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A novel method for accurate division of the gait cycle into seven phases using shank angular velocity

Mikko Salminen [a], Jarmo Perttunen [b], Janne Avela [b], Antti Vehkaoja [a,*]

[a] Faculty of Medicine and Health Technology, Tampere University, Korkeakoulunkatu 3, Tampere 33720, Finland
[b] Faculty of Sports and Health Sciences, Jyväskylä University, Seminaarinkatu 15, Jyväskylä 40014, Finland

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ABSTRACT

Background: Accurate detection of gait events is crucial for gait analysis, enabling the assessment of gait patterns and abnormalities. Inertial measurement unit (IMU) sensors have gained traction for event detection, mainly focusing on initial contact (IC) and toe-off (TO) events. However, effective detection of other key events such as heel rise (HR), feet adjacent (FA), and tibia vertical (TBV) is essential for comprehensive gait analysis.
Research question: Can a novel IMU-based method accurately detect HR, TO, FA, and TBV events, and how does its performance compare with existing methods?
Methods: We developed and validated an IMU-based method using cumulative mediolateral shank angular velocity (CSAV) for event detection. A dataset of nearly 25,000 gait cycles from healthy adults walking at varying speeds and footwear conditions was used for validation. The method's accuracy was assessed against force plate and motion capture data and compared with existing TO detection methods.
Results: The CSAV method demonstrated high accuracy in detecting TO, FA, and TBV events and moderate accuracy in HR event detection. Comparisons with existing TO detection methods showcased superior performance. The method's stability across speed and shoe variations underscored its robustness.
Significance: This study introduces a highly accurate IMU-based method for detecting gait events needed to divide the gait cycle into seven phases. The effectiveness of the CSAV method in capturing essential events across different scenarios emphasizes its potential applications. Although HR event detection can be further improved, the precision of the CSAV method in TO, FA, and TBV detection advance the field. This study bridges a critical gap in IMU-based gait event detection by introducing a method for subdividing the swing phase into its subphases. Further research can focus on refining HR detection and expanding the method's utility across diverse gait contexts, thereby enhancing its clinical and scientific significance.

1. Introduction

Accurate detection of gait events is a crucial part of automated gait assessment. Gait events refer to specific moments in gait cycle that mark important transitions and actions during walking. They enable researchers and clinicians to analyze detailed temporal parameters and gait patterns across distinct phases, facilitating the measurement of abnormalities or asymmetries in walking [1].

In recent years, inertial measurement unit (IMU) sensors have gained popularity in event detection [2]. The focus has primarily been on initial contact (IC) and toe-off (TO), which can be used to separate gait cycles and delineate distinct phases such as stance, swing, and double and single-limb support. For a more nuanced IMU-based analysis of stance and swing subphases it is essential to detect also the heel rise (HR), feet adjacent (FA), and tibia vertical (TBV). These five gait events, along with the opposite foot IC and TO events, allow us to divide the gait cycle into seven gait phases: loading response (Opposite TO), mid-stance (HR), terminal stance (opposite IC), pre-swing (TO), initial swing (FA), mid-swing (TBV), and terminal swing (IC) [1,3] with the events serving as the respective ending points of each phase.

Currently, a common approach for IMU-based gait analysis involves attaching IMU sensors, equipped with a triaxial accelerometer, gyroscope, and sometimes a magnetometer, to the shank [2,4–8]. This placement is closely influenced by the movement from the knee and ankle joints [1] and provides valuable information about various gait parameters, such as the shank-to-vertical angle [9,10]. The development

* Corresponding author.
E-mail address: antti.vehkaoja@tuni.fi (A. Vehkaoja).

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of methods that use IMU data from this type of easily accessible location promotes the advancement of user-friendly and ambulatory gait analysis systems [11].

The detection of IC and TO events is commonly performed by identifying the two distinct local minima in shank angular velocity (SAV) around the mediolateral axis of the sensors, referred to as mediolateral SAV [12]. However, while this method has demonstrated high accuracy in detecting IC, its ability to detect TO has faced criticism [13,14]. Alternative methods for TO detection using SAV [14,15] and accelerometer anteroposterior signals [16–18] have been proposed. Recently, Romijnders [19] employed a deep learning approach to detect both IC and TO events, which showed promising results.

