Deep learning-based foot placement prediction models reveal multi-timescale control

Wei-Chen Wang[1], Antoine De Comite[1], Alexandra Voloshina[2], Monica Daley[2], and Nidhi Seethapathi[1]
[1]Massachusetts Institute of Technology, Cambridge, MA, USA
[2]University of California, Irvine, Irvine, CA, USA
[1] Email: wangeric@mit.edu

Summary

During locomotion in complex settings humans integrate information about the environment and body states to dynamically select foot placements. Despite this, existing data-driven models of foot placement control assume single-input and fixed-timescale linear control. We introduce a deep learning-based data-driven framework to identify the influence of multiple input modalities on foot placement control across timescales in different kinds of uneven terrain.

Introduction

Human locomotion in the real world uses multi-sensory feedback — proprioceptive, vestibular, and visual — to estimate environmental and body states to guide dynamic foot placement. Existing data-driven models are limited to treadmill walking with linear assumptions [1] that may not generalize to multi-modal and context-dependent control inherent in the real world. To address this, we develop a deep learning framework to analyze large-scale locomotion data in uneven terrain running [2] and uneven terran overground walking [3]. By comparing the predictive power of different input modalities on future foot placement to a baseline model, our framework eliminates significant inter-trial variability, revealing input modality-dependent control.

Methods

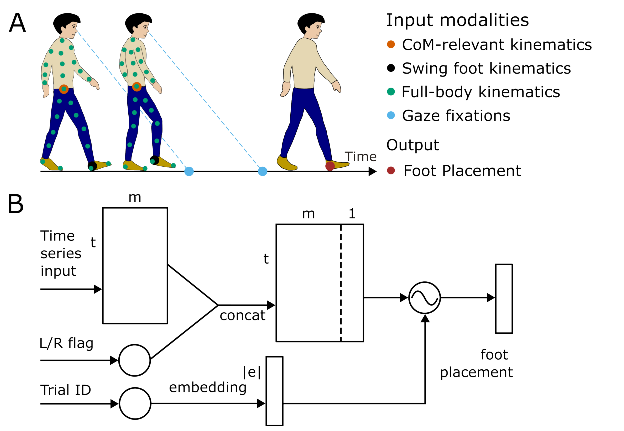

Figure 1: Overview of the modeling framework. **A** Hypothesized input modalities and foot placement output. **B** Network architecture of the controller.

We hypothesize that foot placement control depends on the history of body and environmental states. To test this, our deep learning framework is trained on input modalities including kinematics of the CoM-relevant states, swing-foot states, full-body states, and gaze fixations (Figure 1A), to predict future foot placement. These inputs are integrated over different windows to identify the amount of history needed for prediction at each gait phase. We incorporate a trial ID embedding in our deep learning framework to separately learn the trial-specific components of the foot placement, reducing inter-trial variability in prediction (Figure 1B). Given the high correlation between modality-based and baseline prediction intercepts across trials (Figure 2B), we analyze the relative predictive power as shown in Figure 2A, further reducing inter-trial variability.

Results and Discussion

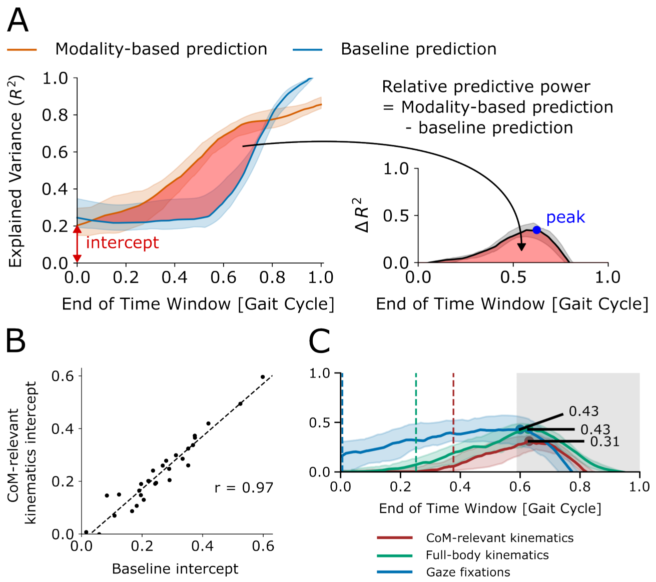

Figure 2: Relative predictive power. **A** R^2 across gait phase for modality-based and baseline predictions. The intercept is the R^2 at gait phase 0. The red shaded area represents the relative predictive power (ΔR^2). **B** Correlation between baseline and CoM-relevant kinematics intercepts. **C** ΔR^2 of CoM-relevant, full-body kinematics and gaze fixations for lateral foot placement prediction during overground rough terrain walking. The vertical lines indicate the control timescale of each input modality when its predictive power outperforms the baseline model by 5%. The gray shaded region represents swing phase.

The relative predictive power reveals distinct control timescales across modalities. During overground walking on rough terrain, we observe that lateral foot placements are visually guided, with gaze fixations contributing earlier to prediction than both CoM-relevant and full-body kinematics (Figure 2C), possibly to inform path planning to navigate around terrain obstacles. This result quantifies the extent to which, in challenging environments, individuals rely on vision to plan foot placement before relying on postural body state information. Our finding that full-body kinematics predict future foot placement before CoM-relevant kinematics could reflect the role of whole-body angular momentum in foot placement control.

Conclusions

We put forth a data-driven deep learning framework to make trial-specific foot placement predictions, revealing input modality-dependent control timescales during locomotion in the real world.

References

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