



Technical Note

# Automatic Markerless Motion Detector Method against Traditional Digitisation for 3-Dimensional Movement Kinematic Analysis of Ball Kicking in Soccer Field Context

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**Abstract:** Kicking is a fundamental skill in soccer that often contributes to match outcomes. Lower limb movement features (e.g., joint position and velocity) are determinants of kick performance. However, obtaining kicking kinematics under field conditions generally requires time-consuming manual tracking. The current study aimed to compare a contemporary markerless automatic motion estimation algorithm (OpenPose) with manual digitisation (DVIDEOW software) in obtaining on-field kicking kinematic parameters. An experimental dataset of under-17 players from all outfield positions was used. Kick attempts were performed in an official pitch against a goalkeeper. Four digital video cameras were used to record full-body motion during support and ball contact phases of each kick. Three-dimensional positions of hip, knee, ankle, toe and foot centre-of-mass ( $CM_{\text{foot}}$ ) generally showed no significant differences when computed by automatic as compared to manual tracking (whole kicking movement cycle), while only z-coordinates of knee and calcaneus markers at specific points differed between methods. The resulting time-series matrices of positions ( $r^2 = 0.94$ ) and velocity signals ( $r^2 = 0.68$ ) were largely associated (all  $p < 0.01$ ). The mean absolute error of OpenPose motion tracking was 3.49 cm for determining positions (ranging from 2.78 cm ( $CM_{\text{foot}}$ ) to 4.13 cm (dominant hip)) and 1.29 m/s for calculating joint velocity (0.95 m/s (knee) to 1.50 m/s (non-dominant hip)) as compared to reference measures by manual digitisation. Angular range-of-motion showed significant correlations between methods for the ankle ( $r = 0.59$ ,  $p < 0.01$ , *large*) and knee joint displacements ( $r = 0.84$ ,  $p < 0.001$ , *very large*) but not in the hip ( $r = 0.04$ ,  $p = 0.85$ , *unclear*). Markerless motion tracking (OpenPose) can help to successfully obtain some lower limb position, velocity, and joint angular outputs during kicks performed in a naturally occurring environment.

**Keywords:** image processing; human estimation; COCO; MPIO; deep learning; team sports

## 1. Introduction

Kicking is a frequent technical action taken in football matches, and achieving high-velocity and accurate targeting standards usually contributes to winning matches [1,2].

Extracting players' movement kinematics data derived from ball kicking, such as passing actions or shooting against goalposts, is arguably important in the coaching process since it assists in identifying and understanding (a) body mechanical factor determinants for performance outputs; (b) practice constraints' (e.g., acute-to-chronic exercise or recovery related) effects on coordination aspects [3]; most importantly, (c) individual weaknesses in need of improvement, thereby allowing the provision of specific feedback to refine movement patterns [4]. Currently, among the tools available to examine kicking movement performance, video analysis originates the most objective and sensitive kinematic metrics, which are not always captured by only visual ratings [5]. In fact, video analysis has been used in some other research fields (e.g., animal displacement detection and analysis), as well as in a range of sports [6–14]. However, while ecologically valid assessment protocols using an on-field multiple-camera setup (such as high-speed action sport cameras [15]) have made it possible to record the three-dimensional and open nature of soccer kicks, flexible/reliable and boosting image processing methods are still required to provide useful information to practitioners in due time [3,16,17].

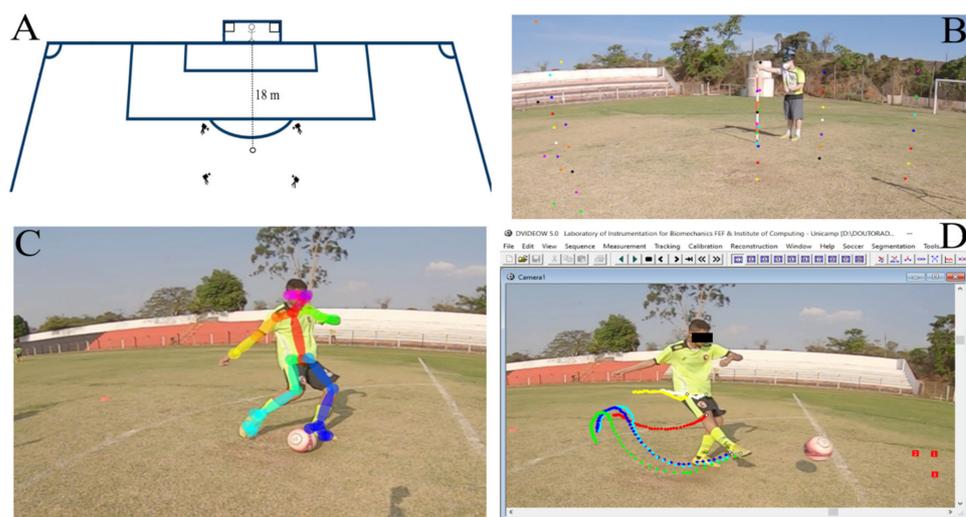
Traditional excess of the manual digitisation necessary in obtaining body landmark position time-series information is one important issue related to video kinematic investigations of kicking [18–20], which would render as long as half a year of data processing depending on sample sizes [21]. Indeed, manual tracking generally results in the existence of both inter- and intra-operator variability in labelling [22] and is highly dependent on marker sharpness/contrast in relation to the skin and environment [23,24]. Furthermore, game rules do not always allow players to wear objects [25], implying that kick assessment routines should attempt to respect the realities of competition [3]. The latter can also prevent athlete monitoring with foot-mounted sensors [26], or otherwise attaching any apparatus to the player's body may interfere with their normal technique [27–29]. Thus, publicly available markerless motion estimation algorithms seem to be a potential solution in analysing video data and extracting kick kinematics in a likely less time-consuming, more cost-effective, and non-invasive way. For such purposes, advanced computer vision and deep learning techniques (e.g., convolutional neural network (CNN) mask) [30] have been applied whilst the validity of the various contemporary markerless systems is still lacking consensus in research (for a recent review, see Cronin [31]).

To date, results on the performance of a widespread, state-of-the-art open-source pose estimation tool called 'OpenPose' [32] are found for a range of dynamic tasks, including human walking [33], running [34], jumping [35], and ball throwing [36]; this method demonstrated acceptable functioning in two- [33,37] or three-dimensional [34–36] plane analysis (e.g., agreement with measures derived from 'gold-standard' marker-based kinematic systems). Either of these previous experiments assessing movements pertaining to team sports was notably performed indoors in such controlled environments as a laboratory room. To our knowledge, no studies determined its measurement error under field conditions such as a soccer pitch scenario and considering the inclusion of ballistic (explosive) tasks involving object manipulation using the lower limbs such as in ball kicking. Differently from a throw, during kicking actions, one limb is fixed on the ground while another moves in parallel, generating some blocking between these body segments in the camera's view, which can influence tracking effectiveness [31]. Notwithstanding, as this method involves the recognition/estimation of key body points in each image (i.e., video frame) separately, the implementation of tracking strategies represents an important attempt to further improve such a tool in motion analysis, despite the fact that it was almost overlooked in the existing works specifically interested in sports tasks. Additionally, non-controllable aspects comprising lighting, possible mutual occlusions and diversified subject/background configurations may often collectively interfere during image processing in team sport real-world contexts [13,29,38]. Therefore, the purpose of the current preliminary study was to compare traditional frame-by-frame manual and modified OpenPose automatic motion tracking methods in determining soccer kicking movement kinematic parameters in a naturally occurring environment.

