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Comparison of lower limb kinematic and kinetic estimation during athlete jumping between markerless and marker-based motion capture systems

Changzhi Yang[1], Linyu Wei[2,3], Xi Huang[2], Lili Tu[2], Yanjia Xu[4], Xiaolong Li[5]✉ & Zhe Hu[2,3]✉

Markerless motion capture (ML) systems, which utilize deep learning algorithms, have significantly expanded the applications of biomechanical analysis. Jump tests are now essential tools for athlete monitoring and injury prevention. However, the validity of kinematic and kinetic parameters derived from ML for lower limb joints requires further validation in populations engaged in high-intensity jumping sports. The purpose of this study was to compare lower limb kinematic and kinetic estimates between marker-based (MB) and ML motion capture systems during jumps. Fourteen male Division I movement collegiate athletes performed a minimum of three squat jumps (SJ), drop jumps (DJ), and countermovement jumps (CMJ) in a fixed sequence. The movements were synchronized using ten infrared cameras, six high-resolution cameras, and two force measurement platforms, all controlled by Vicon Nexus software. Motion data were collected, and the angles, moments, and power at the hip, knee, and ankle joints were calculated using Theia3D software. These results were then compared with those obtained from the Vicon system. Comparative analyses included Pearson correlation coefficients (r), root mean square differences (RMSD), extreme error values, and statistical parametric mapping (SPM).SPM analysis of the three movements in the sagittal plane revealed significant differences in hip joint angles, with joint angle RMSD ≤ 5.6°, hip joint moments RMSD ≤ 0.26 N·M/kg, and power RMSD ≤ 2.12 W/kg showing considerable variation, though not reaching statistical significance. ML systems demonstrate high measurement accuracy in estimating knee and ankle kinematics and kinetics in the sagittal plane during these conventional jump tests; however, the accuracy of hip joint kinematic measurements in the sagittal plane requires further validation.

Keywords Athletic performance, Sports injury, Jumping, Biomechanics, Lower limb joints, Statistical parametric mapping

Motion capture technology is crucial for human motion analysis[1] particularly in sports science and rehabilitation medicine, where it plays a vital role. By precisely recording and analyzing the movements of athletes, this technology provides a scientific foundation for improving athletic performance and preventing injuries[2]. However, traditional marker-based motion capture (MB) systems have several limitations. These systems require the attachment of numerous reflective markers to the subject's body, a time-consuming and labor-intensive process that can disrupt the subject's natural movement patterns[3]. Additionally, marker placement requires specialized technicians, and in some complex motion scenarios, markers may shift or fall off, leading to inaccurate data[4]. These limitations hinder the widespread use of MB systems in practical settings. In recent years, markerless motion capture (ML) technology has emerged as a significant advancement in the field[5,6]. ML systems employ advanced computer vision and deep learning algorithms to track human body movement

[1]Shandong Sport University, Jinan 250000, China. [2]School of Physical Education, Southwest Medical University, Luzhou, China. [3]Hainan Provincial Key Laboratory of Sports and Health Promotion, Key Laboratory of Emergency and Trauma, Ministry of Education, The First Affiliated Hospital, Hainan Medical University, Haikou 571199, China. [4]Department of Physical Education, Jeonbuk National University, Jeonju 54896, South Korea. [5]Department of Physical Education, Chengdu Sport University, Chengdu 610041, China. ✉email: 136897531@qq.com; huzhe0710@swmu.edu.cn

using cameras, eliminating the need for body markers[5]. his approach offers the dual benefits of convenience and more natural motion, allowing athletes to move freely and providing a more accurate representation of their performance[7]. Furthermore, ML systems are typically more user-friendly, enabling data acquisition without the need for specialized technicians, which lowers the barriers to entry. ML technology has already shown promising results in gait analysis, daily exercise monitoring, and injury assessment, demonstrating its potential for broader applications.Scataglini[8] conducted a study comparing the accuracy, validity, and reliability of a markerless camera-based 3D motion capture system with a traditional marker-based system for gait analysis. They found moderate to excellent inter-system agreement in hip and knee kinematics, but poor concurrent validity and reliability for ankle measurements. Barzyk[9] et al. evaluated the agreement between the Vicon motion capture system and the SMARTGAIT system for knee, hip, and ankle angular kinematics, as well as spatiotemporal gait parameters in both the frontal and sagittal planes in patients with stroke. They found strong agreement between the two systems, with Pearson's correlations of ≥ 0.79 for the sagittal plane and ≥ 0.79 for the frontal plane across all lower-body angular kinematics parameters. The root mean square error (RMSE) values were ≤ 4.6°.Song[10] et al. presented the estimation of lower limb joint kinematics and dynamics by Vicon Nexus and Theia3D in eight common sports in healthy researchers. They observed strong correlations between marker-based and markerless estimates of knee and ankle kinematics and dynamics for the sports tested, and the root-mean-square difference (RMSD) was minimal. Laupattarakasem[11] et al. used DARI Motion for the functional assessment of Division I collegiate athletes and concluded that the markerless motion capture system was effective in providing data for identifying pre-injury functional differences in lower extremity non-contact injuries. A study by Needham[12] et al.evaluated the performance of OpenPose in comparison to Oqus during ground running, walking, and reverse-motion jumping. The results demonstrated high consistency in lower limb joint angles, indicating that the markerless approach could be effectively applied to biomechanical assessments.

