Realtime Smart Gait Poser for foot augmentation

Hiroyuki Deguchi*
Ryosuke Hori*
deguchihiroyuki@keio.jp
hori-rysk@keio.jp
Keio University
Yokohama-shi, Kanagawa, Japan

Tsubasa Maruyama
Mitsunori Tada
tbs-maruyama@aist.go.jp
m.tada@aist.go.jp
National Institute of Advanced Industrial Science and Technology
Koto-ku, Tokyo, Japan

Hideo Saito
Keio University
Yokohama-shi, Kanagawa, Japan
hs@keio.jp

Abstract

Walking is one of the most fundamental human motions, characterized by periodic movement patterns, and gait analysis is critically important in clinical applications. This study presents a real-time system for gait posture estimation that requires only two inertial measurement units (IMUs), each embedded in shoe midsole. We propose a framework that sequentially processes IMU data to estimate full-body meshes in real-time, and we demonstrate its effectiveness through experimental validation.

CCS Concepts

• **Human-centered computing → Systems and tools for interaction design**.

Keywords

Gait pose estimation, Foot IMUs, Realtime pose estimation, Gait analysis, Foot augmentation

ACM Reference Format:
Hiroyuki Deguchi, Ryosuke Hori, Tsubasa Maruyama, Mitsunori Tada, and Hideo Saito. 2025. Realtime Smart Gait Poser for foot augmentation. In *Proceedings of Make sure to enter the correct conference title from your rights confirmation email (Conference acronym 'XX).* ACM, New York, NY, USA, 3 pages. https://doi.org/XXXXXXX.XXXXXXX

1 Introduction

Gait is a fundamental lifetime activity, defined as a series of cyclic movements of the lower limbs. It is also understood to be the activity which includes synthesized coordination of the brain, nerves, and muscles. Thus, it is believed that gait analysis provides crucial information about the condition of the human health, and any deviation from normal gait indicates an underlying abnormality or affliction. Indeed, the importance of gait analysis has become evident through its wide range of applications in numerous fields, including medicine, sports, rehabilitation, and diagnostic research, among others.

*Both authors contributed equally to this research.

Conference acronym 'XX, Woodstock, NY

ACM ISBN 978-1-4503-XXXX-X/2018/06
https://doi.org/XXXXXXX.XXXXXXX

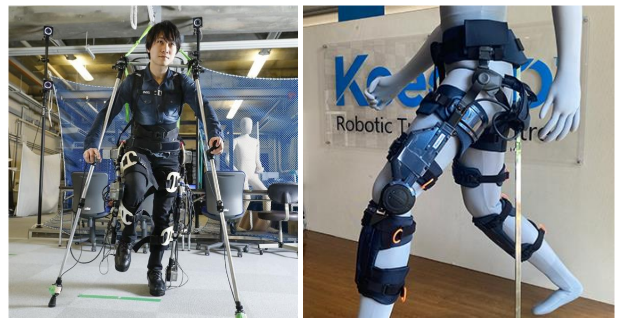

Figure 1: Various robots and suits for gait support have been proposed, and there is ongoing research on high-dimensional gait interventions using AI.[3, 5]

Figure 2: As the smart shoes shown above, the sole has a recess in sole. As the below one, an IMU sensor can be perfectly embedded there.

We consider "sensor simplicity" and "realtime capability" to be critically important factors in gait analysis.

In wearable sensor-based measurement, "sensor simplicity" is critical. By collecting data from simple sensor units, it will significantly reduce the invasiveness, and we will be able to analyze gait in daily environments outside of the laboratory. It is more useful and helps us perform more natural gate.

Considering various application, "realtime capability" is also important. The ability to measure and analyze gait in real time enables immediate clinical feedback. In addition, it also opens the door to realtime foot augmentation, i.e. gait assist suits or robots.