## 2. Materials and Methods

### 2.1. Data Acquisition

In an official, FIFA-standard, natural grass pitch, four tripod-mounted digital video cameras (240 Hz,  $1920 \times 1080$  pixel; Hero 7/Black Edition, GoPro® GmbH, München, Germany) were distributed perpendicular to each other and 2.5 m laterally to the established kick mark (18 m apart from the midpoint goal line). An experimental dataset (unpublished observations) including six outfield—defenders, midfielders and forwards—U17 academy players was used ( $16.1 \pm 1$  years old,  $176 \pm 6$  cm,  $71 \pm 11$  kg). Spherical markers (25 mm diameter) were attached externally on the participant's greater femoral trochanter and also, on the non-dominant side, the lateral malleolus, calcaneus, and distal phalanx of the fifth metatarsal head (dominant limb). As illustrated in Figure 1A, kick attempts were performed near the entrance of the penalty area (18 m from the midpoint goal line), and participants were instructed to strike the target's centre ( $1 \times 1$  m in both goalpost upper corners) while avoiding a teammate goalkeeper intercepting the ball. A detailed description of the design of the field assessments and the test–retest reliability measures of the task adopted to measure soccer kicking characteristics are both available elsewhere [39]. Following collection, image sequences were transferred to a computer Ubuntu 20.04.2 LTS (Intel i7-8750H (12) @ 2.208 GHz; 16 GB RAM; Intel Corporation, Santa Clara, CA, USA) with GPU (GeForce GTX 1050 Ti; 4096 MB GDDR5; NVIDIA Corporation, Santa Clara, CA, USA), and 30 kicking attempts were randomly selected (<https://www.random.org>; accessed on 8 July 2021) for further analysis.



**Figure 1.** Illustration of (A) experimental setup used for data collection, (B) calibration, (C) a given kicking trial digitised using OpenPose markerless system and (D) manual tracking frame by frame.

### 2.2. Motion Tracking

#### 2.2.1. Manual Digitisation

Manual frame-by-frame tracking of markers was completed (Figure 1D) by a single experienced (>10 years) examiner using the DVIDEOW interface (v.5.0; Laboratory of Instrumentation for Biomechanics & Institute of Computing UNICAMP, Brazil—see Figueroa et al. for more information [40]). This motion tracking method is considered as the reference measurement in the current study. The audio-band feature embedded into the software was employed to synchronise the video cameras before tracking [41]. The image sequences of the same initial and final events and the duration (i.e., number of frames) were inputted in DVIDEOW and OpenPose tracking methods. A common calibration frame containing 49 control points was also defined for both in order to completely cover the kicking area ( $3.6 \times 3.2 \times 1.3$  m, respectively, in antero-posterior, medio-lateral and vertical directions—Figure 1B). Reconstructed calibration points were compared to the reference values entered by the operator to compute a global error.

### 2.2.2. Markerless System

OpenPose is a bottom-up deep-learning-based approach designed to estimate human pose and joint angles. In brief, this approach estimates and encodes the locations (Figure 1C) and orientations of the limbs, in addition to the association score between body parts. For this, the method produces confidence maps that encode the location of each body part in the image domain. Then, a set of 2D vector fields of part affinity fields (PAFs) is used to encode both location and information. Next, the PAFs are used to estimate the degree of association between the body parts, which is used to assemble the limbs and thus come up with a full-body pose for all people in the scene. A more detailed description of this method can be found in [32]. Although OpenPose can detect the pose of all people in a scene, a tracking strategy is necessary for associating a set of poses found in the frame  $t$  with their respective poses detected in a subsequent frame  $t + 1$ . In this work, we proposed a simple tracking strategy that firstly consists of computing the centre of mass of a given pose in the frame  $t$ . Then, we associate it with the pose in the frame  $t + 1$  whose centre of mass presents the smallest Euclidean distance. We take advantage of the K-Means algorithm [42] for efficiently computing the pairwise distances between a set of poses found in the frame  $t$  and frame  $t + 1$ . The source code is freely available for scientific purposes on GitHub repository (<https://github.com/allansp84/allansp84-markerless-motion-detection>, accessed on 9 November 2021).

### 2.3. Data Treatment and Measures

In a Matlab<sup>®</sup> environment (R2019a; MathWorks Inc., Natick, MA, USA), 3-dimensional coordinates were obtained from Direct Linear Transformation (DLT) [43], with previous correction for radial lens distortion [44] caused by the type of action that the sports cameras used. The raw data from both methods were treated with a dual filter fourth-order Butterworth plus rloess [45,46], using a span equal to 0.1 and a cut-off frequency of 25 Hz as smoothing parameters, which were set after a residual analysis. The dependent variables of the current study were determined for all kick attempts using custom-built routines and included: (a) time-series reconstructed 3-dimensional position of each marker; (b) its associated time-series velocity; (c) foot centre-of-mass ( $CM_{\text{foot}}$ ) velocity at impact; (d) angular range of motion (ROM). Velocity outputs were taken from finite central differences using time-series data of the entire attempt duration as input arguments [18].  $CM_{\text{foot}}$  velocity at impact was calculated from the three final frames just before ball contact considering the centroid of malleolus, calcaneus, and toe coordinates. Local reference frames and segment centres were defined as per previous studies [21,47]. Joint ROMs were then computed as the difference between the lowest and the highest joint (hip, knee, and ankle) angle values observed in the sagittal plane [47]. Independent variables were the two distinct methods used (DVIDEO software for manual tracking and OpenPose markerless system) for the digitisation of the kicking motion.

### 2.4. Statistical Analysis

The data were time normalised and presented as medians and 95% confidence intervals (CI). Significant differences between methods in time-series analysis were flagged when CIs did not overlap [21,45,48]. Mean absolute error (MAE) was computed according to Equation (1) [36] separately to support phase (1% to 65% of the cycle—starting from the take-off of the kicking limb until complete touchdown of the supporting limb in the last step before impact), contact phase (from 66% to 100% of the cycle, starting immediately following termination of the support phase until foot–ball impact [45]) as well as considering the whole kick cycle. Correlation coefficients were determined (time-series (corrcoef.m Matlab function) and single-point measures (Pearson product-moment ( $r$ ) and intraclass correlation coefficients—ICC)) to gain insights about the random error and interchangeability of signals obtained among the two methods. For the latter, the statistical significance level was pre-set at  $p \leq 0.05$ . The correlation values ( $r$ , 95% CI) were deemed as being trivial ( $<0.1$ ), small ( $>0.1$ – $0.3$ ), moderate ( $>0.3$ – $0.5$ ), large ( $>0.5$ – $0.7$ ), very large ( $>0.7$ – $0.9$ ) or almost perfect

(>0.9–1.0). If the resulting CIs overlapped both small positive and negative values, then the correlation was deemed unclear [49]. Shared variance was considered small ( $r^2 < 0.30$ ), moderate ( $r^2 > 0.3–0.5$ ) or large ( $r^2 > 0.50$ ). Ratio limits of agreement (RLOA) were also computed for the non-time-series parameters (joint ROMs and  $CM_{\text{foot}}$  velocity at impact) as a measure of systematic bias [50]. Finally, effect sizes (ES) assumed as standardised mean differences (Cohen's  $d$ ) were calculated [51] for each comparison (Equation (2)) and interpreted as trivial ( $d < 0.2$ ), small ( $d > 0.2–0.59$ ), moderate ( $d \geq 0.6–1.19$ ) or large ( $d \geq 1.2$ ).

$$MAE = \frac{1}{n} \sum_{i=1}^n |d_m(i) - d_a(i)| \quad (1)$$

$$ES(i) = \frac{M_m(i) - M_a(i)}{\sqrt{\frac{\sigma_m^2(i) + \sigma_a^2(i)}{2}}} \quad (2)$$

where  $d_m$  = the data point obtained from manual tracking;  $d_a$  = the data point obtained from automatic tracking;  $n$  = the number of data samples;  $i$  = a given frame;  $M_m$  = the average obtained from manual tracking;  $M_a$  = the average obtained from automatic tracking;  $\sigma_m$  = the standard deviation of the values obtained from manual tracking;  $\sigma_a$  = the standard deviation of values obtained from automatic tracking.

