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Accuracy of a markerless system to estimate the position of taekwondo athletes in an official combat area

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ABSTRACT

Obtaining kinematic analysis through a gold-standard method on sports during official competitions is challenging. Markerless tracking system can be an alternative to provide physical and technical-tactical performance data about the athletes. Therefore, we aimed to verify whether the markerless system (OpenPose) accurately tracks taekwondo athletes' positions on the official combat area. Six taekwondo athletes performed steps and kicks in a self-selected way in two conditions: with and without an opponent. To capture the movement, seven optoelectronic (marker-based system) and two digital cameras (OpenPose markerless system) were placed around the combat area at an acquisition frequency of 120 Hz and 30 Hz, respectively. Positions of the body centre of mass and mid-point of the feet were calculated and analysed through two and three-dimensional reconstruction both. The root mean square (RMS) error comparing both methods ranged from 0.13 to 0.32 m and 0.05 to 0.16 m for two and three-dimensional analysis, respectively. Bland-Altman analysis accepted the agreement between the capture systems, and the intraclass coefficient correlation (ICC) values were classified as excellent (ICC > 0.90) in all analysis. In conclusion, the OpenPose markerless system presents promising results for its use in tracking taekwondo athletes' position on the competition area.

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OpenPose; deep learning; combat sports; kinematics; martial arts; biomechanics

1. Introduction

Extracting accurate athletes' kinematics profiles is crucial to understanding their physical and technical-tactical behaviour in competitions or training (Lara et al., 2018). Currently, several tools can track players on the field/court, such as GPS, marker-based, and markerless systems (Lara et al., 2018; Linke et al., 2018; Palucci Vieira et al., 2022).

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The gold-standard method for determining the athlete's position as a function of time is through the marker-based optical system (Needham et al., 2021). However, this approach has some restrictions. For example, it is required highly controlled lighting environment conditions and the placement of markers should be done by an expert evaluator (Nakano et al., 2020; Ong et al., 2017). Furthermore, markers need to be attached to bony landmarks on the skin to avoid errors (Bini et al., 2022), but this is not viable during official sports competitions, such as taekwondo. Thus, markerless systems are an alternative to tracking athletes.

Recently, deep learning technology has been developed to estimate human pose estimation and joint centre identification (Bini et al., 2022; Yamamoto et al., 2021). This method uses algorithms that are trained on several images of different people performing various activities (e.g. walking, jumping, dancing, etc.), resulting in good detection of body landmarks on images similar to the data training (Bini et al., 2022; Needham et al., 2021; Stenum et al., 2021). It is necessary the use of red, blue, and green (RBG) images as input to produce the 2D locations of anatomical key-points (joins centre and body segment) for each person in the image as output (Qiao et al., 2017). In addition, it is possible to make a three-dimensional analysis if synchronised with two or more cameras (Stenum et al., 2021). In this regard, OpenPose is one of the most popular free library able to detect up to 135 key-points (including body, hand, facial, and foot) on a single image (Ota et al., 2020; Stenum et al., 2021).

To date, OpenPose has been demonstrated to be acceptable for kinematic analysis in different sports activities, including human walking (Stenum et al., 2021), running (Needham et al., 2021), jumping (Nakano et al., 2020), cycling (Bini et al., 2022), ball throwing (Nakano et al., 2020), and soccer (Palucci Vieira et al., 2022). Although previous studies revealed high accuracy, agreement, and reliability, most of them were performed indoors, in controlled environments, or without the possibility of mutual occlusion. To our knowledge, no studies determined its measurement error considering specific taekwondo actions or involving an opponent, which can generate some occlusion between participants.

The most common kinematical analysis of athletes during official competition with video-based systems are based on image segmentation to estimate the centre of mass (CM) or the positioning of specific body segments (Barros et al., 2007; Needham et al., 2021). In Taekwondo, the detection of athletes trajectories was reported using the midpoint between the feet (MPF) (Maloney et al., 2018). Consequently, it is crucial to investigate whether a markerless system can effectively track athletes' CM and MPF.

Therefore, the purpose was to evaluate the two-dimensional (single-camera setup) and three-dimensional (two cameras setup) accuracy of a markerless system (OpenPose) to determine the position of taekwondo athletes in an official competition area. For this study, we used OpenPose to estimate the body segments and, posteriorly, calculated the centre of mass and the midpoint between the feet, projected them on the ground, and compared them with a gold-standard method. We hypothesised that OpenPose is an accurate tool to track taekwondo athletes' position as a function of time during simulated competition.

2. Materials and methods

2.1. Participants

Six taekwondo athletes (three male, three female) participated in this study (competitive level: national $n = 2$, international $n = 4$; mean (standard deviation) age: 22.3 (3.4) years; body mass: 65.2 (9.7) Kg; height: 1.71 (0.08) m; training experience: 11.2 (2.7) years). Their taekwondo skills ranged between 1° gub and 1° dan. Exclusion criteria included previous musculoskeletal injuries in the lower limbs. All participants gave written informed consent to participate. The experimental procedures of the study were approved by the research ethics committee of the local university.

