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Foot Clearance Estimation Under Varying Gait Speeds: Comparative Analysis of Real-Time and Time-Normalized Approaches Using Inertial Measurement Units

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Article

Keywords:

Posted Date: July 6th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-10032014/v1

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Additional Declarations: No competing interests reported.

Abstract

Foot clearance is an important biomechanical marker of swing-phase control and trip-related gait stability, but accurate wearable estimation across varying walking speeds remains challenging. This study developed and evaluated an inertial measurement unit based machine learning framework for estimating continuous foot-clearance trajectories during treadmill walking. Sixty-eight healthy young adults walked at slow, preferred, and fast speeds while synchronized foot-mounted inertial measurement units and optical motion capture data were recorded. Motion-capture-derived foot clearance was used as the reference standard. A Bagged Tree Regression model was trained and tested using two temporal representations, time-normalized and real-time data, and two sensor-feature configurations, a full accelerometer, gyroscope, and magnetometer feature set and a reduced accelerometer and gyroscope feature set. Across conditions, the model showed strong agreement with reference trajectories, with R^2 values of approximately 0.75–0.83 and intraclass correlation coefficients of approximately 0.75–0.88. Estimation error was significantly influenced by walking speed, temporal representation, feature set, and their interactions. The full feature set generally produced lower error, although the reduced magnetometer-free configuration remained reliable. These findings support the feasibility of foot-mounted inertial sensors for estimating continuous foot clearance and provide methodological guidance for future wearable gait-monitoring and real-time feedback systems.

Introduction

Foot clearance during walking is a key biomechanical marker of swing-phase control and an important determinant of safe locomotion. The vertical trajectory of the foot, particularly the minimum foot clearance or minimum toe clearance event, reflects the ability of the locomotor system to advance the limb while maintaining sufficient separation from the walking surface [1–4]. Because inadequate or highly variable clearance may increase the likelihood of unintended foot-ground contact, this variable has been widely used as an indicator of tripping risk, gait stability, and neuromotor control [2, 4, 5]. Accordingly, foot clearance has become an important outcome measure in biomechanical and gait-related research [2, 4, 6].

Three-dimensional motion capture remains the reference standard for measuring foot kinematics and foot clearance because it provides direct marker-based estimates of heel, toe, and virtual foot-marker trajectories [7, 8]. However, motion capture systems are expensive, laboratory-bound, and unsuitable for continuous monitoring or real-time biofeedback in daily environments. Inertial measurement units provide a practical alternative because they are portable, low-cost, and capable of recording foot-mounted acceleration, angular velocity, magnetic-field information, and orientation-related signals during walking [9]. Recent validation studies and systematic reviews support the growing utility of IMUs for gait analysis, while also emphasizing that accuracy depends on sensor placement, calibration, signal processing, target outcome, and the choice of reference system [10]. In addition, variations in walking speed may influence IMU-based estimation performance by altering swing duration, foot trajectory, segmental coordination, and the temporal relationship between gait events and peak foot motion [11].

Consequently, estimation models developed under preferred walking-speed conditions may not generalize consistently across slow and fast gait conditions.

Despite these advances, estimating foot clearance from IMU signals remains technically challenging. Traditional IMU-based approaches often require sensor fusion, coordinate transformation, integration of acceleration, drift correction, and event detection, all of which are inherent sources of error [12–15]. These errors may be further amplified under varying walking speeds because changes in gait timing and foot trajectory can alter the relationship between raw inertial signals and reference foot-clearance trajectories. Because these conventional signal-processing approaches depend on multiple sequential processing steps and assumptions, error propagation can limit their robustness for continuous gait estimation. Magnetometer data may improve heading estimation, but magnetic disturbances can reduce robustness in real-world settings, supporting the need to compare full inertial-magnetic feature sets with reduced magnetometer-free feature sets [16, 17]. Machine learning offers a promising alternative because it can learn nonlinear relationships between multi-axis inertial signals and motion-capture-derived foot-clearance trajectories without relying entirely on double integration or rigid analytical assumptions [14, 18–20]. Consequently, accurate and robust continuous foot-clearance estimation across varying walking speeds remains an unresolved challenge, particularly because many existing studies focus on discrete events, limited sample sizes, and restricted walking conditions, thereby limiting the ability to model foot clearance as a continuous time-varying signal across different walking speeds.

Another unresolved methodological issue is how gait time series should be represented before modelling. Time normalization to a fixed percentage of the gait cycle is common in biomechanics because it facilitates comparison across participants, strides, and conditions [21, 22]. However, this process removes absolute temporal information, including gait-cycle duration and sampling-density differences that may be relevant for speed-dependent estimation. In contrast, real-time, non-normalized data preserve the native temporal structure of the signal and are more aligned with future online wearable applications, but they introduce variable-length sequences and may increase modelling complexity. Direct comparison of time-normalized and real-time approaches is therefore necessary to determine whether conventional biomechanical normalization improves estimation performance or whether preserving original timing provides better information for wearable foot-clearance prediction.

