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Short communication

Fast reconstruction of centre of mass and foot kinematics during a single-legged horizontal jump: A point-cloud processing approach

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ABSTRACT

Horizontal jumps are discrete, fast, over-ground movements requiring coordination of the centre of mass (CoM) and base of support and are routinely assessed in sports settings. There is currently no biomechanics-based system to aid in their quick and objective large-scale assessment. We describe a practical system combining a single low-cost depth-sensing camera and point-cloud processing (PCP) to capture whole-body CoM and foot kinematics. Fourteen participants performed 10 single-leg horizontal jumps for distance. Foot displacement, CoM displacement, CoM peak velocity and CoM peak acceleration in the anterior-posterior direction of movement were compared with a reference 15-segment criterion model, captured concurrently using a nine-camera motion capture system (Vicon Motion Systems, UK). Between-system Pearson's correlations were very-large to near-perfect ($n = 140$; foot displacement = 0.99, CoM displacement = 0.98, CoM peak velocity = 0.97, CoM peak acceleration = 0.79), with mean biases being trivial–small (-0.07 cm [0.12%], 3.8 cm [3.5%], 0.03 $m{\cdot}s^{-1}$ [1.6%], 0.42 $m{\cdot}s^{-2}$ [7%], respectively) and typical errors being trivial–small for displacement (foot: 0.92 cm [0.8%]; CoM: 3.8 cm [3.4%]) and CoM peak velocity (0.07 $m{\cdot}s^{-1}$ [4.3%]), and large for CoM peak acceleration (0.72 $m{\cdot}s^{-2}$ [15%]). Limits of agreement were −1.9 to 2.0 cm for foot displacement, −11.3 to 3.6 cm for CoM displacement, −0.17 to 0.12 $m{\cdot}s^{-1}$ for CoM peak velocity and −2.28 to 1.43 $m{\cdot}s^{-2}$ for CoM peak acceleration. The practical system captured CoM and foot kinematics during horizontal jumps with acceptable precision. Further work to improve estimates of CoM accelerations and different populations are warranted.

1. Introduction

Movement screening forms a regular component of athlete monitoring, providing important information on general movement skills and physical performance potentials (Read et al., 2017). Horizontal jumps are common to many screening batteries as a proxy measure of explosive ability (e.g., Strokosch et al., 2018). These tests involve a coordinated pattern of countermovement, body rotation and arm swing to generate maximal anterior-posterior displacement, velocity, and acceleration of the centre of mass (CoM) on take-off and then control CoM above the new landed position of the feet (Wakai and Linthorne, 2005). In research settings, these kinematic outcomes are quantified directly using force plates or marker-based motion capture (Colyer et al., 2018). In field settings, jump performance is assessed using a tape measure (McCubbine et al., 2018) and technique assessed visually (Padua et al., 2015). Such methods are time-consuming and often with low inter-rater reliability (Lindblom et al., 2021). There are other commercial systems used in the field based on planar switches (e.g., Optojump (Microgate, Italy)) but these are can only track the feet, potentially missing important features of jump performance.

There are several emerging technologies for the simultaneous measurement of foot and whole-body CoM kinematics which have potential for monitoring jump performance. Studies using multi-segment inertial measurement units have reported errors for feet and CoM positions of

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<1 cm and <2.57 cm, respectively (Fasel et al., 2017). While likely to be acceptable for the present purposes, the costs and ease-of-use for large-scale screening programmes are prohibitive. A potential alternative is computer vision (Colyer et al., 2018). Skeletal tracking, in which artificial intelligence (AI) is used on images to infer on whole-body joint positions (Colyer et al., 2018), provides accurate estimates of kinematic parameters in some poses (Galna et al., 2014; Eltoukhy et al., 2017). The errors for foot position, however, can be quite high (>10 cm (Xu and McGorry, 2015)). In contrast, point cloud processing (PCP), in which raw depth data is converted directly into 3D landmark coordinates, has been shown to achieve greater levels of accuracy. Notably, studies using PCP have consistently reported errors of <1 cm for the foot (Paolini et al., 2014), ankle (Geerse et al., 2019), pelvis (MacPherson et al., 2016) and knee (Timmi et al., 2018). In addition, PCP has also been applied (albeit using multiple cameras) to measure CoM kinematics with similar levels of accuracy (Kaichi et al., 2019).