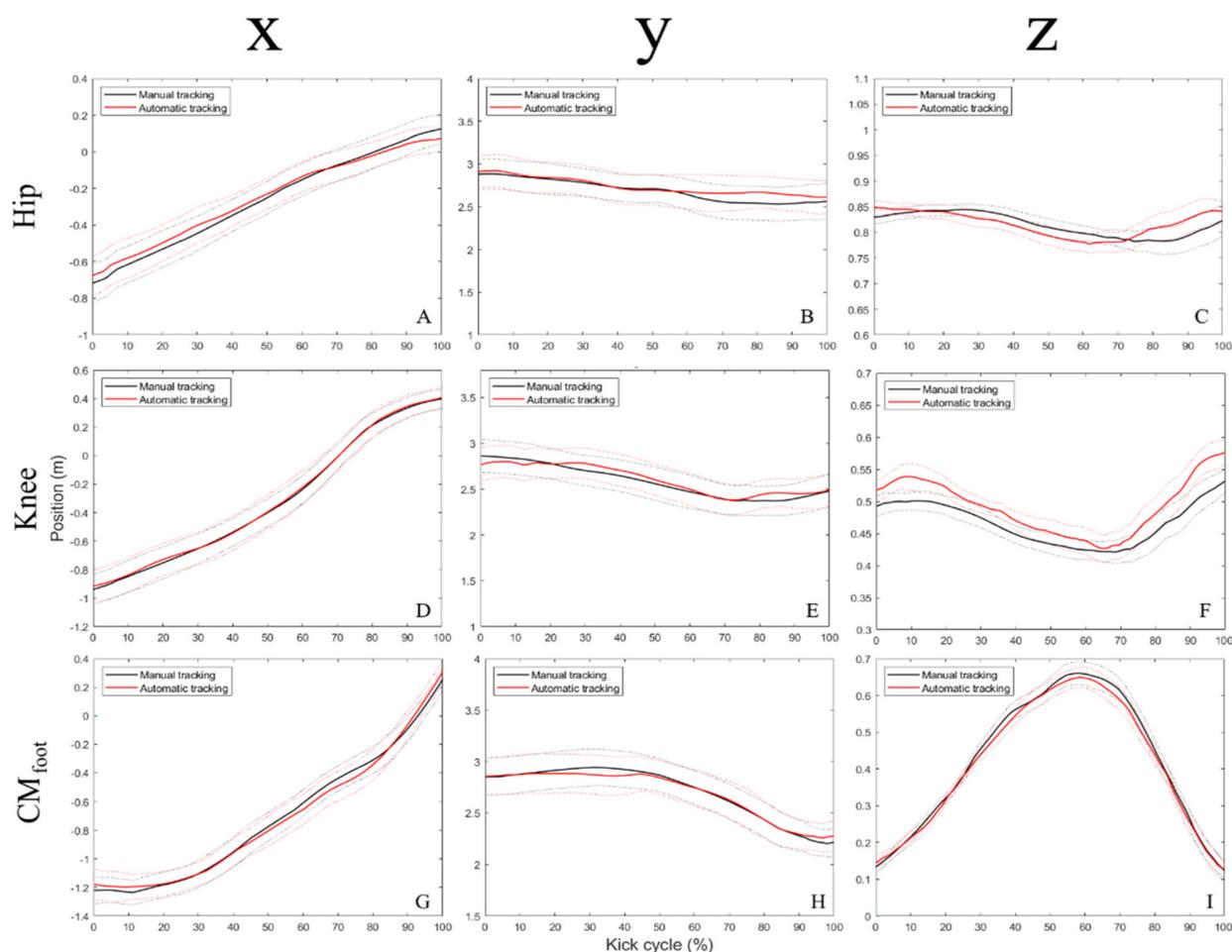
### 3. Results

Figure 2 shows the time series of the absolute position data (x, y and z coordinates) of selected markers obtained from OpenPose automatic and DVIDEOW manual tracking methods, while Figure 3 contains its three-dimensional resultant velocity observed across the whole kicking movement cycle. Separate figures for all markers/axes are provided in Supplementary online material S1. Global calibration errors were 0.9, 1.1 and 1.8 cm, respectively, in the x (antero-posterior), y (medio-lateral) and z (vertical) directions.

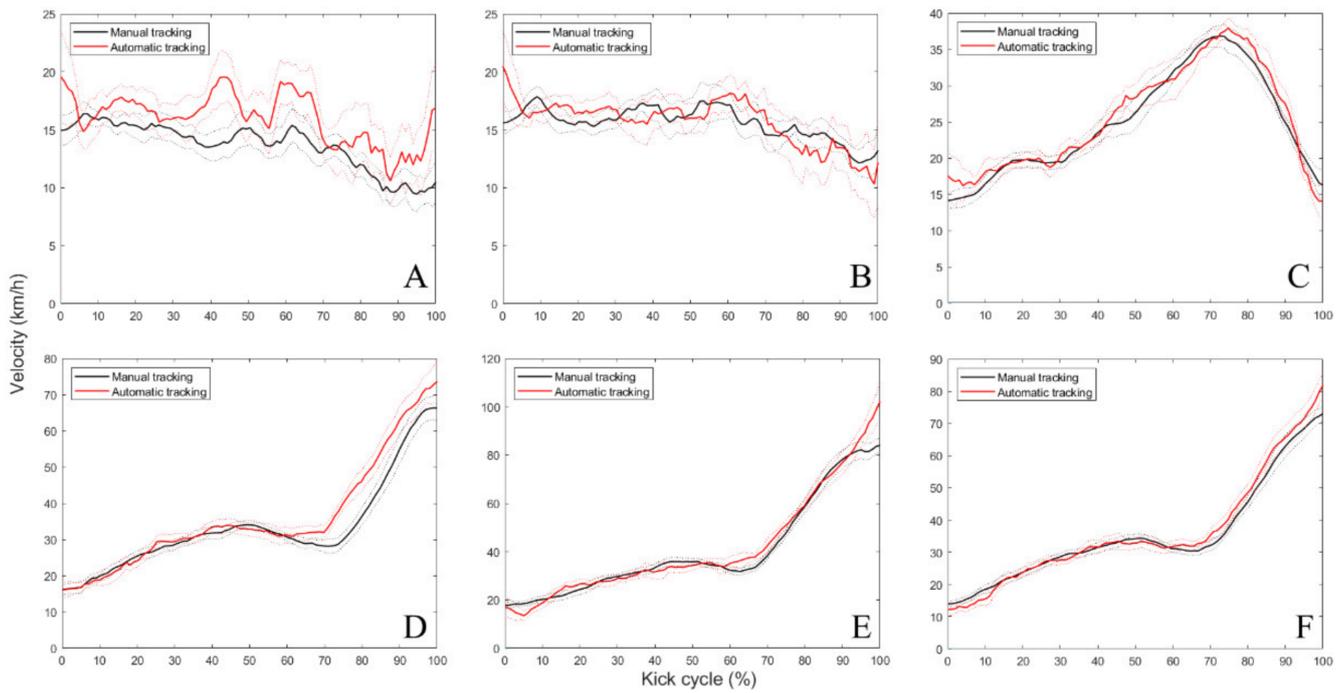
Positional differences were observed between the two methods only in the z-coordinates of the knee (from 6 to 12%; 20% instant and 90 to 100% of kicking movement cycle—Figure 2F) and calcaneus markers (from 16 to 18%—Supplementary online material S1, Figure 1M). Hip (dominant and non-dominant), ankle, fifth metatarsal head and  $CM_{\text{foot}}$  (Figure 2G–I) showed no significant differences in their three-dimensional positions (x, y or z coordinates), computed by automatic as compared to manual tracking methods, during the whole kicking movement cycle. Overall effect sizes (Table 1) were trivial to small for the x coordinates (ES = 0.01 to 0.39 (mean = 0.17)) and y coordinates (ES = 0.06 to 0.32 (mean = 0.14)) and small to large concerning z coordinates (ES = 0.34 to 6.40 (mean = 1.59)).