2.2. Procedures

The task consisted of executed skipping and kicks, according to the relationship between effort and pause reported in the literature (Avakian et al., 2016). Thus, the athletes performed steps for 6 s and kicks for 3 s for 2 min, corresponding to one round. Participants were instructed to perform steps and kicks in a self-selected way and speed. However, they were oriented to explore the entire combat area and execute kicks in the trunk and head. Therefore, they used forward, backward, and lateral steps and performed attack and counterattack actions by circular or spinning kicks with both legs. This procedure was applied in two conditions: with and without an opponent. For the condition without an opponent, athletes did not have a target to hit. In contrast, for the condition with an opponent, athletes aimed to hit taekwondo-specific trunk protection or reach the feet closest to the head.

2.3. Data acquisition and treatment

Motion data were captured concurrently using marker-based and markerless motion capture systems. We adopted two different distinct procedures to analyse marker-based and markerless system variables: two-dimensional reconstruction and three-dimensional reconstruction. Further details are explained below.

2.3.1. Marker-based system

Seven cameras (Optitrack® - Optical Motion Capture Solutions, NaturalPoint, EUA) were positioned to obtain the landscape view of the entire competition area at a sampling rate of 120 Hz. Seventeen spherical markers were attached externally on the participant's suprasternal and right and left side of the acromion, lateral epicondyle of the humerus, styloid process of the ulna, greater femoral trochanter, lateral epicondyle of the femur, lateral malleolus, calcaneus, and at the base of the hallux (de Leva, 1996).

The Optitrack system was calibrated according to the manufacturer's specifications. The coordinate system was defined for the volume of the competition space as width (x), length (y), and vertical (z). Markers were identified and reconstructed in Motive Body 1.0 Software (Natural Point, U.S.A.). In a Matlab environment (The MathWorks, Natick, Massachusetts, U.S.A.), the coordinates of markers were filtered using a fifth-order low-pass Butterworth filter using a cut-off frequency of 12 Hz, defined after spectral and residual analysis. To compare to the markerless system, the data were reduced to a sampling rate of 30 Hz, maintaining the synchronisation between the systems.

2.3.2. Markerless system

Two digital cameras (Casio EX10) at a sampling rate of 30 Hz and full high definition (FHD) resolution (1920 × 1080 pixels) were positioned to obtain the landscape view of the entire competition area. Joint centre locations were computed using OpenPose, a deep-learning-based approach. Twenty-five key-points of the participant's body were outputted independently, for each frame, using the execution of the OpenPose (2017, V1.7.0) body_25 model (https://github.com/CMU-Perceptual-Computing-Lab/openpose).

Two-dimensional (2D) and three-dimensional (3D) reconstruction were measured using a calibration pole with seven markings. A common calibration frame containing 56 control points on the competition area was defined to cover the competition area completely. The coordinate system was described for the volume of the competition space as width (x), length (y), and vertical (z). In the two-dimensional reconstruction, we focused on calibrating the surface of the competition area (X and Y). On the other hand, for the three-dimensional reconstruction, we performed a calibration of the volume of the competition space (X, Y, and Z). Thus, the calibration parameters of the mathematical image – object transformation were calculated based on the DLT (Direct Linear Transformation) (Abdel-Aziz & Karara, 1971). Once the global coordinate systems did not coincide, the Optitrack global coordinate system was rotated and translated to the markerless global coordinate system. 2D and 3D reconstructions were realised in DVideo Software (Figueroa et al., 2006a, 2006b). In a Matlab environment, gaps were filled up to 30 frames (~1 s), and the coordinates of markers were filtered using a fifth-order low-pass Butterworth filter using a cut-off frequency of 0.5 and 3.5 Hz, for 2D and 3D analysis, respectively, defined after spectral and residual analysis. To evaluate experimental errors, an accuracy test was performed (Barbieri et al., 2010). The calculated accuracy value of this study was 0.003 m; precision was 0.002 m, and bias was 0.002 m.

OpenPose can detect the pose of one or more people in each frame. Therefore, in the condition with interaction, a tracking strategy was necessary for associating a set of poses in a reference frame (t) with subsequent frames ($t+1$). Firstly, key-points were determined in the reference frame, and posteriorly they were associated with the pose in the frame $t+1$ by the smallest Euclidean distance. The adjustments were made for the whole body, then errors in the exchange of member identification among the participants were identified and removed from the analysis. In 5.5% of the total frames, OpenPose erroneously switched the key-points identification with the opponent.

