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TECHNICAL NOTE

Validation of a LiDAR-based player tracking system during football-specific tasks

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Abstract

Tracking players' movements in sports is important to monitor and optimise exercise volume, avoid injuries, and enhance game performance. A new LiDAR-based system (Sportlight®) purports to provide accurate velocity and acceleration metrics derived from player movements. This study examined the validity of the LiDAR-based system against a 3D motion analysis system. Two competitive football players (age: 18 years, height: 1.74 ± 0.01 m, mass: 66.5 ± 7.8 kg; playing experience at this level: 3 years) completed nine trials each of six sport-specific movements, consisting of straight-line sprints, cuts, and curved runs. Trials were recorded concurrently by a four-unit LiDAR system and a 64-camera 3D motion analysis system. Instantaneous velocity and acceleration, and time spent within key performance indicator bands (defined by velocity and acceleration thresholds) were compared between systems. Agreement between the systems was evaluated by root mean square error. Differences in time spent within each key performance indicator band between systems were assessed with *t* tests and standardised effect sizes. Velocity root mean square error values ranged from 0.04 to 0.14 m·s^{-1} across all movements and acceleration root mean square error values ranged from 0.16 to 0.7 m·s^{-2}. Differences between systems for time spent within each key performance indicator band were mostly trivial. These results show that the LiDAR-based system can provide valid measures of velocity and acceleration in football-specific tasks, thus providing accurate tracking of players and calculation of relevant key performance indicators.

Keywords Accuracy · Movement analysis · Performance analysis · Sports technology · Sports analytics

1 Introduction

Recent advances in electronic performance and tracking systems (EPTS) have allowed tracking football players' movements in training and competition [1]. Such player tracking has helped avoid injuries and overtraining by monitoring and optimising exercise volume and progression [2, 3]. Additionally, live tactical changes are facilitated by in-game physical and tactical performance assessment [3]. Common EPTS used include global navigation satellite systems (GNSS; e.g. [4]), semi-automatic cameras systems (e.g. [5]) and local positioning measurement systems (LPM; e.g. [6]).

GNSS technology is amongst the most popular EPTS [2], and can provide relevant data alongside embedded inertial measurement units, offering measures of exercise volume, forces or stride variables [2]. GNSS yielded good validity for instantaneous speed and acceleration, and total distance travelled measures (as indicated by lower error values) in comparison to a video-based system and a local positioning system (LPS) when evaluated against a 3D motion capture system (the 'gold standard' method for motion capture) [7]. Moreover, GNSS's portable nature has the advantage that it can be used at both training and competition grounds, enabling consistent monitoring [1, 7]. Video-based systems, another popular option for player tracking, provide similar data to GNSS, but with less invasiveness (no units to be worn), and loss of data, as video footage can restore any initial data loss [8]. The validity is very high when compared to timing gates (Pearson's

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r ranging 0.72–1.00 for various movements) [9] or a 3D motion capture system (as indicated by lower error values) [8]. However, they require ground installation, which limits measurements to activities taking place in the stadium, thus impacting on training monitoring [1]. LPM systems, although used in football to track the position of each player [6, 10], are less well-researched, possibly due to the development of GNSS technology shortly after the introduction of LPM. Nonetheless, LPM was also found to be less accurate for non-linear running than for straight-line running (approximately double the CV% for total distance covered) [11], which is frequently seen in football games [12].

Light detection and ranging (LiDAR) remote sensing is an emerging technology that can record variable distance. LiDAR uses infrared lasers to measure distances between a given target and a sensor [13]. Distance is calculated from the time the laser beam takes to reach, reflect and return from the intended target. Such positioning identification subsequently allows calculation of speed and acceleration. LiDAR has been used in fields such as earth and ecological sciences [14], transportation [15], object recognition [16], archaeology [17], and motion tracking [18]. It can also assess human walking and running speed with good accuracy (ICC $>$ 0.88 and $R > 0.89$ for all comparisons) when compared to a 3D motion capture system [13].

Recently, Sportlight® (Oxford, UK) capitalised on the application of LiDAR to measure player velocity and acceleration. Their LiDAR-based system consists of portable units that can be placed around indoor or outdoor pitches for training and matches. It provides a continuous measure of distance from the unit without requiring calibration or placement at known distances [13], thus increasing its usability by practitioners. Multiple units provide greater coverage, but measurements can take place with one unit, as each one is claimed to be capable of tracking players independently to the other units. Proprietary software then directly uses the unfiltered velocity and acceleration data to provide player relevant metrics to the user.

