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The head is an excellent proxy for the whole body center of mass when measuring running velocity in competition

Short Communication

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Abstract

Whole body digitizing used to calculate whole body center of mass (CM) variables from competitions is particularly time-consuming, and “shortcut” methods that substitute for it could expediate the calculation of spatiotemporal variables. The aim of this study was to measure the appropriateness of using the head as a proxy for the CM when calculating running velocity in competition. Fifty-six athletes in the IAAF World Championship marathons were recorded using two high-definition cameras (50 Hz) on two laps so that 112 running sequences were analyzed. The video files were imported into SIMI Motion and manually digitized. The horizontal running velocity during one gait cycle was obtained using four methods: horizontal velocity of the CM; horizontal velocity of the head (raw data); horizontal velocity of the head (Butterworth filtered); and horizontal displacement of the head (a single measurement using SIMI Motion 3D still image measurement) divided by time taken. In comparison with the criterion CM measurements for mean horizontal velocity, the filtered head data had the best 95% confidence interval (95% CI) for intraclass correlation coefficient (ICC) (0.999 – 1.000), the least bias (–0.006 m/s), and the lowest root mean square difference (0.024 m/s). The filtered head condition also had the best 95% CI for ICC for maximum and minimum horizontal velocities during the stride (> 0.988) and the lowest bias (–0.001 m/s and –0.003 m/s, respectively). With the application of an appropriate filter, the head is thus an excellent proxy for whole body CM velocity calculations.

Keywords: digitizing, gait analysis, kinematics, running, videography

1. Introduction

Biomechanical analyses of human movement can be considerably time-consuming and, in particular, finalizing studies of competitive performances can take years to complete (Ae, 2020). In laboratories, devices external to the athlete such as OptoJump Next can provide reliable measures of spatiotemporal variables (Hanley and Tucker, 2019), whereas timing gates are frequently used in many testing environments to estimate running velocity (Waldron et al., 2011). However, laboratory testing can lack external validity and, therefore, the use of wearable technology that can be used outdoors or in training has become more prevalent (Wixted et al., 2010). Inertial sensors, for example, are single-unit devices that are placed on the individual's body and can provide data on spatiotemporal variables such as step frequency (Caporaso et al., 2020). However, in situations such as elite-standard competition, it is not feasible to request participants to wear such devices or to place equipment such as timing gates in the field of competition, and more time-consuming analysis methods, such as videography, are required.

Videography is also necessary in competitive circumstances because sportspeople cannot wear intrusive marker sets (e.g., for optoelectronic systems), but the lengthy digitizing procedures involved mean that "shortcuts" that reduce the time taken to obtain fundamental data could be beneficial. For instance, a biomechanist might want to establish an athlete's running velocity quickly before committing to whole body analysis, or as a substitute for lengthy digitizing procedures. Markerless, automated systems are progressively being developed (Cronin et al., 2019), but even with these potentially faster methods, analysing athletes' performances in competition can be affected by obscured body segments, and as such manual digitising is still a standard procedure. Using a single marker to represent the whole body's movement, such as on the sacrum (Mapelli et al., 2014), could reduce the time-consuming processes involved; however, the choice of digitizing the head might be more suitable in competition given it is not usually obscured by clothing. The aim of this short communication was to measure the appropriateness of using the head as a proxy for the whole body center of mass (CM) when calculating horizontal distance running velocity in competition. Different methods to measure head horizontal velocity, each taking more or less time to complete, were compared.

2. Methods

2.1. Participants

Data were collected as part of the London 2017 World Championships Biomechanics Project, and the use of those data was approved by World Athletics, who control the data, and locally through the institution's research ethics procedures. Twenty-eight men and 28 women provided their written informed consent and were analyzed in their respective marathon races, held on the same day and on the same course, on both of the last two laps (approximately 10.5 km apart), so that a total of 112 running sequences were analyzed.

