

Development and validation of a 3D kinematic-based method for determining gait events during overground walking

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ABSTRACT

A new signal processing algorithm is developed for quantifying heel strike (HS) and toe-off (TO) event times solely from measured heel and toe coordinates during overground walking. It is based on a rough estimation of relevant local 3D position signals. An original piecewise linear fitting method is applied to these local signals to accurately identify HS and TO times without the need of using arbitrary experimental coefficients. We validated the proposed method with nine healthy subjects and a total of 322 trials. The extracted temporal gait events were compared to reference data obtained from a force plate. HS and TO times were identified with a temporal accuracy \pm precision of $0.3 \text{ ms} \pm 7.1 \text{ ms}$, and $-2.8 \text{ ms} \pm 7.2 \text{ ms}$ in comparison with reference data defined with a force threshold of 10 N. This algorithm improves the accuracy of the HS and TO detection. Furthermore, it can be used to perform stride-by-stride analysis during overground walking with only recorded heel and toe coordinates.

Index Terms—3D, kinematic-based method, gait events, heel strike, toe-off, validation, walking.

1. INTRODUCTION

Accurate detection of temporal heel strike (HS) and toe-off (TO) events is a crucial step in 3D gait analysis. HS and TO are needed to determine the stance and the swing phases, which constitute essential data that could distinguish normal gait and pathological gait [1] and contribute to the understanding of motion disorders [2,3].

The HS and TO event times can be accurately determined by a force plate measuring ground reaction forces. However, the size and the relative position of the force plate are not always suitable for subjects with short step lengths (e.g., children, and patients with gait disorders), or with long step lengths (e.g., athletes) [4]. A trial with the force plate is considered successful when the subject is able to land with only one foot on the force plate, with this foot fully within it. In addition, an individual force plate can only measure the gait events from a single step, and thus the number of steps analyzed is limited by the number of available force plates [5,6].

Several kinematic-based methods have been proposed to extract HS and TO times during overground walking. ("Overground walking" is used by contrast with "treadmill walking".) Algorithms have been developed for identifying gait features from velocity [4,7,8] and acceleration derived from heel and toe positions [9]. These methods rely, however, on the numerical differentiation of position data, and may require that the data be smoothed as pointed out in [9]. Very few publications report both a method that extracts gait events directly from heel and toe coordinates and its validation against reference data provided by, e.g., a force plate. In [10], Zeni *et al.* introduced algorithms using the relative displacement between the sacral and foot markers to determine treadmill and overground gait events from coordinate data. Novel techniques based on miniature inertial sensors have also been validated and used to determine gait events during overground walking, e.g., [11,12].

This work is part of a project that deals with the 3D analysis of normal and pathological gait [12]. Neurologists specialized in human motion disorders are indeed very interested in the development of innovative, quantitative techniques, and their possible use in clinical practice, e.g. in the diagnostic and analysis of Parkinson's disease.

In this paper, we present a new signal processing algorithm that automatically extracts HS_{kin} and TO_{kin} times from only heel and toe coordinates measured by a kinematic 3D analysis system. We validate this kinematic-based method using nine healthy volunteers and a total of 322 trials against reference data (denoted HS_{ref} and TO_{ref}) provided by a force plate. Throughout the paper, the subscripts *kin* and *ref* refer to the developed method and to the reference method, respectively.

2. METHODS AND MATERIALS

2.1. Participants and gait test procedure

Kinematic and force plate data were recorded during overground walking tests performed by nine healthy participants (8 males; 1 female; (mean \pm standard deviation) age = 27 ± 2.5 years; height = 180 ± 7 cm; weight = 79 ± 12 kg). All of them gave informed consent. The gait procedure of this paper is similar to the one reported in [12]. None of the participants suffered from any known gait and lower limb pathology. The participants started the walking tests after taking sufficient time to get used to the gait procedure. During the tests, they were asked to walk on a 12-m long track, at their preferred, self-selected usual speed, while looking forward (in the walking direction) and thus not paying attention to hitting the force plate. The duration of a single gait test was 60 s. The participants wore their own regular shoes. All of the walking tests were performed at the Laboratory of Human Motion Analysis (LAMH) of the University of Liège, Belgium.

