Design and Evaluation of Sensor-Instrumented Footwear for Clinical Gait Assessment

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***Abstract*— Falls are a major concern for individuals with mobility impairments, yet current assessment methods are largely clinic-based and fail to capture the underlying biomechanics associated with fall risk. Gold-standard motion analysis systems provide detailed measurements but are impractical for routine or remote use. To address this gap, we developed and evaluated a sensor-instrumented overshoe system, termed GAIT, designed to estimate gait parameters in out-of-lab settings. The system integrates custom underfoot contact sensors, a foot-mounted inertial measurement unit (IMU), and an onboard microprocessor to detect gait events, foot orientation, and displacement. Preliminary validation was conducted in both clinical and able-bodied populations. Three individuals post-stroke used an early version of the system (temporal parameters only) bilaterally, while six able-bodied participants tested a final IMU-integrated prototype with spatial measurement capability during walking trials at self-selected and fast speeds. GAIT-derived spatiotemporal metrics were compared against reference systems (GAITRite and Vicon). The temporal-only system demonstrated high accuracy for contact-dependent metrics (e.g., cadence, stride time, step time), while metrics dependent on foot-off detection (e.g., stance and swing time) showed higher error (20%). In the final iteration, integration of IMU data with contact sensing reduced swing time error to less than 10%. Spatial parameters were also estimated with good accuracy, with errors within 4 cm for stride length and 1 cm for minimum toe clearance. These findings demonstrate the feasibility of a wearable overshoe system for remote gait assessment, enabling quantification of clinically relevant metrics associated with fall risk in real-world environments.**

***Keywords*— gait assessment, fall risk, inertial measurement units, wearable sensors,**

I. Introduction

Falls are a major concern for individuals with neurologic and orthopedic mobility impairments, often leading to injury, hospitalization, and long-term loss of independence [1]. Current clinical practice relies primarily on performance-based assessments — such as the Timed Up and Go (TUG)[2], Berg Balance Scale (BBS) [3], and the Functional Gait Assessment (FGA) [4] — as well as self-reported measures of balance confidence or fall history [5]. While these tools are quick to administer and easily work into established clinical workflows, they provide coarse summaries of mobility. As a result, they cannot capture the underlying biomechanical mechanisms that contribute to falls, such as step-to-step variability [3-5], foot-clearance deficits [6,7], postural sway [11], [12], or irregular foot–floor interactions; nor can they reflect how these factors evolve during unstructured, everyday walking. Consequently, there is a clinical need for objective, biomechanically informed assessments to reveal when an individual may be at risk of falling, informing targeted gait and balance interventions.

Quantitative gait analysis offers a promising alternative, by using optical motion capture, musculoskeletal modeling, or instrumented walkways, which provide more granular data on walking quality and stability [8,9] than clinical assessments. However, these "gold standard" systems suffer from a number of practical limitations, namely high cost, large physical footprints, specialized setup and expertise, and usability restrictions to laboratory environments making them impractical for widespread or continuous monitoring during activities of daily life. Capturing biomechanical signatures during routine e.g., home and community walking could thus be essential for identifying elevated fall risk and guiding prospective intervention.

Advances in wearable sensor technologies offer a practical path toward real-world gait monitoring, but current systems have important limitations as well. Inertial measurement unit (IMU)-based solutions can continuously track foot motion, yet they suffer from unmitigated drift, calibration demands, and reduced spatial accuracy over multiple steps without external references [10,11]. Pressure insoles or force-sensing wearables provide reliable temporal (but not spatial) measures via gait event detection, but can be cost prohibitive, require individualized fitting, and are impractical for rapid clinical deployment. These limitations highlight the need for a clinic-friendly, wearable solution that combines accurate event detection with robust spatial estimation.

In this paper, we present a wearable footwear system ("GAIT") designed to capture spatiotemproal gait parameters and foot kinematics during overground and treadmill walking. The long-term motivation is to enable biomechanics-based detection of fall risk during clinical assessment and community ambulation. As a first step, here we describe the design of the prototype system and preliminary validation in both older, healthy adults and individuals post-stroke.

