# Inferring Height-Induced Changes in Postural Control via Inverse Optimal Control

**Tahmineh A. Koosha**[1], **Fabian Hahne**[2], **Alap Kshirsagar**[2], **Nick Augustat**[1], **Christiane A. Melzig**[1], **Frank Bremmer**[1], **Jan Peters**[2], **Dominik M. Endres**[1]

[1]Philipps-Universität Marburg, Marburg, Germany
[2]Intelligent Autonomous Systems, Technische Universität Darmstadt, Darmstadt, Germany

## Abstract

**Humans adapt their postural control strategies in response to fear, but traditional sway metrics cannot directly reveal the underlying control objectives. We outline a preprocessing pipeline to enable inference of latent cost functions through our ongoing inverse optimal control (IOC) analysis. We exposed participants to ground (GC) and height (HC) conditions in virtual reality, while recording joint kinematics using Kinect-based motion capture. After aligning and denoising the data, we extracted joint angles (hip, knee, ankle) and computed summary metrics such as Mean, RMS, and Mean Power Frequency (MPF). Using Bayesian estimation, we found condition-dependent shifts in joint angle distributions, including reduced hip flexion and increased ankle stability under height. Our findings provide evidence of postural adaptation under perceived threat and lay the groundwork for the modeling of control strategies that govern balance in fear-inducing environments.**

**Keywords: Postural Control; Fear of Height; Joint Angles; Virtual Reality; Inverse Optimal Control**

## Introduction

Humans adapt their postural control strategies in response to fear-inducing environments, such as standing at great heights (Spartakov et al., 2024). While traditional sway metrics (e.g., mean amplitude, frequency) capture behavioral responses, they do not reveal how threat modulates the underlying control strategies. Building on recent work (Koosha et al., 2025) showing sway frequency changes under virtual height exposure, we now focus on inferring the latent cost functions that shape postural behavior.

Inverse optimal control (IOC) offers a principled framework to infer such latent costs. By modeling the nervous system as optimizing a control objective, IOC allows us to ask: "What trade-offs are being made to produce these movements?" Applied to posture, this method can quantify shifts in control priorities—e.g., increased velocity penalties or reduced motor noise—in threatening versus neutral contexts.

This paper presents a dataset and preprocessing pipeline designed to support our ongoing IOC analyses. Participants were exposed to low-threat (Ground) and high-threat (Virtual Height) conditions in virtual reality, while full-body kinematics were recorded via Kinect. These signals were reduced to sagittal-plane joint angles and mapped onto a simplified biomechanical model of posture (a three-link inverted pendulum) inspired by prior work (Reimann & Schöner, 2017).

We demonstrate the utility of our pipeline through Bayesian estimation of condition effects on joint-level kinematics. We also outline how the prepared data support our ongoing work on the application of a probabilistic IOC method (Straub, Schultheis, Koeppl, & Rothkopf, 2023) for inferring changes in the underlying control strategies.

## Materials & Methods

**Data and Preprocessing.** We analyzed Kinect v2 motion capture data from 29 participants exposed to a virtual height manipulation. Each participant stood still under two conditions: *Ground* (GC), simulating a flat floor, and *Height* (HC), with the floor visually removed. Full-body 3D joint positions were recorded at 30 Hz.

We corrected each trial for sensor tilt (via spine vector) and yaw (via hip alignment). We removed spike artifacts using a median absolute deviation (MAD) filter (5×MAD) and applied a 4$^{\text{th}}$-order zero-phase Butterworth low-pass filter (3 Hz). We retained only stable signal segments (25–45 s post-onset) and discarded trials with abnormal dynamics (e.g., excessive velocity or jitter). Subjects with sufficient valid trials in both conditions were included, yielding a final sample of $N = 22$.

**Joint Angle Computation.** Sagittal-plane joint angles were extracted using geometric relationships between Kinect joint positions:

- **Ankle:** $\theta_{\text{ankle}}(t) = \arctan 2(z_{\text{knee}} - z_{\text{ankle}}, y_{\text{knee}} - y_{\text{ankle}})$
- **Knee:** angle between hip-knee and knee-ankle vectors
- **Hip:** torso inclination (from spine vector) minus knee and ankle angles

**Bayesian Statistical Analysis.** To quantify condition effects, we computed delta values (HC $-$ GC) for each subject and joint-level metric (Mean, RMS, MPF, etc.). We fit Bayesian models in PyMC (v5.10) using a normal likelihood and weakly informative priors. Posterior distributions were sampled using the No-U-Turn Sampler (2 chains, 1000 draws). For each metric, we report the posterior mean, 94% highest density interval (HDI), ROPE mass (±0.005), and directional probability $P(\mu > 0)$. Results are summarized in Table 1.

**Planned Inverse Optimal Control.** To interpret changes in the control strategies, we plan to apply IOC to these joint trajectories using a three-link inverted pendulum model (Reimann & Schöner, 2017). The model includes joint angles and velocities as state variables, and joint torques as control inputs. Cost terms will include velocity penalties, torque effort, and motor noise. Using a probabilistic IOC method (Straub et al., 2023), we aim to recover cost parameters that explain postural adjustments under threat. While IOC analysis is ongoing, this pipeline establishes the empirical and computational foundation for the IOC-based inference.

## Results

**Joint Angle Trajectories.** Figure 1 shows example time-resolved joint angles (hip, knee, ankle) from one participant under Ground (gray) and Height (orange) conditions. Visual inspection reveals elevated knee flexion and reduced hip extension under Height, suggesting altered lower-limb posture consistent with increased postural threat.

