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Mobility Monitoring for Geriatrics: Gait Detection and Parameter Extraction using an e-Textile Garment IMU and Deep Learning.

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***Abstract*—This study introduces and validates a practical, two-stage pipeline for the unobtrusive detection and analysis of gait using a single Inertial Measurement Unit (IMU) integrated into a smart undershirt, positioned at the abdomen, aimed at enabling reliable long-term geriatric monitoring. Data were collected from 15 healthy young adults performing free movement and quiet standing. The pipeline first employs a 1D Convolutional Recurrent Neural Network (1D-CRNN) classifier using six IMU signals and derived features to segment gait versus standing activity. Subsequently, a routine utilizing bandpass filtering and peak detection on the Euler angle magnitude is used to count steps and derive cadence and step variability. The 1D-CRNN achieved excellent classification performance with an Accuracy of 0.981 $\pm$ 0.022 and a PR_AUC of 0.995 $\pm$ 0.005. The step detection successfully isolated continuous walking segments, yielding plausible cadence estimates (e.g., 94.6 steps/min) and measures of step variability (0.236 s). The smart-textile-based system provides a robust and lightweight solution for reliable gait detection and the extraction of fundamental mobility metrics from an unobtrusive trunk location. This foundation is crucial for developing practical wearable technologies for assessing functional health in older adults, with future work focusing on clinical validation in geriatric cohorts and expanding the activity classification spectrum.**

***Index Terms*—Gait Analysis, Smart Textiles, Inertial Measurement Unit (IMU), Convolutional Recurrent Neural Network (CRNN), Activity Classification, Mobility Monitoring**

INTRODUCTION

Gait is one of the most informative indicators of functional mobility and overall health in older adults [1]. Characteristics such as cadence, variability, and step symmetry are vital for assessing frailty, fall risk, and cognitive decline in geriatric populations [2], [3]. In clinical practice, slow or unstable gait is often an early predictor of reduced independence, risk of hospitalization, or increased mortality in elderly individuals [1].

Shin et al. (2025) demonstrated significant associations between sensor-derived gait metrics (such as cadence and step length) and clinical measures of muscle mass and physical performance in community-dwelling seniors [4].

From a methodological perspective, Oudre et al. developed a robust algorithm for automatic gait event detection (heel strikes, toe-offs) in both healthy subjects and severely impaired patients using filtered IMU acceleration and pattern matching [5]. In a similar vein, Stenger et al. (2025) validated an approach for gait event detection and step-length estimation using a single waist-mounted IMU, achieving high accuracy compared to a GAITRite reference system [6].

Together, these studies underscore both the clinical relevance and technical feasibility of using wearable IMUs for real-world gait monitoring in older adults, motivating our work that combines activity classification with step detection in a non-invasive, smart-textile-based setup. To address these gaps, this work introduces a novel, two-stage pipeline for unobtrusive gait analysis. Our main contributions are: 1) The development and validation of a 1D-CRNN model for accurate classification of gait versus standing using data from a single abdomen-mounted IMU integrated into a smart undershirt. 2) The reliable extraction of clinically relevant gait parameters (cadence, step count, and variability) from the segmented gait episodes, suitable for future geriatric mobility assessment.

MATERIALS AND METHODS

Data set

The study protocol for the development of the smart undershirt was submitted to and favorably assessed by the Ethics Committee of the Brandenburg University of Technology Cottbus-Senftenberg on August 30, 2024 (File Number: EK2024-26).

The investigation included healthy adult participants. Inclusion criteria required participants to be able to ambulate without assistance. As the test was entirely voluntary, the primary exclusion criterion was participant unwillingness to proceed.

The current dataset, which represents a partial evaluation of the larger four-part experimental design, comprises recordings from a total of 15 participants (4 males and 11 females). The participants had a mean age of $22.27 years$ ($\sigma = 3.31 years$).