2.2. 3D analysis systems and reference gait events

Simultaneous measurements of heel and toe marker coordinates and ground reaction forces were performed by a kinematic 3D analysis system (Codamotion system; Charnwood Dynamics; Rothley, UK), and a force plate (Kistler force plate; Kistler Instrument Corp.; Amherst, NY, USA), respectively.

The kinematic system is based on active optical technology; it can accurately measure the 3D positions of active markers placed in the body locations of interest. The force plate consists of a rectangular metal plate (400 mm x 600 mm), which is inserted into the track in the middle of the distance selected for walking tests [12]. Each corner of the plate is fitted with a piezoelectrical transducer capable of measuring ground reaction forces in the direction of the x -axis (horizontal), y -axis (transverse), and z -axis (vertical).

A force plate trial is considered successful when one whole foot (either left or right) hits the force plate, whereas the other foot does not hit this force plate. During each overground walking test, we collected simultaneous vertical ground reaction force data at 1,000 Hz, and marker position data at 400 Hz, both for heel (calcaneus) and toe (hallux) markers. The kinematic data were upsampled in order to match the sampling frequency of the plate force data (1,000 Hz).

The reference gait timing, HS_{ref} , is defined as being the timing of the first frame where the vertical force rises above a given force threshold. TO_{ref} is defined as being the timing of the first frame where the vertical force drops below a given force threshold. In this paper, the extraction of reference data is based on the following force thresholds: 5 % of BW (body weight) [12,13], 2% of BW, and 1% of BW, 10 N [1,4,7-9], and 5 N [1,4,8].

2.3. New signal processing algorithm

We developed a new signal processing algorithm to detect HS and TO times using recorded kinematic data. In this paper, we consider position signals in the sagittal plane. The proposed algorithm/method extracts automatically HS and TO from z -axis positions used in conjunction with x -axis positions.

The algorithm first detects the time intervals during which the right and left feet are on the ground, i.e., when the heel and toe markers are at rest. In this paper, we call "heel flat phase" the interval during which the heel marker is at rest, and "toe flat phase" that when the toe marker is at rest. These "flat phases" are characterized by x -axis position signals that are almost constant (Figs. 1(a)-(b)). Throughout, x_h (x_t) and z_h (z_t) are the measured positions along the x -axis and z -axis, respectively. The subscripts h and t refer to heel and toe, respectively.

The algorithm exploits, as follows, the endpoints of the flat phases to locally extract the gait events:

- HS_{kin} is automatically extracted using x_h and z_h (Fig. 1(a)). A time subinterval $[t_1 t_7]$ is first determined: t_1 is the time of the local maximum of z_h occurring before the heel flat phase; and t_7 is the time of the middle of the heel flat phase. The signals x_h and z_h are then restricted to $[t_1 t_7]$ defining local signals in $[t_1 t_7]$. In order to estimate the locations of convex curvature in these local position signals (i.e., the transition regions of these segmented signals), we use a piecewise linear fitting method using two linear segments that best fit these position signals in the least-square sense (a detailed description is provided in Appendix A). These locations of convex curvature correspond to the breakpoints I_1 and I_2 . Their times are t_2 and t_3 , respectively. We apply the previous linear fitting method twice on the interval $[\max(t_2, t_3) t_6]$, where t_6 is the middle of $[(\max(t_2, t_3) t_7]$; the time of the corresponding breakpoint is t_4 . It is then assumed that HS_{kin} is estimated as follows

$$HS_{kin} = \min(t_4, t_5), \quad (1)$$

where t_5 is the time of the local minimum in z_h reached by the heel marker as the foot hits the ground.

