2025 IEEE/SICE International Symposium on System Integration (SII)
January 21-24, 2025, Munich, Germany

Validation of real-time gait event detection between in-shoe IMUs and force plates during walking

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Abstract— **The effectiveness of lower limb mobility assistance heavily relies on accurate gait pattern detection. Optimal support is achieved when sensors reliably detect gait information. This study aims to evaluate the accuracy of gait event detection using force plates compared to in-shoe IMUs under real-time conditions. Despite favorable sensor placement for real-time data collection, several challenges arose in assessing the system's accuracy. Four healthy adults participated, performing self-paced walking on force plates while wearing in-shoe IMUs. Sagittal angular velocity ($\omega_{sagittal}$) is the rate of rotational movement around the sagittal plane. As these measures demonstrated the most importance to accurate event identification, we concentrated on them in our investigation, together with the norm of jerk (J), as key characteristics for recognizing gait events using IMU data. We found that accurate gait event detection of initial contact and toe-off was achieved when the $\omega_{sagittal}$ was within the range of -300 to -340 [deg/sec] and the J fell between 100 and 440 [G/sec]. These specific parameter ranges were effective in providing precise gait event detection. The accuracy of these measurements was approximately 25 msec, with no misclassified events detected for the specified parameter ranges.**

I. INTRODUCTION

The average aging population (aged 65 and over) of Japan by 2030 will be approximately one-third of its total population [1]. Based on these alarming statistics, there is a huge demand for establishing rehabilitation services. This also leads to the development of new assistive technologies which could offer mobility assistance [2]. The fundamental critical key aspects of mobility aid development involve gait events [3].

The features of joint movement and muscle activation patterns can also be evaluated by accurately identifying gait events. The two gait-related events are initial contact (IC) and toe-off (TO). Force plate information along with motion capture data was considered the traditional gold standard way for analyzing gait patterns [4]. However, the fundamental issue of such systems is that they are not portable and have stringent environmental limits with limited forward motion. Wearable motion analysis devices such as foot switches, pressure sensors, and inertial measurement units (IMUs) sensors have become useful for sensing gait events as technology has advanced in recent years.

Nonetheless, IMU will be the only sensor that can provide information during the entire phase of the gait cycle [5]. However, they also have several challenges in real-time gait event detection. The IMU sensors have both event and data transmission latency and are sensitive to threshold-based detection methods. Several studies have been conducted to examine the potentialities of the IMU, particularly with accelerometers and gyroscopes. According to Aung et al., the foot sensor placement offers better results for precise gait event identification than the ankle or shank sensor placement [6]. Furthermore, Mariani et al. reported that the use of solitary 3D accelerometer data and its derivatives exhibited reduced sensitivity to misalignment of the foot and sensor [7].

Heuristic thresholds and decision criteria were derived from finite-state machines. Nevertheless, these computational techniques had several drawbacks. However, with well-defined thresholds and optimized algorithms, heuristic rules can be implemented for real-time gait event detection, providing quick and efficient feedback during gait analysis. There have been numerous detection techniques reported so far for recognizing gait events. The differences for IC detection while walking at normal and slow speeds were 5.7 (±6.8) and 12.8 (±7.8) msec, respectively [8].

Nevertheless, there are only very few reports on incorrectly detected gait events. Therefore, for reliable gait event identification, we propose in-shoe IMU sensors with two state transitions to detect the IC and TO of the gait phase. The two-state transition uses dominant features of the IMU such as the norm of jerk (J) and sagittal angular velocity ($\omega_{sagittal}$). Furthermore, a wearable device with minimal sensors would replicate the capabilities of a real-time environment. Using in-shoe IMUs and force plates for real-time gait event accuracy estimation along with misclassified events, this validation study serves as a benchmarking standard for more accurate real-time gait event identification.

The study aims to assess the accuracy of gait event recognition using in-shoe IMUs and identify the best dominant features (J, $\omega_{sagittal}$) of IMU with 0% misclassified events. This research targets users with asymmetric gait patterns, as precise gait event recognition is essential for personalizing tailored assistance. The practical application entails the use of smart shoes that are equipped with in-shoe IMUs. These shoes are designed to assist in walking by integrating real-time gait event detector with a soft exosuit for hip assistance. In order to modulate assistance based on swing phase data,

*This work was supported by Council for Science, Technology and Innovation, "Cross-ministerial Strategic Innovation Promotion Program (SIP), Development of foundational technologies and rules for expansion of the virtual economy" (JPJ012495). (Funding agency: NEDO). This work was also supported by JST SPRING, Grant Number JPMJSP2132.