The data presented here were collected based on two phases:

1) Free-Movement Phase: Participants were first instructed to engage in unrestricted movement within a defined

Fig. 1. Prototype of the smart undershirt.

space for a period of **five minutes (5 minutes)**. Participants performed a variety of movements commonly encountered in Activities of Daily Living (ADL), such as walking backward, ascending/descending stairs, and normal ambulation. Participants were granted full creative freedom, provided the movements remained representative of routine daily activities.

2) Quiet Standing Phase: Subsequently, participants were instructed to stand still for a duration of five minutes (5 minutes).

The smart undershirt was designed to capture comprehensive physiological and movement data. It was equipped with a diverse array of integrated sensors [8]. For this analysis we use the Bosch/CEVA BNO085 IMU Sensor on Abdomen [7]. We recorded Euler angle and linear Acceleration with a frequency at 80 Hz, see Figure 1.

Activity Classifier

We convert quaternions to Euler angles (ZYX: yaw, pitch, roll) using standard rotation conventions and SciPy's spatial transform routines. Zero quaternions (all zeros) are replaced with the identity quaternion to avoid numerical errors. A time axis is generated with a frequency of 80 Hz. Channels used as model input: $yaw, pitch, roll, a_x, a_y, a_z$. For each sliding window we compute derived features: first differences of Euler and acceleration, acceleration magnitude, and Euler magnitude. The final per-sample feature vector contains the original 6 signals plus the first differences (6), plus two norms, resulting in 14 features per time step.

We segment each labeled region using a sliding window of length W samples and step size S. Each window inherits the label of the region it falls into (gait or standing). To avoid data leakage between subjects/recordings we perform group-wise cross-validation using GroupKFold, where groups correspond to file identifiers.

The RCNN architecture consists of two Conv1D layers (32 and 64 filters, kernel size 5) with max-pooling, followed by an LSTM (64 units), dropout (0.5), a dense layer (32 units) and a single-unit sigmoid output for binary classification. Binary cross-entropy loss and class weighting (computed from training folds) handle label imbalance.

We train with Adam optimizer and early stopping (patience can be added). Evaluation metrics include accuracy, precision, recall, F1-score, ROC-AUC and average precision (PR-AUC). GroupKFold (K=5) provides unbiased estimates across recordings.

Step Detection

For windows classified as gait, the step detection pipeline is:

1) Compute Euler angle magnitude: $e_{mag} = \sqrt{yaw^2 + pitch^2 + roll^2}$.
2) Bandpass filter e_{mag} within $0.5-3Hz$ using a 4th-order Butterworth filter and zero-phase filtering (filtfilt).
3) Smooth the filtered signal with a moving average with size 5 ($0.0625s$) to reduce residual noise.
4) Detect peaks with *scipy.signal.find_peaks* using adaptive criteria: minimal distance (e.g., 0.3 f_s samples), prominence proportional to the signal standard deviation, and optional height threshold.

This procedure produces peak timestamps corresponding to detected steps. From these we compute step count, inter-step intervals, cadence (steps per minute), and step-time variability (std of intervals).

RESULTS

Activity Classification

Table I summarizes the classification performance of the proposed 1D-CRNN model for detecting gait versus standing across different window sizes. All evaluated window configurations demonstrate high performance, with accuracy consistently above 0.97. Among them, the window size of 150 samples ($\approx$ 1.875 s) yielded the best overall performance across all metrics. Specifically, it achieved the highest F1 score, precision, and recall, indicating a strong balance between sensitivity and specificity.

Notably, the ROC_AUC and PR_AUC scores for the 150-sample window outperform the smaller window sizes by a significant margin, highlighting the model's superior ability to distinguish between gait and standing activities, even under class imbalance. These results suggest that slightly longer temporal windows allow the model to better capture the dynamic characteristics of gait patterns while maintaining generalization stability, as reflected by the low standard deviations across folds.