This study aimed to develop and evaluate an IMU-based machine learning framework for estimating continuous foot clearance during treadmill walking at slow, preferred, and fast speeds in healthy young adults. Using synchronized optical motion capture as the reference standard, this study compared two temporal representations, time-normalized and real-time data, and two feature configurations, a full accelerometer–gyroscope–magnetometer feature set and a reduced accelerometer–gyroscope feature set. Model performance was assessed using agreement, error, reliability, and variability metrics, and the effects of walking speed, temporal representation, and feature set were statistically examined. This work addresses an important methodological gap in wearable gait analysis by clarifying how temporal representation and sensor-feature selection influence IMU-based foot-clearance estimation under varying gait speeds.

Methods

Participants

A total of 68 healthy young adults (38 females, 56%) voluntarily participated in this study (mean ± SD: age 21.8 ± 3.6 years; height 171.7 ± 8.3 cm; body mass 71.3 ± 12.2 kg). An a priori power analysis was conducted using G*Power (version 3.1.9.7), indicating that a minimum sample size of 68 participants would be sufficient to achieve a statistical power of 0.95 (α = 0.05, effect size = 0.25) [23].

Participants were excluded if they had: (1) any current injury or illness limiting physical activity; (2) a history of lower limb surgery within the past 12 months; (3) neurological or cardiovascular disorders; or (4) back or foot pain during walking. All procedures were explained to the participants prior to testing, and written informed consent was obtained. The study protocol was conducted in accordance with the Declaration of Helsinki and approved by the Ethics Committee of Yazd University (Approval Code: IR.YAZD.REC.1403.078).

Experimental Protocol

Following a detailed explanation of the study aims and protocols, participants were familiarized with treadmill walking using a motorized treadmill (HP Cosmos, Mercury, Germany) to adapt their gait pattern and determine their preferred walking speed. Subsequently, the dominant leg was identified using the ball-kicking test [24].

For kinematic data acquisition, four reflective markers were attached to the heel and fifth metatarsal head of both the left and right feet. Participants were then instructed to stand in an anatomical position on the treadmill for static calibration recording. Each participant performed walking trials under three speed conditions: (1) preferred speed, (2) slow speed (20% below preferred), and (3) fast speed (20% above preferred). The order of speed conditions was randomized [25]. After reaching a steady-state walking condition, gait data were recorded for one minute in each trial [26]. Each condition was repeated three times to ensure measurement reliability.

Data Acquisition

Kinematic data were captured using an optoelectronic motion capture system (OptiTrack Duo 120, USA) at a sampling frequency of 120 Hz. Simultaneously, two inertial measurement units (IMUs; BSNlab, Rasht, Iran) were attached to the dorsum of each foot using double-sided adhesive tape [14]. Each IMU comprised a tri-axial accelerometer (± 16 g), tri-axial gyroscope (± 2000°/s), and tri-axial magnetometer. It should be noted that the recorded IMU data were not strictly raw measurements. Manufacturer-level processing, including sensor calibration, bias compensation, scaling to physical units, and basic signal conditioning, had already been applied within the device firmware. Therefore, the IMU signals used in this study are more accurately described as preprocessed sensor-level measurements. In addition,

orientation estimation was performed using a Madgwick-based sensor fusion algorithm to obtain drift-reduced orientation information from the inertial signals [27].

To preserve the temporal resolution of IMU signals, motion capture data were up-sampled to 250 Hz using a cubic spline interpolation method implemented in MATLAB (MathWorks Inc., USA). Finally, synchronization between the motion capture system and IMUs was achieved using a hardware trigger.

Data Processing

Numerical analysis of motion capture and IMU data was performed using custom MATLAB scripts (R2021B, MathWorks Inc., USA). IMU signals were not additionally filtered in this study, as the recorded data were already preprocessed at the firmware level by the manufacturer, including sensor calibration, bias removal, unit scaling, and basic signal conditioning [28]. Therefore, the signals represented clean sensor-level measurements suitable for subsequent biomechanical analysis without further digital filtering. In contrast, motion capture marker trajectories were processed by first filling potential gaps using cubic spline interpolation. The reconstructed trajectories were then smoothed using a second-order low-pass Butterworth filter with a cutoff frequency of 6 Hz to reduce high-frequency noise while preserving gait kinematics.

Data Preparation Based on the Time-Normalized Approach

After removing the first and last 15 seconds of each trial, gait events were identified using the Foot Velocity Algorithm (FVA). This method, based on only two markers (heel and toe), detects heel strikes (HS) and toe-offs (TO) with errors of less than 17ms and 9ms, respectively [29]. The maximum number of complete right-foot gait cycles performed by all participants across all three speeds was 13 cycles, which were normalized to the percentage of the gait cycle. Consequently, for each participant at each speed, 1300 time-normalized data points were generated.

Data Preparation Based on the Real-Time Approach

In the real-time approach, data were not normalized to the percentage of the gait cycle. Instead, raw data from the first HS of the first gait cycle to the end of the 13th cycle (as defined in the time-normalized approach) were extracted. These data were stored at their original sampling rate of 250 Hz, without segmentation or resampling. The number of data points per participant varied based on their walking speed, ranging from approximately 2500 to 3500 data points.

