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Smarter Canes: Low-Cost Sensing for Step Counting and Self-Supervised Gait Assessment

Giacomo Salici and Roberto Vezzani

AlmageLab, University of Modena and Reggio Emilia, Italy

name.surname@unimore.it

Abstract—Wrist-worn wearables are the dominant paradigm for step counting, but their performance degrades noticeably when used by people with motor impairments. We instrument a standard cane with a low-cost sensing framework to address this and, at the same time, to lay the foundation for a self-supervised gait-quality assessment in which a convolutional autoencoder trained only on normal walking uses reconstruction error as an anomaly score. A downward-facing time-of-flight sensor measures the distance of the cane tip from the ground and provides the reference against which step counting is validated, reaching 92.9% accuracy, while on the same recordings the anomaly detector reaches 98.7% AUPRC under session-level cross-validation, also ordering the types of gait problems by how strongly they deform the signal.

Index Terms—gait monitoring, smart cane, step counting, anomaly detection, self-supervised learning, assistive technology

I. MOTIVATION AND RELATED WORK

Step counting and, more broadly, gait monitoring are recognised indicators of health, autonomy, and fall risk in elderly or motor-impaired populations. Nearly all commercial counters rely on wrist- or ankle-worn accelerometers calibrated on the regular gait of healthy subjects, and they lose accuracy precisely on asymmetric or assisted walking [1]. Trackers that agree closely with observed counts when unaided *degrade as soon as an aid is introduced* [2], [3], and the same happens to healthy adults simply asked to use one [4], so it is the aided gait pattern rather than any pathology that defeats the counter. Since people who walk atypically are often those who use walking aids, we place the sensor on the walking *aid*: each cane-to-ground contact produces a distinct acceleration transient that can be analysed. The design is easy to adapt to existing canes and fully open-source: hardware schematics, firmware, software, and dataset are publicly available.¹

Inertial gait analysis is well established, with models able to extract clinical parameters and step counts from foot- and shank-mounted units [5], [6]. Such pipelines are, however, supervised, and labels for pathological gait are expensive, scarce, and condition-specific, which is why laboratory-validated algorithms lose accuracy in free-living use [7].

Instrumented canes address a different problem. Most are designed to assist people with visual impairments by detecting obstacles ahead of the user [8], or act as telemonitoring devices reporting alarm events to a remote carer [9]. Closest to our first task, a cane-mounted step-counting algorithm has been proposed within a connected assistive platform [10].

¹All code and materials will be available at cane.jacksalici.com.

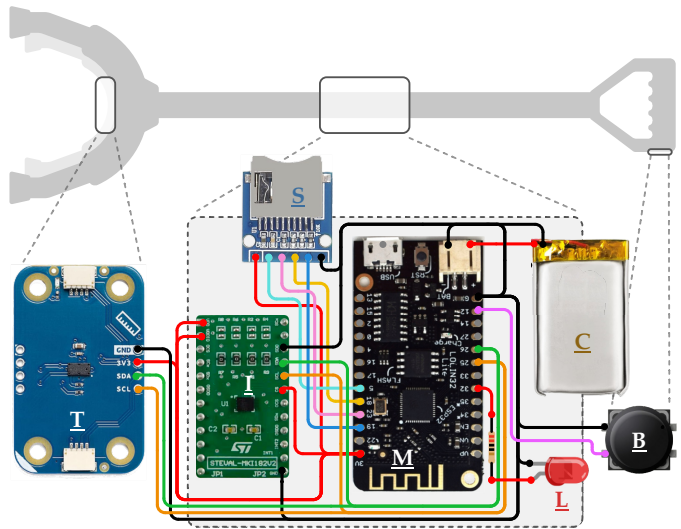


Fig. 1. Structure and schematics of the smart cane. A 3D-printed core enclosure on the shaft holds the Microcontroller, the IMU, the microSD shield, the status LED, and the LiPo Cell; a second unit under the quad base carries the Arduino Modulino Time-of-flight sensor. The Button on the handle starts and stops a session and annotates events during it.

To our knowledge, no previous work has addressed gait *quality* from an instrumented cane: existing canes sense the environment or report discrete events; that is, they measure *how much* a person walks, not *how well*. The framing is close to anomaly detection, where reconstruction-based methods mitigate the need for extensive labelled data: an autoencoder learns a representation of *normal* patterns, and its error on unseen input is a usable novelty score [11], [12]. This suits gait: normal walking data are abundant and require no anomaly annotation, while abnormal patterns are rare and diverse.