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TABLE I
CLASSIFICATION PERFORMANCE OF THE 1D-CRNN MODEL WITH DIFFERENT WINDOW SIZES FOR 5 FOLDS. VALUES ARE REPORTED AS MEAN ± STANDARD DEVIATION. THE BEST PERFORMANCE WAS ACHIEVED FOR A WINDOW SIZE OF 150 SAMPLES ($\approx 1.875s$) (HIGHLIGHTED IN BOLD).

Metric	Window Size 100	Window Size 110	Window Size 150
Accuracy	0.979 ± 0.023	0.981 ± 0.023	**0.981 ± 0.022**
Precision	0.967 ± 0.045	0.968 ± 0.043	**0.970 ± 0.042**
Recall	0.994 ± 0.003	0.997 ± 0.003	**0.995 ± 0.003**
F1 Score	0.980 ± 0.022	0.981 ± 0.022	**0.982 ± 0.021**
ROC_AUC	0.985 ± 0.021	0.985 ± 0.021	**0.995 ± 0.004**
PR_AUC	0.979 ± 0.029	0.980 ± 0.028	**0.995 ± 0.005**

Step Detection and Stride Estimation

The proposed model successfully segmented the gait activity into three distinct walking episodes, as shown in Table II and Figure 2. Segment 1 represents the longest continuous gait interval with a duration of 145.88 s, during which 230 steps were detected, corresponding to a cadence of 94.6 steps/min. The step variability in this segment was 0.236 s, indicating a relatively stable walking pattern with moderate temporal consistency.

Segment 2 covers a shorter walking interval of 69.75 s and includes 113 steps, resulting in a cadence of 97.2 steps/min. The step variability (0.229 s) is comparable to Segment 1, suggesting similar gait regularity despite the reduced duration.

Segment 3 is a very short gait episode lasting only 1.88 s, containing 4 detected steps with a cadence of 128.0 steps/min. This unusually high step frequency and low variability (0.120 s) likely indicate a brief acceleration or transitional movement rather than steady-state gait.

Overall, the results confirm that the model reliably identifies gait segments of varying durations and accurately estimates key step-related metrics such as cadence and step variability. Longer segments demonstrated more stable gait patterns, whereas very short gait intervals exhibited higher variability and were less representative of typical walking behavior.

TABLE II
SEGMENT-WISE GAIT DETECTION AND STEP CHARACTERISTICS.

Metric/ Segments	1	2	3
Start (s)	5.94	153.69	468.69
End (s)	151.81	223.44	470.56
Duration (s)	145.88	69.75	1.88
Steps	230	113	4
Steps/min	94.6	97.2	128.0
Step Variability (s)	0.236	0.229	0.120

DISCUSSION

This study successfully validates a two-stage pipeline for unobtrusive mobility assessment using a single abdomen-mounted IMU integrated into a smart undershirt. The results confirm the robustness of the activity classification and the plausibility of the extracted gait metrics.

The proposed 1D-CRNN model demonstrated excellent performance in distinguishing gait from standing, achieving an accuracy above 0.98 and a PR_AUC of 0.995 (for W=150 samples, Table I). This performance is highly competitive and validates the use of the abdominal sensor placement in a textile format, which is key for high user acceptance in long-term geriatric monitoring [1]. The superior performance of the 150-sample window suggests that this duration effectively captures the dynamic characteristics of trunk movement during ambulation. The low standard deviations across cross-validation folds indicate strong model generalization within the healthy cohort.

The subsequent step detection pipeline, based on filtering the Euler angle magnitude, reliably extracted clinically relevant parameters like cadence and step variability (Table II). The mean cadence (94.6 to 97.2 steps/min) is consistent with typical walking speeds for healthy adults, and the low variability ($\approx$0.23 s) confirms a stable, steady-state gait. The results demonstrate the pipeline's capability to provide basic mobility parameters critical for assessing frailty and fall risk [3].