Jumping movements are essential for assessing athletic performance and preventing sports injuries[13]. These movements reflect an athlete's explosive lower limb strength and neuromuscular coordination, providing insights into their stability and control during high-speed actions[14]. Analyzing the kinematic and kinetic parameters of the lower limbs during jumping can offer a scientific foundation for developing targeted training plans. Such analyses can help coaches optimize training programs, enhance competitive performance, and reduce the risk of injury[15]. Among the various jump types, the squat jump (SJ), drop jump (DJ), and countermovement jump (CMJ) are the most commonly used for evaluating lower limb motor performance[16,17]. Mackala[18] et al. have shown that SJ and CMJ performance measures help assess or develop lower limb strength capacity, both unilaterally and bilaterally, across different sports. Additionally, these tests can serve as guidelines for preventive or rehabilitation programs for the lower limbs prior to training. In a study by Melick[19] et al., reference values for the two-legged jump tests (SJ and CMJ) were summarized for athletes undergoing anterior cruciate ligament reconstruction (ACLR) and non-athletes, focusing on common rotational sports such as football and basketball. Comparing pre- and post-injury SJ and CMJ test results can help determine an athlete's recovery progress and guide the intensity and frequency of rehabilitation.Kotsifaki[20] and colleagues found that the DJ test is a standard method for assessing performance in healthy athletes due to its simplicity and time efficiency. This test can help reduce injury risk and improve performance by restoring symmetry in kinematic and kinetic data during jumping. However, few comparative studies[21,22] have estimated lower limb parameters for athlete-specific jumping movements using ML and MB systems. This gap is primarily due to the complexity and high speed of these movements, which demand high accuracy and reliability from the motion capture systems. ML systems may encounter image blurring and key-frame capture errors during high-speed motion, leading to inaccuracies[23]. Furthermore, ML systems may struggle with complex motor scenarios and multi-angle motions.

Previous studies have primarily focused on comparing the performance of ML and MB systems in gait analysis[9,24–29] or low-intensity exercise[10,30]. However, few studies have specifically compared the accuracy of these two systems in high-intensity, high-velocity sports scenarios, such as athletes' jumping movements[31]. Jumping movements require the accurate measurement of intricate kinematic and kinetic parameters from the lower limbs, which places increased demands on the accuracy and reliability of motion capture systems. This study addresses this gap by comparing ML and MB systems during high-intensity jumping activities and evaluating their performance in complex motor scenarios. Specifically, we aim to assess the accuracy and reliability of the ML and MB systems by comparing their estimates of lower limb kinematic and kinetic parameters during an athlete's jump. The sparse labeling of key points in neural network-based markerless system datasets limits their utility for comprehensive kinematic and kinetic analyses, particularly in accurately capturing non-sagittal planes of motion[12]. Consequently, we will analyze the differences between the two systems in terms of measuring sagittal plane hip, knee, and ankle joint angles, moments, and power.We hypothesized that the difference between ML and MB in measuring hip parameters would be more pronounced during high-intensity jumping exercises, primarily due to errors in pelvic motion tracking[31], skin artifacts[32], or misalignment of anatomical landmarks[33].

Materials and methods

Participants

This study recruited 14 male Division I collegiate athletes from sports institutions to participate in the experiment. The participants had an average age of 19.38 ± 0.76 years, height of 182 ± 4.83 cm, weight of 72.71 ± 4.37 kg, and BMI of 21.86 ± 0.62 kg/m^2. The inclusion criteria were as follows: (1) no lower extremity or low back injuries for at least 6 months prior to the experiment, (2) a minimum of 6 years of training experience, and (3) participants were required to refrain from high-intensity exercise for 48 h before the formal experiment[10]. This research strictly adheres to the principles outlined in the Declaration of Helsinki revised in 2013. Also, the Institutional Review Board of Jeonbuk National University approved this study under the approval number JBNU2022–04 – 008 – 001. All experimental protocols have been thoroughly reviewed by the ethics committee before implementation.