2.2. Protocol

A section of straight, wide road near the end of the marathon course loop was chosen for video capture. Two stationary Sony NXCAM HXR-NX3 full high-definition digital cameras (Sony, Tokyo, Japan) were placed on one side of the course, approximately 45º and 135º to the plane of motion, respectively. Each camera was approximately 8 m from the path of the runners. The sampling rate for each camera was 50 Hz, the shutter speed was 1/1250 s, and the resolution was 1920 x 1080 px. The reference volume was 7.50 m long, 3.08 m wide and 1.99 m high. The reference poles were placed so that the 3.08 m width coincided with the path taken by all analyzed runners. The poles were aligned vertically with the use of a spirit level and plumb line with calibration procedures conducted before and after competition.

2.3. Data processing

The video files were imported into SIMI Motion (SIMI Motion version 9.2.2, Simi Reality Motion Systems GmbH, Germany) and manually digitized by a single experienced operator to obtain spatiotemporal data. An event synchronization technique (synchronization of four critical instants) was applied to synchronize the two-dimensional coordinates from each camera. Digitizing started 10 frames before the beginning of the first identified gait event (i.e., initial contact or toe-off) and completed 10 frames after the same event during the next gait cycle to provide padding during filtering (Smith, 1989). Each file was first digitized frame-by-frame and, upon completion, adjustments were made as necessary using the points-over-frame method (Bahamonde and Stevens, 2006), where each point was tracked through the entire sequence. The magnification tool in SIMI Motion was set at 400% to aid identification of body landmarks. The three-dimensional (3D) Direct Linear Transformation algorithm (Abdel-Aziz et al., 2015) was used to reconstruct the 3D coordinates from each camera's x- and y-image coordinates. De Leva's 14-segment body segment parameter model (de Leva, 1996) was used to obtain data for the CM and the head. Both sides of the body were digitized; occasionally, dropout occurred where joint positions were not visible, and estimations were made by the operator. A recursive second-order, low-pass Butterworth digital filter (zero phase-lag) filtered the same raw data and first derivatives were subsequently obtained (Giakas and Baltzopoulos, 1997). The cut-off frequencies were calculated using residual analysis (Winter, 2005) and ranged between 4.0 and 7.5 Hz.

Running velocity was calculated as the horizontal velocity during a complete gait cycle and obtained from the same digitized files using different methods: 1) the horizontal velocity of the CM; 2) the horizontal velocity of the head (raw data, with no filter applied); 3) the horizontal velocity of the head (Butterworth filter applied, calculated for the head alone separately from the calculations made for the CM); and 4) the horizontal displacement of the head from the beginning of the gait cycle to the end (a single measurement using the SIMI Motion 3D still image measurement tool) divided by the time taken. The 3D still image measurement tool does not involve digitizing except for the beginning and end frames; therefore, the calculations of minimum and maximum velocity during each gait cycle that were conducted for the other methods were not possible using still image measurements. For the other three methods, the whole body (14 segments) was digitized first and the head analyzed from those data (i.e., the head segment was identically digitized regardless of the data extraction method).

To measure reliability of the digitizing process, repeated digitizing (two trials) of one running sequence (all 14 segments) was performed with an intervening period of 48 h. Three statistical methods for assessing reliability were used: 95% limits of agreement (LOA), coefficient of variation (CV) and intraclass correlation coefficient (ICC) (Atkinson and Nevill, 1998). The data for each tested variable were assessed for heteroscedasticity by plotting the standard deviations (SD) against the individual means of the two trials (Atkinson and Nevill, 1998) in Bland-Altman plots (Bland and Altman, 1986). The LOA (bias ± random error), CV and ICC (3,1) values for CM horizontal velocity were 0.000 ± 0.015 m/s, ± 0.13%, and 1.00, respectively.

2.4. Analysis

The objective of the analysis was to compare velocity values from the head during a running gait cycle to the measurement standard (CM velocity values) for agreement. Statistical analyses were conducted using SPSS Statistics 26 (IBM SPSS, Inc., Chicago, IL, USA). The CM measurements were considered the measurement standard criteria for running velocity, and agreement was assessed using ICC (including 95% confidence intervals), and 95% LOA (bias and random error). The root mean square difference (RMSD) was also found between the CM measurements and those obtained from the three head conditions.