2.4. Measures

The dependent variables of the current study were determined for both conditions (with and without an opponent) and included 2D and 3D positions of the CM and MPF (Figure 1). CM was calculated using the adapted model of De Leva (de Leva, 1996), excluding the head and hands. MPF was calculated from the CM of each foot. Thus, 2D and 3D reconstruction of the CM and MPF positions were calculated, and subsequently,

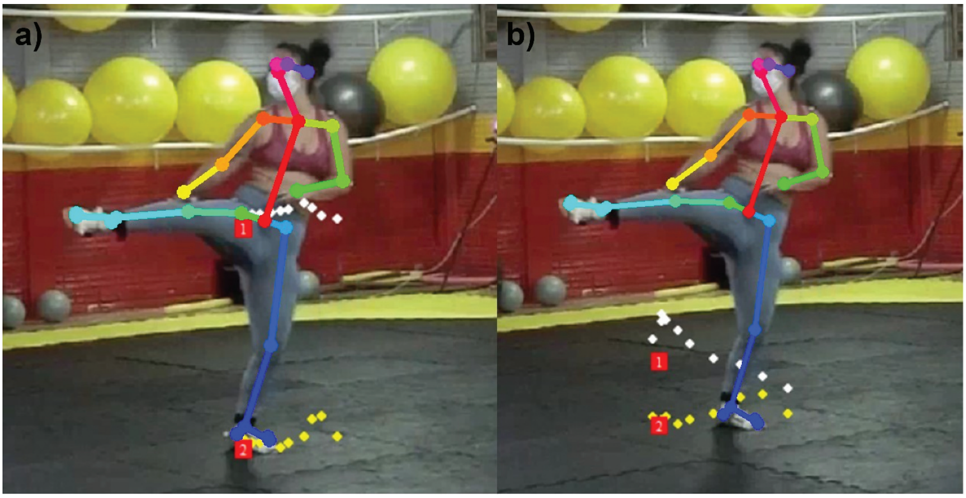

Figure 1. Illustration of the position projection on the ground of the (a) centre of mass and (b) midpoint between the feet, digitised using OpenPose in a condition without an opponent. Point 1: represents the centre of mass (figure A) and midpoint between the feet (figure B). Point 2: represents the projection on the ground of the centre of mass (figure a) and the midpoint between the feet (figure b).

these positions were projected onto the ground of the competition area. In both methodologies of reconstruction, the variables are compared with the standard gold method (Optitrack). Independent variables were the projected coordinates by both distinct methods used (OpenPose markless system and Optitrack marker-based system) for tracking.

2.5. Statistical analysis

Accuracy was analysed by the root mean square error (RMSE), standard error of the mean (SEM), and coefficient of variation (CV) for the x and y coordinates in both conditions. To analyse the agreement between the capture systems, we used the Bland Altman graphics analysis, using the limits of agreement of 95%. The reliability of the CM and MPF was analysed by the intraclass coefficient correlation (ICC). An ICC < 0.40 will be considered as "low"; between 0.40 and 0.70 as "acceptable"; between 0.70 and 0.90 as "good" and > 0.90 as "excellent" (Tayech et al., 2018). All statistical analyses were performed using Matlab software, with a significance level set at 5%.

3. Results

3.1. Two-dimensional reconstruction

Considering all participants 19,187 frames (~10.7 min) were processed in the condition without an opponent and 17,061 frames (~9.5 min) with an opponent. Figure 2 illustrates

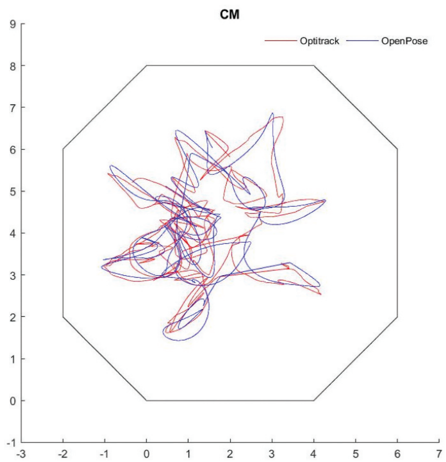

Figure 2. Representation of positions of the centre of mass (CM) and the midpoint of the feet (MPF) in a two-dimensional reconstruction in a condition without an opponent.

Table 1. Root mean square error (RMSE), standard error of the mean (SEM), and coefficient of variation (CV) for x and y coordinates in two-dimensional positions (m) of the centre of mass and midpoint of the feet in a condition without an opponent derived from the comparison between marker-based and markerless systems.