- TO_{kin} is automatically identified using x_t , z_t , and z_h (Fig. 1(b)). A time subinterval $[t_8 t_{11}]$ is first determined: t_8 is the time of the middle of the toe flat phase; and t_{11} is the time of the first local maximum of z_h after the toe flat phase. The signal z_t is then restricted to $[t_8 t_{11}]$ defining a local signal in $[t_8 t_{11}]$. We apply the piecewise linear

fitting method (see Appendix A) to the resulting local signal in order to estimate the location of convex curvature, I_3 , in that local signal. The time of I_3 is t_{10} . We define TO_{kin} as

$$TO_{kin} = \min(t_9, t_{10}), \quad (2)$$

where t_9 is the time of the local minimum in z_t reached by the toe marker as the toe leaves the ground.

Table 1

Accuracy (mean of the differences), precision (std. dev. of the differences), limits of agreement, 95% confidence interval (CI) of the differences, and 95% CI of the lower and the upper limits of agreement between the developed 3D kinematic-based method and the reference method (with various force thresholds), for gait events obtained in a total of $n=322$ trials.

	Thresholds defining HS_{ref} and TO_{ref}	Accuracy (ms) (Precision (ms))	Limits of agreement (ms)	95% CI of the differences (ms)	95% CI of the lower limit (ms)	95% CI of the upper limit (ms)	Nbr. of trials
HS	5% of BW	-6.0 (7.3)	[-20.6 8.6]	[-6.8 - 5.2]	[-21.9 - 19.2]	[7.2 10.0]	322
	2% of BW	-0.6 (6.9)	[-14.2 13.3]	[-1.3 0.2]	[-15.8 - 13.1]	[12.0 14.6]	322
	1% of BW	0.8 (7.3)	[-13.8 15.3]	[-0.0 1.6]	[-15.1 - 12.4]	[13.9 16.7]	322
	10N	0.3 (7.1)	[-13.7 14.6]	[-0.4 1.1]	[-15.3 - 12.6]	[13.3 16.0]	322
	5N	1.2 (7.6)	[-13.8 16.5]	[0.4 2.1]	[-15.5 - 12.6]	[15.1 18.0]	322
TO	5% of BW	15.9 (8.1)	[0.0 32.0]	[15.0 16.7]	[-1.8 1.2]	[30.5 33.5]	322
	2% of BW	1.5 (6.9)	[-12.1 15.4]	[0.6 2.3]	[-13.8 - 11.0]	[13.9 16.8]	266
	1% of BW	-4.5 (7.2)	[-18.6 9.8]	[-5.4 - 3.6]	[-20.3 - 17.4]	[8.3 11.3]	266
	10N	-2.8 (7.2)	[-16.9 11.5]	[-3.7 - 2.0]	[-18.7 - 15.7]	[10.0 13.0]	266
	5N	-6.4 (7.3)	[-20.7 8.2]	[-7.3 - 5.5]	[-22.5 - 19.5]	[6.7 9.7]	266

3. RESULTS AND DISCUSSION

The developed 3D kinematic-based method was successfully employed to automatically extract the HSs and TOs from a total of 322 trials performed by nine healthy volunteers. The agreement between the new method and the reference method was investigated using Bland-Altman analysis. In addition, the accuracy and the precision of detection are computed as the mean and the standard deviation (std. dev.) of the differences between these gait event times, i.e., $HS_{kin} - HS_{ref}$ and $TO_{kin} - TO_{ref}$.

Table 1 provides a quantitative one-by-one comparison of gait events considering different force thresholds. Because of the limited number of extracted TO_{ref} , the number of trials was not always the same but was either 266 or 322.

Results of HS_{kin} and TO_{kin} were comparable across the different force thresholds. The accuracy and precision of HS_{kin} detection ranged from -6.0 ms to 1.2 ms, and 6.9 ms to 7.6 ms, respectively. The accuracy and precision of TO_{kin} detection ranged from -6.4 ms to 15.9 ms, and 6.9 ms to 8.1 ms, respectively. Given the sampling frequency 400 Hz of the recorded marker positions, the accuracy and the precision of detection are less than the durations of 1 frame (2.5 ms) and 3 frames (7.5 ms) for a force threshold of 10 N, respectively.