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Fig. 1: ORPHE smart shoes with in-shoe IMUs [9]

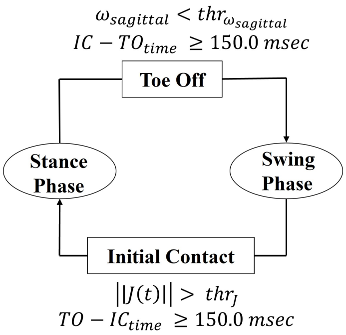


Fig. 2: Gait transition states; *thr* represents threshold applied for event detection

the study necessitates both spatiotemporal characteristics and real-time responsiveness, it is imperative to employ IMU sensors over pressure sensors. IMUs also offer comprehensive kinematic data that is essential for the precise timing of gait events, particularly during the swing phase, which is essential for the fine-tuning of exosuit assistance. This study is organized as follows: Section II describes the methodology used to obtain accurate gait events in detail. Results are presented in Section III. The discussion and conclusion are presented in Sections IV and V, respectively.

II. Methods

A. Subject demographics

Four healthy male volunteers (age: 22.25 ± 6.5 years; height: 171.75 ± 6.23 cm; weight: 66.5 ± 5.06 kg) were recruited for this study. Subjects were asked to walk a 3 m walkway during the experiment. At least 5 successful trails were conducted at self-paced walking speed, with clear landing of the entire foot on at least two force platforms. All subjects were asked to wear smart shoes (EASYRUN SHIBUYA 3.0, ORPHE Inc., Tokyo, Japan) [9] with midsole space to embed the motion sensor (ORPHE CORE, ORPHE Inc., Tokyo, Japan; size: 45 mm × 29 mm × 14 mm; weight: 20 g; Fig. 1) of their respective foot size. To get familiar with the experiment, subjects were asked to walk for a few minutes in the walkway. The experimental protocol was instructed to all the subjects and informed consent was obtained for conducting this study.

B. System Components

An integrated IMU sensor (LSM6DSOX, STMicroelectronics) was used to record the tri-axial accelerations and angular velocities data at a 200 Hz sampling frequency. The

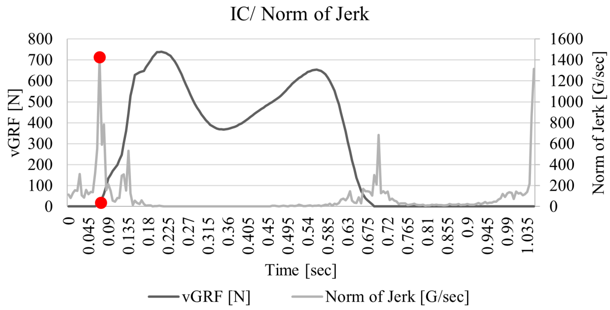


Fig. 3: vGRF IC event aligns with norm of jerk peak profile during walking

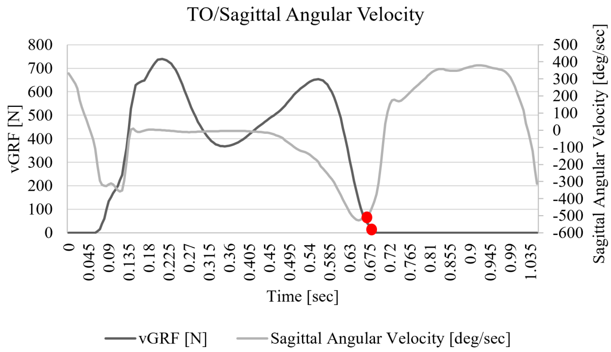


Fig. 4: vGRF TO event aligns with sagittal angular velocity negative peak profile during walking

measured data are transmitted to a host PC through BLE, and recorded with UNIX time on the storage of the host PC. The time alignment between left and right was achieved using UNIX time. Additionally, the vertical ground reaction forces were recorded from the four force platforms (FP4060-07, Bertec, USA) with a sampling frequency of 1000 Hz. The synchronization of the IMUs and force platform systems was achieved by timing the identical event (three right-leg free kicks on the force platform) at the start of every trial.