In reference to the marker's velocity outputs, the overall differences between methods were trivial (ES  $\leq$  0.08 (mean = 0.03)) but reached significance in the non-dominant hip (from 15 to 20%, from 37 to 47%, from 58 to 67%, and from 98 to 100%—Figure 3A), dominant hip (from 1 to 2% and 65% instant—Figure 3B), calcaneus (from 68 to 90%—Figure 3D), fifth metatarsal head (from 5 to 7%, 17% instant, from 64 to 68%, and from 97 to 99%—Figure 3E) and  $CM_{\text{foot}}$  (from 6 to 8%, 71% instant, and from 99 to 100% of kicking movement cycle—Figure 3F). Knee showed two separate differences (48% and 97% instants—Figure 3C), whilst ankle velocity was similar (Supplementary online material S2) between OpenPose automatic and DVIDEOW manual tracking methods (ES  $\leq$  0.07 (trivial)) across the whole kicking cycle (Supplementary online material S3).

The overall MAEs of the OpenPose motion tracking method as compared to manual digitisation was 3.49 cm for determining positions and 1.29 m/s for calculating markers' velocity (all pooled). In particular (Table 2), these values ranged, respectively, from 2.78 cm ( $CM_{\text{foot}}$ ) to 4.13 cm (dominant hip) and 0.95 m/s (knee) to 1.50 m/s (non-dominant hip). ROM showed *large-to-very large* correlations between OpenPose automatic and DVIDEOW manual tracking methods, respectively, for the ankle ( $r = 0.59 (\pm 0.40)$ ,  $p < 0.01$ ; ICC = 0.47,  $p < 0.01$ ; RLOA =  $0.655 \times / \div 1.758$ ; 1.08 [0.92; 1.24] and 1.41 [1.33; 1.49] rad) and knee joint displacements ( $r = 0.84 (\pm 0.08)$ ,  $p < 0.001$ ; ICC = 0.82,  $p < 0.001$ ; RLOA =  $1.072 \times / \div 0.323$ ; 1.91 [1.83; 1.99] and 1.86 [1.76; 1.96] rad), but it was *unclear* in the hip ( $r = 0.04 (\pm 0.15)$ ,  $p = 0.85$ ; ICC = 0.01,  $p = 0.48$ ; RLOA =  $0.520 \times / \div 1.940$ ; 0.86 [0.43; 1.28] and 1.14 [1.08; 1.20] rad), while  $CM_{\text{foot}}$  velocity at impact showed a moderate correlation ( $r = 0.48 (\pm 0.23)$ ,  $p < 0.01$ ; ICC = 0.47,  $p < 0.01$ ; RLOA =  $1.021 \times / \div 0.046$ ; 21.57 [20.77; 22.36] and 19.70 [19.04; 20.36] m/s, respectively). Finally, large average shared variances were found among methods in their resulting matrix of position ( $r^2 = 0.94 [0.73; 0.99]$ , all  $p < 0.001$ ) and velocity signals ( $r^2 = 0.68 [0.46; 0.92]$ , all  $p < 0.01$ ).



**Figure 2.** Time series containing median values (solid lines) and associated confidence intervals of marker's absolute position (x, antero-posterior; y, medio-lateral; z, vertical) computed across the whole kick movement cycle for both tracking methods (dominant hip x-axis (A), dominant hip y-axis (B), dominant hip z-axis (C), knee x-axis (D), knee y-axis (E), knee z-axis (F),  $CM_{\text{foot}}$  x-axis (G),  $CM_{\text{foot}}$  y-axis (H),  $CM_{\text{foot}}$  z-axis (I)).



**Figure 3.** Time series containing median values (solid lines) and associated confidence intervals of marker’s resultant three-dimensional velocity computed across the whole kick movement cycle for both tracking methods (non-dominant hip (A), dominant hip (B), knee (C), calcaneus (D), fifth metatarsal head (E) and CM<sub>foot</sub> (F)).

**Table 1.** Effect sizes (ES) obtained for pairwise comparisons between OpenPose automatic tracking and DVIDEOW manual tracking positional data (x, antero-posterior; y, medio-lateral; z, vertical) and velocity outputs.

Marker	Position									Velocity		
	X-Axis			Y-Axis			Z-Axis			Overall	Min	Max
	Overall	Min	Max	Overall	Min	Max	Overall	Min	Max			
Non-dominant hip	0.01	−0.14	0.15	−0.10	−0.29	0.11	−0.77	−5.03	4.22	−0.08	−0.25	0.00
Dominant hip	−0.19	−0.34	0.44	−0.32	−0.63	−0.16	1.40	−3.99	6.33	−0.01	−0.11	0.08
Knee	−0.04	−0.39	0.45	−0.15	−0.23	0.00	−6.40	−12.32	−2.78	−0.02	−0.13	0.12
Ankle	−0.39	−0.84	−0.17	−0.15	−0.38	0.05	0.88	−4.71	4.12	0.00	−0.07	0.05
Calcaneus	0.29	−1.07	0.96	0.06	−0.08	0.22	0.75	−4.57	5.50	−0.05	−0.21	0.05
5th metatarsal head	−0.19	−1.71	0.15	−0.10	−0.39	0.05	−0.34	−6.22	1.85	−0.02	−0.11	0.04
CM <sub>foot</sub>	−0.11	−1.23	0.26	−0.07	−0.23	0.10	0.61	−3.76	2.36	−0.02	−0.11	0.05

**Table 2.** Mean absolute error (MAE) for three-dimensional positions (cm) and resultant velocity (m/s) of each joint derived from comparisons between DVIDEOW manual digitisation and OpenPose automatic tracking algorithm.

