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A novel kinematic detection of foot-strike and toe-off events during noninstrumented treadmill running to estimate contact time

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ABSTRACT

Contact time (t_c) relies upon the accuracy of foot-strike and toe-off events, for which ground reaction force (GRF) is the gold standard. However, force plates are not always available, e.g., when running on a noninstrumented treadmill. In this situation, a kinematic algorithm (KA) – an algorithm based on motion capture data – might be used if it performs equally for all foot-strike angles across speeds. The purpose of this study was to propose a novel KA, using a combination of heel and toe kinematics (three markers per foot), to detect foot-strike and toe-off and compare it to GRF at different speeds and across foot-strike angles. One hundred runners ran at 9 km/h, 11 km/h, and 13 km/h. Force data and whole-body kinematic data were acquired by an instrumented treadmill and optoelectronic system. Foot-strike and toe-off showed small systematic biases between GRF and KA at all speeds (≤5 ms), except toe-off at 11 km/h (no bias). The root mean square error (RMSE) was ≤9 ms and was mostly constant across foot-strike angles for toe-off (7.4 ms) but not for foot-strike (4.1–11.1 ms). Small systematic biases (≤8 ms) and significant differences ($P \leq 0.01$) were reported for t_c at all speeds, and the RMSE was ≤14 ms (≤5%). The RMSE for t_c increased with increasing foot-strike angle (3.5–5.4%). Nonetheless, this novel KA computed smaller errors than existing methods for foot-strike, toe-off, and t_c. Therefore, this study supports the use of this novel KA to accurately estimate foot-strike, toe-off, and t_c from kinematic data obtained during noninstrumented treadmill running independent of the foot-strike angle.

1. Introduction

Running is defined by a duty factor, i.e., a ratio of contact time (t_c) over stride duration, under 50% (Folland et al., 2017; Minetti, 1998), which makes t_c a key parameter of running biomechanics. This parameter is computed from foot-strike and toe-off events, obtained from the ground reaction force (GRF). However, force plates are not always available (Abendroth-Smith, 1996; Maiwald et al., 2009), e.g., when running on a noninstrumented treadmill. In this situation, foot-strike and toe-off, and therefore t_c, can be obtained with a kinematic algorithm (KA) based on motion capture data.

Several algorithms were developed and compared to the use of GRF (De Witt, 2010; Fellin et al., 2010; Hreljac and Stergiou, 2000; Leitch et al., 2011; Maiwald et al., 2009; Milner and Paquette, 2015; Smith et al., 2015) or a footswitch device (Alvim et al., 2015), but they did not all offer the same accuracy. Moreover, previous datasets were limited to <30 runners (Alvim et al., 2015; Leitch et al., 2011), which may be too small to allow generalizing the algorithm to every runner. In addition, rearfoot, midfoot, and forefoot strike patterns (Hasegawa et al., 2007), which can be determined based on the foot-strike angle (Altman and Davis, 2012), can impact kinematic data and algorithm accuracy because they involve different biomechanical strategies (Ruder et al., 2019; Wei et al., 2019). Relatively different errors (up to 30 ms) were reported for both foot-strike and toe-off among rearfoot, midfoot, and forefoot strikers using five methods (Smith et al., 2015). Similarly, Leitch et al. (2011) showed that the most accurate algorithm for detecting foot-strike was dependent on the foot-strike pattern but not on toe-off detection. These previous algorithms were based on heel kinematics, which differ based on foot-strike patterns. Indeed, Milner and Paquette (2015) and Smith et al. (2015) reported larger errors for non-

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rearfoot strikers than for rearfoot strikers when using these heel-based algorithms.

It also seems necessary to compare t_c based on GRF and KAs, due to its biomechanical importance (Moore et al., 2019). For instance, a larger error in t_c was observed for an algorithm that was more precise in foot-strike and toe-off detection than for those that were less precise (Smith et al., 2015) due to the accumulation of errors in foot-strike and toe-off detection.

Hence, the purpose of this study was to propose a novel KA to detect foot-strike and toe-off and compare it to the use of GRF at several treadmill speeds and across foot-strike angles. In addition, foot-strike and toe-off were used to estimate t_c which was then compared to that based on GRF. This algorithm uses a combination of heel and toe kinematics to detect foot-strike. We hypothesized that i) no systematic bias would be reported between GRF and KA for foot-strike and toe-off at any of the speeds examined and that the error in foot-strike and toe-off would be similar independent of foot-strike angle and ii) no systematic bias, significant difference between t_c derived from GRF and KA, or effect of foot-strike angle would be obtained.