II. Methods

A. Prototype Design

The GAIT prototype was developed to quantify spatiotemporal gait parameters and foot kinematics using a combination of underfoot contact sensors and an embedded inertial measurement unit (IMU; BNO085, Bosch SensorTec, Fort Wayne, IN), sampled at 100 Hz (Fig. 1). The sensing system is integrated into a modified overshoe crampon. The overshoe incorporates a flexible rubber structure with a Boa dial closure system, enabling rapid don/doff (>5500 cycles) and accommodating a wide range of shoe sizes (Men 7–14, Women 8–12). A three-region contact sensor array (heel, midfoot, toe) enables robust detection of foot–ground interactions (Fig. 1). Each sensing region consists of: (1) opposing brass electrodes separated by polyurethane foam, (2) conductive silicone-rubber pads (Ni–Gr filler), (3) a compression-activated switching mechanism, and (4) a molded protective housing. In the second iteration of the system, an IMU was integrated at the forefoot to enable estimation of foot kinematics and spatial gait parameters.

B. Signal Processing and Communication Protocol

Two processing pipelines were developed and evaluated corresponding to successive system iterations.

B.1. Contact Based Temporal Pipeline

In the initial system foot switch signals were monitored to detect gait events; when loaded the foam compression closes the circuit between brass sheets and conductive pads, generating a digital logic signal indicating foot contact. Gait events were derived from footswitch signals and stored on internal board memory until the host device requested updates at 25Hz via Bluetooth Low Energy (BLE). Temporal gait parameters—including step time, stride time, stance time, and swing time—were computed directly from these contact transitions.

B.2. IMU-Integrated Spatiotemporal Pipeline

In the second iteration, raw IMU data and footswitch signals were streamed via BLE to a host computer at 100Hz (Figure 2). On the host computer, sensor signals were filtered using a low pass Butterworth filter (cutoff 5Hz) to attenuate noise and missing samples due to packet loss were reconstructed using linear interpolation. Gait events were identified using a hybrid approach combining contact sensors and gyroscope features.

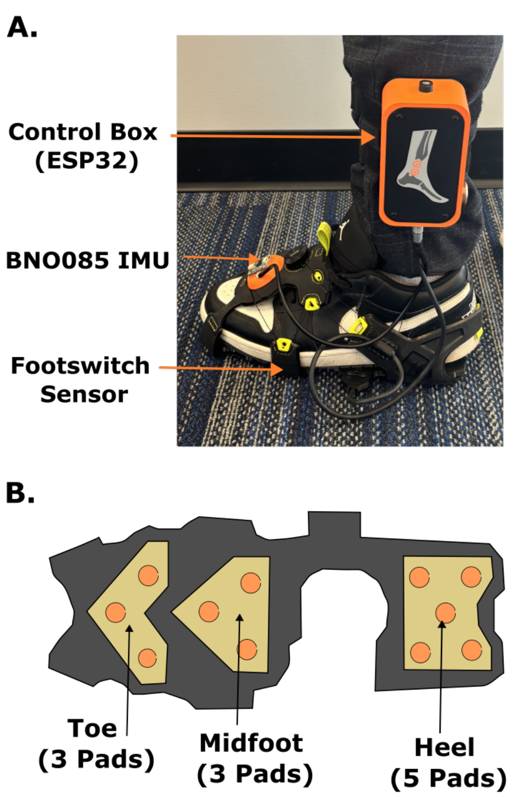

Figure 1: (A) Full instrumented crampon system. (B) Contact sensor layout showing the placement of sensor pads.

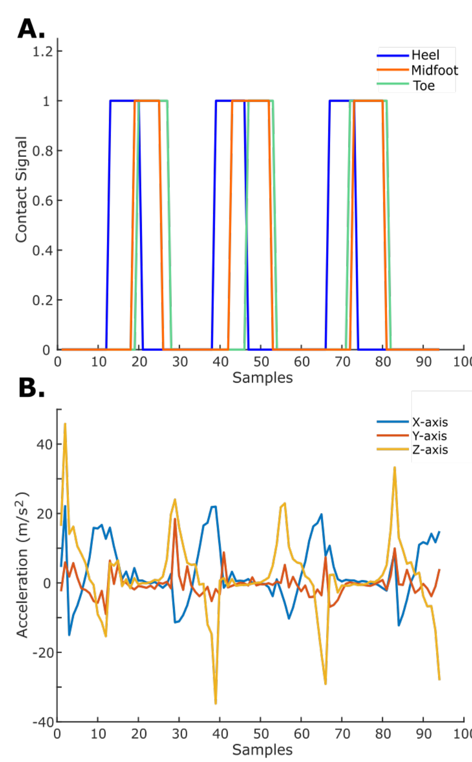

Figure 2: Raw data from three consecutive steps in the GAIT system (A) depicts signals from contact sensors in each region and (B) depicts acceleration signal from IMU.