II. THE INSTRUMENTED CANE

To record gait and evaluate the proposed algorithms, we built a low-cost prototype from off-the-shelf components, adaptable to commercial tripod and quadripod canes with minimal modification (Fig. 1). A Lolin32 Lite ESP32 board, chosen for its on-board LiPo connector and charging circuit, as well as its low unit cost, samples an ISM330DLC six-axis IMU and a VL53L4CD time-of-flight (ToF) sensor, storing data on a microSD card. The ToF sensor, part of the Arduino Modulino Distance component, uses a Qwiic connector, easing replacement or integration of compatible sensors.

The electronics are housed in a 3D-printed enclosure mounted on the cane shaft, while the ToF sensor is positioned under the base and points towards the ground to measure the distance between the cane tips and the ground. A handle-mounted button controls recordings and allows event annotation, while an LED reports the recording status. To make sure that the recording timestamps are correct, the Wi-Fi connection synchronises the device clock over NTP. A LiPo battery provides approximately one day of operation. Electronics, battery, and enclosure weigh about 20 g, 19 g, and 40 g, for a total added mass below 80 g. The bill of materials amounts to roughly €50 at single-unit retail prices, dominated by the IMU and the ToF module. A small production run may further reduce manufacturing cost and device mass.

III. DATASET

No public dataset records cane-mounted inertial and tip-to-ground signals together, so a small dataset was collected for this work by a person with gait impairments: 29 sessions lasting from a few tens of seconds to several minutes. Each recording is annotated at the session level using the button on the cane’s handle. Whether a session is normal or abnormal throughout can be marked with a double or a long press, respectively, while individual events can be annotated by pressing once while recording. In this way, labelling needs no video alignment or second observer. As summarised in Table II, five abnormality classes are represented: *tremors and short steps*, *short and irregular steps*, *anomalous long steps*, *unsteadiness*, and *various falls*. The recordings sample seven channels: the three accelerometer axes, the three gyroscope axes, and the tip-to-ground distance. The 18 normal sessions are used for step counting and for fitting the anomaly detector, while the 11 abnormal ones are used for testing only.

IV. STEP COUNTING

The first analysis evaluated the accuracy of the step-counting algorithm, which reaches $92.9\% \pm 5.6\%$ across 45 windows of 30 s using a leave-one-session-out (LOSO) estimate: the parameters are selected on all sessions but one and scored on the held-out session, in turn for each session.

The algorithm uses only inertial data, detecting peaks in the deviation of the acceleration magnitude from gravity, $|\text{acc}| - 1\text{ g}$, because a cane strike is a broadband mechanical shock rather than a smooth periodic oscillation. Three conditions identify a valid step (values selected on all sessions): (i) an adaptive height threshold, defined as $\max(\mu + 3.2\sigma, 0.30\text{ g})$, which adapts to the noise level of each recording; (ii) a minimum peak prominence of 0.5 times the detection threshold, which rejects oscillations following the impact; and (iii) a refractory period of 1.15 s between consecutive detections, which prevents multiple detections of the same strike.

The ToF sensor provides an independent reference: the measured distance stays within a stable range while the cane is planted and increases when the tip leaves the ground, so a step is detected when it crosses a lift threshold, with hysteresis suppressing small fluctuations during the swings.

We applied the ToF sensor only to validate the counter, not as the counter itself: an IMU is less expensive and more readily available, and needs no downward-facing mount, making an IMU-only counter easier to deploy.

V. GAIT QUALITY ASSESSMENT

Step counting quantifies the number of steps, whereas the second task assesses deviations from normal gait patterns. To this end, we apply an autoencoder trained to reconstruct steps from normal walking. In this setting, the reconstruction error represents the so-called anomaly² score: when a window contains a pattern that differs substantially from those observed during training, the model is expected to produce a larger reconstruction error.

A. Window alignment and preprocessing

Every channel is resampled to 25 Hz and segmented into 6 s windows, spanning roughly three steps at this cadence, with a stride of 1.5 s. To ensure that each window falls at a comparable point in the gait cycle, we centre it on the nearest detected step whenever one is found within the window. Otherwise, we shift it by the lag that best matches a template of normal gait under cross-correlation, following the strategy used by other anomaly detectors [13]. This mixed policy reduces the bias that relying solely on the second method would introduce, and because windows slide continuously, a failed detection triggers the fallback rather than producing a missing window. The channels are also z-scored, with statistics fitted on the training windows only, so that every channel is on the same scale when analysed by the model.

B. Model and decision

The anomaly detector is a lightweight 1-D convolutional autoencoder operating on (8, 150) windows, the eight channels being the six inertial axes, the derived acceleration magnitude, and the tip-to-ground distance; the last is optional, as investigated in Section V-C. The encoder uses three strided convolutions (kernel 7, stride 2, padding 3), ReLU activations and a 16-dimensional latent space, mirrored by the decoder, with approximately 34,000 trainable parameters.