2. Materials and methods

2.1. Participant characteristics

One hundred recreational runners participated in this study, including 75 males (age: 31 ± 8 years, height: 180 ± 6 cm, body mass: 70 ± 7 kg, foot size: 270 ± 4 mm, and weekly running distance: 37 ± 24 km) and 25 females (age: 30 ± 7 years, height: 169 ± 5 cm, body mass: 61 ± 6 kg, foot size: 244 ± 6 mm, and weekly running distance: 20 ± 14 km). For study inclusion, participants were required to be in good self-reported general health with no lower-extremity injury (≤1 month) and to have an estimated maximal aerobic speed ≥14 km/h. The study protocol was approved by the Ethics Committee (CER-VD 2020–00334) and adhered to the latest version of the Declaration of Helsinki of the World Medical Association.

2.2. Experimental procedure

After providing written informed consent, retroreflective markers were positioned on participants to assess their running biomechanics (Appendix A). For calibration purposes, a 5-second standing static trial using a standard anatomical position was recorded on an instrumented treadmill (Arsalis T150–FMT-MED, Louvain-la-Neuve, Belgium) for each participant. Then, a 7-minute warm-up run was performed (9 km/h). After a short break (<5 min) participants completed three 1-minute runs (9 km/h, 11 km/h, and 13 km/h) performed in a randomized order with a 1-minute recovery between each run. These speeds were chosen because they are like those used in prior studies (Alvim et al., 2015; Leitch et al., 2011; Milner and Paquette, 2015). Three-dimensional (3D) kinematic (200 Hz) and kinetic (1000 Hz) data were collected during the static trial and for the first 10 strides following the 30-second mark of the running trials. The 3D kinetic data were down sampled to 200 Hz to match the sampling frequency of 3D kinematic data. Participants were familiar with running on a treadmill and wore their habitual running shoes during testing (shoe mass:257 ± 49 g and shoe heel-to-toe drop:7 ± 3 mm).

2.3. Ground reaction force for events detection

The gold standard foot-strike and toe-off were identified with Visual3D Professional software v6.01.12 (C-Motion Inc., Germantown, MD, USA) by applying a 20 N threshold to the z-component of the GRF (Smith et al., 2015).

2.4. Kinematic algorithm for events detection

The KA was implemented within Visual3D to detect foot-strike and toe-off from kinematic data. A mid-toe landmark was created midway between markers placed at the head of the first and fifth metatarsals. The mid-toe landmark position was rescaled by subtracting its respective global minimum (within the 10 strides) to overcome bias due to shoe height. Heel and mid-toe accelerations were calculated as the second derivative (second order central method) of the heel marker (foot calcaneus: aspect of the Achilles tendon insertion) and rescaled mid-toe landmark positions, respectively. Following visual observations of heel and mid-toe z-acceleration curves, an approach similar to that of Hreljac and Stergiou (2000), was followed. The KA was constructed such that foot-strike was detected within a time window of 120 ms centered around the instant when the mid-toe z-position reached 3.5 cm on descent. Foot-strike was defined as the first occurring maximum between the maxima of the heel marker and mid-toe landmark on z-acceleration curves within this time window (Figs. 1 and 2A). Toe-off was detected at the instance when the mid-toe z-position reached 3.5 cm on ascent after the preceding foot-strike, following a similar approach to that of Alvim et al. (2015). If such a threshold did not exist, 4 and 4.5 cm thresholds were used instead (Figs. 1 and 2.B). The distance between the mid-toe landmark and the end part of the shoe (on the toe-side) being close to 5.5 cm, the global minimum of the mid-toe landmark being close to 2 cm, and the foot angle at toe-off being close to 90° justified the 3.5 cm threshold. The KA requires three markers per foot to detect foot-strike and toe-off but 39 markers were used because a whole-body biomechanical model was needed to construct foot segment angles to obtain the foot-strike angle (see Appendix A), which permitted to validate the KA across foot-strike angles.

2.5. Statistical analysis

All data are presented as mean ± standard deviation. Bland-Altman plots were constructed to examine the presence of systematic bias in foot-strike, toe-off, and t_c obtained based on GRF and the KA for each speed (Atkinson and Nevill, 1998; Bland and Altman, 1995). The corresponding lower and upper limits of agreement and 95% confidence intervals were calculated. Positive systematic biases indicate overestimation by the KA, while negative values indicate underestimation. The root mean square error (RMSE) was calculated for foot-strike, toe-off, and t_c for each participant and each running trial. The RMSE was also calculated in relative units for t_c, i.e., by normalizing by the mean t_c value obtained using the GRF for each participant and running trial. In addition, the RMSE for foot-strike, toe-off, and t_c (averaged over speed) were given for forefoot, midfoot, and rearfoot strikers using the classification proposed by Altman and Davis (2012), i.e., using foot-strike angles <-1.6°, ≥-1.6° but <8°, and ≥8°, respectively.