Motion capture system and experimental setup

For our experiments, we used 10 Vicon MX-F40 motion capture cameras (Vicon Inc., Denver, Colorado, USA) with a resolution of 2352 × 1728 pixels. These cameras tracked the three-dimensional positions of markers at a frequency of 100 Hz, enabling the generation of three-dimensional skeleton models of individuals as they jumped. Additionally, we employed the Theia3D system, provided by Theia Markerless in Kingston, Ontario, Canada. This markerless motion capture method utilizes deep learning algorithms and six Oryx 10GigE cameras (Teledyne FLIR, Wilsonville, Oregon, USA) to calculate the 3D skeleton of the human body from multi-view 2D pose data[34]. Camera calibration was achieved using Direct Linear Transformation (DLT), which maps 3D spatial coordinates to 2D image plane coordinates, enabling the reconstruction of 3D scenes from 2D images[16,17]. Two force measurement platforms (model BP600900, AMTI, Watertown, Massachusetts, USA) were embedded in the floor of the Capture Space Centre to record ground reaction forces at a frequency of 1000 Hz. Synchronized recording of the force platforms and the two motion capture systems was performed using Vicon Nexus software (version 2.16, Vicon Motion Systems Ltd., Oxford, UK) with the synchronization module. The cameras were mounted on rails or tripods around the perimeter of the capture space and tilted towards the force plates. (Fig. 1) Prior to data collection, the cameras were calibrated in three dimensions by setting the origin (reference point) of both systems at the intersection of the two force platforms, ensuring that motion data recorded by the two systems were aligned across all concurrently captured trials[10].

Before the experiment, each participant was introduced to the test protocol and provided written informed consent. Participants changed into shorts provided by the laboratory and wore running shoes to standardize measurement conditions and minimize discrepancies due to clothing or footwear when measuring their height and weight. Prior to the jump test, 28 reflective spherical markers (14 mm) were affixed to specific anatomical landmarks. These included 12 markers on the right and left anterior superior iliac spines, posterior superior iliac spines, knee joints, and ankle joints. Additionally, 12 markers were placed on the upper and lower thirds of the right and left lateral legs, and four markers were positioned on the heels and second metatarsal phalanges of each foot. Participants then stood in the center of the ergometry platform in an anatomical position with arms extended. A static model was recorded, after which four non-tracking markers (medial left and right knees and medial left and right ankles) were removed to minimize movement constraints[35] (Fig. 2) Each participant performed three types of jumps—SJ, DJ, and CMJ—in a fixed order, with 60 to 90 s of rest between trials, to ensure that the same state completed the test. Each participant performed a minimum of three trials for each movement, with the total number of trials varying based on individual performance. Valid data were collected from at least three trials of each movement.