C. Gait events detection

Using the vertical ground reaction force (vGRF) of the force plate data and a 5 N threshold, the timings of IC and TO were ascertained. Those data were taken as the reference for this study. To detect IC and TO, the in-shoe IMUs make use of the gait event detector transition states, as seen in Fig. 2. The IMU's salient characteristics, such as the sagittal angular velocity and norm of jerk, were employed to identify gait episodes.

The norm of jerk (J) is given by

$$J = \sqrt{\left(\frac{da_x}{dt}\right)^2 + \left(\frac{da_y}{dt}\right)^2 + \left(\frac{da_z}{dt}\right)^2}$$

where $\frac{da_x}{dt}$, $\frac{da_y}{dt}$ and $\frac{da_z}{dt}$ are the first derivatives of the acceleration with respect to time (i.e., the jerk components along the x, y, and z axes).

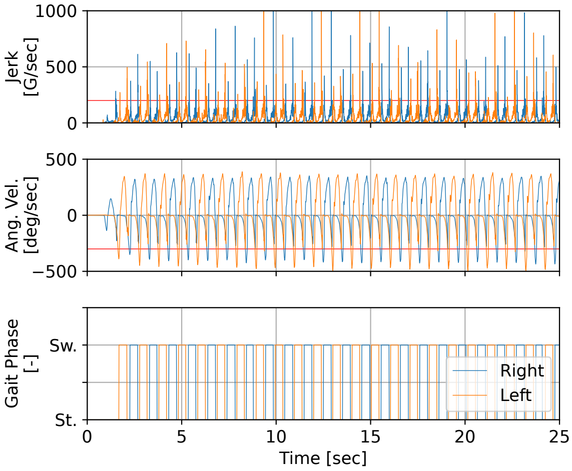


Fig. 5: Real-time gait event detector based on the norm of jerk and sagittal angular velocity thresholds

The sagittal angular velocity ($\omega_{sagittal}$) is directly measured by the IMU.

The threshold features were chosen based on signal traits seen during the walking motion. The range of threshold for norm of Jerk was selected because the peak value of the J consistently aligns with the IC, as indicated by the peak in the vGRF signal as shown in Fig. 3. Similarly, the range of threshold for sagittal angular velocity was established from the negative peak of the $\omega_{sagittal}$ signal, which consistently correlates with the TO event in the vGRF as shown in Fig. 4. This alignment facilities accurate identification of IC and TO events using IMU derived features.

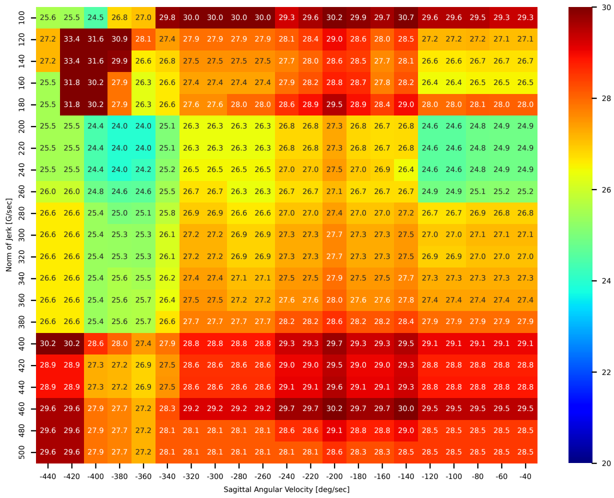
Based on the norm of jerk threshold and the sagittal angular velocity threshold, the initial contact and toe-off times were identified as shown in Fig. 5. Additionally, both transitions confirm that the time from the prior event should have been greater than 150 msec.