3. Results

The mean values for running velocity (m/s) using the CM and head (all three methods) differed by no more than 0.03 m/s, with similar differences for maximum and minimum values (Table 1). When comparing with CM measures, the reliability results showed the Butterworth filtered head condition had the lowest RMSD and bias, as well as the highest ICC values for all conditions (Table 2). The still image condition performed the worst of all three conditions used for mean horizontal velocity calculations. There was no heteroscedasticity found for any testing condition; Bland-Altman plots for mean running velocity are shown in Figure 1.

4. Discussion

The aim of this study was to measure the appropriateness of using the head as a proxy for the whole body CM when calculating horizontal running velocity in competition. Based on ICC values, all three shortcut methods used had excellent agreement with the gold standard whole-body digitizing method when calculating mean horizontal velocity, although the 95% CI for still image measurements was lower than for either set of digitized head data. The still image measurement method also had higher RMSD, bias and random error values than the digitized sequence files and, given that it also cannot be used to measure maximum or minimum velocities during a gait cycle, is not recommended for use if the researcher’s aim is to provide a reliable measurement of running velocity. However, if the purpose of using the still mode measurement technique is merely to estimate running velocity expediently (for example, to identify an athlete’s fastest trial for further analysis or for a coach to give quick feedback), this method is appropriate for these basic applications.

There was little difference between the agreement statistics for the two methods used to calculate mean running velocity using the head (i.e., with a Butterworth filtered applied and without one), and there would therefore seem little value in filtering the data if particularly rapid results are required. However, the time required to filter data (in our case, using the residual analysis method) was inconsequential and therefore filtering should be conducted to obtain more noise-free results. This holds true particularly if the researcher wishes to obtain a more detailed velocity curve for a gait cycle, given that the RMSD and bias values were lower, and the ICC and 95% CI values higher, when the head data were filtered in calculating the maximum and minimum velocities.

Obtaining accurate and quick measurements of whole body horizontal velocity in competition settings involving numerous athletes can be achieved by tracking the head alone and filtering the data appropriately. The differences in mean values were extremely small (bias of –0.006 m/s), and ICC values for mean, maximum and minimum velocities ranged from 0.992 to 0.999. The head was chosen in this study as it was easily visible in all videos, did not move backward relative to the rest of the body during any gait phase (unlike the arms, for example), was not obscured by clothing (unlike the sacrum, for instance) and was considered a single segment. However, the head might not be suitable for measuring CM movements in other directions, such as vertically, especially in faster running such as sprinting and hurdling that can have greater vertical oscillation, or in non-cyclical activities (e.g., shot putting). As recent research found that a single sacral marker was a valid proxy for CM trajectory in the vertical and anteroposterior directions during the stance phase of treadmill running (Napier et al., 2020), the use of a single location closer to the theoretical CM could be more accurate than the head where conditions permit. However, for distance running gait recorded in restrictive competitive circumstances, the head is an excellent proxy for whole body CM velocity calculations, and further studies could examine whether this is also true for other competitive gaits (e.g., sprinting, hurdling, race walking). These findings are not only applicable to manual digitising, but also markerless systems, as tracking the head alone makes training of machine learning algorithms far simpler, and the time needed for the computation of velocity variables can be reduced to shorter durations to accommodate immediate feedback. It should be noted that we did not assess the validity of our method (because we had no other measures to compare against, for example) and that, because of manual digitization errors and the assumptions inherent in de Leva's whole body CM model, the analysis solely represents agreement between different estimation methods. Access to the athletes for better anthropometric measures and more cameras would have allowed greater accuracy of the reference method of CM velocity estimation.

Conflict of interest statement

The authors have no conflicts of interest that are relevant to the findings of this manuscript. The data collection and initial data analysis were supported by funding provided by the IAAF / World Athletics as part of a wider development / education project; however, the nature of the data is purely descriptive and not associated with any governing body, commercial sector or product. No funding was provided for the writing of this manuscript. The results of the present study do not constitute endorsement by World Athletics.

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Table 1. Mean, maximum and minimum horizontal velocity values found during one gait cycle for the CM and head (three different data extraction methods) (mean ± SD).