To date, PCP has so far been restricted to the analysis of cyclical, slow and relatively stationary activities. Whether this technology can track simultaneously the kinematics of the foot and CoM during discrete, fast over-ground movements involved in the horizontal jump remains to be

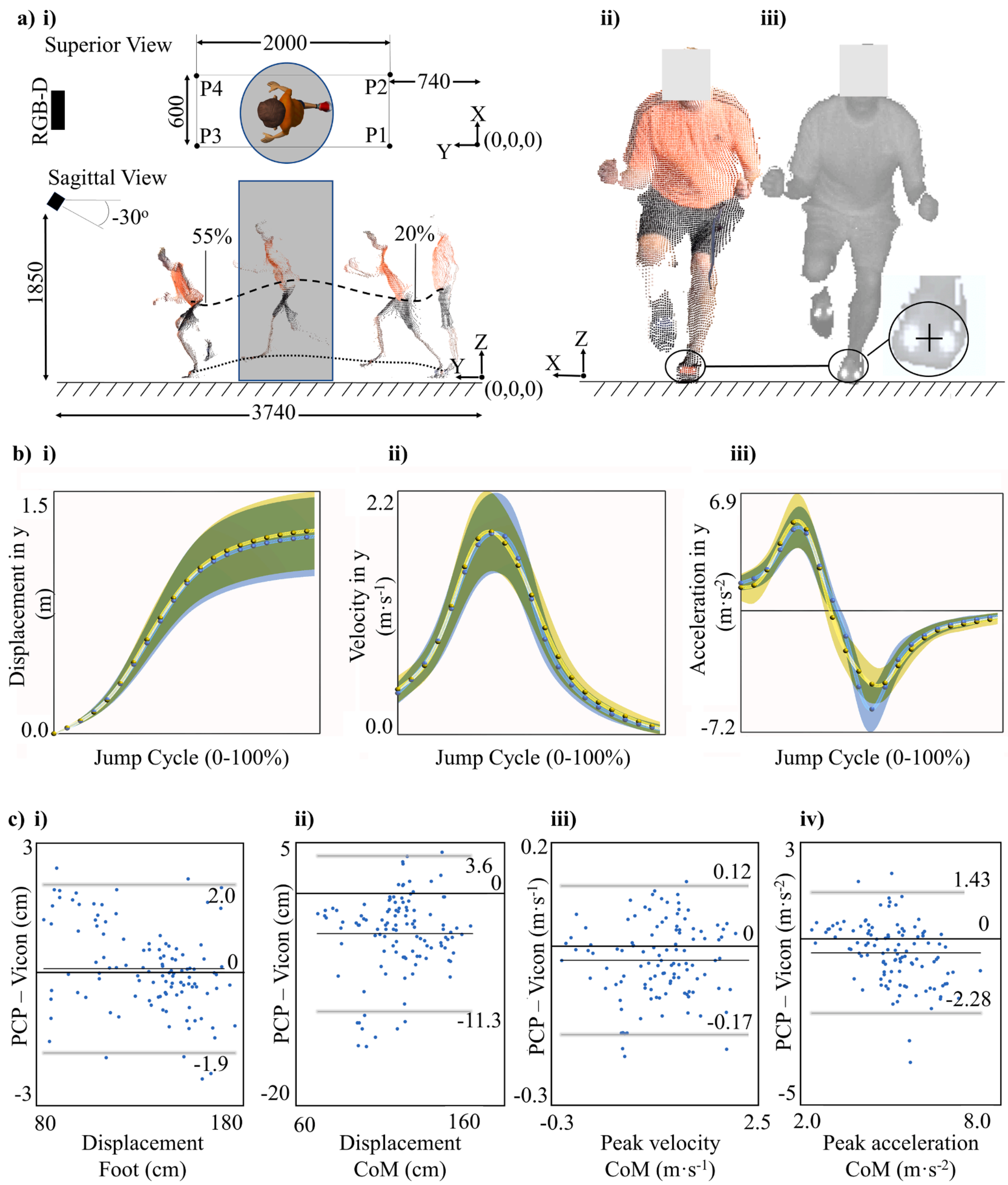

Fig. 1. a) Schematic representation of the capture setup (i) used by the two systems to capture concurrently the movements of athlete during a single-legged jump (right to left). Also shown is the global origin (0,0,0) of the criterion system and the rigid calibration frame (P1, P2, P3 and P4). Jumping was performed in the positive y-direction (anterior) towards the low-cost camera. In the sagittal view (lower image), the 'clean' point cloud along with the trajectories of the whole-body CoM (long-dashed line) and the left foot marker (short-dashed line) are shown. Note the two localised minima of the y-position of the whole-body CoM that were used to anchor the data from the two systems (20% and 55% of the jump cycle). Also shown are the 'clean' point clouds in frontal view (z-x plane) in colour (ii) and infrared (iii). The calculation of whole-body CoM uses all these points, whereas calculation of foot marker position uses only the point at the virtual midpoint between the 2 strips of reflective (highlighted with a cross on the infrared image (iii). b) Time-normalised kinematics from Vicon (blue) and PCP (yellow) (mean ± SD) for the CoM in the y-direction (n = 1200) are shown. Overlapping regions of the standard deviations are shown in green. Note that all y-axes are scaled to span the range between maximal and minimal data points on the time-series. c) Limits of agreements (Bland and Altman, 1986) for the two systems (±1.96SD) for foot displacement (i), CoM displacement (ii), CoM peak velocity (iii) and CoM peak acceleration (iv).

determined. This study will describe the development and examine the criterion validity of PCP for the quantification of single-leg horizontal jump performance (Fig. 1ai) in terms of displacement, velocity and acceleration outcomes. This single-legged jump is a more challenging version of the standing long jump, requiring the athlete to jump as far as possible horizontally from one foot to the other - requiring them to control their CoM in relation to a small base of support on landing. The specific aim of our study is to quantify the criterion validity of the displacement, velocity and acceleration outcomes based on PCP against those from a laboratory-grade system for the single-legged jump.