The clear segmentation of activity into "Gait" and "Standing" is not only valuable for mobility assessment but also provides distinct periods for extracting additional physiological data. Notably, the identified quiescent "Standing" phases can be leveraged for highly accurate measurements of other vital signs. This is reinforced by our parallel work, which has demonstrated the successful application of a 1D-CRNN for respiration monitoring using the same smart textile platform during periods of low activity [9]. This integration capability underscores the potential of the smart undershirt as a truly multi-functional monitoring system.

While effective, the current study has limitations: The data was collected exclusively from young adults, requiring validation on the target geriatric population where gait patterns and sensor signals are expected to differ significantly [2]. Furthermore, the extracted step metrics require validation against a gold standard system to confirm their absolute clinical accuracy, and the activity scope must be extended to a broader range of Activities of Daily Living (ADL).

CONCLUSION

We presented a practical and reproducible two-stage pipeline for gait detection and step analysis utilizing data from a single abdomen-mounted Inertial Measurement Unit (IMU) integrated into a smart undershirt. The 1D-CRNN model achieved an excellent activity classification accuracy (Accuracy > 0.98) between gait and standing, demonstrating the robust capability of the textile-integrated sensor setup. Following classification, key gait parameters such as cadence and step variability were reliably extracted, making the approach suitable for assessing fundamental mobility metrics.

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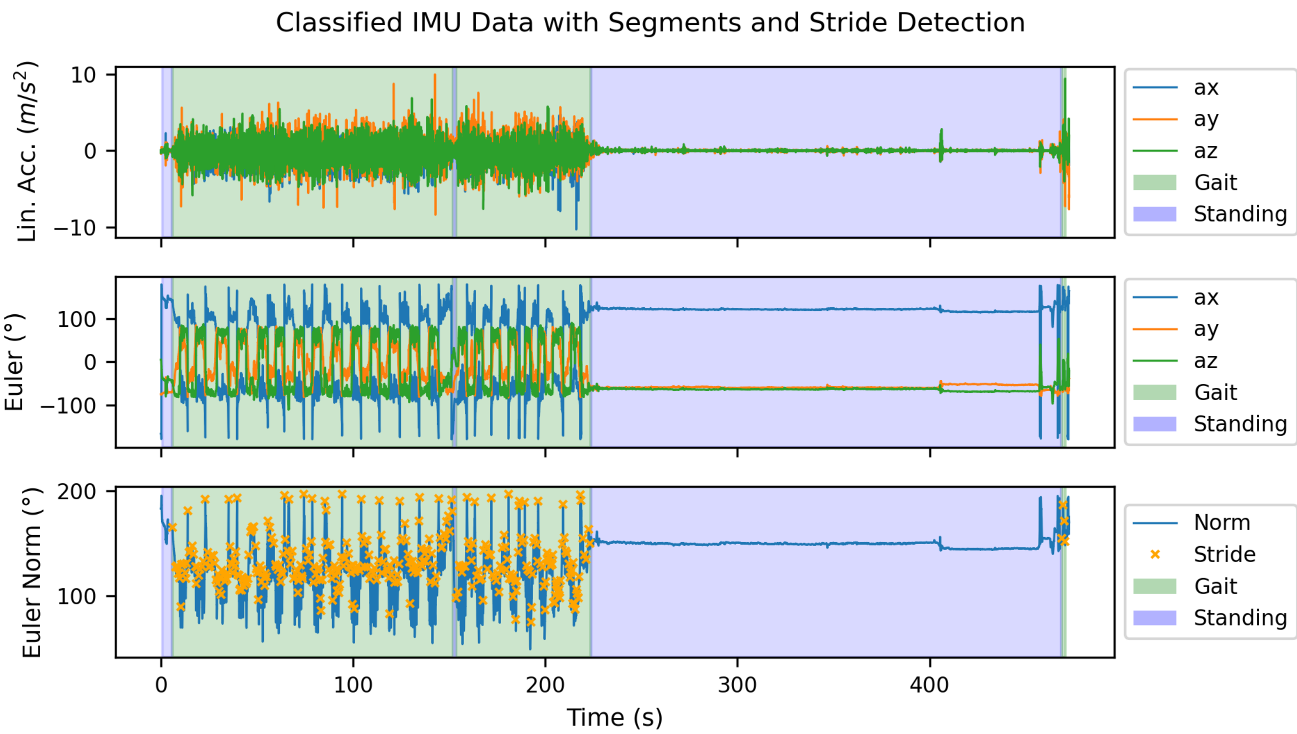