Machine Learning Input Data

The raw IMU data consisted of three-dimensional acceleration, gyroscope, and magnetometer signals from both IMUs, providing a total of 18 features. In this study, two different input sets were used for the

machine learning model: (1) all 18 features and (2) a reduced set of 12 features, excluding the magnetometer data. All features were normalized using z-scores [30]. To compute foot clearance—the model's target variable—the three-dimensional positions of the heel and toe markers were averaged to create a virtual marker, and its vertical trajectory was extracted from the gold standard motion capture system for use as the supervised learning target [31].

Dataset and Modelling

The dataset consisted of 68 full timeseries files with 1300 data points each for the time-normalized approach, and 68 full timeseries files with variable lengths (2500 to 3500 data points) for the real-time approach. Of these, 85% (58 participants) were used for model training, and 15% (10 participants) were reserved for testing. For foot clearance estimation, various regression models were tested, and the Bagged Tree Regression model was selected [32]. Hyperparameter optimization was performed using grid search with 5-fold cross-validation [33].

Statistical Analysis

The agreement and variability between IMU-derived estimates and motion capture data were assessed using Bland–Altman analysis. To evaluate the performance and reliability of the prediction model, several statistical metrics were computed, including mean difference (bias), coefficient of determination (R^2), root mean square error (RMSE), coefficient of variation (CV), and intraclass correlation coefficient (ICC).

In addition, a three-way repeated-measures analysis of variance (ANOVA) was conducted on RMSE to examine the effects of Speed (Low, Mid, High), Temporal representation (time-normalized vs. real-time), and Feature set (full vs. reduced), as well as their interactions. Post-hoc pairwise comparisons were performed using Bonferroni correction. Statistical significance was defined as $p < 0.05$.

Results

Figure 3 is presented here to illustrate representative foot clearance trajectories for a single subject, comparing ground truth (GT) with model estimates obtained using two feature configurations (full: 18 features; reduced: 12 features) across three gait speeds (Low, Mid, High). Time-normalized (TN) and real-time (RT) representations are shown in the upper and lower panels, respectively. The left panels display time-series comparisons, while the right panels show Bland–Altman plots including bias and limits of agreement (LoA).

Quantitative performance metrics for foot clearance estimation are summarized in Table 1, which reports mean difference (bias), RMSE, coefficient of determination (R^2), coefficient of variation (CV), and intraclass correlation coefficient (ICC) across all combinations of Speed, Temporal representation, and Feature set.

Table 1
Performance metrics of the machine learning model for foot clearance estimation across different gait speeds (Low, Mid, High), temporal representations (time-normalized vs. real-time), and feature sets (full: 18 features; reduced: 12 features). Model performance is reported using mean difference (Diff-mean), root mean square error (RMSE), coefficient of determination (R^2), coefficient of variation (CV), and intraclass correlation coefficient (ICC).

Speed	Temporal Representation	Feature Set	Diff-mean	RMSE	R2	CV	ICC
Low	**Time Normalized**	**Full**	0.001	0.02	0.826	30.757	0.874
		Reduced	-0.001	0.027	0.754	36.714	0.776
	Real Time	**Full**	0.001	0.019	0.826	30.629	0.88
		Reduced	-0.001	0.026	0.761	36.002	0.792
Mid	**Time Normalized**	**Full**	-0.001	0.026	0.806	33.132	0.866
		Reduced	-0.003	0.028	0.782	34.092	0.836
	Real Time	**Full**	0	0.019	0.823	30.445	0.873
		Reduced	-0.002	0.025	0.758	35.899	0.779
High	**Time Normalized**	**Full**	-0.001	0.035	0.766	38.194	0.827
		Reduced	-0.003	0.036	0.767	37.474	0.818
	Real Time	**Full**	-0.001	0.035	0.763	38.333	0.83
		Reduced	-0.003	0.035	0.768	37.187	0.824

Across all conditions, R^2 values ranged approximately from 0.75 to 0.83, while ICC values ranged from 0.75 to 0.88, indicating strong agreement between predicted and ground truth signals. A comparative overview of RMSE and ICC across all experimental conditions is shown in Fig. 4.

A three-way repeated-measures ANOVA on RMSE revealed significant main effects of Speed ($F(2,18) = 32.56$, $p < 0.001$), Temporal representation ($F(1,9) = 86.35$, $p < 0.001$), and Feature type ($F(1,9) = 34.02$, $p < 0.001$). Significant interaction effects were also observed for Speed × Temporal ($F(2,18) = 19.53$, $p < 0.001$), Speed × Feature ($F(2,18) = 18.71$, $p < 0.001$), Temporal × Feature ($F(1,9) = 16.25$, $p = 0.003$), and the three-way interaction Speed × Temporal × Feature ($F(2,18) = 17.34$, $p < 0.001$). These findings indicate that RMSE was jointly modulated by Speed, Temporal representation, and Feature type.

Post-hoc pairwise comparisons (Table 2) showed that the High speed condition differed significantly from both Low and Mid conditions, whereas the Low–Mid comparison exhibited a comparatively smaller effect. RMSE also differed significantly between RT and TN temporal representations, and the Full

feature set yielded significantly lower RMSE values than the Reduced feature set. For the interaction effects, under the RT condition, significant differences were observed between High and both Low and Mid speeds, while the Low–Mid comparison was not significant. In contrast, under the TN condition, all pairwise Speed comparisons reached significance. Similarly, within the Reduced feature set, the Low–Mid speed comparison was not significant, whereas all other contrasts remained significant.