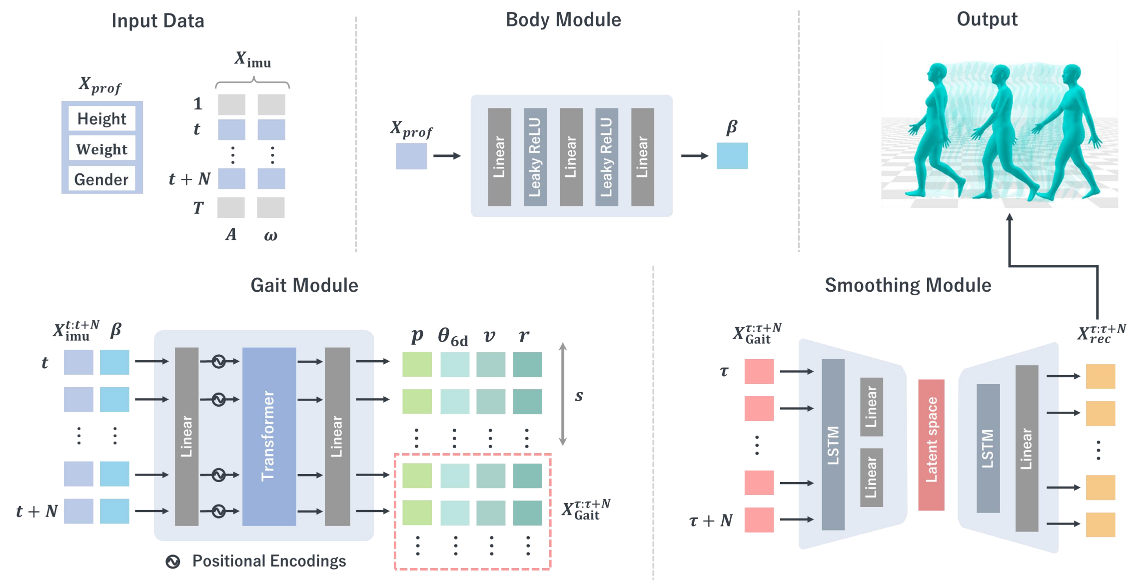

Figure 3: Network architecture.

We develop Realtime Smart Gait Poser for foot augmentation. Our system can immediately provide human gait 3D pose from simple sensor units, only two IMU sensors embedded in smartshoes [6] as shown in Fig. 2. Our system also fulfills the requirements for realtime functionality by proposing system with efficent computation.

2 Backgrounds

2.1 Motion Capture for Gait analysis

Traditionally, gait analysis has relied on subjective assessments based on visual observation by medical professionals and self-reports from patients. However, these subjective methods lack efficiency and accuracy. With advances in technology, it has become possible to capture and analyze human gait more precisely using various equipment. Instrumented Gait Analysis (IGA), which utilizes devices such as optical motion capture (MoCap) systems, force plates, instrumented walkways, and treadmills, has long been regarded as a reliable method for accurately quantifying gait patterns and characteristics in research and clinical practice [7].

However, such large-scale, laboratory-based measurements has problems such as invasiveness, expensiveness, and limitation on the space volume for subjects. In response to these problems, there has been increasing interest in using Inertial Measurement Units (IMUs) for gait analysis.

An IMU measures 3D acceleration, 3D angular velocity, and the direction of the magnetic North. It offers advantages such as low cost, minimal setup time, lightweight, and portability, and makes it possible to measure natural walking in diverse environments. In the field of biomechanics, many approaches have been proposed to attach multiple IMUs to the lower limbs for measuring and analyzing gait [1]. However, to the best of our knowledge, no prior study has focused on estimating the full-body 3D pose during gait from lower limbs IMUs.

2.2 Pose estimation from sparse IMUs

In the fields of computer vision and computer graphics, 3D human pose estimation using IMU sensors has been extensively investigated. Xsens [8], which is a widely used commercial IMU system, already provides full-body pose estimation by placing 17 IMUs on the body. Furthermore, recent approaches such as TransPose [10] and Physical Inertial Poser [9] leveraged deep learning and optimization to achieve high-accuracy full-body pose estimation with as few as six IMUs. Our method narrows its focus to walking, a characteristic motion, and leverages its specific features to estimate gait posture using only two IMUs attached to the feet.