Marker	Support Phase					Contact Phase					Whole Kick Cycle				
	X	Y	Z	All	VEL	X	Y	Z	All	VEL	X	Y	Z	All	VEL
Non-dominant hip	2.76	1.86	6.54	3.72	1.42	3.11	2.82	7.03	4.32	1.66	2.88	2.20	6.71	3.93	1.50
Dominant hip	2.65	2.49	5.88	3.67	1.06	3.04	2.91	8.98	4.98	1.29	2.79	2.63	6.96	4.13	1.14
Knee	1.91	2.45	4.40	2.92	0.84	1.91	3.19	3.31	2.80	1.14	1.91	2.71	4.02	2.88	0.95
Ankle	3.29	2.09	5.48	3.62	1.54	3.02	1.99	4.68	3.23	1.06	3.19	2.05	5.20	3.48	1.37
Calcaneus	4.44	2.22	5.47	4.04	1.10	4.62	2.59	3.84	3.68	2.12	4.50	2.35	4.90	3.92	1.45
5th metatarsal head	2.60	1.98	5.59	3.39	1.23	3.40	2.13	3.70	3.08	1.81	2.88	2.03	4.93	3.28	1.43
CM <sub>foot</sub>	2.50	1.41	4.87	2.93	1.14	2.93	1.41	3.18	2.51	1.24	2.65	1.41	4.28	2.78	1.17
Overall	2.88	2.07	5.46	3.47	1.19	3.15	2.43	4.96	3.51	1.47	2.97	2.20	5.29	3.49	1.29

VEL = resultant three-dimensional velocity; X = antero-posterior; Y = medio-lateral; Z = vertical directions.

#### 4. Discussion

The current study aimed to compare the OpenPose automatic motion detector method [32] against traditional frame-by-frame manual digitisation (DVIDEOW software) conducted through a relatively flexible interface [40] in determining on-field soccer kicking movement kinematics. Furthermore, a simple tracking algorithm was proposed to overcome the original limitation of OpenPose that provides a set of full-body poses per frame without any tracking information, allowing us to determine the set of poses for a specific person over time. To the extent of our knowledge, no previous work has investigated the reliability aspects of markerless tracking in ball kicking drills. In the following paragraphs, the strengths and weaknesses relating to the application of such advanced tracking methods are discussed—in particular, within the context of kicking kinematics analysis—and recommendations for possible further improvements are also provided.

Manual tracking systems (marker-based) are one of the most common computer methods adopted in measuring the kinematics of soccer kicks to date, despite their possible impractical characteristics. According to the original results obtained, a markerless algorithm can help to successfully obtain lower limb position and velocity outputs during kick tasks performed in an official outdoor pitch. Critical parameters related to kicking effectiveness, such as those derived from knee and ankle joint kinematics, showed acceptable levels of error when computed by the OpenPose algorithm as compared to traditional tracking (i.e., manual frame-by-frame tracking of kick movement features [18,19,52–54]). Conversely, hip motion demonstrated the worst outcomes using this procedure in all of the position, velocity and angular aspects. Notwithstanding, while the accuracy of the x axis and y axis was generally preserved, most sources of uncertainties when using the contemporary tracking tool were likely due to discrepancies identified in the z-axis (vertical) coordinates among methods, indicating that advances in the OpenPose motion detector are still necessary, mainly in the hip segment. Regardless, such a markerless system can be helpful for performance-enhancing purposes (training to correct occasional inefficient movements) as well as possible clinical cases (e.g., identifying athletes with potentially excessive plantar flexion amplitude; Tol et al. [55]) owing to the presumable interchangeability of its signals with manual digitisation.

In biomechanical investigations, the validity of the measures is invariably a concern, notably in field testing where non-controllable/unexpected factors usually exist. In a first analysis, the error values found were within the range reported previously by applying OpenPose to other human movements—primarily performed with the lower limbs—which were found to be 2 cm in walking at a comfortable pace [56], about 3–4 cm in walking plus quick jumping conditions [36] and up to 5 cm on average in sprinting bouts [28]. However, variable acquisition frequencies (30 [56], 120 [36] or 240 [35] Hz), number of cameras (one [33], two [34,35,56], five [36] or nine [28]), their positioning (e.g., 1.8 [34], 2.3 [56] or 6.35 m [33] away from the subjects) and recording resolution (640 × 480 [56], 1280 × 720 [35], 1920 × 1080 p [28] or 4 K [36]) may constrain such a direct comparison of

our results and literature. In general, such previous studies also used experimental setups including cameras with apparently traditional optical systems (e.g., linear field of view) in which no mention was made concerning whether the image sequences were corrected for eventual distortions. Thus, it is plausible to state that action sport cameras were not tested among existing works, which highlights another innovative aspect of the current study. Regardless, these documented results indicate that, similar to that occurring with other biomechanical position monitoring systems [57], uncertainties of OpenPose may be speed dependent. In accordance, we have verified some increases in error values (e.g., average +8.23% and +15.07% in  $x$ -axis positions and resultant velocities across markers, respectively) from the support to contact phase of kicking (Table 2). Of note, distal endpoint kicking velocity increased from ~33–37 km/h in toe-off to 84–102 km/h at the ball contact instant, as exhibited in Figure 3E. These sudden changes in velocity could alter the image properties (e.g., might add some blurred pixels), thereby influencing motion estimation [31]. Furthermore,  $CM_{\text{foot}}$  velocity—a key parameter of performance—showed infrequent but significant systematic bias across time moments of the kicking cycle, including ball impact. Conversely, random error appears to be low given the significant correlations between methods, whilst the RLOA of  $CM_{\text{foot}}$  velocity at impact is also compatible with previous studies measuring kick velocity [58,59]. In this sense, given the habitual distortion caused by foot–ball impact on the kicking kinematics data, excluding the last few frames of the contact phase is not uncommon [3,45,60] and could also solve this issue despite improvements in the precision of foot detection being mainly required in investigations focused on depicting the full ball-impact phase.

Here, the OpenPose method had superior performance in determining antero-posterior /medio-lateral (respectively,  $x$  and  $y$  axis) than vertical ( $z$  axis) positions (Table 1). The same occurred for intermediate-to-distal (knee, ankle, and foot) limb kinematics—position, velocity and angular amplitude—of the contact limb as compared to the proximal joint (hip) involved in the action (Table 2). It should be noted that the resulting velocity was slightly impacted by the worse results in the  $z$  coordinates/vertical direction that are seemingly cancelled by acceptable functioning in the remaining pair of axes. The strong similarity of signals between methods (e.g., as indicated by  $r$ -squared outcomes and also the waveforms—Figures 2I and 3C) indicates the presence of more systematic rather than random error. This is further illustrated by the significant associations observed from the resulting ROM (knee and ankle) and  $CM_{\text{foot}}$  velocity outcomes among the two methods. As shown in Figure 3, all important events such as continuous knee acceleration throughout the support phase followed by a reversal to deceleration—around 70% of the cycle—concomitantly with the foot acceleration, which is a typical illustration of proximal–distal energy transference during kicks, were correctly identified. The highest discrepancies between automatic and manual tracking in  $z$  coordinates might be partly attributed to a concomitant greater global calibration error magnitude that was observed in this specific axis, meaning that uncertainties in the vertical direction are themselves the poorest. Lower precision in obtaining hip movements is also observed elsewhere in squat and locomotion tasks [34,37]. The hip is generally entirely covered by clothing (shorts/t-shirt) [61], with unconstrained portions that are not well fixed to the body, and this probably causes an undefined /more variable pattern of appearance in image sequences, while this is not the case or might be at least reduced in the remaining equipment (socks and clothes) covering the leg and foot segments. In addition to being wider, by the under-17 age, the hips and thighs are also longer [21] as compared to the lower leg, thereby involving image processing of a greater number of pixels, perhaps increasing the complexity in keypoint detection of the former. In the case of kicking assessed using only lateral cameras, given the common path of players in the approach run and subsequent ball flight, issues in markerless tracking can be also attributed to a longer mutual occlusion of hip joints as compared to the knee and ankle—in particular, the overlapped proximal region of both thighs in the image sequences across a substantial trial duration. Taken collectively, it can make the process to precisely detect and track the hip joint more challenging in some instances. Therefore, hip

kinematic outcomes of kicking should be interpreted with caution when using OpenPose. The possible advantages of including a camera behind the player trajectory (i.e., posterior view) in addition to a higher sampling frequency should be tested in future research.