A linear mixed model (a model including both random and fixed factors fitted by restricted maximum likelihood) was used to compare t_c obtained using the GRF and KA for the different speeds and across foot-strike angles. The fixed factors were speed (ordinal variable), method (GRF vs KA; nominal variable), and foot-strike angle (continuous variable). The within-subject nature was controlled for by including random effects for participants. Pairwise post hoc comparisons were performed using Holm corrections, and only those comparing the GRF and KA methods for a given speed were investigated. Statistical analysis was performed using Python (v3.7.4, http://www.python.org) and Jamovi (v1.6.23, https://www.jamovi.org), with the level of significance set at $P \leq 0.05$.

3. Results

Systematic biases were obtained for both foot-strike and toe-off at all speeds (Table 1 and Fig. 3) and were ≤5 ms (≤1 frame), except for toe-off at 11 km/h (no bias; the zero line is between the 95% confidence

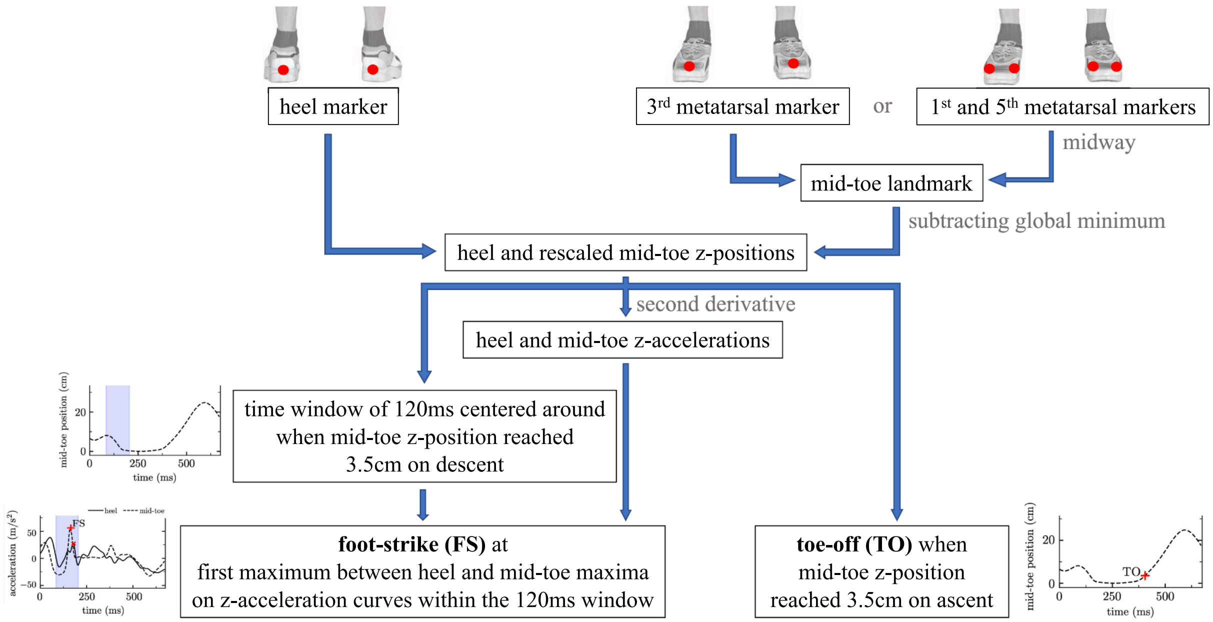

Fig. 1. Description of the kinematic algorithm for detecting foot-strike and toe-off. The mid-toe landmark could be a mid-toe marker (third metatarsal) in a simplified marker set.