	Without an Opponent											
	CM X			MPF X			CM Y			MPF Y		
	RMSE (m)	SEM (m)	CV (%)	RMSE (m)	SEM (m)	CV (%)	RMSE (m)	SEM (m)	CV (%)	RMSE (m)	SEM (m)	CV (%)
Participant 1	0.191	0.003	81.71	0.262	0.004	83.31	0.144	0.002	78.93	0.207	0.003	78.94
Participant 2	0.170	0.001	61.32	0.195	0.002	77.58	0.164	0.002	74.68	0.186	0.002	77.41
Participant 3	0.259	0.003	75.93	0.277	0.004	85.44	0.246	0.004	79.67	0.260	0.004	79.86
Participant 4	0.196	0.002	73.47	0.228	0.003	74.54	0.134	0.002	78.99	0.216	0.003	78.49
Participant 5	0.252	0.003	79.24	0.251	0.003	77.40	0.198	0.002	81.45	0.209	0.002	83.87
Participant 6	0.188	0.003	79.94	0.216	0.003	88.77	0.191	0.003	87.21	0.219	0.003	84.85
Mean	**0.209**	**0.002**		**0.238**	**0.003**		**0.180**	**0.002**		**0.216**	**0.003**	
SD	**0.037**	**0.001**		**0.031**	**0.001**		**0.042**	**0.001**		**0.024**	**0.001**	

CM: Center of Mass; SD: Standard Deviation; SEM: standard error of the mean; MPF: Midpoint between the feet; X: anteroposterior; Y: mediolateral.

an example of one participant's CM and MPF positions in the condition without an opponent.

Tables 1 and 2 present the RMSE, SEM, and CV for the x and y coordinates of CM and MPF obtained by OpenPose and Optitrack systems. For the condition without an opponent, the CM and MDF RMSE values ranged from 0.13 to 0.25 m and 0.18 to 0.27 m, respectively. Concerning the condition with an opponent, the CM and MDF RMSE values ranged from 0.19 to 0.30 m and 0.21 to 0.32 m, respectively (Tables 1 and 2).

In condition without interaction, the mean of systematic errors (mean bias) ranged from 0.073 to 0.188 m for the CM and from 0.073 to 0.168 m for MPF on the x coordinate, and from 0.001 to 0.152 m for the CM and from 0.008 to 0.137 m for the MPF on the y coordinate. In condition with interaction, mean bias ranged from 0.038 to

Table 2. Root mean square error (RMSE), standard error of the mean (SEM), and coefficient of variation (CV) for x and y coordinates in two-dimensional positions (m) of the centre of mass and midpoint of the feet in a condition with an opponent derived from the comparison between marker-based and markerless systems.

	With an Opponent											
	CM X			MPF X			CM Y			MPF Y		
	RMSE (m)	SEM (m)	CV (%)	RMSE (m)	SEM (m)	CV (%)	RMSE (m)	SEM (m)	CV (%)	RMSE (m)	SEM (m)	CV (%)
Participant 1	0.224	0.003	81	0.242	0.004	89.6	0.198	0.003	96.02	0.238	0.004	100.13
Participant 2	0.229	0.002	66.63	0.254	0.003	75.60	0.198	0.003	70.1	0.223	0.003	79.38
Participant 3	0.306	0.005	64.38	0.324	0.005	74.52	0.262	0.004	75.38	0.284	0.005	85.73
Participant 4	0.264	0.004	96.02	0.295	0.005	104.47	0.243	0.003	86.25	0.266	0.004	85.78
Participant 5	0.231	0.003	78.06	0.273	0.004	99.39	0.231	0.003	80.86	0.231	0.004	84.96
Participant 6	0.210	0.004	83.71	0.228	0.004	86.27	0.215	0.004	85.52	0.214	0.004	76.54
Mean	**0.244**	**0.003**		**0.269**	**0.004**		**0.224**	**0.003**		**0.243**	**0.004**	
SD	**0.035**	**0.001**		**0.036**	**0.001**		**0.026**	**0.001**		**0.027**	**0.001**	

CM: Center of Mass; SD: Standard Deviation; SEM: standard error of the mean; MPF: Midpoint between the feet; X: anteroposterior; Y: mediolateral.

0.189 m for the CM and from 0.016 to 0.174 m for MPF on the x coordinate, and from 0.018 to 0.156 m for the CM and from 0.013 to 0.144 m for the MPF on the y coordinate (Supplementary Material). Considering the mean difference of all participants between the methods and the limits of agreement of 95%, only for the x coordinate in the condition with an opponent 5.2% of the data did not fall within the Bland Altman limits of agreement.

OpenPose demonstrated high reliability, with ICC values classified as excellent (ICC > 0.90), for both conditions (without an opponent and with an opponent) and reconstruction (2D and 3D) (Table 3).

3.2. Three-dimensional reconstruction

Adding all participants 20,192 frames (~11.2 min) were processed in condition without an opponent and 15,295 frames (~8.5 min) with an opponent. Figure 3 illustrates an example of one participant's CM and MPF positions in the condition without an opponent.

Tables 4 and 5 illustrate the RMSE, SEM, and CV x and y coordinates of CM and MPF obtained by OpenPose and Optitrack systems. For the condition without an opponent, the CM and MDF RMSE values ranged from 0.05 to 0.09 m and 0.05 to 0.13 m, respectively. Concerning the condition with an opponent, the CM and MDF RMSE values ranged from 0.07 to 0.12 m and 0.10 to 0.16 m, respectively (Tables 4 and 5).