2. Methods

The study received ethical approval from The University of Sunderland's Ethics committee. Fourteen physically active males (age: 28 ± 10 years, stature: 181 ± 9 cm, body mass: 82 ± 10 kg, BMI: 24.9 ± 2.7 kg·m^{-2}) volunteered and provided written informed consent. All participants were free from injury and, after a warm-up, performed single-legged horizontal jumps at one-minute intervals within the capture volume of the PCP and laboratory systems (Fig. 1ai).

Criterion three-dimensional system: The criterion method of quantifying foot and CoM kinematics was a nine-camera optoelectronic system (Bonita B10, Vicon motion systems, Oxford, UK) at 100 Hz. Using a 19-segment plug-in gait model, markers were placed bilaterally on anatomical landmarks (Vicon motion systems, Oxford, UK). Trajectory data were low-pass filtered using a fourth-order Butterworth filter with cut-off frequency of 6 Hz.

Depth sensor system: The PCP-based system created is based on custom-written algorithms developed by Pro-Football Support Ltd using C# script in the Unity3D gaming engine. A low-cost depth sensing camera (Kinect™ V2, Microsoft, USA) was positioned at 0 mm, 1850 mm, and 3740 mm in the medial–lateral (x-axis), superior-inferior (z-axis) and anterior-posterior (y-axis) directions relative to the global origin of the criterion system (Fig. 1ai). The camera was tilted by −30° about the x-axis. This configuration was considered optimal in terms of maximising the capture volume, as determined by trial-and-error. Before the tests, a rigid calibration frame (600 × 2000 mm) positioned 740 mm anterior to the global origin was used to create a transformation matrix. Specifically, four strips (5 × 5 mm) of retroreflective tape were glued to the apices of the frame (Fig. 1ai, Superior View) giving four coplanar points (P1, P2, P3 and P4) in both systems. The calibration frame was then removed from the testing area, and subsequent point cloud data were transformed from the camera to the criterion global system.