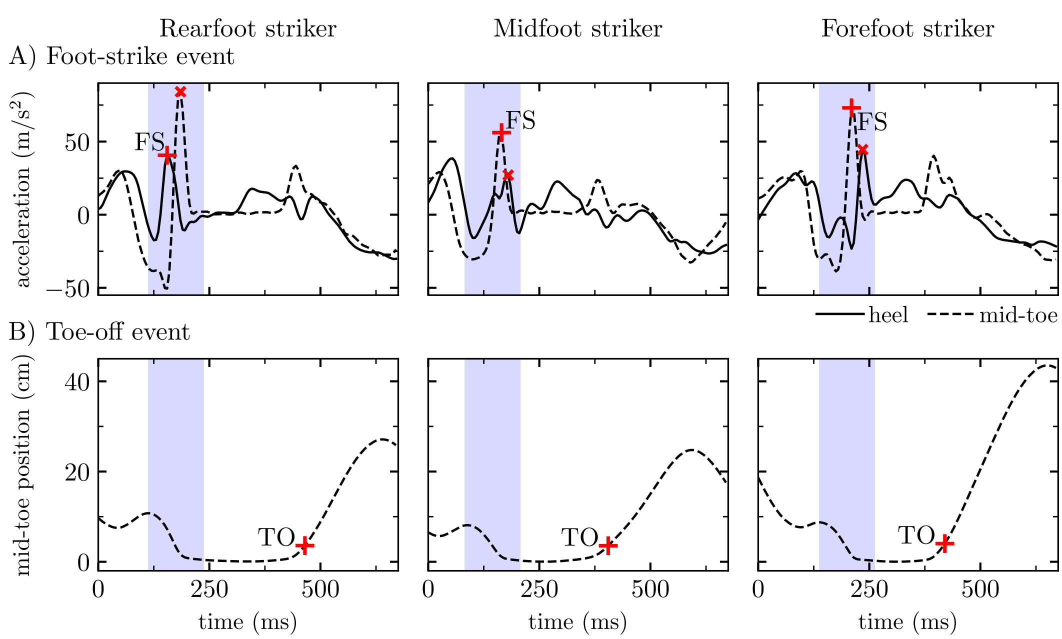

Fig. 2. Typical trajectory characteristics for a portion of a stride for three different runners at 11 km/h [rearfoot striker with foot-strike angle = 19.2°, midfoot striker with foot-strike angle = 1.4°, and forefoot striker with foot-strike angle = -16.5°] used by the kinematic algorithm to detect (A) foot-strike (FS) and (B) toe-off (TO; + sign; in red). The blue shaded area depicts the 120 ms time window during which foot-strike is examined. This time window is centered around the instant where the mid-toe *z*-position reached 3.5 cm on descent. The × sign (in red) denotes the second maximum detected by the algorithm during this time window. The first maximum defined foot-strike (+ sign; in red) and corresponded to a spike in heel *z*-acceleration for rearfoot strikers and in mid-toe *z*-acceleration for both midfoot and forefoot strikers. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

interval).

The RMSE was ≤9 ms for both foot-strike and toe-off and decreased slightly with increasing speed (Table 2). The RMSE for foot-strike increased with increasing foot-strike angle while the RMSE was mostly constant across foot-strike angles for toe-off (Fig. 4). The RMSE (averaged over speed) was 4.1 ± 2.2, 10.0 ± 3.5, and 11.1 ± 2.3 ms for foot-strike and 7.1 ± 3.1 ms, 8.2 ± 3.6 ms, and 6.9 ± 3.2 ms for toe-off for forefoot, midfoot, and rearfoot strikers, respectively.

Systematic biases were reported for t_c at all speeds (<8 ms), and the corresponding RMSE was ≤14 ms (≤5%; Table 3). The RMSE for t_c increased with increasing foot-strike angle (Fig. 5). Forefoot, midfoot, and rearfoot strikers had RMSEs for t_c (averaged over speed) of 8.6 ± 3.6 ms (3.5 ± 1.4%), 13.0 ± 6.2 ms (5.1 ± 2.3%), and 13.9 ± 5.3 ms (5.4 ± 1.9%), respectively.

The linear mixed model depicted significant effects of method, speed, foot-strike angle, and method × speed interaction ($P \leq 0.004$). t_c was significantly overestimated by the KA, decreased with increasing speed, and increased with increasing foot-strike angle. Holm post hoc tests

Table 1
Systematic bias, lower limit of agreement (lloa), and upper limit of agreement (uloa) for foot-strike and toe-off detected using ground reaction force and the kinematic algorithm at three running speeds. 95% confidence intervals are given in square brackets [lower, upper].

	9 km/h			11 km/h			13 km/h		
	Bias (ms)	lloa (ms)	uloa (ms)	bias (ms)	lloa (ms)	uloa (ms)	bias (ms)	lloa (ms)	uloa (ms)
Foot-strike	−4.4 [−4.8, −4.0]	−20.8 [−21.4, −20.2]	12.0 [11.3, 12.6]	−4.8 [−5.2, −4.5]	−20.1 [−20.7, −19.6]	10.5 [9.9, 11.0]	−4.6 [−5.0, −4.3]	−19.1 [−19.7, −18.6]	9.9 [9.3, 10.4]
Toe-off	3.5 [3.1, 3.9]	−13.9 [−14.6, −13.2]	20.9 [20.2, 21.6]	0.2 [−0.1, 0.5]	−13.6 [−14.1–13.1]	14.1 [13.5, 14.6]	−1.8 [−2.1, −1.5]	−15.9 [−16.4–15.4]	12.3 [11.7, 12.8]

Note: for bias, positive and negative values indicate that the kinematic algorithm overestimated and underestimated gait events, respectively.