The purported advantages of this system (i.e. non-invasive nature, portability enabling assessment by the same tool across training or games, ability to continuously track motion) make it an attractive option for motion tracking. However, while these are important parameters in determining possible uptake by practitioners [2], such devices must be accurate to allow appropriate exercise volume prescription and correct monitoring [1, 11], particularly with the rapidly increasing demand for individualised velocity and acceleration thresholds for training decisions [2, 3]. This study aimed to examine the validity of the LiDAR-based system against a 3D motion capture system during football-specific movements.

2 Methods

2.1 Participants

Two competitive male football players (mean ± SD: age 18 years, height 1.74 ± 0.01 m, mass 66.5 ± 7.8 kg, 3 years of playing experience at this level) free from self-reported injury in the past 12 months, agreed to participate in the study. Both players were from a local professional football club. The study was approved by the Institutional Ethics Committee, and both players gave written informed consent.

2.2 Protocol

Both players completed individually and on one day a course of distinct sport-specific movements (SSM), outlined by FIFA [19] and described in Linke et al. [7]. The full course was performed in an indoors facility, on a 10 × 20 m hardwood floor area, with a ~ 10 m 'run-off' area allowing deceleration outside the recording area. The course was marked with non-reflective cones and incorporated (in order): SSM1) a 20 m run (15 m sprint, 5 m deceleration), SSM2) 20 m sprint, SSM3) a 20 m run (10 m backward running, 10 m forward running), SSM4) the 5–0-5 agility test, SSM5) two rapid 90° cuts (one left, one right); and SSM6) five curved runs (sprint/jog/jog/sprint/jog). Following a standardised warm-up, the players familiarised themselves with the full course (marked with non-reflective cones) by performing it once with sub-maximal and once with maximal effort. The players then completed the course nine times, with three minutes rest between each repetition, and data was collected from those nine repetitions. The decision for the number of trials in the present study was based on what was deemed a balance between achieving a sufficiently large number of repetitions per player to make the statistical comparisons presented below [27], while ensuring that a high number of repeated efforts did not result in slower movements due to fatigue, thus not appropriately replicating higher velocities across trials [20].

2.3 Data collection

Data were recorded from a 64 × camera motion capture system (MoCap) sampling at 100 Hz (Vantage, Vicon, Oxford, UK; 3D) and a 4 × unit Sportlight® system sampling at 10 Hz (Sportlight®, Oxford, UK; LiDAR). The MoCap cameras were calibrated by the facility's dedicated technician following standard manufacturer protocols. The cameras were positioned around and overhead the course, allowing unobstructed and full coverage of the testing area. Four reflective markers (18 mm diameter) were securely attached on the left

Fig. 1 LiDAR unit

and right anterior and posterior superior iliac spine of each participant. LiDAR units (Fig. 1) were placed outside of and near the four corners of the testing area.

2.4 Data analysis

2.4.1 Parameters

To validate the LiDAR system, we firstly compared its proprietary velocity and acceleration data to velocity and acceleration derived from the MoCap system. One would typically compare positional data between such systems for validation purposes. However, at the time of testing, the LiDAR system did not provide positional data to the user.

Secondly, we compared time spent within key performance indicators (KPIs) derived from both systems velocity and acceleration data. We calculated our own KPIs using the same thresholds as Linke et al. [7] rather than the KPIs (and their thresholds) provided by the LiDAR system. This enabled a more transparent analysis, considering the proprietary nature of the LiDAR algorithms, in addition to a more effective comparison of the results with previous literature. The velocity bands chosen for the KPIs were low speed (slow) (0.3 to $<$ 1.6 m·s^{-1}); moderate speed (moderate) (1.6 to $<$ 4.2 m·s^{-1}); elevated speed (fast) (4.2 to $<$ 5.5 m·s^{-1}); high speed (very fast) (5.5 to $<$ 6.9 m·s^{-1}); and very high speed (sprint) ($\geq$ 6.9 m·s^{-1}). High acceleration and deceleration thresholds were $\geq$ 3 m·s^{-2} and $<$ 3 m·s^{-2}, respectively. These KPIs were calculated from data recorded throughout each entire course run through (combining all sport specific movements).