Only a few studies [14,20] have proposed methods that use shank-based IMU data for detecting HR event. Some studies [21,22] have employed IMU data from the foot for HR detection. However, the accuracy and precision of these methods have generally been rather low, except in [21], where two IMUs were used (instep and heel).

Most importantly, there is a gap in the found literature regarding the detection of swing phase events, FA (swinging foot comes adjacent to stance foot) and TBV (tibia reaches vertical position during swing), from IMU-based data. Neither our survey on existing literature nor a recent review [2] on IMU-based gait event and phase detection methods identified any prior approaches for validating these events against a reference system. Bridging this gap would significantly advance the increasingly popular field of shank-attached IMU-based gait analysis.

Therefore, the objective of our study was to develop and validate a new IMU-based method that uses SAV to detect HR, TO, FA, and TBV events. In addition, our objective was to compare the performance of our method with previously proposed detection methods for TO using a new prospectively collected dataset. To validate our method, we used force plates and an optical motion capture (OMC) system, which are considered the 'gold standard' for measuring temporal gait parameters. Our dataset comprises nearly 25,000 gait cycles from a group of healthy adults walking at slow, normal, and fast speeds in shoes and barefoot, as well as with three different heel heights. As an outcome, we aimed to introduce an accurate and robust model for detecting gait events, enabling the separation of the gait cycle into seven phases.

2. Methods

2.1. Experimental set-up

A total of fifteen healthy volunteers (5 males and 10 females) with an age of 23.7 ± 3.5 years (mean ± std), height of 170 ± 10 cm, and weight of 70 ± 14 kg participated in the study. The gait of each participant was simultaneously measured using three different gait measurement technologies: two shank-worn IMUs, two force plates, and an OMC system. Measurements were performed at a biomechanics laboratory along a 12-meter walkway. Before participating in the study, all participants provided a signed informed consent. The study was performed in conformity with the Declaration of Helsinki (2013), and ethical approval was obtained (Approval number: 199/13.00.04.00/2022).

Walking speed was controlled with photocell timing. The target speeds for slow, normal, and fast walking were 4, 5 and 6.5 km/h, respectively (corresponding to 1.11, 1.39, and 1.81 m/s). Data were recorded while each participant performed a targeted number of walks back and forth along the walkway. The scenarios were normal, fast, and slow walking with shoes and barefoot in addition to three different heel heights (2 mm, 6 mm, and 10 mm) while walking in shoes at a normal speed. The data were collected in a randomized order for each participant.

2.2. Optical motion data acquisition

We collected reference kinematic data at 187.5 Hz using a Vicon OMC system (Vicon Motion Systems Ltd, Oxfordshire, UK) equipped with 11 Vicon Vero cameras. Sixteen reflective markers were placed on the pelvic area and lower limbs following the Plug-in-Gait lower body model. Data were processed using Vicon Nexus 2.14.

The acquired reference kinematic data were used to detect HR, FA, and TBV events. These events have been defined in detail in [1,3]. The FA event was detected as the moment when the toe marker of the swinging limb surpassed the heel marker of the opposite limb. The TBV event was identified as the moment when the ankle marker of the swinging limb passed the knee marker of the same limb. These events separate the initial swing, mid-swing, and terminal swing phases [1,3].

The transition from mid-stance to terminal stance phase is defined as the moment the heel begins to lift from the ground. We detected HR from the vertical motion signal of the heel marker. The signal was first filtered with a 4th order zero-lag Butterworth lowpass filter with a 10 Hz cutoff frequency. The event was detected as the sample when the marker acceleration first exceeded 1.9 m/s^2 after the opposite foot FA event (Fig. 1).

