adopted a more conservative strategy, potentially indicative of caution, inexperience, or a different internal model of the task.

Together, these findings support a more nuanced interpretation of variability in human-machine interaction: rather than being an artifact to disregard, the results suggest that variability is valuable as serving as a proxy for engagement, user state, and confidence. Designing interactive systems that respect and accommodate this natural variability could lead to improved user experience and more human-centered assistive technologies.

6. CONCLUSION AND OUTLOOK

This study systematically investigated natural human movement variability during a physically coupled locomotion task using a smart wheelchair. Our results confirmed that variability in human motion is not random, but follows a structured pattern consistent with the theory of task-relevant variability: participants consistently demonstrated low positional variance at the start and endpoint regions and higher variability in task-irrelevant midsections.

This structured variability indicates that human motor strategies are tuned to balance effort, control, and task precision. Importantly, this behavior emerged even without automation or external perturbations, highlighting that stochasticity is a natural and reproducible element of physical human-machine interaction.

By dividing participants into subgroups based on their individual variability profiles, we found preliminary evidence that increased movement variability may be associated with more confident and autonomous interaction styles - an observation that warrants further investigation. These findings challenge the common engineering assumption that human variability should be minimized and instead suggest it can serve as a meaningful indicator of user strategy, engagement, or state.

Looking forward, future research should explore the generalizability of these findings across different interaction tasks, device types, and user populations. In addition, incorporating models of human variability into shared control algorithms may improve system adaptability and user experience by aligning robotic behavior with human tendencies, rather than constraining them. Ultimately, embracing variability in human behavior could lead to more flexible, intuitive, and user-centered assistive technologies.

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