For the gyroscope, heel strike and toe off were defined as the angular velocity peak preceding midstance and the local minima following midstance. Where stance was determined by the contact sensors. The average gyroscope and contact sensor gait event times were used in subsequent analyses.

Foot kinematics were estimated using a 9-state Extended Kalman Filter (EKF), with position, velocity, and accelerometer bias states. The process model assumed constant acceleration, with bias modeled as a random walk. Measured quaternions were used to rotate accelerations from the sensor frame into the global frame. Gravity-compensated accelerations were integrated to estimate velocity and position. During midstance phases, zero-velocity updates (ZUPTs) were applied to constrain velocity drift. Additionally, to limit drift accumulation, velocity states were reset at the end of each stance phase, while orientation and bias states were preserved.

For this preliminary version of the IMU-integrated system, stride length and toe clearance were the sole spatial metrics derived from estimated foot trajectories and added to the computed metrics. Stride length was defined as the displacement of the foot between consecutive heel-strike (HS) events of the same limb, computed from EKF-estimated positions. Toe clearance was defined as the minimum vertical displacement of the foot during swing relative to the preceding toe-off event. Vertical position was obtained from the EKF-estimated trajectory, and toe clearance was computed within the mid-swing phase (40–60% of swing) to reduce sensitivity to noise and early/late swing artifacts. Table I shows the full battery of outcomes within the scope of this system.

TABLE I

BATTERY OF GAIT PROTOTYPE OUTCOMES

Outcome/Sensor	IMU	Contact Pads
Spatiotemporal		
Cadence		•
Step/Stride Time	•	•
Stance/Swing Duration	•	•
Single/Double Limb Support Duration	•	•
Fall Risk		
Digitigrade Landing		•
Plantigrade Landing		•
Minimum Toe Clearance	•	
Inter-Limb Coordination		
Step Time Symmetry		•
Step Length Symmetry	•	

C. Preliminary Validation

System performance was evaluated through two iterative pilot studies designed to assess and refine system capabilities. The first pilot evaluated the footswitch-only system focused on temporal metrics, while the second incorporated an inertial measurement unit (IMU) to enable spatial measurements and improve overall accuracy. These pilot studies were exploratory and conducted for engineering evaluation purposes only. Institutional Review Board (IRB) approval was not obtained; however, informed consent was obtained for all assessments.

C.1. Temporal Measures in Stroke Subjects

The initial system was evaluated in a clinical population of three individuals post stroke (1 male, 2 females, age: 43.8±3.21) to assess the temporal gait metrics. Participants completed a 10 meter walk test at self-selected comfortable and fastest walking speeds. Data were collected simultaneously from the GAIT system and a GAITRite walkway (New Jersey, USA) which served as the reference standard. Key measures included cadence, step and stride times and stance and swing durations.

C.2. IMU Integrated System in Able-bodied Adults

The IMU integrated system was evaluated in six healthy adults (5 males, 1 female, age: 43.1±9.1). Participants completed three 10 meter walk test at self-selected comfortable and fastest walking speeds over the GaitRite walkway. Subsequently completed an identical set of walking trials during which lower limb kinematics were recorded using an optical motion capture system with a lower body marker set (Vicon, 10 cameras, 150 Hz). Data from these trials were used to calculate the minimum toe clearance (MTC).

D. System Evaluation

Spatiotemporal gait parameters derived from the crampon system were averaged across trials and compared against GaitRite and Vicon reference measurements to assess accuracy, quantified as the mean signed deviation (MSD) and mean absolute percent error (MAPE). Only aggregate, anonymized metrics (e.g., mean stride time) were recorded. All data collection followed standard laboratory and human subjects safety procedures.

III. Results

During clinical assessment of temporal metrics, the system demonstrated moderate accuracy for both paretic and non-paretic legs under self-selected (SSC) and fast walking conditions. Cadence was estimated with moderate error (<10%) across all conditions (Table II). Stride and step times were also estimated with high accuracy (<5% error), while stance phase percentage of the gait cycle showed moderate errors (~10%). In contrast, swing phase duration exhibited higher variability, particularly for the non-paretic leg in SSC and during fast walking. These results indicate that the wearable sensor accurately detected foot contact, as reflected by the accuracy of metrics dependent solely on contact events. However, foot-off and swing initiation were likely detected prematurely, resulting in reciprocal errors in stance and swing time estimates of comparable magnitude Table II.