In Fig. 1a, we can observe how the vertical position of the heel starts to accelerate at the time of the HR event, indicating lift-off. The vertical position difference between the detected HR event and feet adjacent event (≈25 %) is 8 mm, 7 mm, and 7 mm for fast, normal, and slow speeds, respectively. However, some of this difference can be attributed to the shoe sole's elasticity and shape, as noted in [23]. The consequent gradually accelerating upward shift in the vertical position of the heel marker during stance introduces complexity to the accurate timing of the HR event. Consequently, the threshold 1.9 m/s^2 was determined on the basis of careful manual observation of the acceleration signal pattern behavior and comparison with heel marker position data.

2.3. Force plate data acquisition

For accurate identification of IC and TO events, we used two centrally positioned AMTI (Advanced Mechanical Technology Inc.) force plates along a 12-meter walkway. The force plate data were sampled at 1125 Hz. We applied a 10 N threshold to the vertical ground reaction force.

We validated each step using the OMC system's heel and toe markers. A step was considered valid if the foot's position, as indicated by these markers, fell within the force plate's positional limits 200 ms after IC detection and 300 ms before TO detection.

2.4. IMU data acquisition

IMU kinematic data were collected using two Vicon Blue Trident sensors. These sensors were attached with Vicon straps to the lateral side of each shank, just above the lateral malleolus similarly as in [16,18]. To achieve the correct alignment, the sensor's vertical axis was parallel to the longitudinal axis of the shank segment, while the anteroposterior axis aligned with the walking direction, following the imaginary line connecting the back of the heel and the second metatarsal head. In this study only the angular velocity signal around the mediolateral axis were used. The sampling rate was set to 225 Hz, and the data were resampled to match the sampling rate of the force plates. Vicon Nexus 2.14 motion capture software was used to control the sensors and acquire the data. To ensure accurate and reliable measurements, a standard calibration procedure [24], as instructed by the manufacturer, was implemented for all IMUs used in this study.

2.5. Data synchronization

The system setup included a Vicon Lock Lab control box for connecting the devices to the system and synchronizing the collected data from cameras and force plates. The IMU sensors were connected to the Vicon Nexus software via a Bluetooth connection, enabling automatic synchronization with other signals.

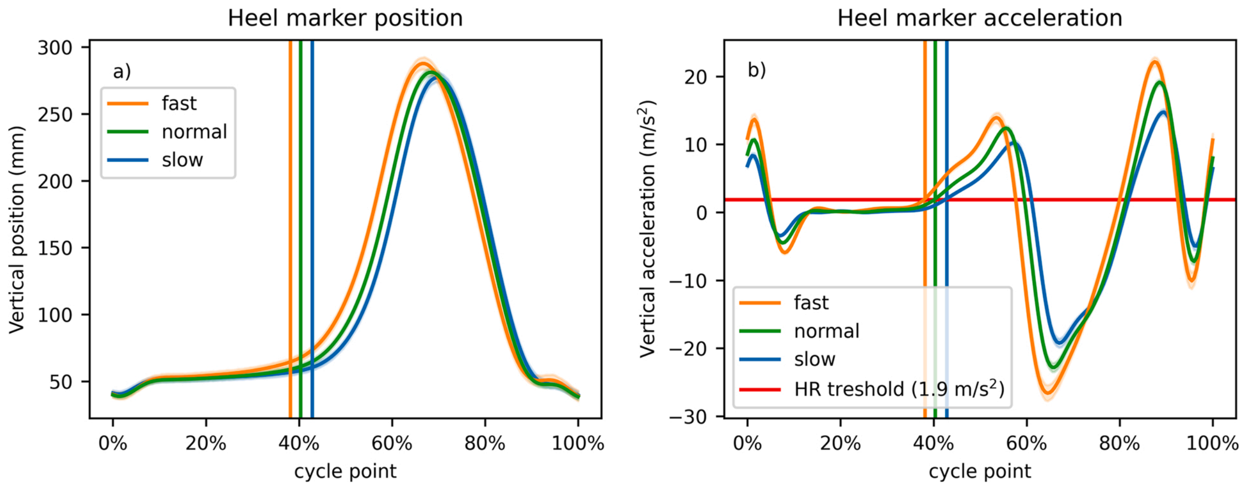

Fig. 1. a) Mean heel marker vertical position throughout the gait cycle for each walking velocity. The vertical lines indicate the mean cycle point of the HR event. b) The HR event is detected when the vertical acceleration of the heel marker exceeds 1.9 m/s^2 during stance. The figure includes data from two trials of both fast and slow walking speeds, as well as four trials of normal walking speed, for each participant while wearing shoes.