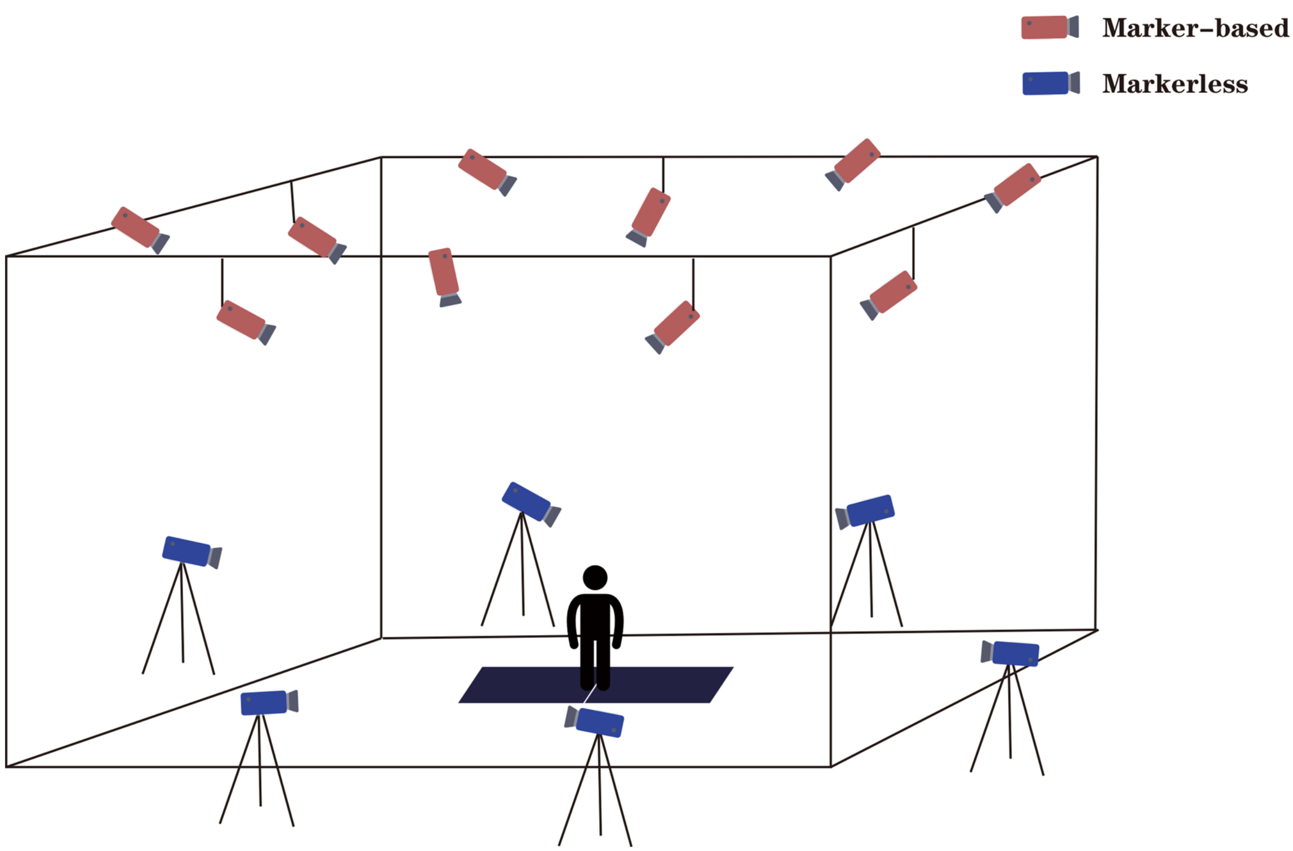

Fig. 1. Overview of the experimental setup; in this example, the research participant is captured in a static model.

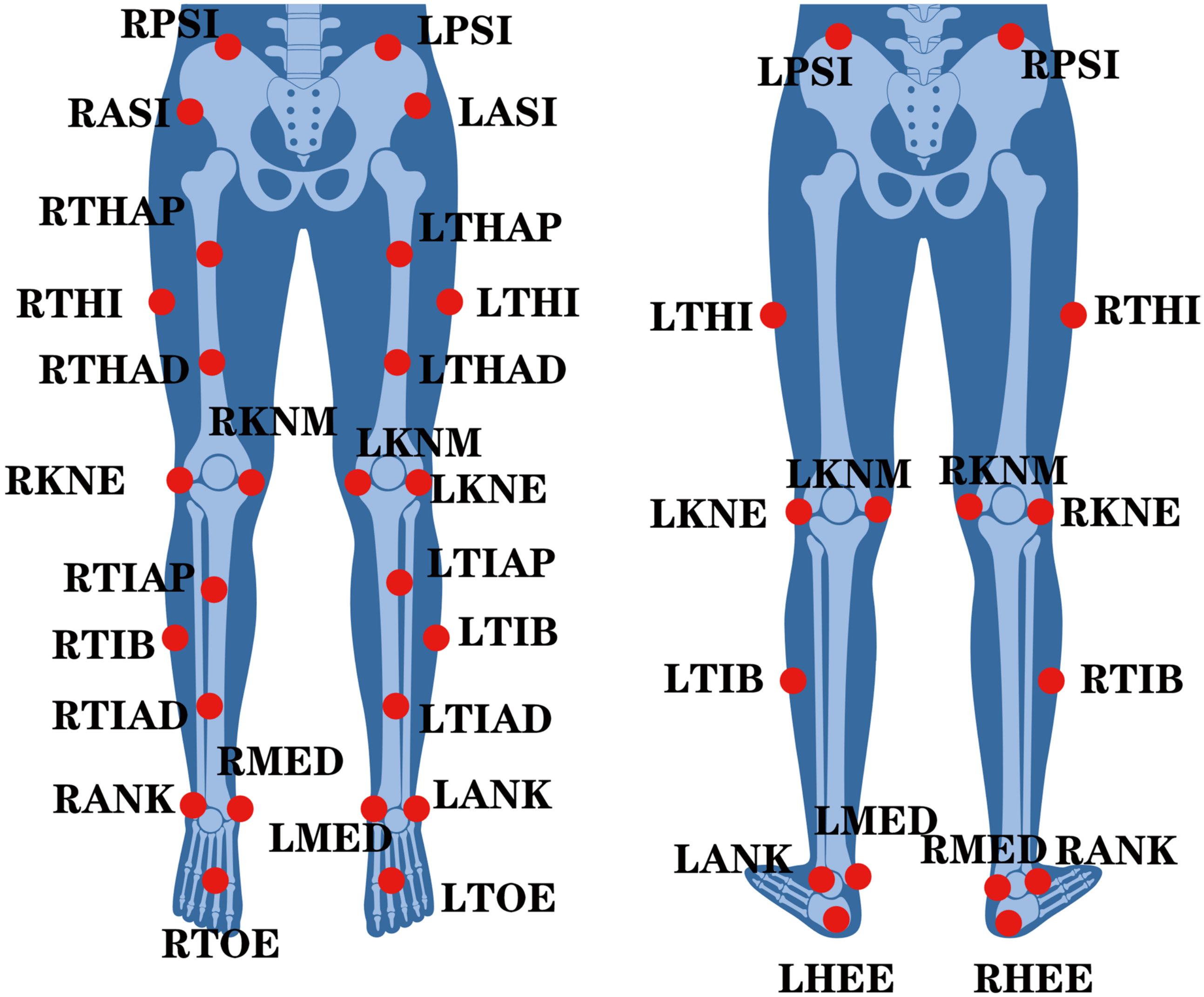

Fig. 2. Setting up markers to track the position of the pelvis and lower limbs during marker-based motion capture.