Additional limitations are also recognised to this study, which collectively indicate taking caution in any generalisations made. Firstly, given the practical difficulties in conducting repeated measurements within soccer clubs, the cross-sectional design of the present comparative analysis prevents the calculation of minimal detectable differences. Secondly, re-training based on our own dataset characteristics may contribute to further reducing errors arising from possible algorithm false detections [62]. Thirdly, a relatively small sample size was used here to evaluate the performance of a markerless algorithm, despite this not being uncommon, as some published pilot or validation studies have included, for example, only two [36,56], six [63], or a maximum of nine participants [64]. Fourthly, assessment outcomes may fail to replicate actual soccer match demands, possibly limiting the results to only testing routines. Finally, as soccer kicking performance is age dependent, a priori extrapolation of results to senior players may not be warranted.

## 5. Conclusions

In short, empirical evidence provided by the current experiment indicates that the OpenPose tracking method may be a reliable tool with which to evaluate soccer kicking kinematics in youth soccer under grassy pitch conditions, providing compatible data to those obtained from traditional frame-by-frame manual digitisation. In particular, we were more confident in knee and ankle joint preliminary outcomes, whilst hip detections should still be improved to reduce between-methods differences. Markerless motion tracking systems such as OpenPose seem to be a pertinent option to help fill a critical gap currently existing between research and soccer practice, mainly in the analysis of ball kicking skills, since it reduces the time spent in processing the data dramatically, while its precision in computing position and velocity is generally not compromised. Future work is recommended to further check the validity of the proposed method against microtechnology devices or ‘gold-standard’ marker-based (semi)automatic tracking measures provided by infrared cameras, despite the difficulties in implementing the latter in the “real-world” rather than within a laboratory or indoor artificial turf soccer pitch.

**Supplementary Materials:** The following are available online at <https://www.mdpi.com/article/10.3390/ijerph19031179/s1>, Supplementary online material S1: Figures illustrating time series of all marker’s absolute position computed across the whole kick movement cycle for both tracking methods, Supplementary online material S2: Figure containing resultant three-dimensional velocity of the ankle computed across the whole kick movement cycle for both tracking methods, Supplementary online material S3: Matfile containing all effect sizes derived from the comparisons made in the current study.

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**Institutional Review Board Statement:** The study was conducted according to the guidelines of the Declaration of Helsinki and approved by the Institutional Ethics Committee of the São Paulo State University, protocol #CAAE85994318.3.0000.5398 (date of approval: 11 May 2018, registered under review number 2.650.204).

**Informed Consent Statement:** Verbal and written informed assent and consent were obtained, respectively, from all subjects involved in the study and their parents/legal guardians.

**Data Availability Statement:** The raw data supporting the findings of the present study were made available by the authors without undue reservation in the Open Science Framework (<https://osf.io/jer9u/>, accessed on 14 January 2022) repository.

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## References

1. Hunter, A.H.; Angilletta, M.J.; Wilson, R.S. Behaviors of Shooter and Goalkeeper Interact to Determine the Outcome of Soccer Penalties. *Scand. J. Med. Sci. Sports* **2018**, *28*, 2751–2759. [[CrossRef](#)]
2. Liu, H.; Hopkins, W.G.; Gómez, M.-A. Modelling Relationships between Match Events and Match Outcome in Elite Football. *Eur. J. Sport. Sci.* **2016**, *16*, 516–525. [[CrossRef](#)] [[PubMed](#)]
3. Palucci Vieira, L.H.; Santinelli, F.B.; Carling, C.; Kellis, E.; Santiago, P.R.P.; Barbieri, F.A. Acute Effects of Warm-Up, Exercise and Recovery-Related Strategies on Assessments of Soccer Kicking Performance: A Critical and Systematic Review. *Sports Med.* **2021**, *51*, 661–705. [[CrossRef](#)]
4. Shan, G.; Zhang, X.; Wan, B.; Yu, D.; Wilde, B.; Visentin, P. Biomechanics of Coaching Maximal Instep Soccer Kick for Practitioners. *Interdiscip. Sci. Rev.* **2019**, *44*, 12–20. [[CrossRef](#)]
5. Marqués-Bruna, P.; Lees, A.; Grimshaw, P. Structural Principal Components Analysis of the Kinematics of the Soccer Kick Using Different Types of Rating Scales. *Int. J. Sports Sci. Coach.* **2008**, *3*, 73–85. [[CrossRef](#)]
6. Kulyukin, V.; Mukherjee, S. On Video Analysis of Omnidirectional Bee Traffic: Counting Bee Motions with Motion Detection and Image Classification. *Appl. Sci.* **2019**, *9*, 3743. [[CrossRef](#)]
7. Velázquez, J.S.; Iznaga-Benítez, A.M.; Robau-Porrúa, A.; Sáez-Gutiérrez, F.L.; Cavas, F. New Affordable Method for Measuring Angular Variations Caused by High Heels on the Sagittal Plane of Feet Joints during Gait. *Appl. Sci.* **2021**, *11*, 5605. [[CrossRef](#)]
8. Amara, S.; Chortane, O.G.; Negra, Y.; Hammami, R.; Khalifa, R.; Chortane, S.G.; van den Tillaar, R. Relationship between Swimming Performance, Biomechanical Variables and the Calculated Predicted 1-RM Push-up in Competitive Swimmers. *Int. J. Environ. Res. Public Health* **2021**, *18*, 11395. [[CrossRef](#)]
9. Castro-Luna, G.; Jiménez-Rodríguez, D. Relative and Absolute Reliability of a Motor Assessment System Using KINECT® Camera. *Int. J. Environ. Res. Public Health* **2020**, *17*, 5807. [[CrossRef](#)]
10. Ferro, A.; Pérez-Tejero, J.; Garrido, G.; Villacieros, J. Relationship between Sprint Capacity and Acceleration of Wrists in Wheelchair Basketball Players: Design and Reliability of a New Protocol. *Int. J. Environ. Res. Public Health* **2021**, *18*, 10380. [[CrossRef](#)]
11. Yu, C.; Wang, F.; Wang, B.; Li, G.; Li, F. A Computational Biomechanics Human Body Model Coupling Finite Element and Multibody Segments for Assessment of Head/Brain Injuries in Car-To-Pedestrian Collisions. *Int. J. Environ. Res. Public Health* **2020**, *17*, 492. [[CrossRef](#)]
12. Camp, N.; Lewis, M.; Hunter, K.; Johnston, J.; Zecca, M.; Di Nuovo, A.; Magistro, D. Technology Used to Recognize Activities of Daily Living in Community-Dwelling Older Adults. *Int. J. Environ. Res. Public Health* **2021**, *18*, 163. [[CrossRef](#)]
13. Barris, S.; Button, C. A Review of Vision-Based Motion Analysis in Sport. *Sports Med.* **2008**, *38*, 1025–1043. [[CrossRef](#)]
14. Baca, A.; Dabnichki, P.; Heller, M.; Kornfeind, P. Ubiquitous Computing in Sports: A Review and Analysis. *J. Sports Sci.* **2009**, *27*, 1335–1346. [[CrossRef](#)]
15. Bernardina, G.R.D.; Monnet, T.; Pinto, H.T.; de Barros, R.M.L.; Cerveri, P.; Silvatti, A.P. Are Action Sport Cameras Accurate Enough for 3D Motion Analysis? A Comparison with a Commercial Motion Capture System. *J. Appl. Biomech.* **2018**, *35*, 80–86. [[CrossRef](#)] [[PubMed](#)]
16. Carling, C.; Bloomfield, J.; Nelsen, L.; Reilly, T. The Role of Motion Analysis in Elite Soccer: Contemporary Performance Measurement Techniques and Work Rate Data. *Sports Med.* **2008**, *38*, 839–862. [[CrossRef](#)]
17. Lees, A.; Kershaw, L.; Moura, F. *The Three-Dimensional Nature of the Maximal Instep Kick in Soccer*; Routledge: London, UK, 2005; p. 65.
18. De Witt, J.K.; Hinrichs, R.N. Mechanical Factors Associated with the Development of High Ball Velocity during an Instep Soccer Kick. *Sports Biomech.* **2012**, *11*, 382–390. [[CrossRef](#)] [[PubMed](#)]
19. Nunome, H.; Asai, T.; Ikegami, Y.; Sakurai, S. Three-Dimensional Kinetic Analysis of Side-Foot and Instep Soccer Kicks. *Med. Sci. Sports Exerc.* **2002**, *34*, 2028–2036. [[CrossRef](#)] [[PubMed](#)]
20. Paulucci Vieira, L.H.; de Souza Serenza, F.; de Andrade, V.L.; de Paula Oliveira, L.; Mariano, F.P.; Santana, J.E.; Santiago, P.R.P. Kicking Performance and Muscular Strength Parameters with Dominant and Nondominant Lower Limbs in Brazilian Elite Professional Futsal Players. *J. Appl. Biomech.* **2016**, *32*, 578–585. [[CrossRef](#)]
21. Palucci Vieira, L.H.; Barbieri, F.A.; Kellis, E.; Oliveira, L.; Aquino, R.; Cunha, S.; Bedo, B.; Manechini, J.; Santiago, P. Organisation of Instep Kicking in Young U11 to U20 Soccer Players. *Sci. Med. Footb.* **2021**, *5*, 111–120. [[CrossRef](#)]