Table 2
Significant post-hoc pairwise comparisons for RMSE

Effect	Comparison	Mean Difference	p-value
Speed	High vs. Low	0.0123	< 0.001
	High vs. Mid	0.0106	< 0.001
	Low vs. Mid	0.0017	0.040
Temporal	RT vs. TN	-0.0023	< 0.001
Feature	Full vs. Reduced	-0.0039	< 0.001
Speed × Temporal (RT)	High vs. Low	0.0125	< 0.001
	High vs. Mid	0.0131	< 0.001
Speed × Temporal (TN)	High vs. Low	0.0120	< 0.001
	High vs. Mid	0.0081	0.002
	Low vs. Mid	-0.0039	0.013
Speed × Feature (Full)	High vs. Low	0.0155	< 0.001
	High vs. Mid	0.0126	< 0.001
	Low vs. Mid	-0.0029	0.002
Speed × Feature (Reduced)	High vs. Low	0.0090	0.003
	High vs. Mid	0.0086	0.002
Temporal × Feature (Full)	RT vs. TN	-0.0030	< 0.001
Temporal × Feature (Reduced)	RT vs. TN	-0.0017	< 0.001

Note: Only statistically significant pairwise comparisons are reported ($p < 0.05$). Mean differences are reported as condition(_1) − condition(_2).

To further interpret the significant interaction effects observed in the three-way repeated-measures ANOVA, complementary follow-up simple effects analyses were conducted. These analyses examined the effect of Speed within each combination of Temporal representation and Feature set, the effect of

Feature set within each combination of Speed and Temporal representation, and the effect of Temporal representation within each combination of Speed and Feature set. Detailed statistical outcomes, including p-values and partial eta squared (ηp^2), are provided in the supplementary tables (Appendix Tables S1–S3).

Complementary ICC analysis demonstrated consistently high reliability across all conditions, with ICC values ranging from approximately 0.75 to 0.88 (Table 1). Full feature configurations generally showed higher reliability compared to Reduced configurations. These results confirm that model outputs are highly reproducible across repeated measurements, indicating that observed variability in RMSE reflects systematic effects rather than random noise.

Discussion

This study evaluated whether foot-mounted IMUs combined with machine learning could estimate foot-clearance trajectories across different walking speeds, temporal representations, and sensor-feature configurations. The model showed strong agreement with motion-capture-derived ground truth, with minimal systematic bias and consistently high reliability across conditions. These findings indicate that the proposed framework can estimate foot-clearance trajectories during treadmill walking with acceptable accuracy, particularly when the full inertial feature set is used. Foot clearance is a critical biomechanical marker of swing-phase control because reduced or unstable clearance may increase the likelihood of unintended foot–ground contact and tripping [34, 35]. Therefore, the present findings support the potential use of IMU-based models for wearable gait assessment and future real-time monitoring applications [36, 37].

Foot clearance is an important marker of swing-phase control because insufficient or unstable clearance can increase the likelihood of unintended foot–ground contact and tripping. Recent work continues to show that minimum toe or foot clearance is relevant to trip risk, although its interpretation depends on the walking context, task constraints, and population under investigation [34, 38]. The present findings extend this literature by showing that wearable inertial signals can be used not only to approximate clearance-related events but also to estimate the continuous trajectory of foot clearance. This is important because the full clearance curve provides richer information about foot lift, mid-swing transport, and pre-contact lowering than a single minimum-clearance value alone [37, 39].

A key methodological finding was that the real-time and time-normalized representations produced broadly comparable estimation performance. Time normalization is common in biomechanical analysis because it standardizes gait cycles and simplifies comparisons across individuals and conditions [40]. However, it removes absolute timing information, including stride duration and speed-related temporal structure [41]. The present results do not indicate that normalization has a uniform or clearly directional effect on the prediction algorithm. Rather, time normalization and real-time representation appeared to perform similarly overall, with possible condition-specific differences depending on walking speed and feature configuration. This interpretation is important because real-time data preserve the native

temporal structure of IMU signals and are more compatible with online monitoring, embedded processing, and feedback systems [42, 43].

The lack of a clear independent effect of walking speed suggests that the model remained broadly robust across slow, preferred, and fast walking. This is encouraging because speed changes alter swing duration, foot trajectory, inertial signal amplitude, and the timing of minimum clearance [34, 44]. However, the significant interaction effects indicate that speed did not influence performance in isolation. Instead, speed modified how temporal representation and feature configuration affected error. This suggests that the model should not be interpreted as entirely speed-independent, but rather as maintaining acceptable performance across speed conditions while showing condition-specific changes in estimation accuracy.