2.6. Data analysis

All post-processing and analysis were performed using the Python 3.10 (https://www.python.org/) programming environment.

Our analysis and model development used a dataset comprising velocity-controlled trials. These trials included a balanced number of strides per participant, foot, and scenario while excluding variations in heel height (Table S2). The included strides closely matched the target speed for each scenario (Table S3). Additionally, leave-one-out cross-validation was employed, meaning the developed model was trained excluding each participant's data, and results were reported using only the respective participant's data [25].

Accuracy of the method was evaluated by measuring true error and agreement against the reference methods. Agreement was evaluated with Bland-Altman plots [26] and intra-class correlation coefficient (ICC). ICC estimates and their 95% confident intervals were calculated based on a single-rater, absolute-agreement, 2-way mixed-effects model [27,28].

2.7. IMU-based gait event detection

IMU-based gait events were derived using algorithms based on the mediolateral angular velocity signal (SAV). Our method detects these events using two signal zero-crossings located on either side of the large angular velocity peak, which indicates the motion during swing (Fig. 2). We refer to the zero-crossing before the peak with a positive slope as ZP and the zero-crossing after the peak with a negative slope as ZN. The IC event was detected as the first local minimum after ZN in the unfiltered signal [15]. To estimate other events, we employed our CSAV method. The method is based on the cumulative (negative) mediolateral shank angular velocity between ZN and ZP during stance, referred to as $CSAV_{ST}$, and the cumulative (positive) angular velocity between ZP and ZN during swing, referred to as $CSAV_{SW}$ (Fig. 2).

First, the total accumulated signal was calculated for both $CSAV_{ST}$ and $CSAV_{SW}$ phases separately. Then, the $CSAV_{ref\ event}$ values were obtained as the cumulative SAV of the phase at the time of the events detected by force plates or OMC. $CSAV\%_{ref\ event}$ was calculated by dividing $CSAV_{ref\ event}$ by the total CSAV of the corresponding gait phase. The mean $CSAV\%_{ref\ event}$ values for each event were then determined using the speed-controlled dataset.

Specifically, HR and TO events occurred during the $CSAV_{ST}$ phase, whereas the $CSAV_{SW}$ phase included FA and TBV events. For HR and TO events, the mean $CSAV_{ST}\%$ values were calculated to be 46.0 % and 95.7 %, respectively. Similarly, the $CSAV_{ST}\%$ values were determined to

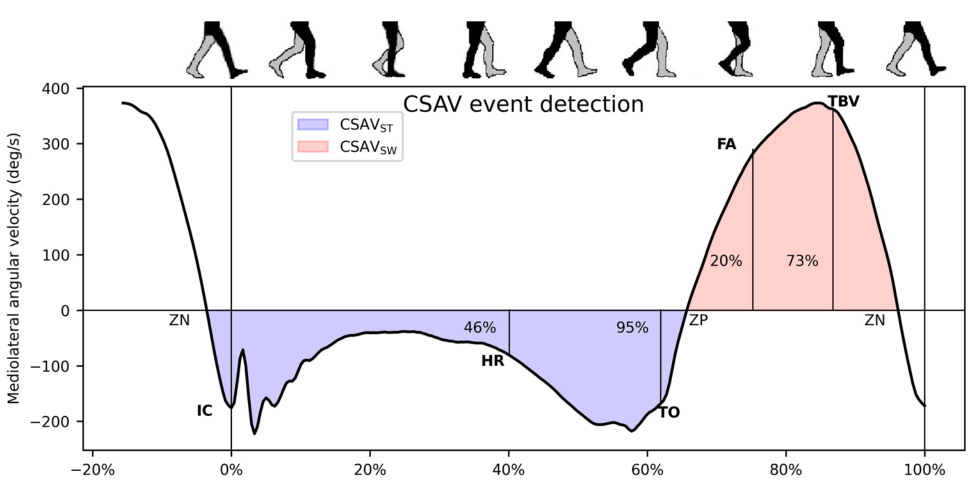

Fig. 2. Mediolateral angular velocity of a typical gait cycle, featuring heel rise (HR), toe-off (TO), feet adjacent (FA), and tibia vertical (TBV) events detected using the CSAV-method. Additionally, the zero-crossings, denoted as ZP and ZN, are highlighted as they define the CSAV-phases.

