Detecting Rule Violations in Race Walking Using Instep- and Waist-Mounted Wearable Inertial Sensors

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Abstract

Race walking has attracted increasing attention in Japan due to the success of Japanese athletes in international competitions such as the World Athletics Championships. However, race walking has unique rules, including Loss of Contact (LC), which make it difficult for beginners to acquire correct walking form. In addition, the number of instructors capable of providing appropriate coaching is limited. Therefore, an approach that supports form acquisition in environments without instructors is required. In this study, we propose an LC detection approach that uses wearable inertial sensors on both shoe insteps and the waist (lower back) to support race walking form acquisition. In our preliminary evaluation using data collected from two participants, the proposed method distinguished normal race walking from intentionally induced LC with approximately 98% accuracy and a macro-averaged F1-score of 98%.

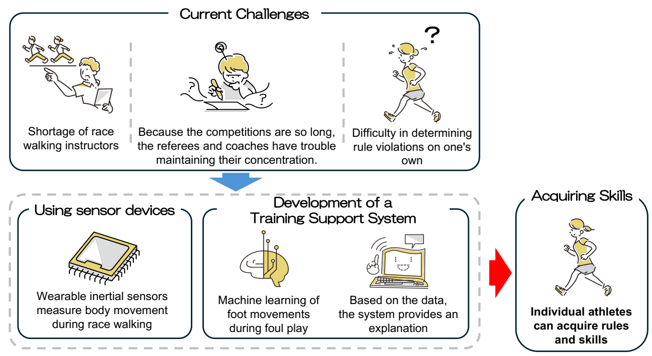

Figure 1: Research overview

CCS Concepts

• **Human-centered computing** → *Ubiquitous and mobile computing systems and tools*; *Ubiquitous and mobile devices.*

Keywords

Race Walking, Coaching System, Violation Detection, Wearable Sensing, Sports Sensing

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1 Introduction

Race walking is a track and field event officially included in the Olympic Games. In recent years, it has attracted increasing attention in Japan due to the success of Japanese athletes and the establishment of world records. On the other hand, race walking faces several challenges, including concerns about the fairness of judging due to the difficulty of its rules and the risk of foul calls, as well as a shortage of judges and instructors capable of coaching it.

Race walking has two unique and important rules: (1) at least one foot of the athlete must remain in contact with the ground at all times, and (2) the advancing leg must remain straight from the moment of ground contact until it reaches the vertical position [6]. Athletes are required to walk a specified distance while continuously complying with these rules. However, rule violations are generally judged through visual observation by referees. In 20 km race walking events, competitions may last longer than one hour, making it difficult for referees to maintain concentration for extended periods of time. In addition, due to the small number of race walking participants, there are only a limited number of instructors with sufficient knowledge and experience to properly teach these rules to beginners. This shortage of instructors is also one of the challenges facing race walking.

In recent years, many studies have investigated sports motion analysis using wearable sensors and cameras, and rule violation detection methods for race walking using inertial sensors, cameras, and other sensors have also been proposed [1, 7–12]. In addition, prior biomechanical studies have examined differences between experienced and novice race walkers, speed-dependent kinematic factors, judges' ability to identify legal and non-legal techniques, and ground-reaction-force characteristics of world-class athletes [2–4, 13]. However, methods requiring sensors attached to the body or external cameras still face several challenges, including limitations in wearability and measurement environments, as well as potential effects on athletic performance. Therefore, a method capable of stable sensing while minimizing interference with athletes' movements and sensations during competition is required.

Against this background, this study aims to support race walking beginners in acquiring proper form in environments without instructors. In our previous study, we proposed a Loss of Contact (LC) detection method using shoe-mounted sensors [5]. In this method, a distance sensor as well as acceleration and gyroscope sensors were attached to the heel of the shoe. However, feature importance

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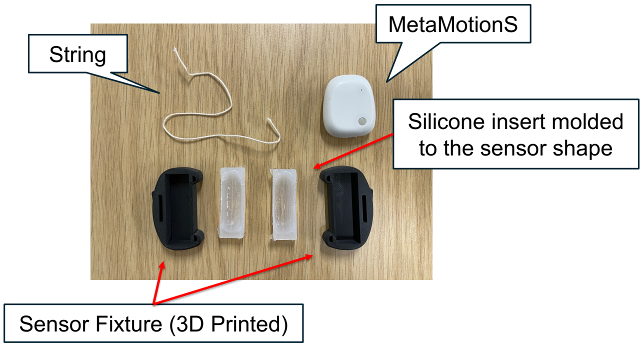

Figure 2: Components of the proposed sensor device

analysis revealed that the contribution of distance data was low, and that the distance data frequently contained unstable values. In addition, our previous method had issues regarding the stability and wearability of the heel-mounted fixture.