	CM	Head (no filter)	Head (Butterworth filter)	Head (still image)
Mean (m/s)	4.26 ± 0.48	4.25 ± 0.47	4.27 ± 0.48	4.24 ± 0.47
Maximum (m/s)	4.39 ± 0.49	4.43 ± 0.49	4.39 ± 0.49	-
Minimum (m/s)	4.13 ± 0.47	4.06 ± 0.46	4.13 ± 0.47	-

Table 2. Measures of agreement for each head data condition; all values are in comparison with the CM horizontal velocity criterion values. All ICC results were $P < 0.001$.

	Head (no filter)	Head (Butterworth filter)	Head (Still image)
Mean horizontal velocity for one gait cycle			
RMSD (m/s)	0.028	0.024	0.053
ICC	0.999	0.999	0.910
95% CI	0.998 - 1.000	0.999 - 1.000	0.870 - 0.938
LOA bias (m/s)	0.014	–0.006	0.021
LOA RE (m/s)	0.028	0.046	0.096
Maximum horizontal velocity during one gait cycle			
RMSD (m/s)	0.079	0.049	-
ICC	0.993	0.997	-
95% CI	0.984 - 0.997	0.996 - 0.998	-
LOA bias (m/s)	–0.039	–0.001	-
LOA RE (m/s)	0.136	0.096	-
Minimum horizontal velocity during one gait cycle			
RMSD (m/s)	0.105	0.084	-
ICC	0.987	0.992	-
95% CI	0.913 - 0.995	0.988 - 0.994	-
LOA bias (m/s)	0.072	–0.003	-
LOA RE (m/s)	0.150	0.166	-

RMSD = root mean square difference; ICC = intraclass correlation coefficient; 95% CI = 95% confidence interval; LOA = limits of agreement; RE = random error.

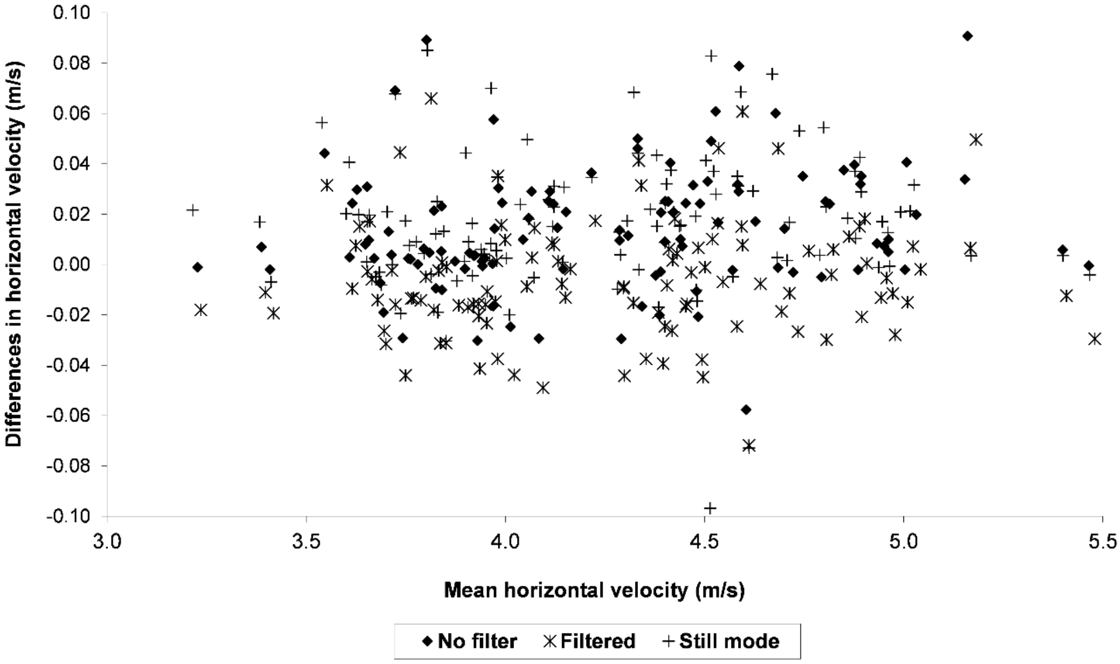

Figure 1. Bland-Altman plot indicating agreement between mean CM velocity and mean head velocity using three different methods: no filter (diamonds), with a Butterworth filter applied (crosses), and using still image measurements (asterisks). The limits of agreement data (bias and random error) for each condition are reported in Table 2.