The strongest determinant of model performance was feature configuration. The full feature set generally provided better estimation than the reduced magnetometer-free set, suggesting that magnetometer-derived information may have contributed useful orientation-related information when the magnetic environment was stable. This is consistent with orientation-estimation literature showing that magnetic information can improve heading correction and reduce orientation drift under controlled conditions [45, 46]. However, the reduced feature set remained reliable and became more competitive under faster walking conditions, suggesting that accelerometer and gyroscope signals may contain sufficient dynamic information when foot motion amplitude increases. This finding is practically important because magnetometers can be vulnerable to magnetic disturbance, especially in real-world environments, around metallic structures, or near electronic systems [45, 47].

The interaction structure is therefore one of the most informative aspects of the results. The effects of speed, temporal representation, and feature set were not simply additive, and no single modelling choice was clearly superior across all conditions. For laboratory-based analysis, using the full feature set may still be reasonable because all available sensor channels can be used under controlled magnetic conditions and may provide additional orientation information. For field-based deployment, however, a real-time representation combined with a reduced accelerometer-gyroscope feature set may offer a more practical solution because it avoids the need for post hoc gait-cycle normalization, preserves native timing for online use, reduces dependence on magnetometer signals that may be disturbed outside the laboratory, and may simplify implementation in embedded wearable systems. This distinction is central to wearable gait analysis, where the optimal model is not necessarily the one with the lowest laboratory error, but the one that balances accuracy, robustness, computational simplicity, and ecological validity [42, 48–50].

Several limitations should be acknowledged. First, this study was conducted in healthy young adults during treadmill walking, which provides a controlled validation context but limits generalizability to older adults, clinical populations, overground walking, turning, uneven surfaces, and fatigue-related gait changes. Second, the IMU data were already processed at the firmware level, meaning that the findings apply to pre-processed sensor-level signals rather than strictly raw inertial measurements. Third,

although optical motion capture was used as the reference standard, marker-based clearance trajectories may still be influenced by marker placement, virtual-marker definition, and soft tissue artefact. Finally, future studies should include external validation in more heterogeneous populations and under real-world walking conditions, especially because IMU validity and reliability can vary across walking speed, fall-risk level, sensor placement, and locomotor task complexity [49–51].

Conclusions

this study demonstrates that foot-mounted IMUs combined with machine learning can estimate foot-clearance trajectories with strong agreement and reliability across varying gait speeds. The comparable performance of real-time and time-normalized representations suggests that preserving native temporal information may be sufficient for accurate estimation and may better support future online applications. Although the full feature set produced the strongest overall performance, the reduced magnetometer-free configuration remained reliable and may be advantageous for real-world deployment. Collectively, these findings clarify how temporal representation and sensor-feature selection influence IMU-based foot-clearance estimation and provide a methodological foundation for future wearable systems for gait monitoring, fall-risk assessment, and real-time locomotor feedback.

Declarations

Ethics approval and consent to participate

All procedures performed in this study were approved by the Ethics Committee of Yazd University (Approval Code: IR.YAZD.REC.1403.078). Written informed consent was obtained from all participants prior to study participation.

Consent for publication

Written informed consent was obtained from all participants for the publication of anonymized data, study results, and the use of gait-related images.

Competing interests

The authors declare that they have no competing interests.

Funding

This research received no external funding.

Author Contribution

M.H.L. contributed to conceptualization, methodology, software development, validation, formal analysis, investigation, data curation, writing the original draft, and project administration.P.A.A. contributed to conceptualization, methodology, validation, formal analysis, writing the original draft, and writing—review and editing.J.S. contributed to conceptualization, methodology, data curation, resource provision, writing the original draft, and writing—review and editing.

Acknowledgement

The authors would like to thank all participants for their valuable cooperation in this study.

Data Availability

The datasets generated and analyzed during the current study are publicly available in the Zenodo repository. The supporting files, including the processed datasets used for model training and evaluation, can be accessed via the following DOI:https://doi.org/10.5281/zenodo.19822541