be 20.0 % for the FA event and 73.1% for the TBV event. Based on the developed method, the event occurs at the first sample when the CSAV-value exceeds the mean $CSAV\%_{ref\_event}$ multiplied by the total $CSAV_{phase}$ of each stride.

Furthermore, motivated by the significant dependencies found in our earlier study [29] between gait characteristics and SAV waveform, we investigated the impact of gait characteristics also on CSAV event detection. We examined the Pearson correlation between the error of CSAV-based events and available parameters: stride time, limb length, ZN and ZP cycle point, stride velocity, and stride length (Fig. S1). The analysis revealed significant dependencies between HR detection error and stride time (cc = -0.48, $p < 0.0001$), as well as between MS detection error and ZP cycle point (cc = 0.62, $p < 0.0001$). These parameters had a notable effect on the detection accuracy (Fig. S2).

We incorporated the identified corrective factor into the detection algorithms for HR and FA events. The algorithms for detecting HR, TO, FA, and TBV events can be found in Eqs. (1)–(4), respectively.

$$t_{HR} = argmin(t, CSAV_{ST}(t) < = CSAV_{ST} * 0.460) - (0.156s - 0.154 * stride \quad time) \tag{1}$$

$$t_{TO} = argmin(t, CSAV_{ST}(t) <= CSAV_{ST} * 0.957) \tag{2}$$

$$t_{FA} = argmin(t, CSAV_{SW}(t) > = CSAV_{SW} * 0.200) - (-0.254s + 0.384s * ZP_{cp}) \tag{3}$$

$$t_{TBV} = argmin(t, CSAV_{SW}(t) >= CSAV_{SW} * 0.731) \tag{4}$$

3. Results

In total, 4860 successful walking trials were completed, yielding 24,519 OMC-captured full strides, in addition to 8524 separate IC and 8146 TO events captured with force plates. The captured data and their key information are described in the supplementary material (Table S1).

The mean error for IC across all speeds and footwear conditions was -1.6 ± 6.3 ms (Table 1). For HR, TO, FA, and TBV events, which were detected with the CSAV method, the mean errors were -0.9 ± 29.3 ms, -0.5 ± 7.4 ms, -0.9 ± 6.4 ms, and 0.4 ± 9.0 ms, respectively. Notably, the 95 % limits of agreement for events other than HR (-62.2, 56.9 ms) were between -13.3 and 19.6 ms, with mean absolute error remaining consistently low (< 7.1 ms). The agreement between the reference methods and CSAV-methods was high, as indicated by ICCs exceeding 0.988 for events other than HR (0.896).

In a comparative analysis, two of the TO detection methods demonstrated substantial overall agreement with the force plate-based method, with ICC values 0.945 and 0.982. However, two out of the four methods exhibited bias and lower ICC scores: 0.740 and 0.803 (Table 1).

Bland-Altman plots, illustrating mean values of each participant's both feet in different footwear and speed conditions, consistently demonstrated excellent agreement between CSAV-methods and reference methods (Fig. 3). The limits of agreement, set as mean $\pm$ 1.96*SD, are visualized with Bland-Altman plots on the right side. Boxplots on the left side show true error in different scenarios, with whiskers representing measured 95 % limits of agreement. Additionally, Fig. 4 provides a visual representation of mean cycle points for events detected with both CSAV-method and reference method.