Following Paolini et al. (2014), coloured markers were attached to the feet of each participant (Fig. 1aii), enabling to reconstruct the foot position from the point cloud data. These foot markers included two retroreflective strips spaced 70 mm apart, causing two regions of localised overexposure of the infrared image (Fig. 1aiii). Following MacPherson et al. (2016), a virtual midpoint between these regions was created (Fig. 1aiii, inset), enabling to identify a pixel at the centre of the foot marker. These pixel coordinates (2D) were then fed into the 3D point cloud data to acquire the relevant 3D position of the foot marker. The whole-body CoM reconstruction used markerless PCP on the entire point cloud (Fig. 1aii and iii). The processing involved 5 stages conducted on a frame-by-frame basis. First, points visible in the current frame and before the tests were identified and removed. Second, points with less than 5 neighbouring points within a radius of 5 cm were identified and removed. Third, a mean 3D centroid position of all remaining points was calculated and used to position a cylindrical volume around the athlete (shown as a blue circle and rectangle in Superior and Sagittal view, respectively [Fig. 1ai]). The dimensions of the cylinder (height = 2 m, diameter 1.2 m) were determined prior to testing and considered to be optimal in terms of maximising the number of points used, whilst minimising the risk of random clusters (due to camera artefacts, reflection etc) in the calculation of CoM. Points outside of this volume were removed, thus leaving a 'clean' point cloud representation of the anterior surface of the athlete (Fig. 1a). The position of the CoM (i.e., the point about which the summed moment of all points in the cloud was zero) was then calculated in the x-, y- and z-directions (i.e., x_{CoM}, y_{CoM}, z_{CoM}) using the following:

$$xCoM = \sum_{k=0}^{n} \frac{mk.xk}{MTotal}$$

$$yCoM = \sum_{k=0}^{n} \frac{mk.yk}{MTotal}$$

$$zCoM = \sum_{k=0}^{n} \frac{mk.zk}{MTotal} \quad (1)$$

where M_{Total} is the mass of the participant, n is the number of points in the 'clean' point cloud, m_k is the mass of each point averaged across the surface (i.e., mass of the participant / number of points) and x_k, y_k and z_k are global (i.e., transformed) coordinates of individual points (Fig. 1aii).

Data processing: The displacement data from both systems were differentiated to yield velocities and accelerations. All data were then time-normalised to a percentage of the jump cycle (Fig. 1b), using the first (20% of jump cycle) and second trough (55% of jump cycle) of the z_{CoM} time-series data as anchor points (shown as dashed line in Fig. 1ai, Sagittal View). The normalised data in the y-direction (anterior-posterior) were processed to yield outcome measures of jump performance, which were: displacement of the feet (cm) defined as the distance between the right and left foot markers at 20% and 55%, respectively; displacement of the CoM (cm) defined as the distance between 20% and 55%; peak velocity and acceleration defined as the highest positive velocity (m·s^{-1}) and acceleration (m·s^{-2}) in the y-direction throughout the cycle.

Statistical Analysis: Since our aims are to assess the agreement between two measurement systems, rather than to examine any biological outcomes, data from all participants (n = 14) and their trials (n = 10 pp) were treated as independent measures (i.e., n = 140 datapoints per outcome measure). We used separate linear regressions (SPSS Version 24, IBM Corp., Armonk, NY, USA) to examine the criterion-related validity of the foot displacement and whole-body COM kinematics. Criterion-derived values of the outcome measures were entered as separate dependent variables and the corresponding PCP-derived values were entered as independent variables. Relationship strength was quantified with Pearson's product moment correlation coefficient (*r*), with the associated R^2 value (coefficient of determination) used to express the proportion of explained variance. Additionally, the intraclass correlation coefficient was calculated using a two-way mixed effects model ($ICC_{3,1}$), but these are not reported given that the values were all within ± 0.0002 of the Pearson's *r* for displacement and velocity and ±0.0274 for accelerations. Typical errors ([TE], or standard errors of the estimate) were used to represent unexplained (random) bias. The mean difference between PCP and the criterion was used to represent systematic (mean) bias. Finally, Bland & Altman's 95% limits of agreement were calculated by adding and subtracting 1.96 times the standard deviation of the difference (PCP–criterion) in paired measurements (Bland and Altman, 1986).