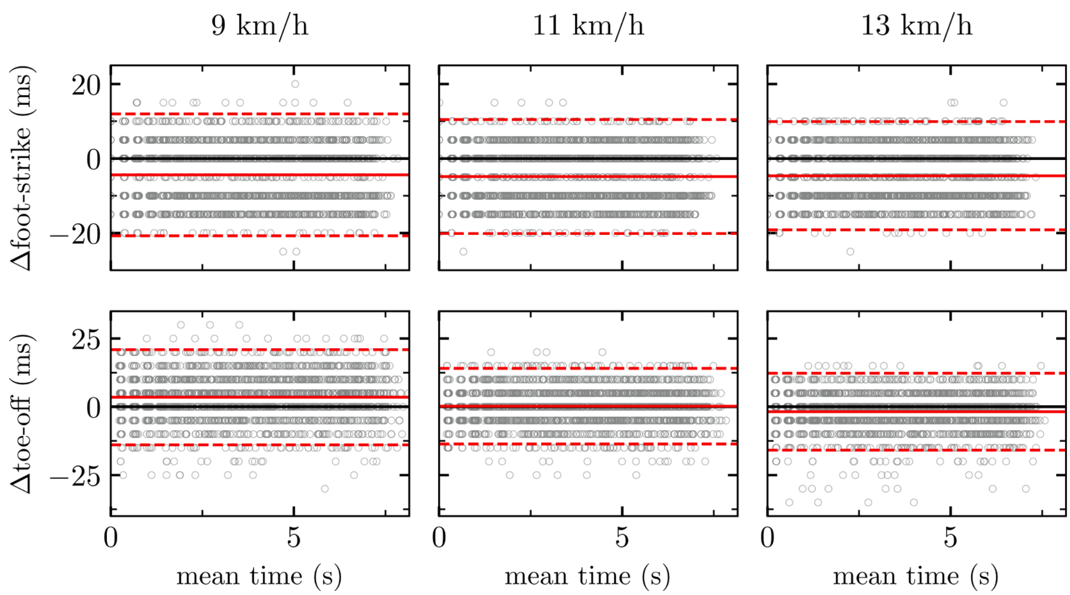

Fig. 3. Comparison of foot-strike and toe-off detection using ground reaction force and the kinematic algorithm [differences (Δ) as a function of mean values for the 10 analyzed strides of each participant (gray empty circles; 2000 values) together with systematic bias (red solid line), lower and upper limit of agreements (red dashed lines), and the zero line (black solid line), i.e., a Bland-Altman plot] for three running speeds. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 2
Root mean square error (RMSE) for foot-strike and toe-off events at three running speeds.

Running speed (km/h)	RMSE for foot-strike (ms)	RMSE for toe-off (ms)
9	8.4 ± 4.4	8.6 ± 4.0
11	8.2 ± 4.2	6.6 ± 2.6
13	7.8 ± 3.9	6.9 ± 2.8

Values are presented as mean ± standard deviation.

yielded significantly higher t_c when calculated by the KA than by the GRF at all speeds ($P \leq 0.01$; Table 3).

4. Discussion

Systematic biases were reported for foot-strike and toe-off at all speeds, refuting the first hypothesis. The RMSE was mostly constant across foot-strike angles for toe-off (7.4 ms) but not for foot-strike (4.1–11.1 ms), which partly refuted the first hypothesis. Systematic biases, as well as significant differences, were reported for t_c at all speeds. The RMSE for t_c increased with increasing foot-strike angle (3.5–5.4%), thus refuting the second hypothesis. Nonetheless, smaller errors than those obtained by existing methods were obtained for foot-strike, toe-off, and t_c. Therefore, this novel KA can be applied to accurately estimate foot-strike, toe-off, and t_c from kinematic data obtained during noninstrumented treadmill running independent of foot-strike angle.

The RMSEs for foot-strike were ≤8 ms at all speeds (Table 2). These errors were smaller than those obtained with existing algorithms (Alvim et al., 2015; Fellin et al., 2010; Leitch et al., 2011; Milner and Paquette, 2015; Smith et al., 2015). However, the RMSE increased with increasing foot-strike angle and was ~3 times smaller in forefoot strikers (RMSE = 4.1 ms) than in rearfoot strikers (RMSE = 11.1 ms; Fig. 4). Milner and Paquette (2015) showed that algorithms based solely on heel kinematics (position, velocity, or acceleration) were less accurate in foot-strike detection for midfoot or forefoot strikers than for rearfoot strikers because heel kinematics around foot-strike differ according to foot-strike pattern, i.e., a non-rearfoot striker does not initiate contact with the ground using the heel. In addition, the heel-based algorithm reported in Smith et al. (2015) had poorer foot-strike detection abilities in non-rearfoot strikers than in rearfoot strikers (RMSE: 22 to 6 ms). Their results are opposed to those of this study, most likely because Smith et al. (2015) used a heel-based algorithm. Moreover, the range of RMSE reported here was less than that in Smith et al. (2015) (4.1–11.1 ms for forefoot to rearfoot strikers; Fig. 4). Leitch et al. (2011) demonstrated that heel-based and mid-foot-based algorithms were best suited for rearfoot and forefoot strikers. Therefore, the novel KA proposed here, which accounts for this recommendation and combines heel and toe kinematic data to detect foot-strike, proved to be useful and showed a smaller error than existing methods.