The KPI measures were used to outline *time spent* at these velocity bands/accelerations/decelerations, rather than distance covered, a metric commonly used in determining football demands [21]. However, the two variables (distance and time) conceptually describe the same aspect in that both longer distances covered at a given speed and longer time spent at a given speed reflect a higher volume of work.

2.4.2 Data processing

MoCap marker trajectories were tri-dimensionally reconstructed in Vicon Nexus (Vicon Motion Systems Ltd., Oxford, England) and exported for offline analysis (SciPy, scientific tools for Python). Trajectories with gaps smaller than 10 frames were interpolated (cubic spline) and filtered with a phase-corrected 4th order low-pass Butterworth filter (10 Hz cut-off). Trajectories with gaps that exceeded 10 frames were excluded from analysis. *X* and *Y* coordinates (*Z* component excluded) were then used to derive 2D centre of mass (CoM) of each player, defined as the mean position of the four markers on the pelvis segment.

Raw velocity was computed using finite differentiation (central difference) of CoM position (change in position over time). Gait-neutralised velocity was calculated by filtering raw velocity with a phase-corrected 4th order low-pass Butterworth filter (1 Hz cut-off) [7, 8]. Gait-neutralised acceleration was computed using finite differentiation (central difference) of gait-neutralised velocity (change in gait-neutralised velocity over time) [7, 8]. Velocity and acceleration from the MoCap and LiDAR systems were then aligned according to the protocol outlined in FIFA [19]. Firstly, LiDAR data were up-sampled to 100 Hz (cubic spline interpolation) in accordance with the motion capture data [19] (Online Resource 1). Secondly, we calculated time off-sets between data sets by computing the root mean square error (RMSE) over all possible time shifts (in intervals of one frame). The shifting of the data that resulted in the lowest RMSE then defined the correct alignment [19].

2.5 Statistical analysis

Level of agreement between velocity and acceleration derived from the MoCap and LiDAR systems was defined as vRMSE (velocity: m·s^{-1}) and aRMSE (acceleration: m·s^{-2}), respectively. We calculated these individually for each SSM. Accuracy of the KPIs derived from the LiDAR data was determined by comparing them to those derived from the MoCap system using *t* tests ($\alpha = p < 0.05$ [9]). The specific outcome evaluated was *time spent* within each KPI band rather than distance covered at each band (as explained above). Whilst only two participants were included in the study, each completed nine full circuits. Therefore, instead of collapsing these to the mean for each player (which would give $n=2$ samples from each system), each trial was treated as an individual sample, thus totalling 18 samples from each system. The t tests were run using these samples. This approach is applied in similar studies (e.g. [20, 22, 27]) and treating the trials as subjects allows repetition to enable assessment of the agreement of the relevant variables. Cohen's d effect sizes are also provided for these comparisons as a standardised relative measure of meaningfulness of the differences shown; they were interpreted as trivial (< 0.20), small (0.2–00.49), medium (0.50–0.79) and large (≥ 0.80). Statistical analyses were performed with the R software package for statistical computing (package: 'stats'; version 4.1.0).

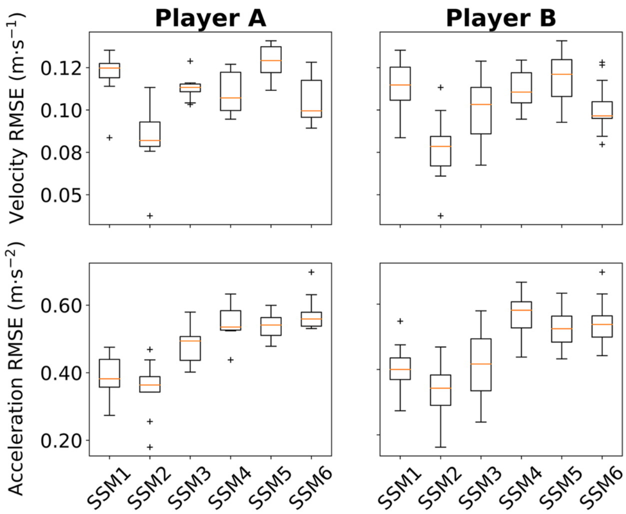

Fig. 2 Root mean square error (RMSE) scores for each player by sport-specific movement (SSM). Velocity (top) and acceleration (bottom) RMSE values for Player **A** (left) and Player **B** (right). The central rectangle represents the first to the third quartile. The gold line represents the median. The 'whiskers' above and below the central rectangle represent the maximum and minimum values, respectively. Crosses indicate outliers. SSM1, 20 m run (15 m sprint, 5 m deceleration); SSM2, 20 m sprint; SSM3, 20 m run (10 m backward running, 10 m forward running); SSM4, the 5-0-5 agility test; SSM5, two rapid 90° cuts (one left, one right); SSM6, five curved runs (sprint/jog/jog/sprint/jog)