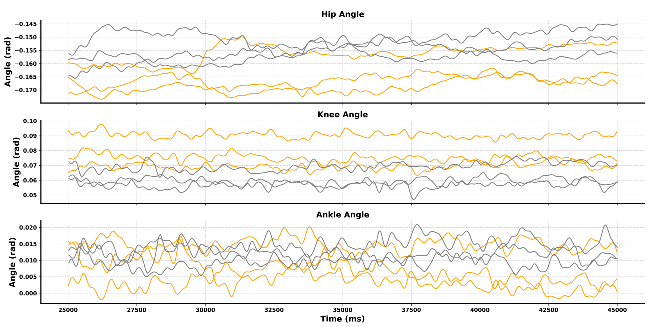


Figure 1: Example joint angle trajectories (hip, knee, ankle) from a single participant during Ground (gray) and Height (orange) conditions. Height induces visibly altered joint configurations.

**Bayesian Estimation of Postural Metrics.** To assess condition differences across participants, we computed within-subject deltas (Height $-$ Ground) for each joint and kinematic metric. Bayesian estimation was used to model the posterior distribution of mean deltas across subjects (see Table 1).

Strong directional evidence for condition-related change ($P(\mu > 0) > 90\%$ or $< 10\%$) was observed in several metrics: **Hip_Mean** showed a robust negative shift ($P(\mu > 0) = 2.4\%$), indicating reduced hip extension under Height. **Ankle_Mean**, **Knee_RMS**, **Knee_STD**, and **Knee_Range** all showed high posterior support for positive deltas ($P(\mu > 0) > 89\%$), suggesting increased knee activity and variability. These findings support the hypothesis that virtual height exposure systematically alters lower-limb joint behavior in standing posture.

## Discussion

Traditional analyses of postural control under threat typically rely on center of pressure (CoP) metrics, such as sway amplitude or frequency (Cleworth, Horslen, & Carpenter, 2012; Wuehr et al., 2019). While these measures capture the gross movement of the body's base of support, they do not reflect the underlying coordination of joint-level mechanics or the strategic adjustments made by the nervous system (Koosha et al., 2025). As a result, they offer limited insight into *why* behavior changes in response to fear-inducing environments like virtual heights.

Table 1: Bayesian posterior estimates for the metrics deltas (Height $-$ Ground). Bold indicates directional posterior support 80% .

| **Feature** | **Mean** | **94% HDI** | **P($\mu > 0$)** |
|---|---|---|---|
| Hip_MPF | -0.031 | [-0.085, 0.022] | 13.6 |
| Knee_MPF | -0.031 | [-0.115, 0.056] | 24.9 |
| Ankle_MPF | 0.017 | [-0.077, 0.095] | 65.0 |
| Hip_Mean | -0.009 | [-0.017, -0.001] | 2.4 |
| Knee_Mean | 0.004 | [-0.006, 0.014] | 75.9 |
| **Ankle_Mean** | 0.005 | [-0.002, 0.013] | **89.3** |
| Hip_RMS | 0.004 | [-0.005, 0.013] | 81.0 |
| **Knee_RMS** | 0.006 | [-0.004, 0.014] | **89.9** |
| Ankle_RMS | -0.000 | [-0.006, 0.005] | 43.2 |
| **Hip_STD** | 0.001 | [-0.001, 0.002] | **86.8** |
| **Knee_STD** | 0.001 | [-0.000, 0.002] | **93.3** |
| **Ankle_STD** | 0.001 | [-0.001, 0.002] | **80.3** |
| **Hip_Range** | 0.003 | [-0.002, 0.008] | **84.1** |
| **Knee_Range** | 0.004 | [0.000, 0.008] | **96.5** |
| Ankle_Range | 0.002 | [-0.002, 0.006] | 78.5 |

In contrast, our approach emphasizes joint angle trajectories, providing a more detailed view of postural adjustments at the level where motor commands are implemented. By capturing joint-specific adaptations—such as increased knee flexion or reduced hip extension under threat—we move beyond coarse sway metrics and toward the control strategies shaping balance. This shift is essential for enabling future model-based analyses aimed at uncovering internal control objectives.

Previous studies have shown that joint-level responses—such as increased ankle stiffness or knee flexion—can reveal subtle adaptations to virtual height (Bzdúšková, Marko, Hirjaková, Riečanskỳ, & Kimijanová, 2023). Joint angles are particularly well-suited for inverse optimal control (IOC) because they can be directly mapped onto biomechanical models, such as the three-link inverted pendulum structure used here (Reimann & Schöner, 2017). This enables the application of probabilistic IOC methods (Straub et al., 2023), which can recover the trade-offs the nervous system is making—such as prioritizing stability, minimizing motor effort, or suppressing variability (Todorov & Jordan, 2002).

By designing our experimental and modeling pipeline around joint-level kinematics, we lay the groundwork for future IOC analyses. These inferred costs will allow us to test whether participants under height exposure emphasize velocity minimization, noise reduction, or effort conservation. Further, we aim to explore individual differences in these inferred control strategies, potentially linking them to psychological traits such as balance confidence or fear of falling.

In doing so, we seek not only to describe *how* posture changes under threat—but to infer *why*.

## Acknowledgments

This work was supported by the Research Cluster "The Adaptive Mind", funded by the Excellence Program of the HMWK, the DFG GRK-RTG 2271 'Breaking Expectations' project number 290878970 and the DFG CRC/TRR 135, project number 222641018, subproject C6.

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