The algorithm proposed by Milner and Paquette (2015) was based on

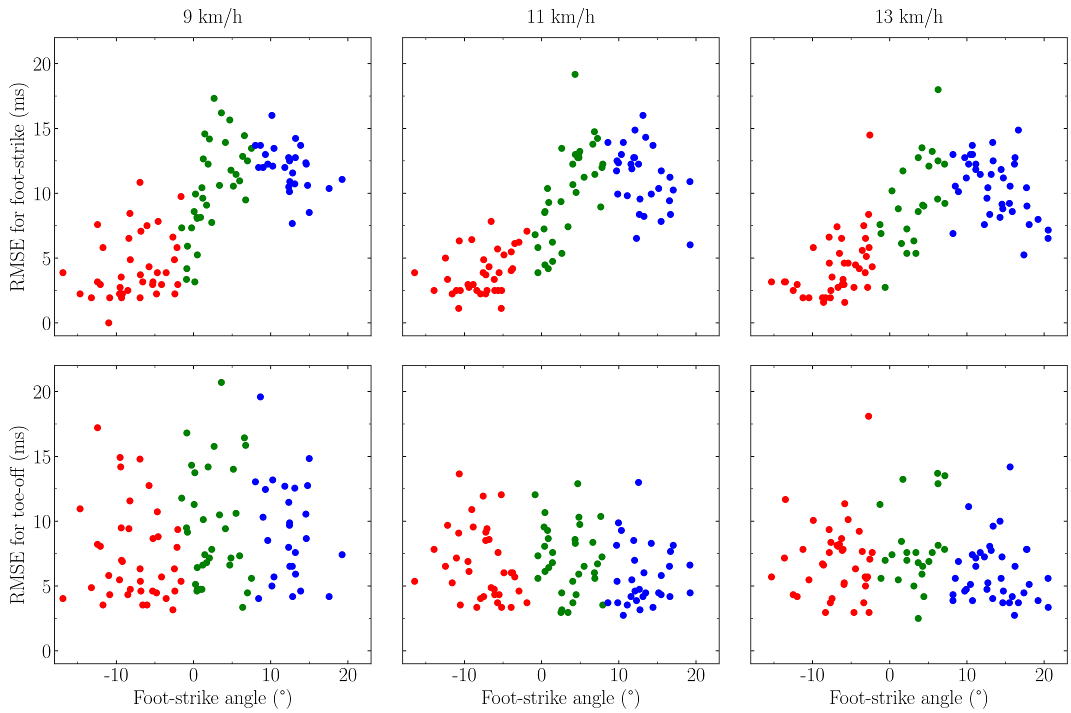

Fig. 4. The root mean square error (RMSE) for foot-strike and toe-off as a function of foot-strike angle for three running speeds. Each dot represents a participant, and colors indicate different foot-strike patterns according to Altman and Davis (2012), i.e., forefoot (red), midfoot (green), and rearfoot (blue) strikers for foot-strike angles <-1.6°, ≥-1.6° but <8°, and ≥8°, respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 3
Contact time (t_c) calculated based on foot-strike and toe-off detected using ground reaction force (GRF) and the kinematic algorithm together with systematic bias, 95% confidence intervals (in square brackets [lower, upper]), and root mean square error [RMSE; both in absolute (ms) and relative (%) units]. Data are presented for three running speeds. The linear mixed model revealed a significant method (kinematic algorithm vs GRF) × speed interaction effect ($P =$ 0.004). *Significant difference ($P \leq 0.01$) between the t_c calculated based on GRF and that calculated based on the kinematic algorithm, as determined by Holm post hoc tests.

	9 km/h	11 km/h	13 km/h
t_c (ms)	286.6 ± 27.5*	255.4 ± 23.7*	230.7 ± 20.5*
t_c GRF (ms)	278.6 ± 24.9	250.3 ± 20.7	227.9 ± 18.4
bias (ms)	7.9 [7.3, 8.5]	5.1 [4.6, 5.6]	2.8 [2.4, 3.3]
RMSE (ms)	13.7 ± 7.0	11.2 ± 4.8	9.9 ± 3.9
RMSE (%)	4.9 ± 2.5	4.5 ± 1.9	4.4 ± 1.7

Values are presented as mean ± standard deviation. Note: for bias, positive and negative values indicate that the kinematic algorithm overestimated and underestimated t_c, respectively.

the velocity of the center of mass of the pelvis and had a 15 ms offset for foot-strike. Similarly, the algorithm of Dingwell et al. (2001), originally designed for walking gait and based on knee extension spikes and used by Smith et al. (2015), depicted a 28 ms RMSE for foot-strike. These algorithms performed worse than the KA proposed here for foot-strike detection (RMSE ≤ 8 ms or |bias| ≤ 5ms). One reason could be that these algorithms used more proximal segments, which might be temporally shifted compared to what is happening directly at the foot.