3 Results

3.1 Velocity and acceleration

vRMSE (Fig. 2) ranged from 0.08 to 0.12 m·s^{-1} across all SSMs and for both players. The 20 m sprint presented the smallest mean RMSE difference, with the rest of the SSMs having slightly increased values. Similarly, aRMSE values ranged from 0.36 to 0.60 m·s^{-2}. As with vRMSE, the 20-m sprint presented the smallest difference, with the SSMs involving change of direction (SSM4, SSM5 and SSM6) showing increased difference between the two systems.

3.2 KPIs

The comparison of velocity and acceleration KPIs between the systems showed mostly trivial differences, except for Sprint and High deceleration where small differences were found (Table 1).

4 Discussion

The aim of the study was to examine the validity of a LiDAR-based system against a 3D motion analysis (MoCap) system. Our results showed that LiDAR velocity and

Table 1 Key performance indicators (KPIs) for velocity and acceleration

	MoCap	LiDAR	p	Cohen's d	N
Velocity KPI					
Slow (s)	9.70 ± 2.94	9.42 ± 2.78	0.024	0.098 (trivial)	18
Moderate (s)	24.97 ± 5.08	24.77 ± 5.13	0.005	0.04 (trivial)	18
Fast (s)	6.19 ± 1.37	6.20 ± 1.33	0.908	0.005 (trivial)	18
Very fast (s)	3.01 ± 0.92	2.97 ± 0.90	0.315	0.044 (trivial)	17
Sprint (s)	0.21 ± 0.21	0.16 ± 0.23	0.119	0.264 (small)	12
Acceleration KPI					
High acceleration (s)	19.79 ± 4.87	19.52 ± 4.82	0.002	0.057 (trivial)	18
High deceleration (s)	4.95 ± 1.27	4.54 ± 1.25	< 0.001	0.325 (small)	18

Velocity thresholds: slow (0.3 to < 1.6 m·s^{-1}); moderate (1.6 to < 4.2 m·s^{-1}); fast (4.2 m·s^{-1} to < 5.5 m·s^{-1}); very fast (5.5 to < 6.9 m·s^{-1}); and sprint (≥ 6.9 m·s^{-1}). High acceleration threshold: ≥ 3 m·s^{-2}. High deceleration threshold: < 3 m·s^{-2}. 3D motion analysis system (MoCap) and LiDAR-based system (LiDAR) data presented as mean ± SD. p: the significance value obtained from the t test ($\alpha = 0.05$). Cohen's d: effect size. N: the number of observations compared from each system; each observation represents time detected running within a given velocity threshold (e.g. sprint) for a unique trial. where MoCap lost the data, no comparison was made acceleration values, obtained during football-specific movements, are in close agreement with those from the MoCap system, indicating LiDAR provided valid measures of velocity and acceleration in football-specific tasks.

RMSE, a standard way to quantify the level of agreement between data [23–25], is recommended in the FIFA guidelines [19] and enables comparison to recent assessments of EPTS with similar measurement protocols. The range of error values we report for velocity (0.08–0.12 $m \cdot s^{-1}$) and acceleration (0.36 0.60 $m \cdot s^{-2}$) are lower than other portable EPTS when they were compared to a 3D motion capture system using the same football-specific course (GNSS: 0.32 $m \cdot s^{-1}$ and 1.18 $m \cdot s^{-2}$; LPS: 0.32 $m \cdot s^{-1}$ and 0.69 $m \cdot s^{-2}$) [7].

When compared to fixed-position systems, LiDAR had lower error values than a video-based system (VIDEO: 0.41 $m \cdot s^{-1}$ and 0.78 $m \cdot s^{-2}$) but higher error values than an optical-based system (0.03–0.09 $m \cdot s^{-1}$ and 0.06–0.27 $m \cdot s^{-2}$) [8]. However, it should be noted that these fixed systems present the issue that Buchheit et al. [1] identified with teams utilising multiple tracking systems that are not interchangeable, impairing the use of such data for monitoring purposes. Therefore, the LiDAR-based system can be considered favourably in this context.