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Figures

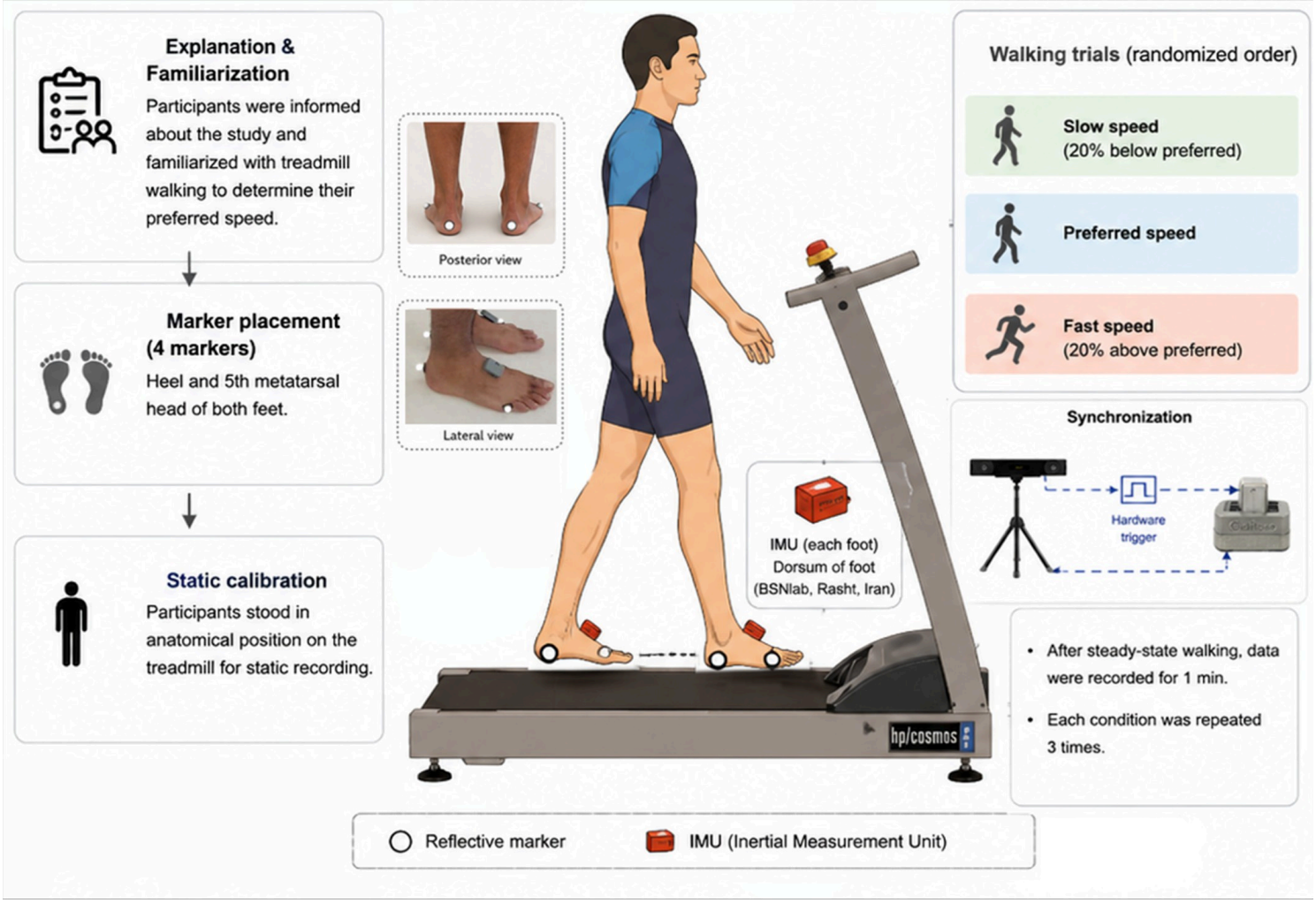


Figure 1

Experimental setup for synchronized gait data acquisition using motion capture and foot-mounted IMU during treadmill walking.