Data analysis

Data pre-procesing

The data captured by the MB system were interpolated using Woltring gap filling in Vicon Nexus software[36]. Raw video data from the markerless motion capture system were preprocessed with Theia3D software to extract the 2D positions of the identified features in each frame. These 2D positions were then converted into 3D spatial coordinates based on the computed camera positions and orientations. Subsequently, an articulated multibody model was scaled to match the subject-specific landmark positions in 3D space. An inverse kinematics (IK) method was employed to estimate the subject-specific positions of the landmarks throughout the physical task[37].

Visual3D processing

Lower limb data were preprocessed and further analyzed using Visual3D software (Preview v2022.06.02, C-Motion, Germantown, MD, USA). The same Visual3D 6-degree-of-freedom (6DOF) algorithm and inter-segment inverse kinematics (IK) constraints from the MB system were applied to the ML data to generate a corresponding model and segment attributes, such as segment mass, center of mass position, and joint center positions[34]. Visual3D models segments as geometries, including cones, cylinders, spheres, and ellipsoids, and calculates the segment mass for each part based on the Dempster regression equation. Using the proximal segment as a reference to calculate the angles of each lower limb joint in the sagittal plane with the Cardan sequence[38], we focused our kinematic analyses on the sagittal plane. This approach was chosen because the sagittal plane provides more insightful information[39], and previous studies have shown that knee motion deviating from the sagittal plane is particularly susceptible to skin artifacts[40]. The Newton-Euler method was applied to calculate the moments and power at each lower limb joint in the sagittal plane, using the proximal segment as a reference[18,41], and values were standardized by body weight to reduce individual differences[42,43]. The knee and ankle joint centers were estimated by calculating the midpoints between external landmarks on the corresponding segments. Hip joint centers were estimated using the method proposed by Bell[44] et al. Joint angles, moments, and power were filtered using a 6 Hz cut-off frequency with a 4th-order bidirectional Butterworth low-pass filter. The action cycle range (Fig. 3) and cycle duration were proportionally normalized to 101 data points.

Statistical analysis
In the trials, we calculated joint angles, joint moments, and joint power for each measurement of the sagittal plane.The Pearson correlation coefficient (Rxy) was computed to quantify the degree of agreement between the ML and MB system estimates for each measurement. This coefficient reflects the correlation between the two systems' estimates. Additionally, Root Mean Square Difference (RMSD) was calculated to assess the deviation between the ML and MB system estimates. RMSD provides a measure of overall error, which is sensitive to outliers and extremes, and was used to quantify the average magnitude of differences for each repetition. Maximum and minimum errors for angles, moments, and power were also calculated separately. Rxy, RMSD, and maximum and minimum errors were averaged across the three trials for each participant, with group means and standard deviations calculated for the 14 participants to evaluate overall consistency and the magnitude of differences between the markerless and marker-based estimates. To assess differences between the systems for each kinematic and kinetic time series, statistical parametric mapping (SPM) analysis was performed. The normality of the data was first tested using the built-in function spm1d.stats.normality.ex1d_ttest_paired.m in SPM. Data conforming to a normal distribution were then analyzed using paired-sample t-tests with the spm1d.stats.ttest_paired.m function. All SPM analyses were conducted in MATLAB (The MathWorks, Natick, MA, USA) using the open-source software package SPM1d Version 0.4. A significance level of $\alpha = 0.05$ was applied for all statistical tests. Following the guidelines of Schober[45]et al., we considered an Rxy coefficient of ≥ 0.7 to indicate a strong correlation between the two systems, while a value of ≥ 0.9 reflects a very strong correlation. Additionally, a root mean square difference (RMSD) in joint angle of $\leq 5°$ was used as the threshold to indicate minimal differences in magnitude between the systems[10].

Result
Table 1 presents the results of the comparison between the ML and MB systems for sagittal plane lower limb biomechanical parameters, including correlation and difference analysis of angles, moments, and power for hip flexion/extension, knee flexion/extension, and ankle dorsiflexion/plantarflexion. Pearson's correlation coefficient (r) and root mean square difference (RMSD) were used to assess the degree of agreement, while the mean magnitude difference between the two systems and the minimum (min_error) and maximum (max_error) absolute errors were used to quantify the range of bias. The Pearson correlation coefficients for the angles, moments, and power of the SJ, DJ, and CMJ at the hip, knee, and ankle joints were all greater than 0.9, indicating a strong correlation. Regarding lower limb joint angles, the RMSD for hip joint angles during both the SJ and CMJ maneuvers exceeded 5°, which did not reach statistical significance, but a large difference was observed. The maximum hip joint angles for all three maneuvers (SJ, DJ, and CMJ) showed significant differences.