Figs. 2(a)–(b) show the Bland-Altman plots with reference data defined by a threshold force of 10 N. We observe very small systematic biases in accordance with the accuracy of detection provided in Table 1. In addition, the limits of agreement (i.e., mean \pm 1.96 std. dev. limits of agreement of the differences $HS_{kin} - HS_{ref}$ and $TO_{kin} - TO_{ref}$) and their associated 95% confidence interval exhibit small variations in the times of gait events (see table 1).

The experimental results show a good agreement between the new signal processing algorithm and the reference, and demonstrate an accurate and precise detection of HS and TO times in a group of healthy people.

The validation of the extraction of HS_{kin} relies on the existence of a local minimum (in z_h) reached by the heel marker as the foot hits the ground. This local minimum was present in all subjects. We also verified the presence of this local minimum in five gait trials performed by one subject who walked barefoot. Similarly, the local minimum (in z_t) reached by the toe marker as the toe leaves the ground was consistent in all subjects. In addition, the proposed algorithm/method is robust with respect to the type of insoles, which can be either quite stiff or quite soft.

The piecewise linear fitting method is completely automatic since it only uses the associated subinterval boundaries as inputs without, e.g., the need for empirical threshold values. To underline the benefit of the detection of HS_{kin} , as proposed in [14,15], we introduce HS_{kin2} as a new definition of HS_{kin} based only on the time of the mentioned local minimum without using the time t_4 defined in Sec. 2.3, with

$$HS_{kin2} = t_5. \quad (3)$$

Fig. 3(a) shows the Bland-Altman plot of HS_{kin2} against reference data obtained with a force threshold of 10 N. HS_{kin2} was detected with an error of $12.5 \text{ ms} \pm 17.4 \text{ ms}$, limits of agreement of $[-21.6 \text{ ms } 47.3 \text{ ms}]$ (i.e., mean \pm 1.96 std. dev. limits of agreement of the difference $HS_{kin2} - HS_{ref}$), and the 95% confidence interval of the difference, $HS_{kin2} - HS_{ref}$, of $[10.6 \text{ ms } 14.4 \text{ ms}]$. The comparison of these results with those of HS_{kin} given in Table 1 and in Fig. 2(a) (for the same force threshold, i.e., 10 N), reveals that the proposed piecewise linear fitting method improves significantly the accuracy and precision of detection of HS_{kin} .

Similarly, TO_{kin} can be replaced by TO_{kin2} defined as [11]

$$TO_{kin2} = t_9. \quad (4)$$

TO_{kin2} does not then take into account the result of the piecewise linear fitting method. The results of its comparison to reference data (with the force threshold of 10 N) are shown in Fig. 3(b). TO_{kin2} is determined with an error of $1.7 \text{ ms} \pm 8.8 \text{ ms}$, limits of agreement of $[-15.6 \text{ ms } 19.3 \text{ ms}]$ (i.e., mean \pm 1.96 std. dev. limits of agreement of the difference $TO_{kin2} - TO_{ref}$), and the 95% confidence interval of the difference, $TO_{kin2} - TO_{ref}$, of $[0.6 \text{ ms } 2.7 \text{ ms}]$. From these results and those of TO_{kin} in Table 1 and in Fig. 2(b), we observe no relevant differences between TO_{kin} and TO_{kin2} . Nevertheless, we could expect that TO_{kin} would be better than TO_{kin2} in case of abnormal gait.

4. CONCLUSIONS AND FUTURE WORK

The proposed 3D kinematic-based method is suitable for the detection of HS and TO times from only measured heel and toe coordinates during overground walking. It is based on an innovative piecewise linear fitting method that identifies accurately HS and TO times in local position signals without the need of applying arbitrary experimental coefficients.