22. Ceseracciu, E.; Sawacha, Z.; Fantozzi, S.; Cortesi, M.; Gatta, G.; Corazza, S.; Cobelli, C. Markerless Analysis of Front Crawl Swimming. *J. Biomech.* **2011**, *44*, 2236–2242. [[CrossRef](#)]
23. Melton, C.; Mullineaux, D.R.; Mattacola, C.G.; Mair, S.D.; Uhl, T.L. Reliability of Video Motion-Analysis Systems to Measure Amplitude and Velocity of Shoulder Elevation. *J. Sport Rehabil.* **2011**, *20*, 393–405. [[CrossRef](#)]
24. Peikon, I.D.; Fitzsimmons, N.A.; Lebedev, M.A.; Nicoletis, M.A.L. Three-Dimensional, Automated, Real-Time Video System for Tracking Limb Motion in Brain–Machine Interface Studies. *J. Neurosci. Methods* **2009**, *180*, 224–233. [[CrossRef](#)]
25. Varley, M.C.; Gregson, W.; McMillan, K.; Bonanno, D.; Stafford, K.; Modonutti, M.; Di Salvo, V. Physical and Technical Performance of Elite Youth Soccer Players during International Tournaments: Influence of Playing Position and Team Success and Opponent Quality. *Sci. Med. Footb.* **2017**, *1*, 18–29. [[CrossRef](#)]
26. Blair, S.; Duthie, G.; Robertson, S.; Hopkins, W.; Ball, K. Concurrent Validation of an Inertial Measurement System to Quantify Kicking Biomechanics in Four Football Codes. *J. Biomech.* **2018**, *73*, 24–32. [[CrossRef](#)] [[PubMed](#)]
27. Colyer, S.L.; Evans, M.; Cosker, D.P.; Salo, A.I.T. A Review of the Evolution of Vision-Based Motion Analysis and the Integration of Advanced Computer Vision Methods towards Developing a Markerless System. *Sports Med. Open* **2018**, *4*, 24. [[CrossRef](#)] [[PubMed](#)]
28. Needham, L.; Evans, M.; Cosker, D.P.; Colyer, S.L. Can Markerless Pose Estimation Algorithms Estimate 3D Mass Centre Positions and Velocities during Linear Sprinting Activities? *Sensors* **2021**, *21*, 2889. [[CrossRef](#)]
29. van der Kruk, E.; Reijne, M.M. Accuracy of Human Motion Capture Systems for Sport Applications; State-of-the-Art Review. *Eur. J. Sport Sci.* **2018**, *18*, 806–819. [[CrossRef](#)]
30. Desmarais, Y.; Mottet, D.; Slangen, P.; Montesinos, P. A Review of 3D Human Pose Estimation Algorithms for Markerless Motion Capture. *Comput. Vis. Image Underst.* **2021**, *212*, 103275. [[CrossRef](#)]
31. Cronin, N.J. Using Deep Neural Networks for Kinematic Analysis: Challenges and Opportunities. *J. Biomech.* **2021**, *123*, 110460. [[CrossRef](#)]
32. Cao, Z.; Hidalgo, G.; Simon, T.; Wei, S.-E.; Sheikh, Y. OpenPose: Realtime Multi-Person 2D Pose Estimation Using Part Affinity Fields. *IEEE Trans. Pattern Anal. Mach. Intell.* **2021**, *43*, 172–186. [[CrossRef](#)] [[PubMed](#)]
33. Takeda, I.; Yamada, A.; Onodera, H. Artificial Intelligence-Assisted Motion Capture for Medical Applications: A Comparative Study between Markerless and Passive Marker Motion Capture. *Comput. Methods Biomech. Biomed. Eng.* **2021**, *24*, 864–873. [[CrossRef](#)]
34. Ota, M.; Tateuchi, H.; Hashiguchi, T.; Ichihashi, N. Verification of Validity of Gait Analysis Systems during Treadmill Walking and Running Using Human Pose Tracking Algorithm. *Gait Posture* **2021**, *85*, 290–297. [[CrossRef](#)]
35. Webering, F.; Blume, H.; Allaham, I. Markerless Camera-Based Vertical Jump Height Measurement Using OpenPose. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, Nashville, TN, USA, 19–25 June 2021; pp. 3868–3874.
36. Nakano, N.; Sakura, T.; Ueda, K.; Omura, L.; Kimura, A.; Iino, Y.; Fukashiro, S.; Yoshioka, S. Evaluation of 3D Markerless Motion Capture Accuracy Using OpenPose with Multiple Video Cameras. *Front. Sports Act. Living* **2020**, *2*, 50. [[CrossRef](#)]
37. Ota, M.; Tateuchi, H.; Hashiguchi, T.; Kato, T.; Ogino, Y.; Yamagata, M.; Ichihashi, N. Verification of Reliability and Validity of Motion Analysis Systems during Bilateral Squat Using Human Pose Tracking Algorithm. *Gait Posture* **2020**, *80*, 62–67. [[CrossRef](#)] [[PubMed](#)]
38. Barros, R.M.L.; Menezes, R.P.; Russomanno, T.G.; Misuta, M.S.; Brandão, B.C.; Figueroa, P.J.; Leite, N.J.; Goldenstein, S.K. Measuring Handball Players Trajectories Using an Automatically Trained Boosting Algorithm. *Comput. Methods Biomech. Biomed. Eng.* **2011**, *14*, 53–63. [[CrossRef](#)] [[PubMed](#)]
39. Palucci Vieira, L.H.; Lastella, M.; da Silva, J.P.; Cesário, T.; Santinelli, F.B.; Moretto, G.F.; Santiago, P.R.P.; Barbieri, F.A. Low Sleep Quality and Morningness-Eveningness Scale Score May Impair Ball Placement but Not Kicking Velocity in Youth Academy Soccer Players. *Sci. Med. Football* **2021**, in press. [[CrossRef](#)]
40. Figueroa, P.J.; Leite, N.J.; Barros, R.M.L. A Flexible Software for Tracking of Markers Used in Human Motion Analysis. *Comput. Methods Programs Biomed.* **2003**, *72*, 155–165. [[CrossRef](#)]
41. De Barros, R.M.L.; Guedes Russomanno, T.; Brenzikofer, R.; Jovino Figueroa, P. A Method to Synchronise Video Cameras Using the Audio Band. *J. Biomech.* **2006**, *39*, 776–780. [[CrossRef](#)] [[PubMed](#)]
42. Lloyd, S. Least Squares Quantization in PCM. *IEEE Trans. Inf. Theory* **1982**, *28*, 129–137. [[CrossRef](#)]
43. Abdel-Aziz, Y.I.; Karara, H.M.; Hauck, M. Direct Linear Transformation from Comparator Coordinates into Object Space Coordinates in Close-Range Photogrammetry. *Photogramm. Eng. Remote Sens.* **2015**, *81*, 103–107. [[CrossRef](#)]
44. Rossi, M.M.; Silvatti, A.P.; Dias, F.A.S.; Barros, R.M.L. Improved Accuracy in 3D Analysis Using DLT after Lens Distortion Correction. *Comput. Methods Biomech. Biomed. Eng.* **2015**, *18*, 993–1002. [[CrossRef](#)] [[PubMed](#)]
45. Barbieri, F.A.; Gobbi, L.T.B.; Santiago, P.R.P.; Cunha, S.A. Dominant–Non-Dominant Asymmetry of Kicking a Stationary and Rolling Ball in a Futsal Context. *J. Sports Sci.* **2015**, *33*, 1411–1419. [[CrossRef](#)]
46. Cunha, S.A.; Lima Filho, E.C. Metodologia Para Suavização de Dados Biomecânicos Por Função Não Paramétrica Ponderada Local Robusta [Methodology for the Smooth of Biomechanics Data for Functions Distribution Free]. *Braz. J. Biomech.* **2003**, *1*, 23–28.
47. Palucci Vieira, L.H.; Carling, C.; da Silva, J.P.; Santinelli, F.B.; Polastri, P.F.; Santiago, P.R.P.; Barbieri, F.A. Modelling the Relationships between EEG Signals, Movement Kinematics and Outcome in Soccer Kicking. *Cogn. Neurodyn.* **2022**. submitted.
48. Mcgill, R.; Tukey, J.W.; Larsen, W.A. Variations of Box Plots. *Am. Stat.* **1978**, *32*, 12–16. [[CrossRef](#)]