Lower limb joint angle
Paired-sample t-tests conducted via statistical parametric mapping (SPM) revealed significant differences between the ML and MB systems for hip angles across all three movement types. Significant discrepancies were observed at 0-7% ($p < 0.05$), 35-42% ($p < 0.05$), and 26-36% ($p < 0.05$) of the movement cycle for the squat jump (SJ), drop jump (DJ), and countermovement jump (CMJ), respectively. The Pearson correlation coefficients for hip, knee, and ankle angles were consistently above 0.93 throughout the movements, indicating strong correlation. Among the three joints, the hip joint exhibited the most significant variability, with RMSD values $\leq 4.1°$ across the three movements. The maximum error (Angle_max_error) in hip flexion at the peak angle was 9.1°, 8.5°, and 9.5° for the SJ, DJ, and CMJ, respectively. Furthermore, all three movements showing significant differences. (Fig. 4)

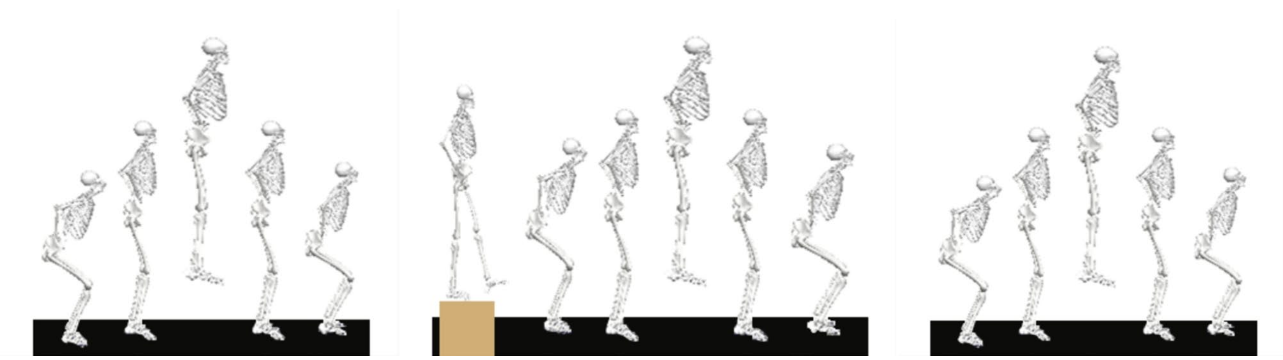

Fig. 3. In Visual3D, the cutoff points for DJ and CMJ include the moment just before the center of mass acceleration reaches zero, maximum knee flexion, the force plateau at zero, the highest point of the center of mass, the force plateau just above 0 N, and maximum knee flexion again. For SJ, there is no initial moment of maximum knee flexion, and the remaining time points align with those of DJ and CMJ.

Parament	Squat Jump			Drop Jump			Countermovement Jump		
	Hip	Knee	Ankle	Hip	Knee	Ankle	Hip	Knee	Ankle
Angle Correlaation(r)	0.947 ± 0.04	0.962 ± 0.02	0.986- ± 0.02	0.93 ± 0.06	0.96 ± 0.04	0.97 ± 0.03	0.94 ± 0.04	0.96 ± 0.03	0.98 ± 0.02
Angle RMSD(°)	5.3 ± 2.1	3.2 ± 1.6	2.2 ± 0.7	4.1 ± 1.7	2.6 ± 1.5	3.8 ± 1.5	5.6 ± 2.4	3.5 ± 1.5	2.4 ± 1.1
Anglemax_error(°)	**9.1 ± 2.7**	7.3 ± 1.9	2.4 ± 0.9	**8.5 ± 2.1**	7.4 ± 1.6	3.4 ± 1.2	**9.5 ± 2.4**	8.1 ± 2.3	3.2 ± 0.9
Anglemin_error(°)	3.9 ± 1.8	2.5 ± 0.7	3.0 ± 0.9	4.1 ± 1.7	2.2 ± 1.2	2.7 ± 1.0	4.8 ± 2.1	2.4 ± 1.3	3.7 ± 0.9
Moment Correlaation(r)	0.96 ± 0.03	0.98 ± 0.02	0.98 ± 0.02	0.97 ± 0.03	0.95 ± 0.04	0.98 ± 0.02	0.95 ± 0.04	0.97 ± 0.02	0.99 ± 0.01
Moment RMSD(N · M/kg)	0.18 ± 0.07	0.15 ± 0.09	0.11 ± 0.05	0.26 ± 0.05	0.20 ± 0.09	0.24 ± 0.17	0.21 ± 0.09	0.16 ± 0.15	0.14 ± 0.06
Momentmax_error(N · M/kg)	0.19 ± 0.12	0.14 ± 0.06	0.13 ± 0.04	0.27 ± 0.09	0.23 ± 0.08	0.29 ± 0.13	0.23 ± 0.10	0.18 ± 0.07	0.19 ± 0.11
Momentmin_error(N · M/kg)	0.28 ± 0.11	0.33 ± 0.16	0.17 ± 0.07	0.32 ± 0.23	0.25 ± 0.12	0.26 ± 0.16	0.29 ± 0.17	0.28 ± 0.21	0.12 ± 0.07
Power Correlaation(r)	0.96 ± 0.03	0.97 ± 0.03	0.98 ± 0.02	0.97 ± 0.03	0.95 ± 0.04	0.92 ± 0.05	0.93 ± 0.04	0.96 ± 0.03	0.96 ± 0.04
Power RMSD(W/kg)	1.54 ± 0.42	1.12 ± 0.29	0.39 ± 0.12	1.26 ± 0.27	0.95 ± 0.35	0.61 ± 0.21	2.12 ± 0.54	1.34 ± 0.38	0.52 ± 0.27
Powermax_error(W/kg)	1.93 ± 0.62	1.35 ± 0.43	0.57 ± 0.21	1.54 ± 0.42	1.21 ± 0.31	1.44 ± 0.36	2.01 ± 0.77	1.73 ± 0.32	0.71 ± 0.22
Powermin_error(W/kg)	2.14 ± 0.91	1.11 ± 0.36	0.47 ± 0.33	1.21 ± 0.63	1.13 ± 0.33	0.61 ± 0.30	2.45 ± 1.22	1.18 ± 0.47	0.59 ± 0.35