We validated the 3D kinematic-based method on a set of nine young and healthy subjects, with a total of 322 trials. Based on different force thresholds, the reference gait event times—used in the validation—were extracted from vertical ground reaction forces measured by a force plate. The experimental results show that the developed method has the advantage to define relevant signal subregions in which gait event times are locally extracted with high accuracy and precision. A stride-by-stride analysis can be then carried out accurately in normal overground gait using only heel and toe coordinates.

Because the validation is based on reproducible relevant signal subregions where HS and TO times are extracted, we could expect that the proposed method would be robust for pathological overground walking and for treadmill running. Further studies are needed to investigate these hypotheses.

APPENDIX A

We present the piecewise linear fitting method used to estimate the locations of the convex curvature in a signal (Sec. 2.2.). For this, we consider a given signal $sig = sig(t_1), sig(t_2), \dots, sig(t_N)$ defined in a time interval $I = t_1, t_2, \dots, t_N$, where N is the total number of samples of sig . This method first computes the coefficients of piecewise linear functions with two linear segments that best fit sig in the least-square sense, leading to the computation of least-square errors. The minimum of these least-square errors is then determined and the associated piecewise linear function provides linear segments that intersect at the breakpoint $(t_b, sig(t_b))$. An illustration of this method is given in Fig. 1(a), where I corresponds to $[t_1 \ t_7]$ and t_b to t_2 .

The main steps to determine the breakpoint $(t_b, sig(t_b))$ are as follows:

- For each $k = 1, \dots, N$, one computes the coefficients $\alpha_1, \alpha_2, \beta_1$, and β_2 of a piecewise linear function p_k that best fits sig by minimizing

$$Err_k = \sum_{i=1}^N (sig(t_i) - p_k(t_i))^2, \quad (5)$$

where

$$p_k(t) = \begin{cases} \alpha_1 * t + \beta_1, & t = t_1, \dots, t_k, \\ \alpha_2 * t + \beta_2, & t = t_{k+1}, \dots, t_N. \end{cases}$$

This error can be expressed as

$$Err_k = \|A X_k - B\|^2, \quad (6)$$

where

$$X_k = \begin{pmatrix} \alpha_1 \\ \beta_1 \end{pmatrix}, \quad A = \begin{pmatrix} t_1 & 1 \\ \vdots & \vdots \\ t_k & 1 \end{pmatrix}, \quad B = \begin{pmatrix} sig(t_1) \\ \vdots \\ sig(t_k) \end{pmatrix}, \quad \text{if } t = t_1, \dots, t_k,$$

and

$$X_k = \begin{pmatrix} \alpha_2 \\ \beta_2 \end{pmatrix}, \quad A = \begin{pmatrix} t_{k+1} & 1 \\ \vdots & \vdots \\ t_N & 1 \end{pmatrix}, \quad B = \begin{pmatrix} \text{sig}(t_{k+1}) \\ \vdots \\ \text{sig}(t_N) \end{pmatrix}, \quad \text{if } t = t_{k+1}, \dots, t_N.$$

The normal equations associated with (3) are

$$A^t A X_k = A^t B. \quad (7)$$

Solving (4) leads to the coefficients α_1 , α_2 , β_1 , and β_2 .

- Finally, one obtains the breakpoint $(t_b, \text{sig}(t_b))$ by determining the minimum of the least-square errors, i.e.,