D. Data Analysis

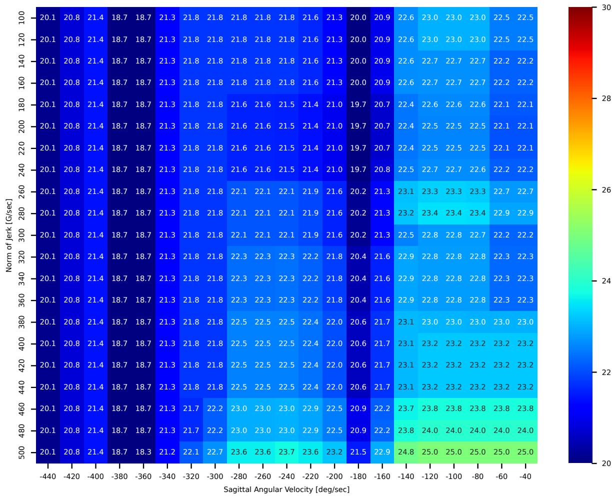
The evaluation of each participant was based on recognized gait occurrences from the second and third force plates. We computed the mean absolute error (MAE), mean relative error (MRE), Type I (false positive), and Type II (false negative) errors. Type I and Type II mistakes were combined to compute the total number of misclassified occurrences. The extent of the magnitude discrepancy between the reference event and the IMU event is shown by the mean relative errors [8]. In this study, 21 combinations of the J and 21 combinations of $\omega_{sagittal}$ were used, and their accuracy in real-time was compared. The ANOVA analysis was used to compare J and $\omega_{sagittal}$ to MAE data, with a significance threshold of $p = 0.05$.

III. Results

A total of 35,280 gait events (17,640 IC and 17,640 TO events) were analyzed to demonstrate the repeatability and time-effectiveness of the method were demonstrated.



(a) Mean absolute error of initial contact

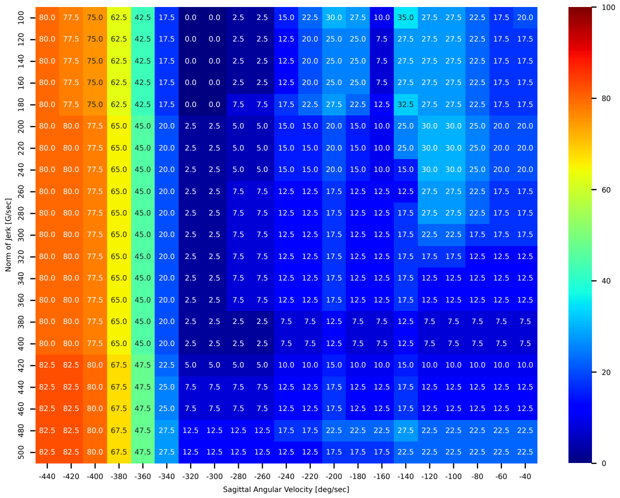


(b) Mean absolute error of toe-off

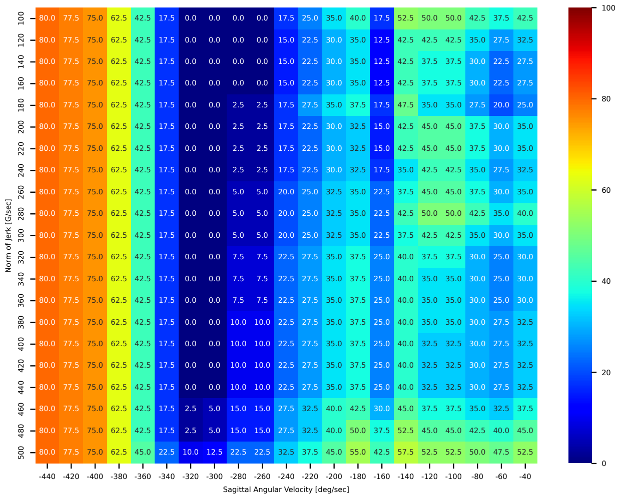
Fig. 6: Comparison of mean absolute error for initial contact and toe-off

This section describes the performance metrics, such as algorithm reliability and timing errors. The mean absolute error between the detected IC and TO timings was computed, and the IMUs' estimated values were determined. The upper and lower bounds for the J and $\omega_{sagittal}$ were determined based on signal characteristics. The latency error between the in-shoe IMUs and force plates was determined to be around 25 msec.

Figs. 6a and 6b show a heatmap depicting the mean absolute errors of IC and TO. The results were more favorable, falling within the range of 3.11 to 33.4 msec reported in earlier investigations [10]. The IC has a larger delay than the TO during gait event detection. In addition to the position of the IMU sensor, locomotion speed has been linked to impact acceleration, which may affect the accuracy of the detected gait events. The ANOVA findings show that $\omega_{sagittal}$ ($p < 0.05$) has a substantial impact on MAE, but J ($p > 1$) does not. The heatmap of misclassified events for IC and