3 Realtime Smart Gait Poser

3.1 Gait Inertial Poser

We propose Gait Inertial Poser (GIP), a deep learning based model which estimates full-body human gait pose with only both foot-attached IMUs. As illustrated in Fig. 3, GIP utilizes basic individual data (Height and Weight) and data from two IMUs embedded in smartshoes to estimate body shape, pose, and velocity. Specifically, the network is composed of three modules: the Body Module, the Gait Module, and the Smoothing Module.

3.1.1 Body Module. When analyzing walking motions, having body shape information is crucial; however, it is challenging to directly obtain such information from IMU data. Therefore, we use individual profile data $\boldsymbol{X}_{\text{prof}} \in \mathbb{R}^3$, height, weight and gender as inputs to a three-layer MLP to estimate the SMPL model's shape parameters $\boldsymbol{\beta} \in \mathbb{R}^{10}$, which represent an individual's body shape.

3.1.2 Gait Module. In this module, we estimate gait posture by taking into account various factors from estimated body shape $\boldsymbol{\beta}$ and $N+1$ sequences of 6DoF IMU data $\boldsymbol{X}_{\text{imu}}^{t:t+N}$ composed of acceleration and angular velocity data. From sequential IMU data,

Table 1: Quantiative Evaluation of our method.

Root Velocity Error [m/s]	MPJRE [deg]	Phase F1 score
3.64	0.090	0.95

we estimate pose parameters with 6D representation $\boldsymbol{\theta}_{\text{6D}}^{t:t+N} \in \mathbb{R}^{(N+1)\times 23\times 6}$, root joint velocity $\boldsymbol{v}^{t:t+N} \in \mathbb{R}^{(N+1)\times 3}$, root joint height $\boldsymbol{r}^{t:t+N} \in \mathbb{R}^{(N+1)\times 1}$, and gait phase $\boldsymbol{P}^{t:t+N} \in \mathbb{R}^{(N+1)\times 8}$, defined based on whether the heel and toe of each foot are in contact with the ground or not. We concatenate these parameters and define it as a gait motion parameter $\boldsymbol{X}_{\text{Gait}}^{t:t+N}$.

3.1.3 Smoothing module. In the Gait module, we sequentially estimate $N+1$ sequences of the gait motion for computational effectiveness. However, with this method, the motion does not connect smoothly at the boundaries of the estimated sequences. So, in the Smoothing module, we input the gait motion parameters shifted by $\boldsymbol{s}$ sequences $\boldsymbol{X}_{\text{Gait}}^{\tau:\tau+N}$ to Variational Autoencoder and generate more smooth gait motion parameters $\boldsymbol{X}_{\text{rec}}^{\tau:\tau+N}$ where $\boldsymbol{\tau} = \boldsymbol{t} + \boldsymbol{s}$.

3.2 Demo system

We propose Realtime Smart Gait Poser, which is an implementation of GIP as real-time and online system. ORPHE CORE[4] can send IMU data via Bluetooth Low Energy, and we use a macOS computer to receive the data and visualize gait posture immediately.

4 Experiments

4.1 Dataset

In this study, we used the AIST Gait Database [2] for both training and evaluation. The AIST Gait Database contains daily straight-line walking motion data from a total of 300 individuals (150 men and 150 women) aged 20 and above, including older adults. Ground-truth posture data were obtained using an infrared motion capture system. In addition, foot IMU data were acquired by virtually synthesizing IMUs.

4.2 Qualiative Results

Fig. 4 shows the qualiative results of our method, and Tab. 1 shows the quantiative result. We report Root Velocity Error [m/s], Mean Per Joint Rotation Error(MPJRE) [deg], Phase F1 score, which represents an accuracy of our gait phase estimation, as metrics. From them, we can say that our method accurately and naturally estimates gait pose. In particular, focusing on the first and third steps in Fig. 4, it can be confirmed that foot skating, which is a common issue in conventional methods, is effectively suppressed.