$$\text{Err}_b = \min_{k=1, \dots, N} (\text{Err}_k). \quad (8)$$

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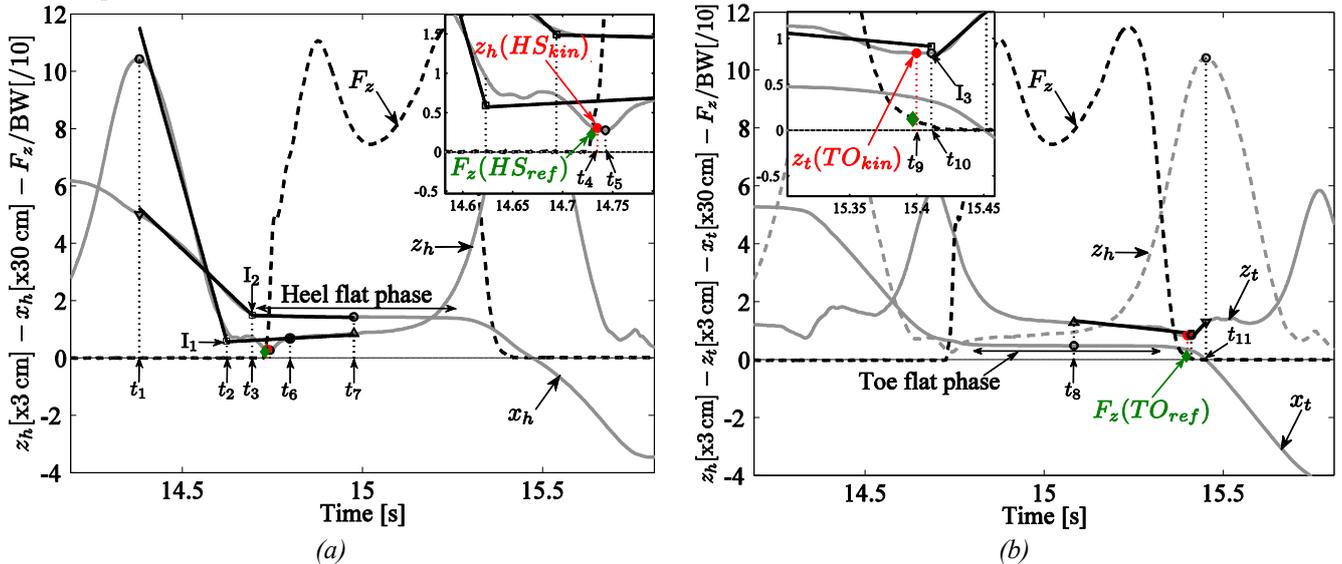


Fig. 1. The 3D kinematic-based method extracts (a) HS and (b) TO from position data of heel and toe makers (in the sagittal plane). The reference data are extracted from vertical ground reaction force signals that are synchronized with the position signals.