In condition without interaction, the mean of systematic errors (mean bias) ranged from 0.005 to 0.045 m for the CM and from 0.011 to 0.036 m for MPF on the x coordinate, and from 0.023 to 0.056 m for the CM and from 0.006 to 0.039 m for the MPF on the y coordinate. In condition with interaction, mean bias ranged from 0.002 to 0.044 m for the CM and from 0.001 to 0.042 m for MPF on the x coordinate, and from 0.018 to 0.156 m for the CM and from 0.005 to 0.055 m for the MPF on the y coordinate (Supplementary Material). Considering the mean difference between the methods and the limits of agreement of 95%, there is an agreement between the methods.

Table 3. Intraclass coefficient correlation (ICC) for x and y coordinates in two-dimensional positions (m) of the centre of mass and midpoint of the feet in a marker-based and markerless system in the conditions with and without an opponent.

	Without an Opponent				With an Opponent			
	CM X	MPF X	CM Y	MPF Y	CM X	MPF X	CM Y	MPF Y
	ICC (IC 95%)	ICC (IC 95%)	ICC (IC 95%)	ICC (IC 95%)	ICC (IC 95%)	ICC (IC 95%)	ICC (IC 95%)	ICC (IC 95%)
Participant 1	0.985* (0.984–0.986)	0.975* (0.973–0.976)	0.991* (0.990–0.991)	0.983* (0.982–0.984)	0.966* (0.964–0.968)	0.963* (0.960–0.965)	0.974* (0.972–0.975)	0.964* (0.962–0.966)
Participant 2	0.987* (0.986–0.988)	0.984* (0.983–0.985)	0.990* (0.989–0.990)	0.988* (0.987–0.989)	0.959* (0.956–0.962)	0.952* (0.948–0.955)	0.976* (0.974–0.977)	0.971* (0.968–0.972)
Participant 3	0.971* (0.969–0.973)	0.968* (0.965–0.970)	0.980* (0.979–0.982)	0.980* (0.978–0.981)	0.965* (0.962–0.968)	0.962* (0.959–0.965)	0.984* (0.983–0.985)	0.982* (0.980–0.983)
Participant 4	0.975* (0.974–0.977)	0.968* (0.966–0.970)	0.983* (0.982–0.984)	0.979* (0.978–0.981)	0.965* (0.963–0.968)	0.959* (0.956–0.962)	0.972* (0.970–0.974)	0.968* (0.966–0.970)
Participant 5	0.970* (0.968–0.972)	0.970* (0.968–0.972)	0.989* (0.989–0.990)	0.988* (0.988–0.989)	0.965* (0.962–0.968)	0.954* (0.951–0.957)	0.989* (0.988–0.990)	0.989* (0.988–0.990)
Participant 6	0.983* (0.982–0.984)	0.979* (0.977–0.980)	0.986* (0.985–0.987)	0.984* (0.983–0.985)	0.974* (0.972–0.976)	0.972* (0.970–0.974)	0.975* (0.973–0.977)	0.977* (0.975–0.979)

*Significant Correlation, $p < 0{,}001$. CM: Center of Mass; MPF: Midpoint between the feet; X: anteroposterior; Y: mediolateral.

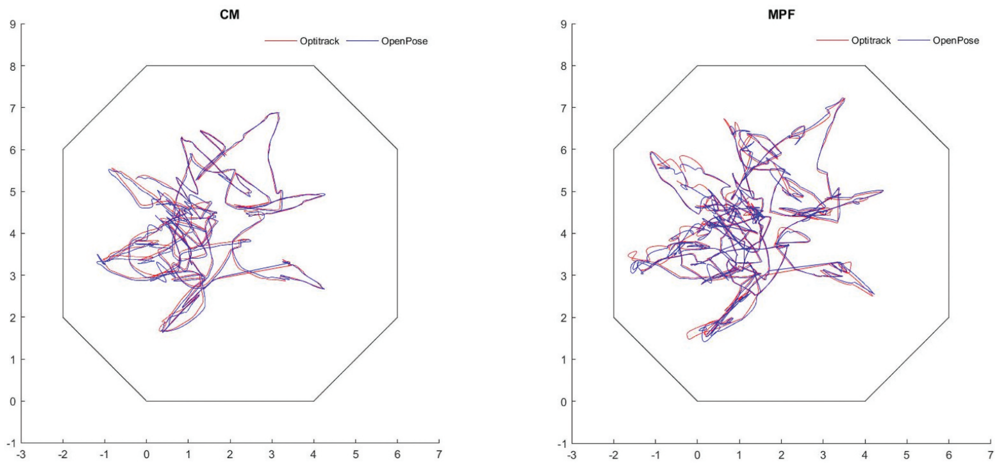

Figure 3. Representation of positions of the centre of mass (CM) and the midpoint of the feet (MPF) in a three-dimensional reconstruction in a condition without an opponent.