To address these issues, this study redesigns the sensing configuration by removing the distance sensor and relying solely on wearable inertial sensors. We also changed the sensor placement from the heel to the instep and introduced an additional waist (lower back) sensor to capture body motion associated with race walking form. In addition, we design a custom sensor fixture that integrates the sensor into a compact module, enabling easy attachment to the shoe instep while improving fixation stability during walking. Using sensor data collected from both insteps and the waist, we construct an LC detection model and evaluate its performance in a preliminary study with two participants. The results show that the proposed method can classify normal race walking and LC with 98% accuracy and a macro-averaged F1-score of 98%.

2 Proposed Method

Building on our previous study [5], we redesign the sensor configuration and attachment positions to improve wearability and measurement stability. We then construct an LC detection model using the collected sensor data and evaluate its effectiveness.

2.1 Sensor Configuration

Our previous method employed a shoe-mounted device that incorporated a distance sensor in addition to accelerometers and gyroscopes. However, feature importance analysis showed that distance-derived features contributed only marginally to classification performance. Moreover, the distance measurements were often missing or unstable, which could compromise the robustness of the method. Therefore, in this study, we redesigned the sensing configuration to rely solely on accelerometers and gyroscopes.

Figure 2 shows the components of the proposed wearable sensor device. We used a MetaMotionS[1] sensor, which measures acceleration and angular velocity. To improve attachment stability during walking, we designed a custom sensor fixture and fabricated it using a 3D printer. A silicone insert molded to the shape of the sensor was placed inside the fixture to securely hold the sensor and reduce displacement during movement.

Figure 3: Sensor assembly process

Figure 4: Sensor devices attached to the shoes and the waist

To assemble each instep-mounted unit, the two fixture components were connected with cords, and the MetaMotionS sensor was held between them. This structure integrated the sensor and fixture into a compact module (Figure 3). The completed module was then attached to the instep of the shoe using hook-and-loop fasteners, allowing it to be easily mounted while keeping the sensor stable during walking (Figure 4a). We attached these modules to both the right and left insteps. In addition to foot motion, race walking involves characteristic movements of the pelvis and trunk as athletes maintain continuous ground contact and comply with race walking rules. We therefore hypothesized that body motion around the waist would provide complementary information for LC detection beyond the information captured by the foot-mounted sensors. Based on this hypothesis, a third sensor was mounted at the center of the participant's lower back. The waist sensor was fixed using hook-and-loop fasteners and a clip (Figure 4b).

2.2 Feature Extraction and Model Training

We performed feature extraction using *tsfresh*[2], a Python library for automated time-series feature extraction. Acceleration and angular velocity data obtained from the sensors mounted on the right instep, left instep, and waist were synchronized by timestamp and integrated into a single multivariate time-series representation. The

[1] https://mbientlab.com/metamotions/

[2] https://tsfresh.com/

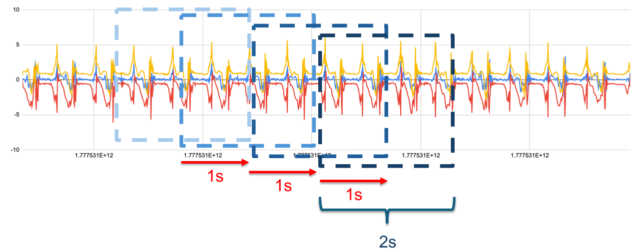

Figure 5: Data segmentation using the sliding-window method (window width: 2 sec, shift width: 1 sec)

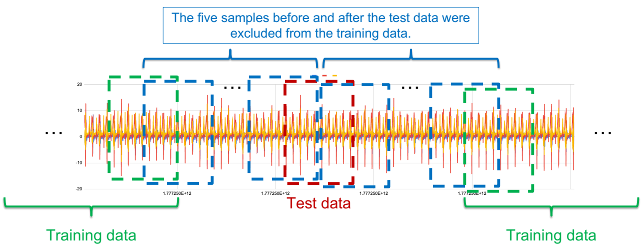

Figure 6: Policy of training and test data preparation

synchronized data were then segmented using a sliding-window approach with a window length of 2 sec and a shift length of 1 sec. For each window, time-domain and frequency-domain features were automatically extracted from the acceleration and angular velocity signals. We used `EfficientFCParameters` to exclude computationally expensive features. In addition, features that were constant across all samples or contained invalid values, such as NaNs, were removed before model training.