Uncertainty in all estimates were expressed using 90% confidence limits (CL), calculated from the *t*-distribution for mean differences, the *z*-distribution for (transformed) correlation coefficients and the chi-squared distribution for SEE. We declared the magnitude of correlation coefficients as small moderate, large, very large and near perfect based on standardized anchors of 0.1, 0.3, 0.5, 0.7 and 0.9, respectively (Hopkins et al., 2009). To provide a standardized interpretation of mean bias (i.e., *d*), we used 0.2, 0.6 and 1.2 of the pooled between-participant standard deviation for each outcome measure (Table 1) to represent small, moderate and large differences (Hopkins et al., 2009). These thresholds were then halved to declare practical magnitudes of SEEs (Smith & Hopkins, 2011). We relied on subjective interpretation of the entire CL (i.e., lower and upper limits) against these thresholds to

Table 1
Validity analysis between point-cloud processing (PCP) and criterion-derived estimates of jump performance during the single-leg jump.

Outcome Measure	Performance* (mean ± SD)	r (±90% CL)*	R^2	Mean bias (±90% CL)		Typical Error (×/÷90% CL)	
				Raw Units	Standardized (d)[a]	Raw Units	Standardized (d)[b]
Total Foot Displacement (cm)	140.5 ± 27.2	0.999; ±0.0002	0.999	−0.07 (0.15)	0.00 (0.01)	0.92 (1.12)	0.03 (1.17)
Total CoM Displacement (cm)	126.5 ± 21.2	0.983; ±0.005	0.967	3.84 (0.6)	0.18 (0.03)	3.83 (1.12)	0.18 (1.17)
CoM Peak Velocity ($m \cdot s^{-1}$)	1.84 ± 0.30	0.973; ±0.009	0.946	0.03 (0.01)	0.09 (0.04)	0.07 (1.12)	0.24 (1.18)
CoM Peak Acceleration ($m \cdot s^{-2}$)	5.49 ± 1.46	0.792; ±0.059	0.627	0.42 (0.15)	0.38 (0.13)	0.72 (1.12)	0.86 (1.23)

CL, confidence limits.
* from the PCP.
[a] < 0.2 = trivial, 0.2–0.6 = small, 0.6–1.2 = moderate, >1.2 = large.
[b] < 0.1 = trivial, 0.1–0.3 = small, 0.3–0.6 = moderate, >0.6 = large.

communicate effect magnitude.

3. Results

Between 0 and 20% of the jump cycle, the CoM moves laterally to above the position of the standing foot and then in a shallow counter-movement (i.e., trunk, hip, knee and ankle flexion) the z-position of the CoM falls (Fig. 1ai). At the same time, the athlete begins to shift the CoM anteriorly relative to the base of support, thus creating anterior misalignment between the COM and base of support. The athlete is then able to move CoM horizontally (Fig. 1bi) during the push-off (20–30%) by extending the joints. The peak velocity of the CoM in the y-direction occurs between 30 and 40% of the cycle (Fig. 1bii) and the CoM is decelerated abruptly thereafter (Fig. 1biii). The athlete attempts to control the CoM above the base of support provided by the landed foot and hold this position until the end of the trial. There was general agreement between the systems for all three kinematic variables in the y-direction, although the PCP tended to overestimate positive accelerations during take-off and underestimate the negative accelerations during landing (Fig. 1biii).