Table 4. Root mean square error (RMSE), standard error of the mean (SEM), and coefficient of variation (CV) for x and y coordinates in three-dimensional positions (m) of the centre of mass and midpoint of the feet in a condition without an opponent derived from the comparison between marker-based and markerless systems.

	Without an Opponent											
	CM X			MPF X			CM Y			MPF Y		
	RMSE (m)	SEM (m)	CV (%)	RMSE (m)	SEM (m)	CV (%)	RMSE (m)	SEM (m)	CV (%)	RMSE (m)	SEM (m)	CV (%)
Participant 1	0.080	0.001	74.95	0.136	0.002	87.57	0.076	0.001	72.58	0.114	0.002	99.14
Participant 2	0.073	0.001	78.35	0.077	0.001	96.21	0.052	0.001	84.04	0.057	0.001	104.03
Participant 3	0.090	0.001	80.70	0.104	0.001	88.73	0.067	0.001	89.38	0.089	0.001	111.30
Participant 4	0.054	0.001	88.94	0.094	0.001	122.60	0.051	0.001	81.27	0.079	0.001	117.29
Participant 5	0.076	0.001	79.49	0.091	0.001	83.30	0.077	0.001	62.31	0.086	0.001	91.19
Participant 6	0.066	0.001	72.42	0.085	0.001	100.45	0.060	0.001	67.12	0.083	0.001	130.56
Mean	**0.072**	**0.001**		**0.090**	**0.001**		**0.061**	**0.001**		**0.079**	**0.001**	
SD	**0.013**	**0.000**		**0.021**	**0.000**		**0.012**	**0.000**		**0.018**	**0.000**	

CM: Center of Mass; SD: Standard Deviation; SEM: standard error of the mean; MPF: Midpoint Between the Feet; X: anteroposterior; Y: mediolateral.

OpenPose demonstrated high reliability, with ICC values classified as excellent (ICC > 0.90), for both conditions (without an opponent and with an opponent) and reconstruction (2D and 3D (Table 6)).

4. Discussion

The current study aimed to compare the accuracy of OpenPose against the gold-standard method in determining taekwondo athletes' position in an official competition area. The results revealed that the method proposed in this study had high reliability and agreement for two and three-dimensional analysis with and without an opponent. In the

Table 5. Root mean square error (RMSE), standard error of the mean (SEM), and coefficient of variation (CV) for x and y coordinates in three-dimensional positions (m) of the centre of mass and midpoint of the feet in a condition with an opponent derived from the comparison between marker-based and markerless systems.

	With an Opponent											
	CM X			MPF X			CM Y			MPF Y		
	RMSE (m)	SEM (m)	CV (%)	RMSE (m)	SEM (m)	CV (%)	RMSE (m)	SEM (m)	CV (%)	RMSE (m)	SEM (m)	CV (%)
Participant 1	0.086	0.001	118.86	0.125	0.002	96.77	0.072	0.001	91.55	0.113	0.002	87.15
Participant 2	0.100	0.001	88.91	0.119	0.002	99.98	0.082	0.001	92.89	0.102	0.001	98.96
Participant 3	0.128	0.002	81.76	0.157	0.003	81.65	0.106	0.001	92.74	0.133	0.002	95.18
Participant 4	0.099	0.002	77.91	0.161	0.003	97.21	0.104	0.002	72.18	0.144	0.003	86.67
Participant 5	0.071	0.001	84.58	0.121	0.002	83.9	0.106	0.001	56.2	0.121	0.002	95.78
Participant 6	0.072	0.001	94.46	0.141	0.002	89.53	0.071	0.001	84.73	0.152	0.002	98.72
Mean	**0.094**	**0.001**		**0.140**	**0.002**		**0.094**	**0.001**		**0.130**	**0.002**	
SD	**0.021**	**0.000**		**0.019**	**0.000**		**0.017**	**0.000**		**0.019**	**0.000**	

CM: Center of Mass; SD: Standard Deviation; SEM: standard error of the mean; MPF: Midpoint between the feet; X: anteroposterior; Y: mediolateral.

following paragraphs, the strengths and weaknesses relating to the application are discussed.

To our knowledge, no previous work has investigated the accuracy of OpenPose in sports situations involving more than one person. Although OpenPose has been trained in activities with single and multiple people, we verified some increase in error values in the condition with an opponent. These can be explained by partial or total athlete occlusion provided by the opponent (Figure 4), which requires a more complex algorithms to solve the assemble issues and to fill the gaps.

In our study, we tracked the participants by the CM and MPF position, using an acquisition frequency of 30 Hz. The literature reported that a low acquisition frequency causes blur images, especially at fast movements, inducing inaccuracies in pose estimation (Ong et al., 2017; Stenum et al., 2021). Although 30 Hz is considered a low frequency, it is acceptable for obtaining information about human tracking in tennis (Lara et al., 2018), soccer (Barros et al., 2007), handball (Barros et al., 2011), and futsal (De Oliveira Bueno et al., 2014). Moreover, high acquisition frequencies are unusually used in cameras broadcasting sports championships.