Toe-off necessarily occurs based on the toes moving away from the ground, suggesting that a toe-based algorithm should accurately detect toe-off. The RMSE for toe-off was mostly constant across foot-strike angles (7.4 ms; Fig. 4), which corroborates the findings of Leitch et al. (2011). This RMSE was similar to the RMSE of rearfoot strikers given by the algorithm proposed by Smith et al. (2015) (ms) but slightly higher than the modified version of the algorithm of Alton et al. (1998) (3 ms) (Smith et al., 2015). However, the RMSE was obtained here was smaller than that obtained for forefoot strikers [7 vs 17 (Smith et al., 2015) or 12 ms (Alton et al., 1998)]. Therefore, toe-off detection with the novel KA showed similar or better accuracy than existing methods.

Small systematic biases, as well as significant differences, were reported for t_c at all speeds (Table 3). Even though the novel KA yielded smaller errors for foot-strike than the algorithm of Smith et al. (2015), those authors did not report significant differences in t_c between methods. The discrepancy might be due to a combination of under- and overestimations in foot-strike and toe-off. Moreover, a high speed (20 km/h) was used in Smith et al. (2015), which makes t_c smaller than that observed in this study, implicitly reducing observed differences and affecting the outcomes of statistical tests. In this study, the RMSE decreased with increasing speed [13.7–9.9 ms (5–4.5%) for 9–13 km/h] and was smaller than that in Smith et al. (2015) [18.4 ms (11%) at 20 km/h]. Hence, the algorithm of Smith et al. (2015) could be less effective at slower speeds because the time scale of kinematic trajectories might be slower, thus resulting in larger errors (i.e., greater differences in the number of frames) than in this study at similar speeds.

The proposed method could further be simplified and reduced to a two-dimensional analysis (Appendix B) though requiring future studies to evaluate its reliability. The strength and limitations of this study are specified in Appendix C.

5. Conclusion

This study proposed a novel KA that uses a combination of heel and toe kinematics (three markers per foot) to detect foot-strike and toe-off. Small systematic biases were reported for foot-strike and toe-off at all speeds. The RMSE was constant across foot-strike angles for toe-off but not for foot-strike. Small systematic biases were reported for t_c at all speeds, and the RMSE for t_c increased with increasing foot-strike angle. However, this novel KA yielded smaller errors than existing methods for foot-strike, toe-off, and t_c. Therefore, it can be applied to accurately

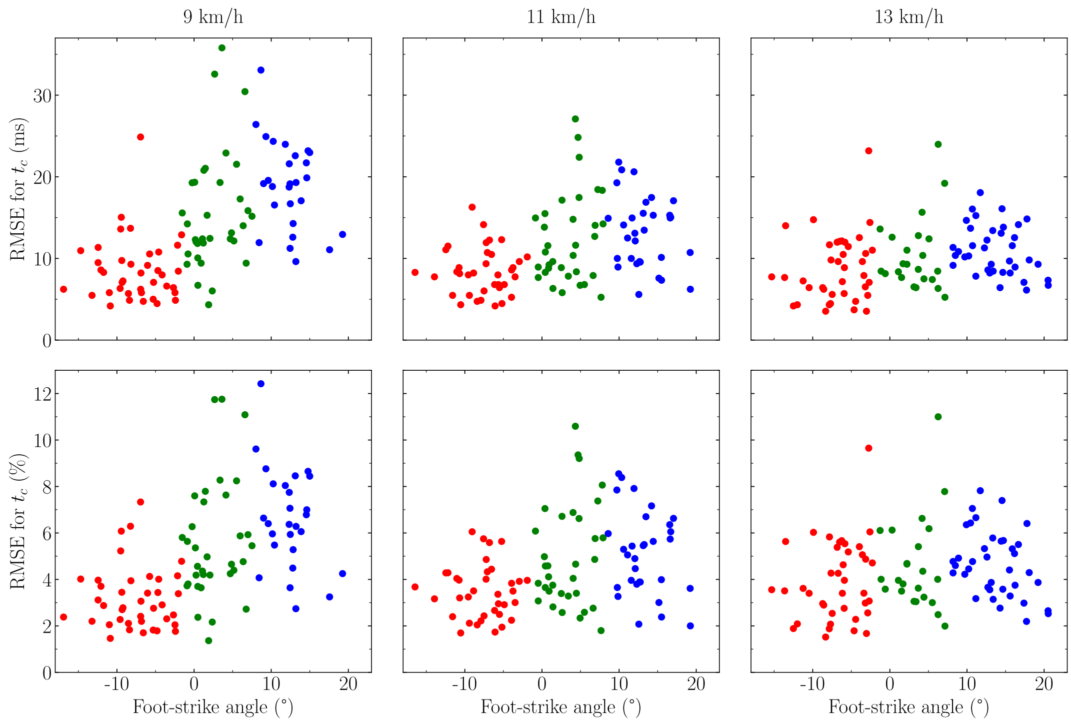

Fig. 5. The root mean square error (RMSE) for contact time (t_c) in both absolute (ms) and relative (%) units as a function of foot-strike angle for three running speeds. Each dot represents a participant, and colors indicate different foot-strike patterns according to Altman and Davis (2012), i.e., forefoot (red), midfoot (green), and rearfoot (blue) strikers for foot-strike angles <-1.6°, ≥-1.6° but <8°, and ≥8°, respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