4. Discussion

We evaluated the performance of the CSAV method in detecting four key events using a cross-validated dataset. These events, along with previously validated IC event are essential for dividing the gait cycle into its seven main phases and analyzing the nuances of gait using wearable IMU technology, which allows ambulatory measurements and does not require expensive measurement infrastructure. The robustness of the CSAV method, demonstrated by its consistency in capturing events across varying speeds and shoe conditions (Fig. 3, Fig. 4), underscores its performance in healthy participants.

Our results demonstrate that the CSAV method achieves high accuracy in detecting TO, FA, and TBV events (Table 1, Fig. 3). Moreover, the CSAV methods showed high agreement with the reference system-based methods, as evidenced by high ICC scores (Table 1) and Bland-Altman plots (Fig. 3). However, for HR event detection, we observed lower agreement with reference compared to other events. It is worth noting that our detection method for IC aligns with the high accuracy reported in previous studies [13,16,18].

Given the significance of precise TO detection and the existence of alternative methods proposed in prior studies [12,14–16], we conducted a comparative analysis. The results indicate that while particularly the method proposed in [14] exhibited high accuracy in TO detection, our CSAV-based TO detection method outperforms all compared methods in terms of both true error and agreement with force plate-based methods (Table 1). It also compares well with the deep learning approach results reported in [19].

It is important to acknowledge the challenges associated with HR

Table 1
Event detection algorithm agreement with reference method. CSAV detection algorithms are indicated by event name and previously proposed toe-off detection algorithms are shown at the bottom. Dataset: cross-validated, including barefoot walking and walking in shoes at slow, normal, and fast speeds. The mean error indicates the difference between the reference and CSAV-based event timings. ICC indicates agreement against reference method.

Algorithm	Mean (SD) reference method event time (s)	Mean (SD) proposed method event time (s)	Mean error (SD) [ms]	Mean absolute error [ms]	95 % limits of agreement [ms]	ICC	n
Initial contact	-	0.00 (0.01)	-1,6 (6.3)	4,7	[-10.7, 11.0]	0.997 [0.995, 0.998]	5073
Heel rise	0.42 (0.05)	0.42 (0.05)	-0,9 (29.3)	22,2	[-62.2, 56.9]	0.896 [0.892, 0.901]	16,128
Feet adjacent	0.79 (0.08)	0.79 (0.08)	-0,5 (7.4)	5,1	[-13.3, 13.3]	0.996 [0.996, 0.996]	16,118
Tibia vertical	0.91 (0.09)	0.91 (0.09)	-0,9 (6.4)	5,1	[-14.2, 11.6]	0.998 [0.998, 0.998]	16,161
Toe-off	0.66 (0.06)	0.66 (0.06)	0,4 (9.0)	7,1	[-15.1, 19.6]	0.988 [0.987, 0.989]	5143
TO Arminian [12]		0.61 (0.05)	-42 (16.7)	42,1	[-90.7, −16.0]	0.740 [-0.037, 0.929]	4937
TO Trojaniello [16]		0.66 (0.06)	1.0 (19.3)	16,1	[-43.7, 26.7]	0.945 [0.941, 0.948]	5235
TO Bötzel [14]		0.66 (0.06)	-1.3 (11.6)	9.2	[-26.0, 20.4]	0.982 [0.978, 0.985]	4937
TO Allseits [15]		0.7 (0.06)	39.5 (10.6)	39.5	[21.3, 61.3]	0.803 [-0.024, 0.951]	5235