Table 1. Pearson's correlation coefficient (r), root mean square deviation (RMSD), and absolute errors for the minimum (min_error) and maximum (max_error) joint angles, torque, and power between the markerless (ML) and marker-based (MB) system estimates.
Bold indicates significant.

Lower limb joint moment

Differences between the three systems for lower limb joint moments in the sagittal plane during the three movements were analyzed using the paired samples t-test of SPM. The results indicated high inter-system agreement for the lower limb joint moments of SJ, DJ, and CMJ. Further analysis revealed that the differences in joint moments between the two systems were more pronounced during DJ than in the SJ and CMJ movements, although no significant differences were observed. The discrepancies between the two systems were most notable at the hip joint for all three movements, particularly during peak power moments; however, these differences were not statistically significant. (Fig. 5).

Lower limb joint power

According to the paired-sample t-test analysis of the SPM, the three sagittal plane lower limb joint power movements demonstrated high inter-system consistency. Throughout the movements, the ankle joint exhibited the highest consistency among the three joints, the knee joint performed more consistently, and the hip joint showed the greatest discrepancy. Notably, the maximum hip joint power during the CMJ was significantly higher than that observed in the other movements, although this difference did not reach statistical significance (Fig. 6).

Discussion

This study compares the effectiveness of the Thiea3D and Vicon motion capture systems in measuring kinematic and kinetic data during three movements: the SJ, DJ, and CMJ. We confirmed our hypothesis that the difference in measuring hip parameters between the ML and the MB system is more pronounced during high-intensity jumping movements.The performance of both systems was evaluated in terms of sagittal plane angle, moment, and power, and the results were analyzed using SPM to assess their comparability and variability. The results revealed inter-system differences across the entire group only with respect to the hip angle. A high Pearson's correlation coefficient, which reflects the consistency between the systems, is considered essential for good comparability[27]. The results demonstrate strong consistency between the systems' estimates for all three movements. The RMSD was used to quantify deviations between the systems[10]. A deviation of less than or equal to 5° in joint angle RMSD indicates minimal difference between the systems[40]. Analysis of the entire group revealed minor deviations between the two systems for all measurements, except for a significant deviation in the hip angle.

Regarding angular measurements, the ML system demonstrated strong agreement with the MB system, particularly in kinematic measurements of the ankle and knee joints. SPM analyses revealed that changes in ankle and knee joint angles were highly correlated between the two systems, with differences of ≤ 3.5° during most phases of the exercise cycle. However, hip angle estimation differed significantly between the two systems during the jumping phase of the SJ and throughout the DJ and CMJ landings until the stage of maximum knee flexion, with SPM analyses showing statistical significance. The RMSD exceeded 5° for both the CMJ and DJ, while the Anglemax_error exceeded 9° at maximal hip flexion. The observed differences may be attributed to the semi-squat position during the SJ take-off phase and the occlusion of markers during the knee-flexion amortization phase following landing in the DJ and CMJ. Specifically, during these phases, the anterior superior iliac spine markers may experience incomplete tracking due to partial occlusion by the participant's upper body positioning[46]. Additional, these differences may be attributed to the markerless system's underestimation of anterior pelvic tilt, which could be transmitted downward to the hip joint, resulting in increased hip flexion[27]. Barzyk[21] et al. validated the effectiveness of a smartphone-based markerless motion capture system (Sbsq-pose) for measuring kinematic parameters of the hip, knee, and ankle in CMJ. SPM analyses in their study showed significant differences between systems only in ankle measurements. This result may be due to their use of a single camera with a frontal view for capturing movements, while our study employed six markerless cameras to capture three different movements. Additionally, the camera placement may have influenced the results[46].