estimate foot-strike, toe-off, and t_c from kinematic data obtained during treadmill running, independent of foot-strike angle.

CRediT authorship contribution statement

Aurélien Patoz: Conceptualization, Methodology, Investigation, Formal analysis, Writing – original draft, Writing – review & editing, Supervision. **Thibault Lussiana:** Conceptualization, Methodology, Investigation, Writing – review & editing, Supervision. **Cyrille Gindre:** Conceptualization, Methodology, Writing – review & editing, Supervision. **Davide Malatesta:** Conceptualization, Methodology, Writing – review & editing, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Availability of Data and Code

The datasets and codes supporting this article are available upon request from the corresponding author.

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Appendix A. . Data collection and processing

Whole-body three-dimensional (3D) kinematic data were collected at 200 Hz using motion capture (8 cameras) and Vicon Nexus software v2.9.3 (Vicon, Oxford, UK). The laboratory coordinate system was oriented such that the *x*-, *y*-, and *z*-axes denoted the mediolateral (pointing toward the right side of the body), anterior-posterior, and inferior-superior axes, respectively. Forty-three and 39 retroreflective markers of 12.5 mm diameter were used for the static and running trials, respectively. They were affixed to the skin and shoes of participants over anatomical landmarks using double-sided tape following standard guidelines (Tranberg et al., 2011). Synchronized kinetic data (1000 Hz) were also collected using the force plate embedded in the treadmill.

3D markers and force (analog signal) were exported in .c3d format and processed in Visual3D. 3D marker data were interpolated using a third-order polynomial least-square fit algorithm, allowing a maximum of 20 frames for gap filling, and subsequently low-pass filtered at 20 Hz using a fourth-order Butterworth filter (Lussiana et al., 2019). The 3D force signal was down sampled to 200 Hz to match the sampling frequency of marker data and filtered using the same filter.

From the marker set, a full-body biomechanical model with six degrees of freedom and 15 rigid segments was constructed. Segments included the head, upper arms, lower arms, hands, thorax, pelvis, thighs, shanks, and feet. In Visual3D, segments were treated as geometric objects, assigned inertial properties and center of mass locations based on their shape (Hanavan, 1964), and attributed relative mass based on standard regression equations (Dempster, 1955). The foot segment angle was defined as the orientation of the foot segment relative to the laboratory coordinate system and computed using an *x*–*y*–*z* Cardan sequence. The foot segment angle at foot-strike defined the foot-strike angle.

Appendix B. . Simplification of the proposed method

The proposed KA used three markers per foot to estimate t_c. This can be simplified by using only two markers. First, assuming that t_c is symmetric between right and left running steps (symmetry index ~ 3%) (Mo et al., 2020), markers could be positioned on a single of both feet. Second, the two markers placed on the head of the first and fifth metatarsals could be replaced by a single marker placed on the head of the third metatarsal. In this case, the 3D analysis could further be simplified to a two-dimensional analysis (in the sagittal plane), which could then more easily be used outside the laboratory and by non-scientific teams (e.g., podiatrists, coaches, etc.). Nonetheless, future studies should be performed to assess the reliability of this simplified method.

Appendix C. Strengths and limitations

The strength of the results is due to the large dataset employed. This dataset allows better generalization of the results than datasets obtained with the smaller cohorts of 10 (Leitch et al., 2011) to 30 (Alvim et al., 2015) runners used previously. Nonetheless, a few limitations to this study exist. The KA was compared to the use of GRF using only treadmill runs, and speeds were limited to endurance speeds. The KA might also perform well for overground running trials because spatiotemporal parameters between motorized treadmill and overground running are largely comparable (Van Hooren et al., 2020). However, it was also concluded that participants behaved differently when attempting to achieve faster speeds overground than on a treadmill (Bailey et al., 2017). Therefore, further studies should focus on comparing this novel KA to the use of GRF using additional conditions, i.e., faster speeds, positive and negative slopes, and different types of ground. Finally, toe-off detection is based on an absolute threshold (3.5 cm), and its accuracy might be influenced by marker placement, shoe size, and footwear characteristics. Nonetheless, the toe-off detection method proposed herein yielded equivalent or smaller errors than existing methods.

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