During able-bodied spatiotemporal evaluation with the IMU integrated iteration, the system demonstrated consistent temporal accuracy compared to clinical assessment, for both legs during self-selected and fast walking. Cadence was estimated with relatively low error across all conditions and stride, and step times maintained the accuracy displayed in clinical testing (Table II). Combined IMU and footswitch gait event detection improved performance as stance phase maintained moderate errors while swing phase showed a substantial improvement compared to the footswitch only system. (Table II) The added spatial metrics showed varied levels of accuracy. Stride length was estimated with modest error at self-selected and fast walking (Table III, Figure 3) Minimum toe-clearance was overestimated by an average of 0.5 cm but had relatively large percentage errors across walking speeds, most likely due to its small absolute magnitude (Table III, Figure 3).

These outcomes indicate that while combining IMU and contact data effectively stabilizes temporal event detection, the system's spatial resolution is still limited when tracking small-magnitude movements. However, despite the relatively larger percentage errors observed in minimum toe-clearance, the overall spatiotemporal accuracy demonstrates the system's foundational feasibility for ambulatory assessment. Collectively, the results demonstrate that the integration of inertial data improved the robustness of swing phase detection, though spatial trajectory estimates remain an area for further algorithmic refinement.

TABLE II
TEMPORAL GAIT PARAMETERS IN STROKE (N=3) AND ABLE-BODIED CONTROLS (N=6)

Condition: Self-Selected Speed					
Cohort/Side	***Cadence (steps/min)***	***Stride Time (s)***	***Step Time (s)***	***Stance (%GC)***	***Swing (%GC)***
Paretic	4.78±4.83 (7.1%)	0.03±0.05 (3.2%)	0.03±0.03 (3.7%)	5.15±3.25 (8.6%)	-5.93±2.91 (15.2%)
Non-Paretic		0.03±0.06 (3.4%)	0.00±0.00 (1.2%)	7.45±1.72 (9.3%)	-7.45±2.54 (28.1%)
Able-bodied	3.91±2.85 (6.4%)	0.01±0.02 (1.2%)	-0.01±0.05 (5.3%)	4.81±3.87 (9.1%)	-4.36±4.89 (10.7%)
Condition: Fastest Speed					
Cohort/Side	***Cadence (steps/min)***	***Stride Time (s)***	***Step Time (s)***	***Stance (%GC)***	***Swing (%GC)***
Paretic	4.90±4.33 (5.7%)	0.02±0.02 (2.8%)	0.03±0.03 (3.9%)	5.35±3.29 (8.8%)	-7.95±3.65 (14.9%)
Non-Paretic		-0.02±0.04 (2.3%)	-0.02±0.03 (4.4%)	5.48±2.78 (7.6%)	-5.15±1.9 (22.5%)5
Able-bodied	4.11±3.71 (5.1%)	-0.02±0.08 (5.0%)	0.01±0.05 (6.9%)	3.38±1.32 (13.1%)	-2.90±1.34 (4.3%)