The velocity values indicate good agreement, as they are sufficiently small to be able to detect practically meaningful changes. The difference of 0.08 $m \cdot s^{-1}$ (from SSM1) is sufficiently small to detect changes in sprinting velocity between different ability athletes in 5, 10 and 20 m sprints, while the difference of 0.12 $m \cdot s^{-1}$ (from SSM4) is sufficiently small to detect differences between the same groups of athletes in change of direction tasks [26]. Finally, it is smaller than the smallest worthwhile change in football (defined as being ahead of the opponent on on-to-one duels) which was deemed to be at least 0.04 s quicker over 20 m sprint [27], a velocity difference of at least 0.09 $m \cdot s^{-1}$ [28].

KPI comparisons between the two systems were good, with most differences being of trivial meaningfulness (range trivial–small). When the same KPIs were compared between 3D motion analysis, an LPS, a GNSS and a video-based system, the differences ranged from trivial to large (for all three systems, across the full sport-specific course) [7], while the present results are very similar to those of the fixed optical tracking system [8]. This is an important finding, since many professionals working in team sports are often interested in quantifying work done, based on velocity or acceleration KPI thresholds in an attempt to design their training and conditioning programmes, monitor players' exercise volume and decrease injury risk [2].

A limitation of the present study is that the system was validated with one player completing the course at a time. Further research is required to examine whether the same accuracy, or indeed ability to distinguish players, will be demonstrated when multiple players (as in a football game) are involved.

5 Conclusion

The present data suggest that the LiDAR-based system provides valid measures of velocity, acceleration and time spent within given KPI bands for individual football-specific movements. Practitioners and coaches that want to examine those metrics can therefore confidently use the LiDAR system to obtain them, while not needing to trade-off between portability and accuracy.

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Data availability Not applicable.

Code availability Not applicable.

Declarations

Conflict of interest Neither Sportlight® nor Vicon® were involved or influenced the study design, data collection and analysis, decision to publish, or preparation of the manuscript. We declare that the authors have no relationship or financial gain that could be perceived as conflict of interest or competing interest.

References

1. Buchheit M, Allen A, Poon TK et al (2014) Integrating different tracking systems in football: multiple camera semi-automatic system, local position measurement and GPS technologies. J Sports Sci 32:1844–1857. https://doi.org/10.1080/02640414.2014.942687
2. Akenhead R, Nassis GP (2016) Training load and player monitoring in high-level football: current practice and perceptions. Int J