Concerning the MPF, errors also may occur due to sudden changes in velocity in these limbs, which will modify the image properties, influencing pose estimation (Palucci Vieira et al., 2022). In addition, the magnitude of the errors increases as the speed of the object/person of interest increases (Linke et al., 2018). In taekwondo, displacement of the feet happens at high velocity, reaching a linear velocity of 14.66 m/s (Gavagan et al., 2017), then higher error values are expected. Previous studies sustain our result, showing higher error values on ankle joints during walking and running than on hip and knees (Ong et al., 2017; Yamamoto et al., 2021), reaching a mean absolute error of 58.1 mm (Nakano et al., 2020).

In 2D reconstruction, the error ranged from 1.62% (0.13 m) to 4% (0.32 m) of the width and length of the competition area. Similar results were found in tennis, where position errors ranged from 0.17 m to 0.24 m, generating an accuracy of 0.36 m, representing 3.3% of the width and 3% of the length of the court (Lara et al., 2018). On the

Table 6. Intraclass coefficient correlation (ICC) for x and y coordinates in three-dimensional positions (m) of the centre of mass and midpoint of the feet in a marker-based and markerless system in the conditions with and without an opponent.

	Without an Opponent				With an Opponent			
	CM X	MPF X	CM Y	MPF Y	CM X	MPF X	CM Y	MPF Y
	ICC (IC 95%)	ICC (IC 95%)	ICC (IC 95%)	ICC (IC 95%)	ICC (IC 95%)	ICC (IC 95%)	ICC (IC 95%)	ICC (IC 95%)
Participant 1	0.997* (0.997–0.997)	0.993* (0.992–0.993)	0.997* (0.997–0.997)	0.994* (0.994–0.995)	0.994* (0.994–0.995)	0.989* (0.989–0.990)	0.996* (0.996–0.996)	0.992* (0.991–0.992)
Participant 2	0.997* (0.997–0.997)	0.997* (0.997–0.997)	0.999* (0.998–0.999)	0.998* (0.998–0.999)	0.993* (0.993–0.994)	0.991* (0.990–0.991)	0.993* (0.993–0.994)	0.990* (0.989–0.991)
Participant 3	0.996* (0.996–0.996)	0.995* (0.995–0.995)	0.998* (0.998–0.998)	0.998* (0.997–0.998)	0.992* (0.991–0.993)	0.989* (0.988–0.990)	0.997* (0.997–0.997)	0.995* (0.995–0.996)
Participant 4	0.998* (0.997–0.998)	0.997* (0.997–0.997)	0.998* (0.998–0.998)	0.994* (0.994–0.994)	0.993* (0.992–0.993)	0.983* (0.982–0.984)	0.995* (0.995–0.996)	0.992* (0.991–0.993)
Participant 5	0.997* (0.996–0.997)	0.995* (0.995–0.996)	0.998* (0.998–0.998)	0.998* (0.997–0.998)	0.994* (0.993–0.994)	0.984* (0.983–0.986)	0.997* (0.997–0.998)	0.997* (0.997–0.997)
Participant 6	0.997* (0.997–0.998)	0.996* (0.996–0.997)	0.998* (0.998–0.998)	0.997* (0.997–0.998)	0.996* (0.996–0.997)	0.988* (0.987–0.989)	0.996* (0.996–0.997)	0.987* (0.986–0.988)

*Significant Correlation, $p < 0{,}001$. CM: Center of Mass; MPF: Midpoint between the feet; X: anteroposterior; Y: mediolateral.

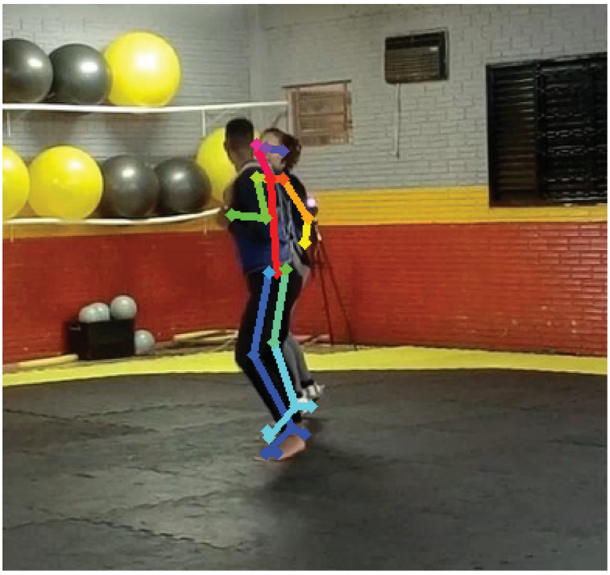

Figure 4. OpenPose errors in detecting multiple people due to the occlusion provided by the opponent.

other hand, our results were better than those found in soccer (0.56 m) (Linke et al., 2018). Although our method presents a relevant result, it is recommended cameras placed above the court or in the highest place to avoid occlusion and perspective errors (Barros et al., 2007; Lara et al., 2018), different from our study, which was fixed a few centimetres from the floor.