The extracted features were used to train a LightGBM-based binary classifier for distinguishing normal race walking from LC. To reduce temporal data leakage from overlapping sliding windows, the five windows immediately before and after each test window were excluded from the training set during cross-validation (Figure 6). This scheme prevented highly similar neighboring windows from appearing in both the training and test data.

3 Experiment and Evaluation

3.1 Experimental Settings

The experiment involved two university students in their twenties, one female and one male. One participant had prior race walking experience, whereas the other had no competitive race walking experience but was familiar with race walking movements.

Data were collected outdoors under three course conditions as shown in Figure 7: 1) an approximately 10 m straight asphalt section of university campus, where the participants repeatedly walked back and forth; 2) a 300 m asphalt loop course around a university building; and 3) a 400 m synthetic polyurethane athletics track. For the loop course and athletics track, the participants walked continuously along the course. In each trial, the participants were instructed to perform one of the following two walking conditions:

- Normal: proper race walking motion without rule violations.
- LC: race walking motion intentionally including loss of contact.

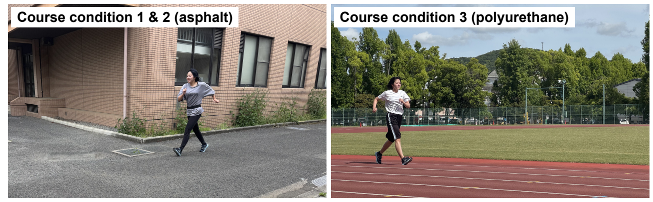

Figure 7: Experimental course conditions

Table 1: Collected data summary under each course condition

Course condition	Surface	Normal (sec)	LC (sec)
1) 10 m straight section	Asphalt	114.6	91.7
2) 300 m loop course	Asphalt	237.4	194.4
3) 400 m athletics track	Polyurethane	159.0	408.1
Total	–	511.0	694.2

The class label was assigned at the trial level according to the instructed walking condition, and all windows extracted from each trial inherited the corresponding label.

Table 1 summarizes the amount of data collected under each course condition. In total, the dataset consisted of 511.0 sec of Normal data and 694.2 sec of LC data. The collected time-series data were then segmented using the sliding-window method. After applying the sliding-window method to each trial, we obtained 489 windows for Normal and 670 windows for LC.

The LC detection model was evaluated using class-balanced paired-window cross-validation. In each fold, one Normal window and one LC window were used as the test data. Test windows were paired randomly without replacement, so that each selected Normal and LC window was used as test data only once. This resulted in 489 folds, corresponding to the number of Normal windows. Because the number of LC windows exceeded the number of Normal windows, the remaining LC windows were used only for training when they did not fall within the exclusion range. The five windows immediately before and after each test window were excluded from the training data, as described in Section 2.2.

3.2 Evaluation Results

The class-balanced paired-window cross-validation showed that the proposed method achieved approximately 98% accuracy over 978 test windows. The macro-averaged precision, recall, and F1-score were all 98%. Figure 8 shows the confusion matrix aggregated over all folds. These results indicate that the proposed method can distinguish normal race walking from LC with high accuracy in this preliminary dataset.

To investigate which features contributed to classification performance, feature importance values were calculated from the trained LightGBM model, as shown in Figure 9. Here, _L, _R, and _W denote the left instep, right instep, and waist sensors, respectively. Features derived from the left instep-mounted sensor contributed substantially to LC detection, and several angular-velocity-related features showed high importance values. In addition, features derived from the right instep and waist sensors were also included among the