Sports Physiol Perform 11:587–593. https://doi.org/10.1123/ijspp.2015-0331

3. Pope N, Kuhn K-AL, Forster JJ. (2009) Digital sport for performance enhancement and competitive evolution: intelligent gaming technologies. https://www.igi-global.com/book/digital-sport-performance-enhancement-competitive/276. Accessed 15 Jun 2020
4. Abbott W, Brickley G, Smeeton NJ (2018) Positional differences in GPS outputs and perceived exertion during soccer training games and competition. J Strength Cond Res 32:3222–3231. https://doi.org/10.1519/JSC.0000000000002387
5. Varley MC, Salvo VD, Modonutti M et al (2018) The influence of successive matches on match-running performance during an under-23 international soccer tournament: the necessity of individual analysis. J Sports Sci 36:585–591. https://doi.org/10.1080/02640414.2017.1325511
6. Frencken WGP, Lemmink KAPM, Delleman NJ (2010) Soccer-specific accuracy and validity of the local position measurement (LPM) system. J Sci Med Sport 13:641–645. https://doi.org/10.1016/j.jsams.2010.04.003
7. Linke D, Link D, Lames M (2018) Validation of electronic performance and tracking systems EPTS under field conditions. PLoS One 13:e0199519. https://doi.org/10.1371/journal.pone.0199519
8. Linke D, Link D, Lames M (2020) Football-specific validity of TRACAB's optical video tracking systems. PLoS One 15:e0230179. https://doi.org/10.1371/journal.pone.0230179
9. Redwood-Brown A, Cranton W, Sunderland C (2012) Validation of a real-time video analysis system for soccer. Int J Sports Med 33:635–640. https://doi.org/10.1055/s-0032-1306326
10. Carling C (2013) Interpreting physical performance in professional soccer match-play: should we be more pragmatic in our approach? Sports Med Auckl NZ 43:655–663. https://doi.org/10.1007/s40279-013-0055-8
11. Sathyan T, Shuttleworth R, Hedley M, Davids K (2012) Validity and reliability of a radio positioning system for tracking athletes in indoor and outdoor team sports. Behav Res Methods 44(4):1108–1114. https://doi.org/10.3758/s13428-012-0192-2
12. Bloomfield J, Polman R, O'Donoghue P (2007) Physical demands of different positions in FA premier league soccer. J Sports Sci Med 6:63–70
13. Clark RA, Pua Y-H, Bolwer KJ, Bechard L, Hough E, Charlton PC, Mentiplay B (2019) Validity of a low-cost laser with freely available software for improving measurement of walking and running speed. J Sci Med Sport 22(2):1878–1861. https://doi.org/10.1016/j.jsams.2018.07.005
14. Eitel JUH, Höfle B, Vierling LA et al (2016) Beyond 3-D: the new spectrum of lidar applications for earth and ecological sciences. Remote Sens Env 186:372–392. https://doi.org/10.1016/j.rse.2016.08.018
15. Williams K, Olsen MJ, Roe GV, Glennie C (2013) Synthesis of transportation applications of mobile LIDAR. Remote Sens 5:4652–4692. https://doi.org/10.3390/rs5094652
16. Che E, Jung J, Olsen M (2019) Object recognition, segmentation, and classification of mobile laser scanning point clouds: a state of the art review. Sensors 19:810. https://doi.org/10.3390/s19040810
17. Beckett RG (2014) Paleoimaging: a review of applications and challenges. Forensic Sci Med Pathol 10:423–436. https://doi.org/10.1007/s12024-014-9541-z
18. Dewan A, Caselitz T, Tipaldi GD, Burgard W. (2016) Motion-based detection and tracking in 3D LiDAR scans. In: 2016 IEEE international conference on robotics and automation (ICRA). IEEE, Stockholm, Sweden, pp 4508–4513
19. FIFA (2019) Handbook of test methods for EPTS devices
20. Vickery WM, Dascombe BJ, Baker JD et al (2014) Accuracy and reliability of GPS devices for measurement of sports-specific movement patterns related to cricket, tennis, and field-based team sports. J Strength Cond Res 28:1697–1705. https://doi.org/10.1519/JSC.0000000000000285
21. Whitehead S, Till K, Weaving D, Jones B (2018) The use of microtechnology to quantify the peak match demands of the football codes: a systematic review. Sports Med Auckl NZ 48:2549–2575. https://doi.org/10.1007/s40279-018-0965-6
22. Duffield R, Reid M, Baker J, Spratford W (2010) Accuracy and reliability of GPS devices for measurement of movement patterns in confined spaces for court-based sports. J Sci Med Sport 13:523–525. https://doi.org/10.1016/j.jsams.2009.07.003
23. Nagymáté G, Kiss RM (2019) Affordable gait analysis using augmented reality markers. PLoS One 14:e0212319. https://doi.org/10.1371/journal.pone.0212319
24. Azizan NA, Basaruddin KS, Salleh AF et al (2018) Leg length discrepancy: dynamic balance response during gait. J Healthc Eng. https://doi.org/10.1155/2018/7815451
25. Thomas NM, Bampouras TM, Donovan T, Dewhurst S (2016) Eye movements affect postural control in young and older females. Front Aging Neurosci. https://doi.org/10.3389/fnagi.2016.00216
26. Loturco IA, Pereira L, Freitas TT, Alcaraz EP, Zanetti V, Bishop C, Jeffreys I (2019) Maximum acceleration performance of professional soccer players in linear sprints: is there a direct connection with change-of-direction ability? PLoS One 14(5):e0216806. https://doi.org/10.1371/journal.pone.0216806
27. Haugen T, Buchheit M (2016) Sprint running performance monitoring: methodological and practical considerations. SportsMed 46(5):641–656. https://doi.org/10.1007/s40279-015-0446-0
28. Comfort P, Stewart A, Bloom L, Clarkson B (2014) Relationships between strength, sprint, and jump performance in well-trained youth soccer players. J Strength Cond Res 28(1):173–177. https://doi.org/10.1519/JSC.0b013e318291b8c7