Concerning 3D reconstruction, errors ranged from 0.63% (0.05 m) to 2% (0.16 m) of the width and length of the competition area. Previous studies reported that approximately 47% of the mean absolute errors were less than 0.02 m, and 80% were less than 0.03 m (Nakano et al., 2020). In accordance, the mean absolute errors of OpenPose in three-dimensional positions were 0.034 m for determining positions during kicks (Palucci Vieira et al., 2022) and 0.05 m in sprints (Needham et al., 2021). Our error values were higher than literature, which could be explained by the differences in the number of cameras (four (Palucci Vieira et al., 2022), five (Nakano et al., 2020), or nine (Needham et al., 2021)), acquisition frequency (200 Hz (Needham et al., 2021) or 240 Hz (Palucci Vieira et al., 2022)), and the task (ball kicking (Palucci Vieira et al., 2022), walking, jumping, and throwing (Nakano et al., 2020), or linear sprints (Needham et al., 2021)).

Uncertainties in the detection of the key-points can suffer influence due to the different positions and perspectives of the participant towards the image field in each frame (Nakano et al., 2020; Stenum et al., 2021). In the present study, participants did not have any restriction of direction to perform steps and kicks. Therefore, accuracy could be influenced due the different positions that the participants assumed during the task, as seen in the diverse outcomes found on the x and y axis (Tables 1, 2, 4, and 5). In addition, neural networks are usually trained in habitual situations (walking, dancing, jumping, etc.) (Bini et al., 2022; Needham et al., 2021). Thereby, it is expected that analyses with similar poses to the training models would create better results. Thus, retraining based on similar dataset characteristics is essential to further reduce errors in the accuracy of determining positions.

Taekwondo combat rules require that the athletes use specified clothes (dobok) and equipment, which was not accomplished in our study. Despite this being a potential source of error, the literature demonstrated that clothing conditions do not significantly affect segment lengths, gait spatiotemporal parameters, and lower-limb kinematics in gait parameters when using a markerless system (Keller et al., 2022). Therefore, we believe that dobok would not have a substantial impact on the detection of key-points, however further studies are required to address this condition in sport contexts.

In general, the key-points detection can be influenced by acquisition frequency, velocity of the segment, and different positions and perspectives. In our study, we only evaluated the CM and MPF positions. However, it is crucial to examine the position of each specific body segment, even though that the CM is influenced by errors introduced by body segments. Previous studies suggest that certain segments may exhibit a higher error estimation (Ong et al., 2017; Stenum et al., 2021; Yamamoto et al., 2021). The uncertainties associated with OpenPose may vary with velocity and, in taekwondo, the velocity of body segments varies during the kicking (Gavagan et al., 2017; Miziara et al., 2019). Therefore, such analysis remains to be explored in future research.

Additional limitations are also recognised in this study. First, we only used two digital cameras. Joint position estimation improves as the number of cameras increases (Nakano et al., 2020). Second, some sources of error may be intrinsic to OpenPose. Although the CM estimation was done for both systems, body key-points identified by OpenPose are likely to differ from the marker landmarks. Third, the marker-based system provides errors from the researcher's experience and skin movement (Benoit et al., 2006; Sinclair et al., 2014). Fourthly, cameras were event-based synchronised. However, acquisition frequency is not constant, causing a delay in temporal series and, consequently, relatively small errors (Nakano et al., 2020). Finally, simulation protocol did not include punches in the analyses of this study, even though they are allowed actions in taekwondo competitions.

Despite all the errors sources presented, the results are promising. OpenPose demonstrated low error values and high ICC values, classified as excellent. Such analysis can be useful for further performance information, such as identifying the total distance covered, velocities reached, the area of the competition often covered, among other position-derived kinematic variables. All these parameters can be analysed during the entire combat or round by round, providing technical and tactical information. As far as we know, our study was the first to evaluate the accuracy of a markerless system in determining taekwondo athletes' position in a condition with and without an opponent. Although our study conducted research in a condition with interaction, there is more information in the official championship's environment (referee, crowd, etc.). In addition, it was instructed that only one of the athletes performed the kicks, a situation that does not occur in an official competition in which both athletes can perform actions simultaneously.

5. Conclusion

In conclusion, the method evaluated in this study provides a viable alternative and an effective approach to tracking the position of taekwondo athletes in official competition areas. An accurate tracking analysis method by markerless systems in taekwondo athletes will allow coaches to extract technical-tactical information from different athletes in different competitions, using accessible and low-cost technology through videos. Future studies should investigate the accuracy of implementing more cameras with varied acquisition frequencies, aiming to provide the best cost benefit.

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Data sharing statement

All data relevant to the study are included in the manuscript or uploaded as supplementary material.

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