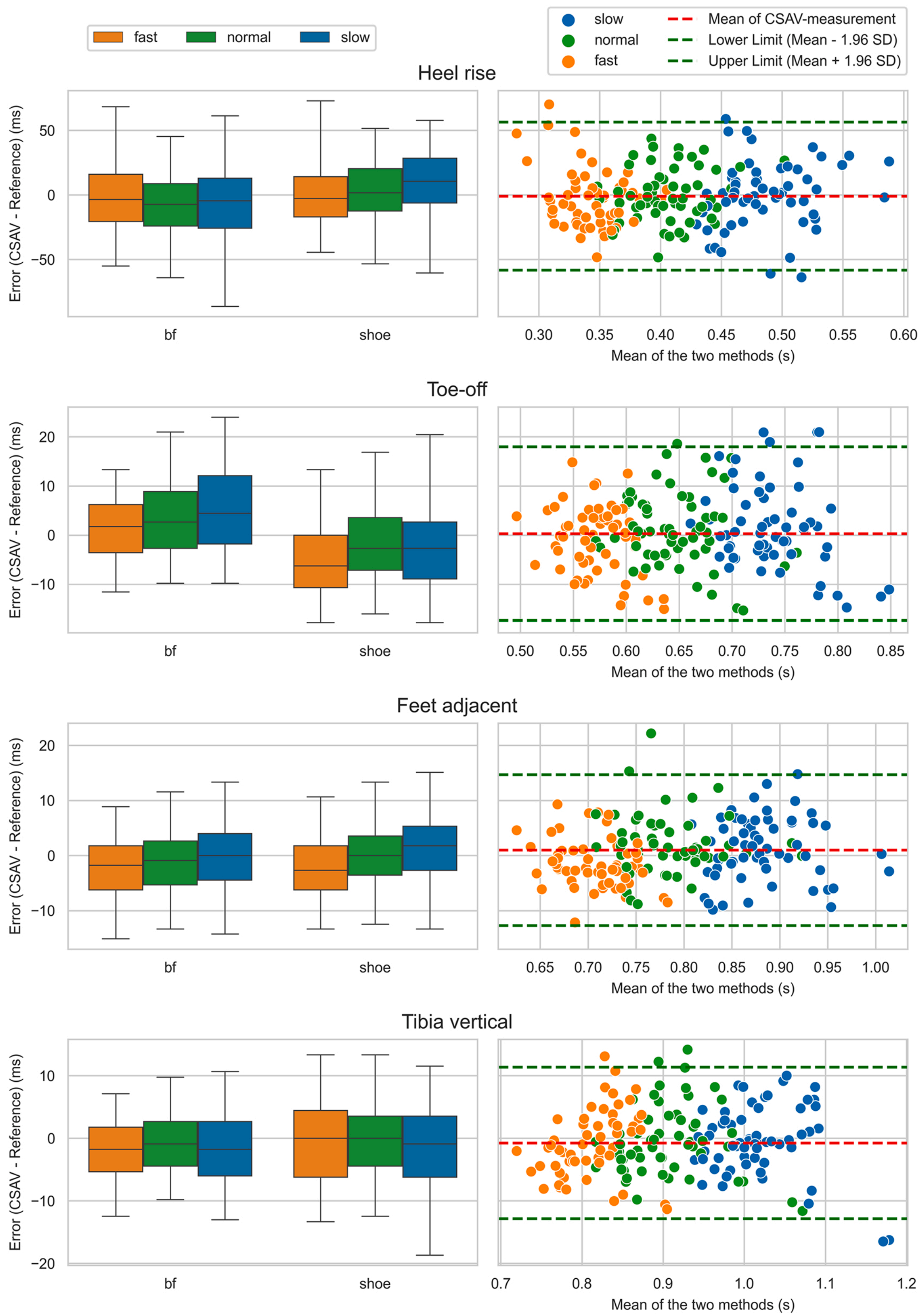

Fig. 3. Event detection error in different scenarios (bf = barefoot walking, shoe = walking in shoes). The analysis is based on cross-validated results from barefoot and shoe scenarios. Bland-Altman plots (right) visualize the agreement between reference method and CSAV-method.

event detection, as indicated by the lower agreement and higher dispersion of error (Table 1). In addition, the finding that HR error correlates the most with stride time points to the inability of CSAV-based HR detection to adjust to different gait styles. Our assumption is that the CSAV method may be less accurate in detecting stance phase events because of the constrained motion of the shank during stance. In contrast, the swing phase, characterized by consistent and flowing motion driven by momentum, gravity, and muscle control [1], is where the CSAV method is highly accurate.