The results of the validity analysis are shown in Table 1 and Fig. 1c. The association (r) between the systems for outcome measures were near perfect for foot displacement, CoM displacement and peak velocity, and very large for peak acceleration. Mean biases were trivial for total foot displacement (<0.2%) and CoM peak velocity (~1.5%), CoM total displacement (3.5%), and small for CoM peak acceleration (~7%). The typical errors were trivial for total foot displacement (~1%), small for total CoM displacement (~3.5%) and CoM peak velocity (~4%), and large for CoM peak acceleration (~15%). The limits of agreement (Fig. 1c) for foot displacement (−1.9 cm to 2.0 cm), CoM displacement (−11.3 cm to 3.6 cm), CoM peak velocity (−0.17 to 0.12 $m \cdot s^{-1}$) and CoM peak acceleration (−2.28 to 1.43 $m \cdot s^{-2}$).

4. Discussion

Biomechanical analysis of movement screening tests could play an important role in both athletic and clinical settings. In these areas, expediency and validity are highly valued. Despite its simplicity, the PCP-system showed excellent criterion validity with a 3D motion analysis system in tracking whole-body CoM and feet markers simultaneously during a single-legged horizontal jump. Typical errors between the systems in foot displacements were 0.94 cm (<1%) which are considered acceptable in field-testing (McCubbine et al., 2018). The errors in CoM displacement were 3.8 cm, being similar to other practical measures used in gait research (3 cm, Yang and Pai, 2014; 4 cm Huntley et al., 2017), but slightly larger than those from inertial suits (2.6 cm, Fasel et al., 2017). A key advantage of the PCP over other technologies is the simplicity of data collection. Following a ten-minute setup, the system was able run continuously to capture and display outcome measures within 300 ms of task completion.

As with most areas of biomechanics, an optimal trade-off may exist between practicality, accuracy and cost (Devetak et al., 2019); this will depend largely on how accurate the system needs to be. Accordingly, we provided a more standardized interpretation of our findings for this task and found trivial mean biases for all outcome measures, with typical errors being trivial for displacement, small for velocity and large for accelerations. Furthermore, the 95% limits of agreement of foot displacement (−1.9 to 2.0 cm), for example, are small compared the variation of performance between young active adults (group standard deviations, male: 19.3; female: 12.8 cm) (Meylan et al., 2009). Our data therefore suggest that, although not perfect, both foot and CoM displacement may be quantified with acceptable precision to detect small but worthwhile changes. However, velocities and accelerations may need further work, and this may entail different camera orientations, higher resolution, multiple cameras and/or higher sampling frequency.

There are important limitations to this study. First, the current single camera was only able to capture at 30 Hz, a possible reason for the only large typical error for peak accelerations (~15%). Further improvements such as higher sampling or multiple cameras may be required to accurately quantify acceleration-based CoM variables. Second, camera position and orientation relative to the movements were optimised to capture volume, but not accuracy. Further work to optimise position and orientation (e.g., Yeung et al., 2021) may assist in reducing the errors present. Third, our sample was quite homogeneous in terms of sex and training status. Further work using female and/or highly trained (elite) athletes may produce different results, possibly being susceptible to differences in body compositions and/or kinematics. Fourth, we have not modelled all possible performance outcomes related to the foot and CoM relationship: it is not known how these errors propagate when other measures, such as dynamic balance (Hrysomallis, 2011), are calculated.

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CRediT authorship contribution statement

S.J. McLaren: Conceptualization, Resources, Validation, Writing – original draft, Writing – review & editing, Methodology, Data curation. **W. Evans:** Investigation, Validation, Data curation. **B. Galna:** Conceptualization, Validation, Writing – review & editing, Methodology. **M.D. Portas:** Conceptualization, Funding acquisition, Project administration, Resources, Writing – review & editing. **M. Weston:** Validation, Writing – review & editing, Methodology. **I.R. Spears:** Conceptualization, Funding acquisition, Investigation, Project administration, Software, Validation, Visualization, Writing – review & editing.

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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