The model minimises mean squared reconstruction error (MSE), with early stopping on the temporally separated validation set. At inference, channel-wise errors are normalised by their median validation error and averaged into a single anomaly score, to which a threshold at the 95th percentile of normal validation scores is applied unchanged to the test data.

C. Results

We evaluate the detector using a session-level cross-validation: the 18 normal sessions are grouped into six duration-balanced folds, each held out in turn together with all abnormal sessions, over three random partitions. The detector reaches an F1 of 92.8% (Table I), most errors being false alarms concentrated in a few normal sessions.

²In this work, the term “anomaly” refers to a deviation from normal walking patterns. It is used in a data-driven sense rather than a clinical one.

TABLE I
WINDOW-LEVEL ANOMALY DETECTION PERFORMANCE (%), MEAN $\pm$ STD
OVER THE CROSS-VALIDATION FOLDS, WITH AND WITHOUT THE
TIP-TO-GROUND CHANNEL.

	AUPRC	ROC-AUC	Accuracy	Precision	Recall	F1
IMU + ToF	98.7 $\pm$ 0.8	98.6 $\pm$ 0.9	92.8 $\pm$ 3.2	90.7 $\pm$ 6.1	95.3 $\pm$ 1.6	92.8 $\pm$ 2.7
IMU only	93.2 $\pm$ 1.9	91.9 $\pm$ 2.7	84.5 $\pm$ 3.0	90.9 $\pm$ 5.8	74.9 $\pm$ 3.2	82.0 $\pm$ 2.6

TABLE II
DATASET SUMMARY AND SCORES PER ANOMALY CLASS, REPORTED AS
THE MEDIAN OUT-OF-FOLD SCORE OVER THE P95 THRESHOLD.

Anomaly class	Sessions	Windows	Score/threshold
Normal gait	18	973	0.62
Short, irregular steps	4	55	1.49
Various falls	3 events	3	2.97
Tremors, short steps	4	40	2.99
Anomalous long steps	1	15	10.13
Unsteadiness	1	29	13.35

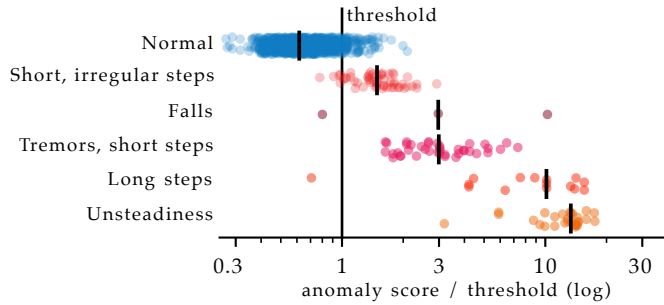


Fig. 2. Out-of-fold anomaly score of every labelled window, in units of the calibrated threshold (solid line) and on a logarithmic scale. Black ticks mark the per-class medians. Normal and abnormal gait separate clearly, and the error magnitude further orders the anomaly classes.

Without the tip-to-ground channel, AUPRC drops from 98.7% to 93.2% and F1 from 92.8% to 82.0%, almost entirely via recall (95.3% to 74.9%): the ToF channel captures deviations the IMU misses, but is not mandatory.

D. Analysis of the anomaly classes

Beyond the binary decision, the magnitude of the reconstruction error indicates *which* class of anomaly occurred (Table II and Fig. 2). The pattern is preliminary, but consistent and ordered by how strongly each anomaly deforms the signal. The per-class median reconstruction scores show that *unsteadiness* and *anomalous long steps* exceed the anomaly threshold (defined as the p95 of normal scores) by an order of magnitude, as both produce substantial distortions in the waveform or tip trajectory. *Tremors* exceed the threshold by a factor of approximately three. The *short and irregular steps* class is the most challenging: each step still looks normal in isolation, so the reconstruction-based score is least sensitive to this class. Finally, *various falls* is the least predictable class: depending on the type of fall, the reconstruction error varies widely, from below the threshold to ten times above it, yet the median of the few recorded events still lies about three times above the threshold.

This per-class structure emerges without class labels during training. Although it is not sufficient for reliable multiclass classification, the observed separation suggests that distinguishing between anomaly classes, rather than just binary detection, may be feasible with a larger dataset.

VI. CONCLUSIONS AND FUTURE WORK

A cane instrumented for about €50 counts steps with 92.9% accuracy and, with a small autoencoder, separates abnormal from normal gait at 98.7% AUPRC. The reconstruction error differs systematically across anomaly classes.

Future work may extend the analysis to more subjects, more mounting configurations, and specific pathological gait patterns in collaboration with healthcare professionals. The model may be optimised for deployment on device, enabling real-time inference. The goal would be to anticipate falls rather than merely detect them; and since the anomaly score is continuous in time, an early rise in reconstruction error is a natural candidate for such a warning, making its analysis a key direction for future work.

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