(a) Misclassified events of initial contact



(b) Misclassified events of toe-off

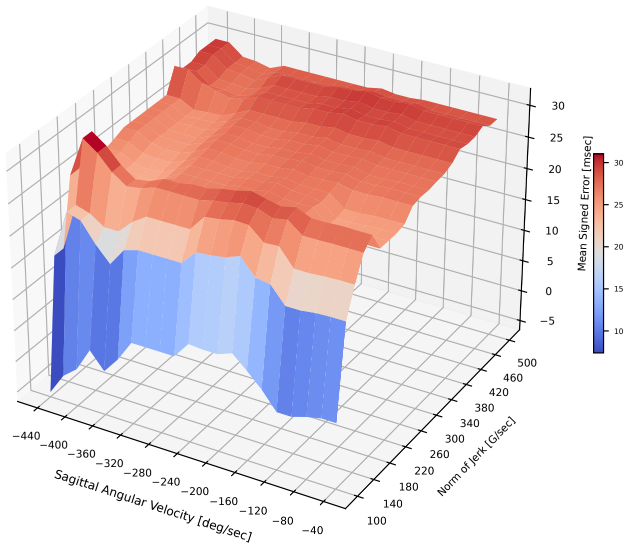
Fig. 7: Comparison of misclassified events for initial contact and toe-off

TO in Figs. 7a and 7b aid in determining the most effective dominating characteristics for detecting gait events with a 0 % zero rate.

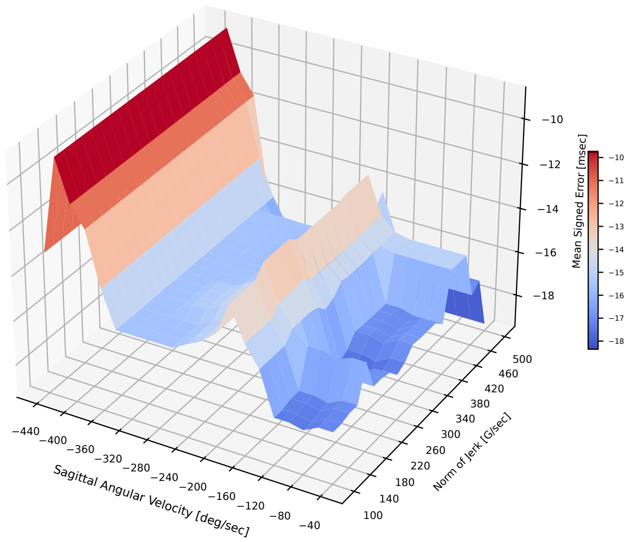
To better understand the magnitude and direction of the errors for IC and TO, the mean relative error is illustrated in Figs. 8a and 8b. Based on the MRE results, it is clear that the TO events are detected earlier with a delay of between 18 to 25 msec. On the other hand, the IC events are detected later with a delay of 24 to 33 msec.

IV. DISCUSSION

In this study, we demonstrated that single in-shoe IMUs affixed to the foot can precisely and correctly identify the important temporal events during the stance phase. The approach of identifying IC and TO using in-shoe IMUs is based on the idea that both gait events are connected with distinct acceleration and velocity characteristics. On the other hand, detected gait events might not match actual gait events



(a) Mean relative error of initial contact



(b) Mean relative error of toe-off

Fig. 8: Comparison of mean relative error for initial contact and toe-off

because of the impact transmission time lag from the feet to the data storage unit. The misclassified events help us to identify the best J and $\omega_{sagittal}$ combination for detecting accurate gait events. Based on the IC and TO false positive results, we observed that a $\omega_{sagittal}$ of −300 to −440 deg/sec with every combination of J identifies zero error. This yields an estimate of misclassified occurrences for both IC and TO. With a $\omega_{sagittal}$ of −300 to −320 deg/sec and a J of 100 to 180 G/sec, precise IC events are detected. With a $\omega_{sagittal}$ of −300 to −320 deg/sec and a J of 100 to 440 G/sec, accurate TO events are detected. We found that the delay was longer due to the shorter pathway and the variance in walking speed. The inter- and intra-subject gait variability might have influenced the results. Hence, in the future study, we propose to extend the experiment walkway with controllable walking speeds.

V. CONCLUSION

For several real-time applications, accurate gait event detection is crucial. The most important aspect is to detect events without any classification errors. The proposed gait event detection method is accurate, wearable, and adaptable to real-time analysis. Further investigation will be carried out to reduce the latency errors between in-shoe IMUs and force plates. In addition, the controllers in assistive technology devices can adjust for the detected delay duration. In this regard, this research is more suited for real-time integration and assistive support.

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