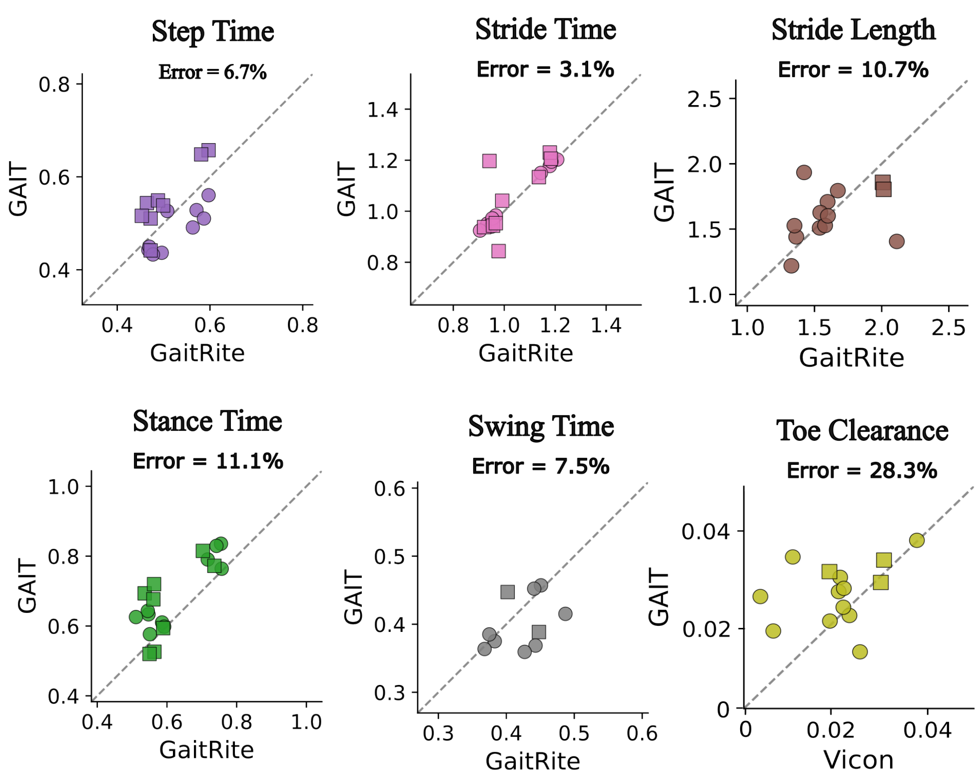

Figure 3: GAIT vs reference systems for IMU integrated iteration shows strong agreement in trial level estimates of spatiotemporal measures

TABLE III
SPATIAL GAIT PARAMETERS IN ABLE BODIED CONTROLS (N=4)

Condition	*MTC (m, %)*	*Stride Length (m, %)*
Self-Selected	0.007 ±0.006 (23.9%)	0.082±0.195 (9.7%)
Fastest	0.003±0.007 (31.2%)	-0.125±0.291 (11.8%)

Values are mean±SD. MTC: minimum toe clearance

IV. DISCUSSION

The current validation results indicate that spatiotemporal gait parameters derived from the GAIT system exhibit relative errors of approximately 3–30% compared to reference measurements from GAITRite and Vicon motion capture, with the majority of metrics exhibiting 10% error or less. While higher than those typically reported for laboratory-based systems, these error magnitudes are consistent with expectations for an early-stage wearable prototype and provide insight into the dominant sources of system-level uncertainty.

Initially, temporal parameter errors arose primarily from systematic bias in gait event detection, particularly the early identification of toe-off. This bias was likely driven by the current sensor configuration and contact thresholding strategy, resulting in an overestimation of swing phase duration and a corresponding underestimation of stance time. Through the incorporation of IMU-derived features into the gait event detection pipeline phase estimation was improved, suggesting that the addition of kinematic information mitigates limitations inherent to binary contact sensing alone.

In contrast, spatial parameter errors most notably minimum toe clearance (MTC)—are dominated by limitations in trajectory estimation fidelity and resolution. MTC was defined as the minimum vertical displacement during mid-swing; however, inspection of the estimated trajectories revealed that the vertical (z-axis) signal often lacked a well-defined local minimum (Figure 4). This attenuation of the mid-swing minimum leads directly to under- or over-estimation of MTC. Several factors may contribute to this behavior. First, packet loss followed by linear interpolation can smooth the trajectory and obscure transient features such as the true minimum. Second, errors in the global frame transformation may introduce cross-axis coupling, where inaccuracies in orientation estimates led to leakage of motion from other axes into the vertical component. Finally, the inherent limitations of drift-prone inertial integration, even with zero-velocity updates, may further reduce sensitivity to small vertical excursions during swing.

Nonetheless, these inaccuracies must be interpreted in the context of the GAIT system's intended use. Unlike fixed, lab-based systems, GAIT prioritizes portability and ease of deployment, enabling the assessment in real-world clinical environments where traditional systems may be impractical. Existing literature provides useful benchmarks for accuracy requirements in real-world health monitoring of gait. Prior

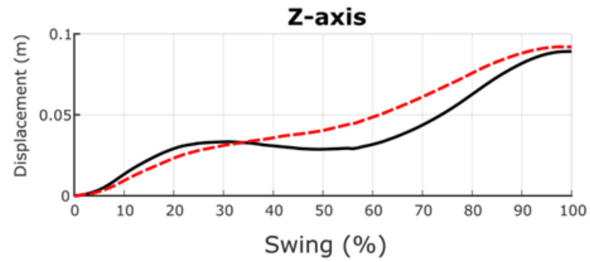

Figure 4: Representative time-normalized foot vertical displacement trajectories during the swing phase (0–100%). Reference motion capture (Vicon, black) and GAIT IMU–derived estimates (red) are shown as mean trajectories across strides.

work has demonstrated that clinically meaningful differences in gait metrics—particularly in older adults and individuals post-stroke—often exceed 10-20%, suggesting that moderate measurement error does not necessarily obscure relevant functional signals [17], [18]. Within this context, the current level of accuracy achieved by the GAIT system is sufficient to support continued development of higher-level, data-driven models aimed at fall risk assessment, even as further refinement of both hardware and algorithms is expected to improve performance in future iterations.