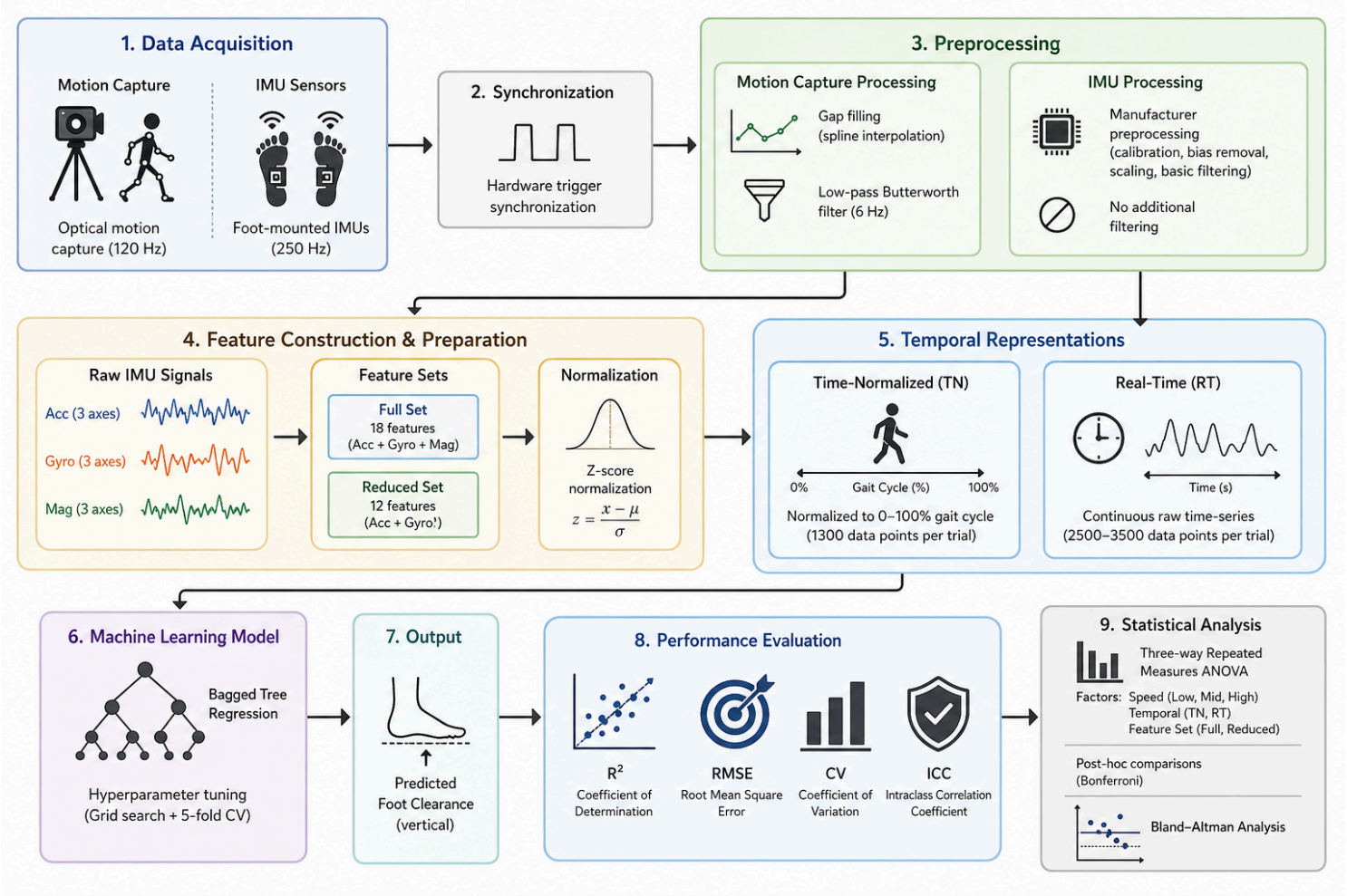


Figure 2

Data processing and machine learning workflow. Synchronized motion capture and IMU data were preprocessed, features were extracted (full and reduced sets) and normalized, and two temporal representations (time-normalized and real-time) were generated. A Bagged Tree Regression model was used to estimate foot clearance, and performance was evaluated using RMSE, R^2, CV, ICC, and statistical analysis (Bland–Altman and repeated-measures ANOVA).