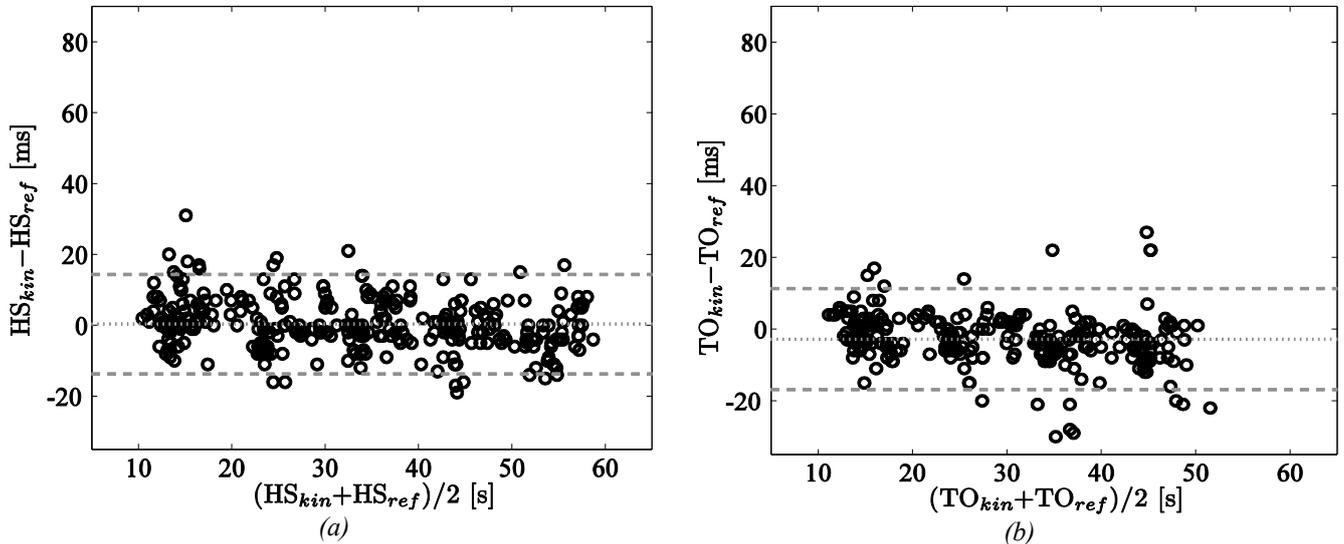


Fig. 2. Bland-Altman plots of (a) the HS and (b) the TO measured by the 3D kinematic-based method and by the reference method for a force threshold of 10 N, with mean (dotted line) ± 1.96 std. dev. limits of agreement (dashed lines) of differences $HS_{kin} - HS_{ref}$ and $TO_{kin} - TO_{ref}$.

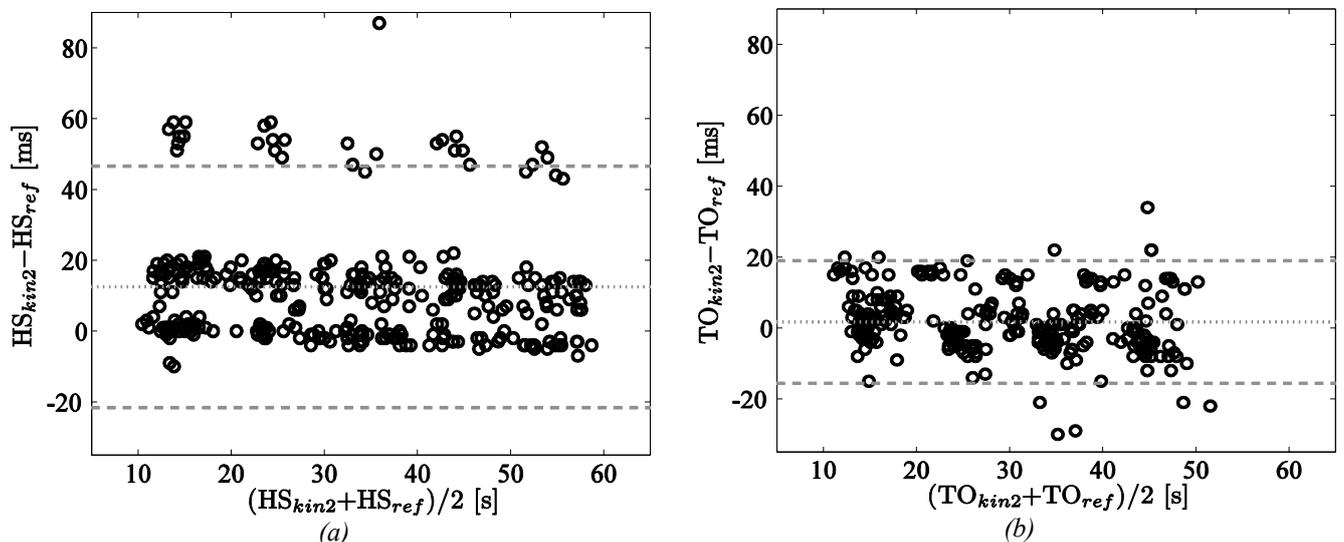


Fig. 3. Bland-Altman plots of (a) the HS and (b) the TO measured by the 3D kinematic-based method without using the piecewise linear fitting method (see Appendix A) and by the reference method for a force threshold of 10 N, with mean (dotted line) ± 1.96 std. dev. limits of agreement (dashed lines) of differences $HS_{kin2} - HS_{ref}$ and $TO_{kin2} - TO_{ref}$.