A body of prior work has established links between specific spatiotemporal gait characteristics and fall risk in older adults and clinical populations. Reduced minimum toe clearance, increased step time variability, altered stance and swing timing, and greater inter-limb asymmetry have each been associated with elevated fall risk and impaired dynamic stability[19], [20], [21]. The core temporal metrics we validated in this initial development can be used to derive these higher-level parameters such as single- and double-support time, symmetry, and variability. Additionally, as IMU development continues, metrics such as step length, step width, and their associated symmetries and variabilities will also be obtained. Given these established associations, the ability of the GAIT system to capture these key spatiotemporal parameters supports its potential utility for fall risk prediction. Even in the presence of moderate measurement error, these features may retain predictive value when incorporated into multivariate or longitudinal models, consistent with prior wearable sensing studies [22], [23], [24]. Continued data collection will enable the development of a data-driven model to compute individualized predictive fall risk scores. Machine learning approaches could leverage core spatiotemporal metrics along with higher-level symmetry and variability features to identify patterns associated with elevated fall risk, enable real-time or longitudinal monitoring, and support early intervention strategies. Over time, as the dataset grows, predictive algorithms may be refined to account for population-specific factors, contextual variations (e.g., speed, surface, assistive device use), and longitudinal changes in gait, providing a robust, individualized, and clinically actionable fall risk assessment tool.

A common question for wearable technologies is whether they are "sufficiently" accurate to provide meaningful data or actionable insights. Validation studies of wearable step counters and activity monitors report mean absolute percentage errors commonly in the ~10–20% range across different devices, body placements, and walking conditions[25], [26], indicating that moderate error is typical for many commercially available monitors. Despite this variability in accuracy, consumer wearable activity monitors are widely adopted in clinical and research settings for monitoring physical activity[27]. The data from these devices have been used to evaluate behavioral change and activity trends in populations, suggesting that even measurements with moderate error can meaningfully inform physical activity monitoring and clinical decision-making. This implies that wearable gait assessment systems with similar levels of error may still provide sufficient information for real-world applications such as functional mobility screening, longitudinal monitoring, or risk stratification, even if they do not achieve precise biomechanical quantification.

Limitations

Limitations of the preliminary testing should be considered when interpreting these results. First, the sample size for both pilots was small, which constrains generalizability and precludes subgroup analyses based on stratification of baseline clinical impairment and functional characteristics. Additionally, data were collected during a single session under controlled walking conditions, limiting assessment of longitudinal sensitivity and gait behavior in more challenging or ecologically valid environments, such as home and community ambulation.

Future Work

Future work will focus on improving both the accuracy and scope of the GAIT system. Algorithmic refinements targeting gait event detection, frame alignment, and state estimation will be implemented to reduce error in the currently validated spatiotemporal metrics. In addition to refining the currently validated parameters, future studies will validate the additional capabilities outlined in Table 1 that were not evaluated in this work. Hardware expansion will further enable new biomechanically meaningful measurements, including the integration of a heel mounted IMU to estimate heel velocity at initial contact as an indicator of slip hazard, and adding an IMU to the control box on the shank will allow ankle kinematics to be obtained. Finally, future hardware and software updates will incorporate force-sensing capabilities to enable assessment of foot–ground interaction forces and loading patterns, further expanding the system's biomechanical and clinical utility. Collectively, these developments will support the creation of a robust, data-driven fall risk prediction system capable of integrating spatiotemporal, kinematic, and loading-related features to enable individualized, clinically actionable assessment in real-world settings.

V. Conclusion

This work demonstrates the technical feasibility of the GAIT system as a portable platform for estimating spatiotemporal gait parameters using an integrated foot-based sensing approach. These results establish a baseline level of performance upon which future iterations can systematically improve through refinements in sensor hardware, gait event detection, and IMU state estimation algorithms, to inform data-guided, predictive fall risk models. Collectively, the findings provide an engineering foundation for continued system optimization and support the development of scalable, real-world gait monitoring tools capable of operating beyond laboratory environments.

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