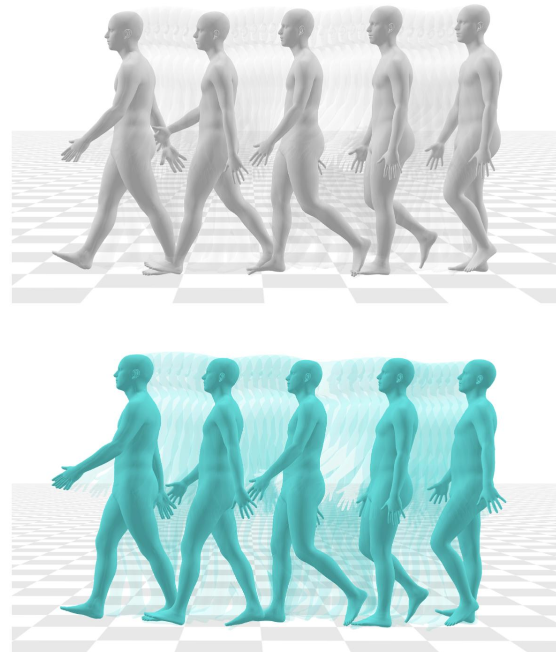

Figure 4: Above one is GT, below one is estimated pose.

5 Conclusion

In this paper, we proposed Realtime Smart Gait Poser for foot augmentation, novel framework for 3D pose estimation specialized in walking. Our approach uses only two IMUs embeded in smartshoes, so it is usefull and free from invasiveness. A notable limitation of our work is that it can only be applied to straight-line walking on level ground, thereby restricting its applicability to more diverse locomotion scenarios involving turns or uneven terrain. Future research directions include collecting diverse gait data in diverse environments and addressing these situations to extend the applicability of this gait posture estimation method to more diverse conditions.

References

[1] Yonatan Hutabarat, Dai Owaki, and Mitsuhiro Hayashibe. 2021. Recent advances in quantitative gait analysis using wearable sensors: a review. *IEEE Sensors Journal*, 21, 23, 26470–26487. doi:10.1109/JSEN.2021.3119658.

[2] Yoshiyuki Kobayashi, Naoto Hida, Kanako Nakajima, Masahiro Fujimoto, and Masaaki Mochimaru. Aist gait database 2019. Accessed: 2025-01-27. https://unit.aist.go.jp/harc/ExPART/GDB2019.html.

[3] Nikkan Kogyo Shimbun. 2020. Ai-powered quadrupedal assistive suit supports lower limb paralysis patients. Accessed: January 30, 2025. (2020). https://newswitch.jp/p/20836.

[4] ORPHE. 2022. ORPHE CORE. https://orphe.io/core. Accessed: 2025-01-27. (2022).

[5] P-Supply. 2023. Ai-powered walking assistance robot "keeogo". Accessed: January 30, 2025. (2023). https://www.p-supply.co.jp/topics/index.php?act=detail&id=818.

[6] Yuki Uno, Issei Ogasawara, Shoji Konda, Natsuki Yoshida, Naoki Otsuka, Yuya Kikukawa, Akira Tsujii, and Ken Nakata. 2023. Validity of spatio-temporal gait parameters in healthy young adults using a motion-sensor-based gait analysis system (orphe analytics) during walking and running. *Sensors*, 23, 1. doi:10.3390/s23010331.

[7] T. A. L. Wren, C. A. Tucker, S. A. Rethlefsen, G. E. Gorton, and S. Õunpuu. 2020. Clinical efficacy of instrumented gait analysis: systematic review 2020 update. *Gait & Posture*, 80, (July 2020), 274–279. Epub 2020 May 23. doi:10.1016/j.gaitpost.2020.05.031.

[8] Xsens Motion Capture. 2020. Xsens motion capture. Accessed: June 18, 2024. (2020). https://www.xsens.com/motion-capture.

[9] Xinyu Yi, Yuxiao Zhou, Marc Habermann, Soshi Shimada, Vladislav Golyanik, Christian Theobalt, and Feng Xu. 2022. Physical inertial poser (pip): physics-aware real-time human motion tracking from sparse inertial sensors. In *IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*. (June 2022).

[10] Xinyu Yi, Yuxiao Zhou, and Feng Xu. 2021. Transpose: real-time 3d human translation and pose estimation with six inertial sensors. *ACM Transactions on Graphics (TOG)*, 40, 4, 1–13.