Nonetheless, the CSAV method performs well in HR detection compared with previously reported methods [14,20–22]. However, the use of different evaluation methods (OMC, pressure sensing insoles,

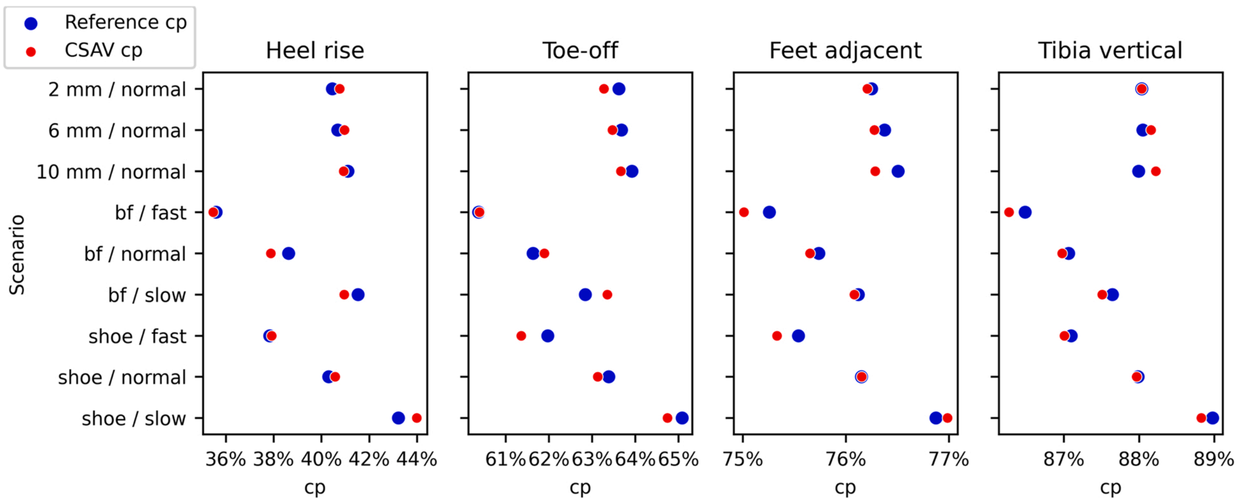

Fig. 4. Event mean cycle point with a reference system (blue) and CSAV-based (red) detection methods in different scenarios. The analysis is based on the cross-validated results of all measured strides.

visual detection) as reference introduces challenges in result comparability and underscores the overall difficulty of HR event detection. Further refinement and implementation of alternative detection methods are necessary to improve shank-attached IMU-based HR event detection accuracy.

Regarding the detection of FA and TBV events, the CSAV method achieves high agreement with OMC-based methods. This is particularly important because no other IMU-based validated methods for detecting these two events were found in the literature search. The high detection accuracy observed in all swing motion-related events, including TO, is intriguing. It highlights the general nature of highly consistent gait patterns during swing and introduces a novel approach to measuring this consistency.

This study has some limitations. First, although many strides were measured in various scenarios, the number of participants was relatively small. Nonetheless, the detection accuracy exhibited minimal deviation between the participants (Table 1), indicating accurate event detection in a normal gait. The participant group consisted of healthy young individuals, which limits the generalizability of the findings to the pathological gait. Therefore, larger and more diverse studies are required to validate these findings across different populations and gait conditions. Additionally, it's important to recognize the presence of soft tissue artifact in such measurements.

5. Conclusion

The findings of this study highlight the stability and accuracy of the developed CSAV method in detecting key gait events. While the performance of HR event detection can still be improved, the CSAV method demonstrates its effectiveness in capturing toe-off, feet adjacent, and tibia vertical events across different footwear and speed scenarios. These results contribute to the advancement of shank motion-based gait event detection techniques and their potential applications in gait analysis. Future research can improve HR event detection and validate the CSAV method in diverse gait contexts.

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CRediT authorship contribution statement

Antti Vehkaoja: Conceptualization, Methodology, Resources, Supervision, Writing – review & editing. **Janne Avela:** Conceptualization, Methodology, Resources, Writing – review & editing. **Jarmo Perttunen:** Conceptualization, Methodology, Writing – review & editing. **Mikko Salminen:** Conceptualization, Investigation, Methodology, Software, Writing – original draft.

Declaration of Competing Interest

The authors report no conflicts of interest related to this study.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.gaitpost.2024.04.006.

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