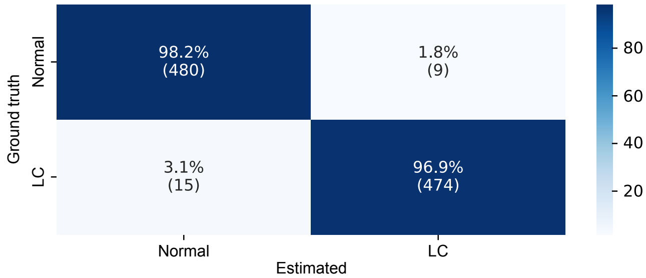

Figure 8: Confusion matrix aggregated over all folds

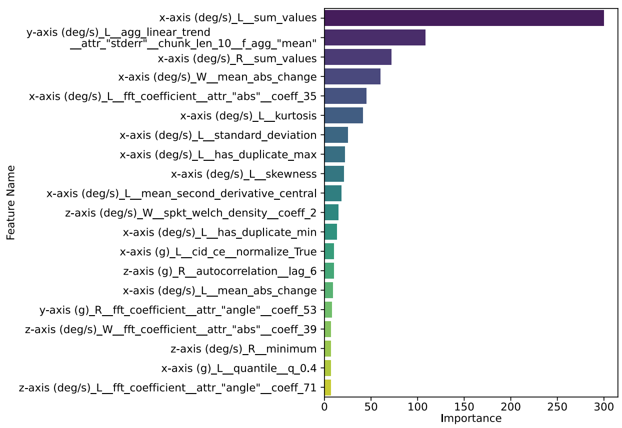

Figure 9: Feature importances

top-ranked features, suggesting that the model used information from multiple sensor locations for classification.

3.3 Discussion

In this study, we redesigned our previous shoe-mounted LC detection method by removing the distance sensor, changing the sensor placement from the heel to the instep, and integrating sensor data from both insteps and the waist. In a preliminary evaluation with two participants, the proposed method achieved approximately 98% accuracy and a macro-averaged F1-score of 98%, which was comparable to or slightly higher than the 96% performance reported in our previous single-participant study [5]. Although the evaluation settings differ from those of the previous study, this result suggests that removing the distance sensor did not substantially degrade classification performance. These results also suggest that instep-mounted inertial sensors can capture gait features relevant to LC detection.

The feature importance analysis provides further insight into the sensing configuration. Many of the highly ranked features were derived from the left instep-mounted sensor, and several important features were related to angular velocity. This suggests that rotational foot motion may be informative for distinguishing normal race walking from LC. In addition, features derived from the waist sensor were also included among the top-ranked features, indicating that body motion around the pelvis may contribute to LC detection. This observation is consistent with our hypothesis that race walking involves characteristic pelvic and trunk movements as athletes maintain rule-compliant form, and that these movements may change when LC occurs. However, because we did not evaluate each sensor configuration separately, the individual contribution of the waist sensor and each sensor placement remains unclear.

From a practical perspective, the proposed device design may improve wearability and attachment stability compared with the previous heel-mounted device. The previous method required a distance sensor and a relatively complicated fixation procedure, and the heel-mounted fixture could interfere with body movement. In contrast, the proposed configuration uses only inertial sensors and a custom fixture that can be attached to the shoe instep using hook-and-loop fasteners. This simplified design is expected to reduce discomfort and improve the practicality of the sensing setup for race walking practice.

Several limitations remain. First, the labels were assigned based on trial-level instructed conditions rather than frame-by-frame judgments by certified race-walking judges; future work should incorporate more precise annotation using expert judgments or synchronized video analysis. Second, the evaluation involved only two participants, so the effects of individual walking characteristics, foot dominance, and prior race-walking experience remain insufficiently verified. Third, although neighboring windows were excluded to reduce temporal data leakage, the window-level evaluation does not fully assess generalization to unseen users or sessions, and the stability of the results across different random pairings should be further examined. Finally, the current implementation analyzes sensor data offline and does not yet support real-time LC detection or feedback presentation.

Future work should evaluate the method with a larger and more diverse set of participants, including beginner race walkers. We also plan to conduct comparative experiments across different sensor configurations and attachment positions to clarify each sensor's contribution. In addition, user-independent and session-independent evaluations will be necessary to assess the robustness of the method. Finally, we aim to extend the approach toward real-time LC detection and feedback for race walking form guidance.

4 Conclusion

In this study, we improved an LC detection method for supporting race walking form acquisition by redesigning the sensor configuration and attachment method of a shoe-mounted sensing approach. Specifically, we removed the distance sensor, changed the sensor placement from the heel to the instep, and constructed an LC detection model using inertial sensor data from both insteps and the waist. Experimental results showed that the proposed method achieved approximately 98% accuracy and a macro-averaged F1-score of 98%. The simplified sensor configuration and instep-mounted design are expected to improve wearability and practicality. Future work will include evaluations with more participants, real-time LC detection and feedback, and extension to KB (bent knee) detection to support overall race walking form acquisition.

Acknowledgments

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