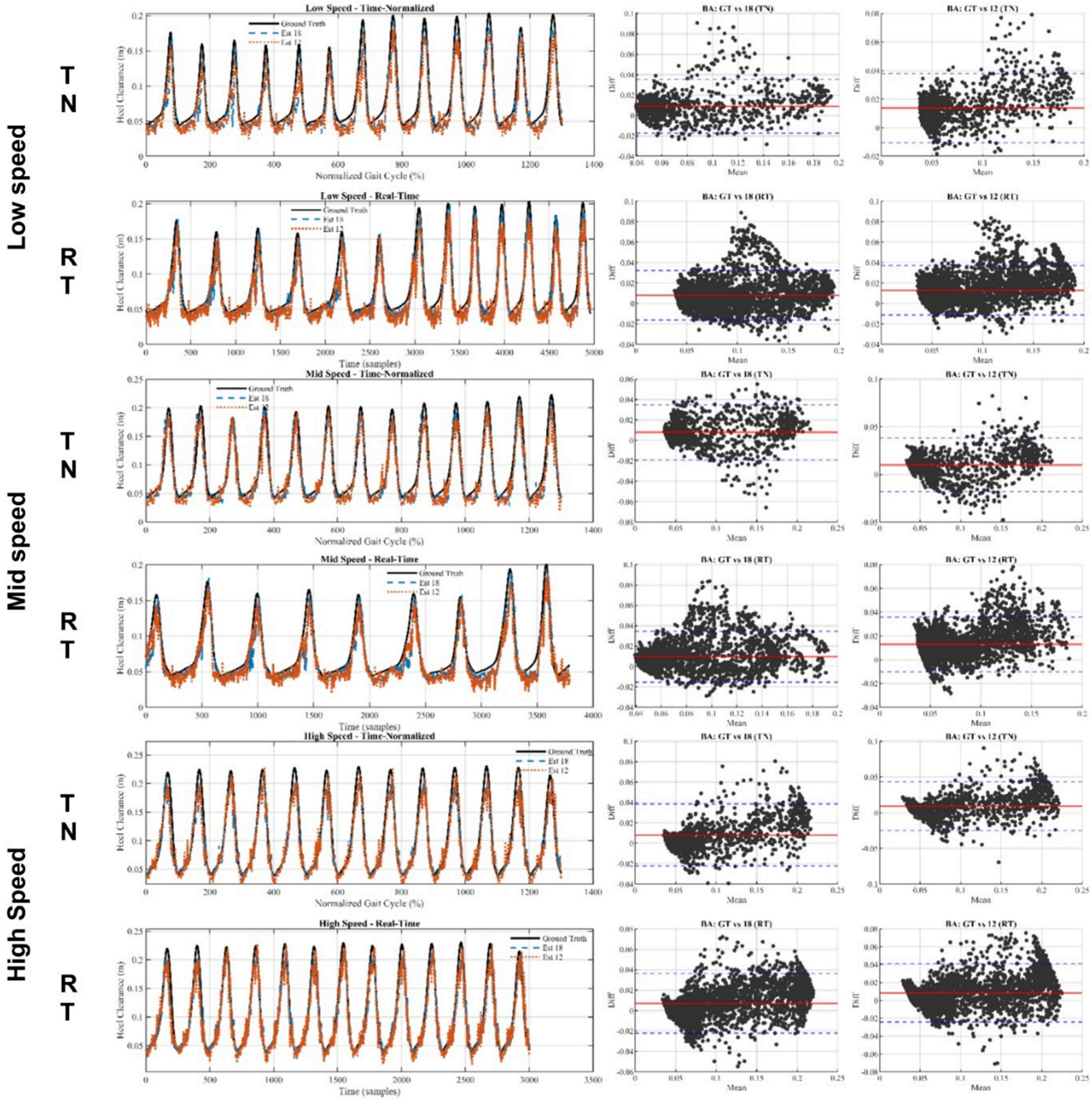


Figure 3

Comparison of foot clearance between ground truth (GT; Ground Truth) and model estimates using two feature sets: full (Est18; 18 features) and reduced (Est12; 12 features), across three gait speeds (Low, Mid, High) for a representative subject (Subject 1). The top row presents the time-normalized (TN) representation, while the bottom row shows the real-time (RT) representation. Time-series signals are displayed in the left column, and agreement between methods is evaluated using Bland–Altman analysis in the right column, including bias and limits of agreement (LoA).

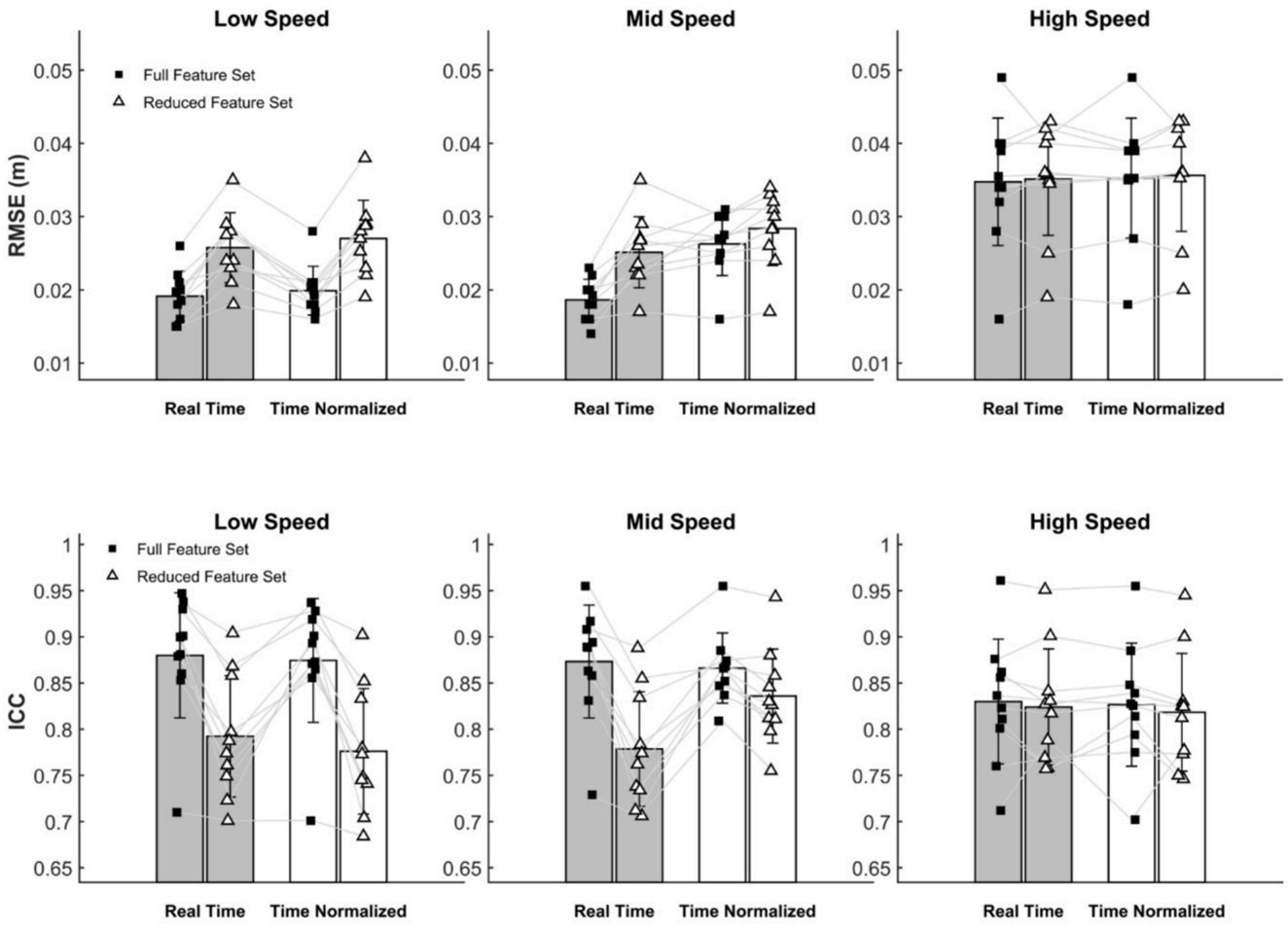


Figure 4

Comparison of RMSE and ICC for foot clearance estimation across gait speeds (Low, Mid, High), temporal representations (real-time vs. time-normalized), and feature sets (Full vs. Reduced). RMSE reflects estimation error, while ICC represents reliability across repeated measurements.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- Appendix.docx