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

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Conflict of interest statement

At the time of this research, IS and MP were providing consultancy support to Pro Sport Support Ltd—a company seeking the development and commercial sale of practical, marker-based tracking systems for athletic movement screening. The novel PCP-based system for assessing horizontal jumps forms part of an athlete assessment tool (AMAT Performance, Pro Sport Support Ltd, UK) and is currently in use in football academies (Laas et al., 2020).

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There are important limitations to this study. First, the current single camera was only able to capture at 30Hz, a possible reason for the only moderate accuracy for the peak accelerations (~16%). Further improvements such as higher sampling or multiple cameras may be required to quantify acceleration-based CoM variables. Second, our sample was quite homogeneous in terms of sex and training status; thus, the accuracy of the system may not be representative of that in other populations. For example, highly trained (elite) athletes may produce faster velocity and acceleration during jump tasks, and further examination of validity at these faster speeds of capture would seem warranted. Third, and finally, 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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Figure Legends

Figure 1.

a) A schematic view of the movements of the skeleton during a single-legged jump (right to left). Note the AP displacements are accentuated for visual purposes. Between 0 to 10% the CoM moves laterally to above the position of the standing foot and the landing foot leaves the floor. During this initial period, there is flexion of the trunk, right hip, right knee and right ankle while the body created a shallow countermovement. 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 then accelerate horizontally during the push-off (0-30%) during which time there is extension at the ankle, knee and hip. The peak height of the CoM occurs between 30 and 40% and for a short period (approximately 5% of the cycle) during which time the body is in free fall. The landing foot then hits the floor (approximately 60%) and the CoM is decelerated. 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. Failure to do so resulted in a retrial after a 1min rest. The jumps were performed in the AP direction towards the camera.

b) Time-normalised kinematics from Vicon (blue) and PCP (yellow) (mean ± SD) for the CoM in the AP 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).

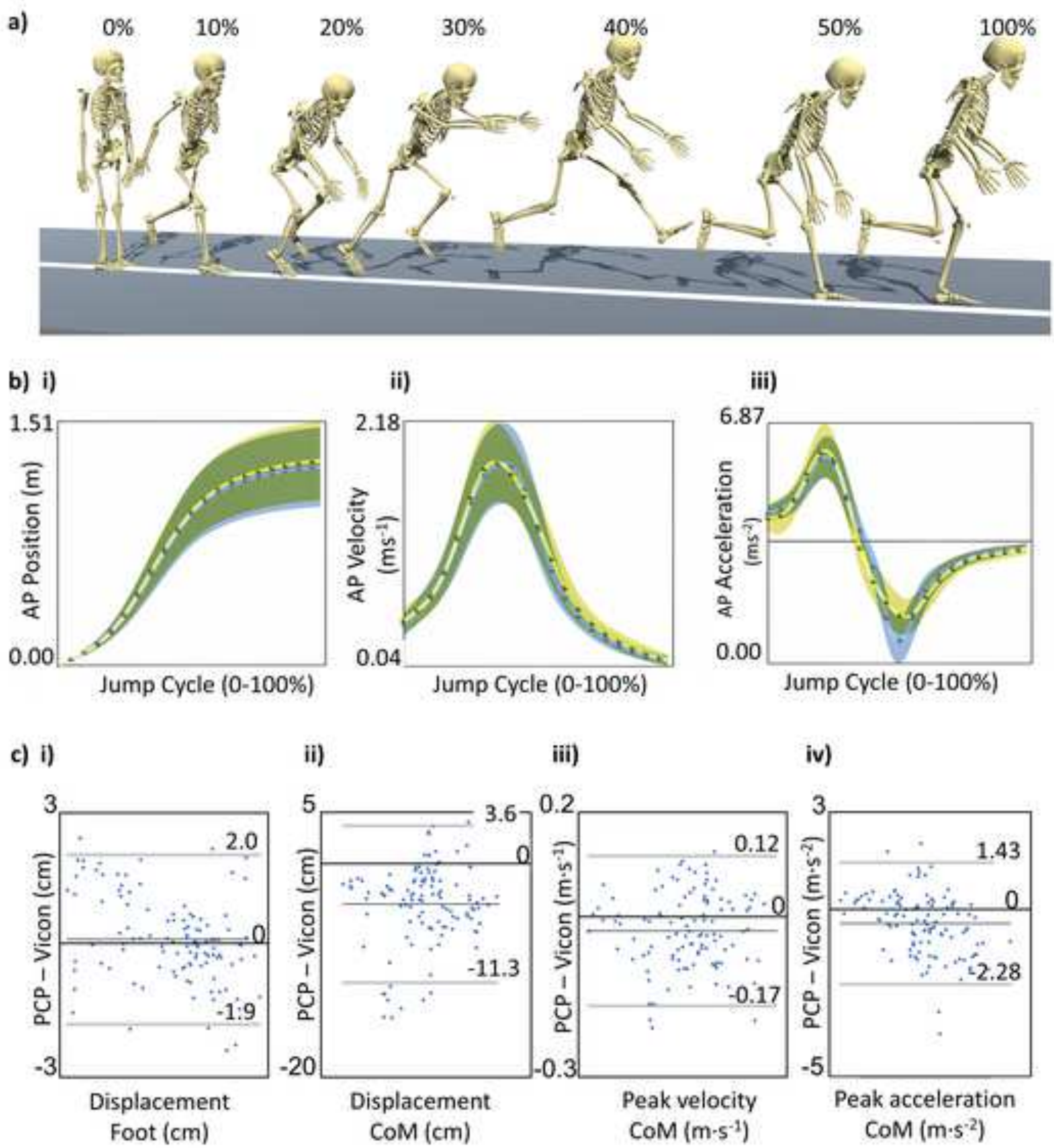
a)
0%
10%
20%
30%
40%
50%
100%
b) i)
ii)
iii)
1.51
0.00
AP Position (m)
Jump Cycle (0-100%)
2.18
0.04
AP Velocity (ms-1)
Jump Cycle (0-100%)
6.87
0.00
AP Acceleration (ms-2)
Jump Cycle (0-100%)
c) i)
ii)
iii)
iv)
3
2.0
0
-1.9
-3
PCP – Vicon (cm)
Displacement Foot (cm)
5
3.6
0
-11.3
-20
PCP – Vicon (cm)
Displacement CoM (cm)
0.2
0.12
0
-0.17
-0.3
PCP – Vicon (m·s-1)
Peak velocity CoM (m·s-1)
3
1.43
0
-2.28
-5
PCP – Vicon (m·s-2)
Peak acceleration CoM (m·s-2)

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)**
Displacement Foot (cm)	140.5 ± 27.2	0.999; ±0.0002	0.999	-0.07 (0.15)	0.92 (1.12)
Total displacement CoM (cm)	126.5 ± 21.2	0.983; ±0.005	0.967	3.84 (0.6)	3.83 (1.12)
Peak velocity CoM ($m \cdot s^{-1}$)	1.84 ± 0.30	0.973; ±0.009	0.946	0.03 (0.01)	0.07 (1.12)
Peak acceleration CoM ($m \cdot s^{-2}$)	5.49 ± 1.46	0.792; ±0.059	0.627	0.42 (0.15)	0.72 (1.12)

*from the PCP

CL, confidence limits.

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