49. Hopkins, W.G.; Marshall, S.W.; Batterham, A.M.; Hanin, J. Progressive Statistics for Studies in Sports Medicine and Exercise Science. *Med. Sci. Sports Exerc.* **2009**, *41*, 3–13. [[CrossRef](#)]
50. Nevill, A.M.; Atkinson, G. Assessing Agreement between Measurements Recorded on a Ratio Scale in Sports Medicine and Sports Science. *Br. J. Sports Med.* **1997**, *31*, 314–318. [[CrossRef](#)]
51. Cohen, J. *Statistical Power Analysis for the Behavioral Sciences*, 2nd ed.; Routledge: Hillsdale, NJ, USA, 1988; ISBN 978-0-8058-0283-2.
52. Palucci Vieira, L.H.; Cunha, S.A.; Moraes, R.; Barbieri, F.A.; Aquino, R.; de Oliveira, L.P.; Navarro, M.; Bedo, B.L.S.; Santiago, P.R.P. Kicking Performance in Young U9 to U20 Soccer Players: Assessment of Velocity and Accuracy Simultaneously. *Res. Q. Exerc. Sport* **2018**, *89*, 210–220. [[CrossRef](#)]
53. Amiri-Khorasani, M.; Abu Osman, N.A.; Yusof, A. Acute Effect of Static and Dynamic Stretching on Hip Dynamic Range of Motion during Instep Kicking in Professional Soccer Players. *J. Strength Cond. Res.* **2011**, *25*, 1647–1652. [[CrossRef](#)]
54. Apriantono, T.; Nunome, H.; Ikegami, Y.; Sano, S. The Effect of Muscle Fatigue on Instep Kicking Kinetics and Kinematics in Association Football. *J. Sports Sci.* **2006**, *24*, 951–960. [[CrossRef](#)]
55. Tol, J.L.; Slim, E.; van Soest, A.J.; van Dijk, C.N. The Relationship of the Kicking Action in Soccer and Anterior Ankle Impingement Syndrome. A Biomechanical Analysis. *Am. J. Sports Med.* **2002**, *30*, 45–50. [[CrossRef](#)] [[PubMed](#)]
56. Zago, M.; Luzzago, M.; Marangoni, T.; De Cecco, M.; Tarabini, M.; Galli, M. 3D Tracking of Human Motion Using Visual Skeletonization and Stereoscopic Vision. *Front. Bioeng. Biotechnol.* **2020**, *8*, 181. [[CrossRef](#)]
57. Buchheit, M.; Simpson, B.M. Player-Tracking Technology: Half-Full or Half-Empty Glass? *Int. J. Sports Physiol. Perform.* **2017**, *12*, S235–S241. [[CrossRef](#)] [[PubMed](#)]
58. Russell, M.; Benton, D.; Kingsley, M. Reliability and Construct Validity of Soccer Skills Tests That Measure Passing, Shooting, and Dribbling. *J. Sports Sci.* **2010**, *28*, 1399–1408. [[CrossRef](#)] [[PubMed](#)]
59. Ali, A.; Williams, C.; Hulse, M.; Strudwick, A.; Reddin, J.; Howarth, L.; Eldred, J.; Hirst, M.; McGregor, S. Reliability and Validity of Two Tests of Soccer Skill. *J. Sports Sci.* **2007**, *25*, 1461–1470. [[CrossRef](#)] [[PubMed](#)]
60. Levanon, J.; Dapena, J. Comparison of the Kinematics of the Full-Instep and Pass Kicks in Soccer. *Med. Sci. Sports Exerc.* **1998**, *30*, 917–927.
61. Büker, L.C.; Zuber, F.; Hein, A.; Fudickar, S. HRDepthNet: Depth Image-Based Marker-Less Tracking of Body Joints. *Sensors* **2021**, *21*, 1356. [[CrossRef](#)]
62. Fani, H.; Mirlohi, A.; Hosseini, H.; Herperst, R. Swim Stroke Analytic: Front Crawl Pulling Pose Classification. In Proceedings of the 2018 25th IEEE International Conference on Image Processing (ICIP), Athens, Greece, 7–10 October 2018; pp. 4068–4072.
63. D’Antonio, E.; Taborri, J.; Mileti, I.; Rossi, S.; Patané, F. Validation of a 3D Markerless System for Gait Analysis Based on OpenPose and Two RGB Webcams. *IEEE Sens. J.* **2021**, *21*, 17064–17075. [[CrossRef](#)]
64. Papic, C.; Sanders, R.H.; Naemi, R.; Elipot, M.; Andersen, J. Improving Data Acquisition Speed and Accuracy in Sport Using Neural Networks. *J. Sports Sci.* **2021**, *39*, 513–522. [[CrossRef](#)]