Fig. 2. The figure displays (top to bottom): Linear Acceleration (ax,ay,az in m/s2), Euler Angles (yaw,pitch,roll in degrees), and the Euler Norm (in degrees). The background color indicates the activity class predicted by the 1D-CRNN: Gait (green) and Standing (purple). In the bottom plot, the Euler Norm is used for step detection; the orange 'x' markers indicate the detected steps (or strides) within the segmented gait periods. The model successfully isolates periods of continuous walking from quiescent standing.

The method is lightweight, relies on highly acceptable, unobtrusive textile sensing, and is thus well-suited for large-scale or near-real-time monitoring applications, particularly in elderly populations.

Future work will focus on:

- Extending the activity classification to include a full spectrum of Activities of Daily Living (ADL).
- Validating the pipeline's performance and the accuracy of the derived gait parameters against a gold standard in the target geriatric cohort.
- Refining step detection and stride estimation through anthropometric calibration or sensor fusion techniques.

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References

[1] Studenski, S., Perera, S., Patel, K., Rosano, C., Faulkner, K., Inzitari, M., ... & Guralnik, J. (2011). Gait speed and survival in older adults. Jama, 305(1), 50-58.

[2] Verghese, J., Wang, C., Lipton, R. B., Holtzer, R., & Xue, X. (2007). Quantitative gait dysfunction and risk of cognitive decline and dementia. Journal of Neurology, Neurosurgery & Psychiatry, 78(9), 929-935.

[3] Hausdorff, J. M., Rios, D. A., & Edelberg, H. K. (2001). Gait variability and fall risk in community-living older adults: a 1-year prospective study. Archives of physical medicine and rehabilitation, 82(8), 1050-1056.

[4] Shin, J., Kweon, H. J., & Choi, J. (2025). Assessment of Gait Parameters Using Wearable Sensors and Their Association With Muscle Mass, Strength, and Physical Performance in Korean Older Adults: Cross-Sectional Study. JMIR Formative Research, 9, e63928.

[5] Voisard, C., De l'Escalopier, N., Ricard, D., & Oudre, L. (2024). Automatic gait events detection with inertial measurement units: healthy subjects and moderate to severe impaired patients. Journal of NeuroEngineering and Rehabilitation, 21(1), 104.

[6] Stenger, R., Hozhabr Pour, H., Teich, J., Hein, A., & Fudickar, S. (2025). Gait Event Detection and Gait Parameter Estimation from a Single Waist-Worn IMU Sensor. Sensors, 25(20), 6463.

[7] CEVA, Inc. (2021): BNO080/BNO085 Intelligent 9-Axis Absolute Orientation Sensor – Datasheet, Rev. 1.11. CEVA Technologies Ltd., Hillcrest Labs Division. Available online: https://www.ceva-ip.com/wp-content/uploads/BNO080_085-Datasheet.pdf(accessed on 13 October 2025).

[8] Steinmetzer, T., Wieczorek, F., Naake, A., Wolf, P., Braun, A., & Michel, S. (2025). Smart e-Textile Singlet Prototype and Concept: Multi Sensor Sensing for Geriatric Monitoring. Bioengineering, 12(11), 1275.

[9] Steinmetzer, T., & Michel, S. (2025). Towards Wearable Respiration Monitoring: 1D-CRNN-Based Breathing Detection in Smart Textiles. Sensors, 25(22), 6832.