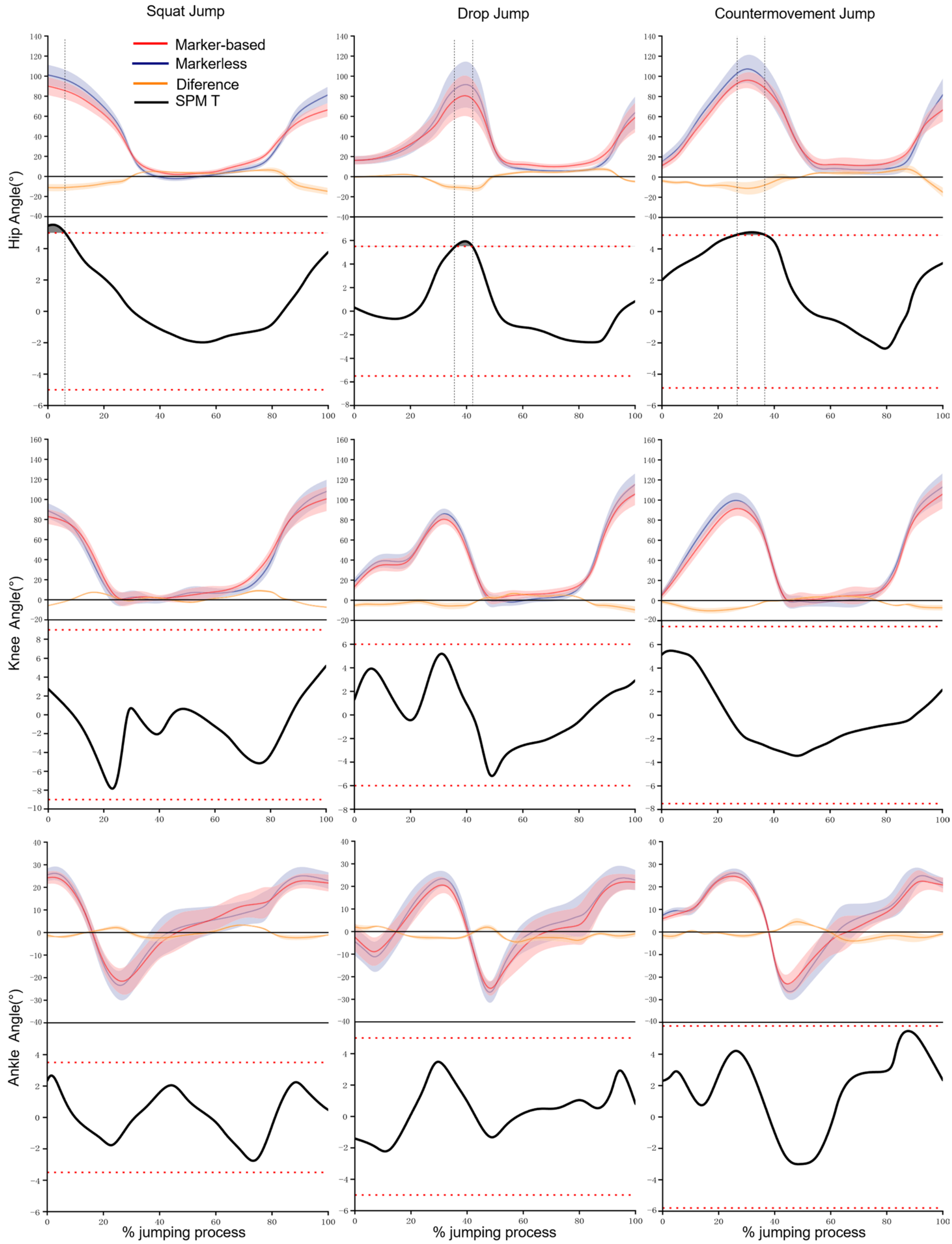

Fig. 4. Rows 1, 3, and 5 display the pooled curves of the differences in lower extremity joint angles between the marker-based (MB) and markerless (ML) motion capture systems for 12 participants completing Squat Jump, Drop Jump, and Countermovement Jump. Rows 2, 4, and 6, corresponding to rows 1, 3, and 5, respectively, show the results of the SPM paired t-test analysis. The horizontal red dashed line represents the critical random field theoretical threshold for significance ($p < 0.05$), while the dashed rectangle highlights the significant region. The blue (MB) and red (ML) lines represent the combined curves of the systematically estimated joint angles, the yellow line shows the difference between MB and ML, and the black line depicts the SPM paired t-test trajectory.

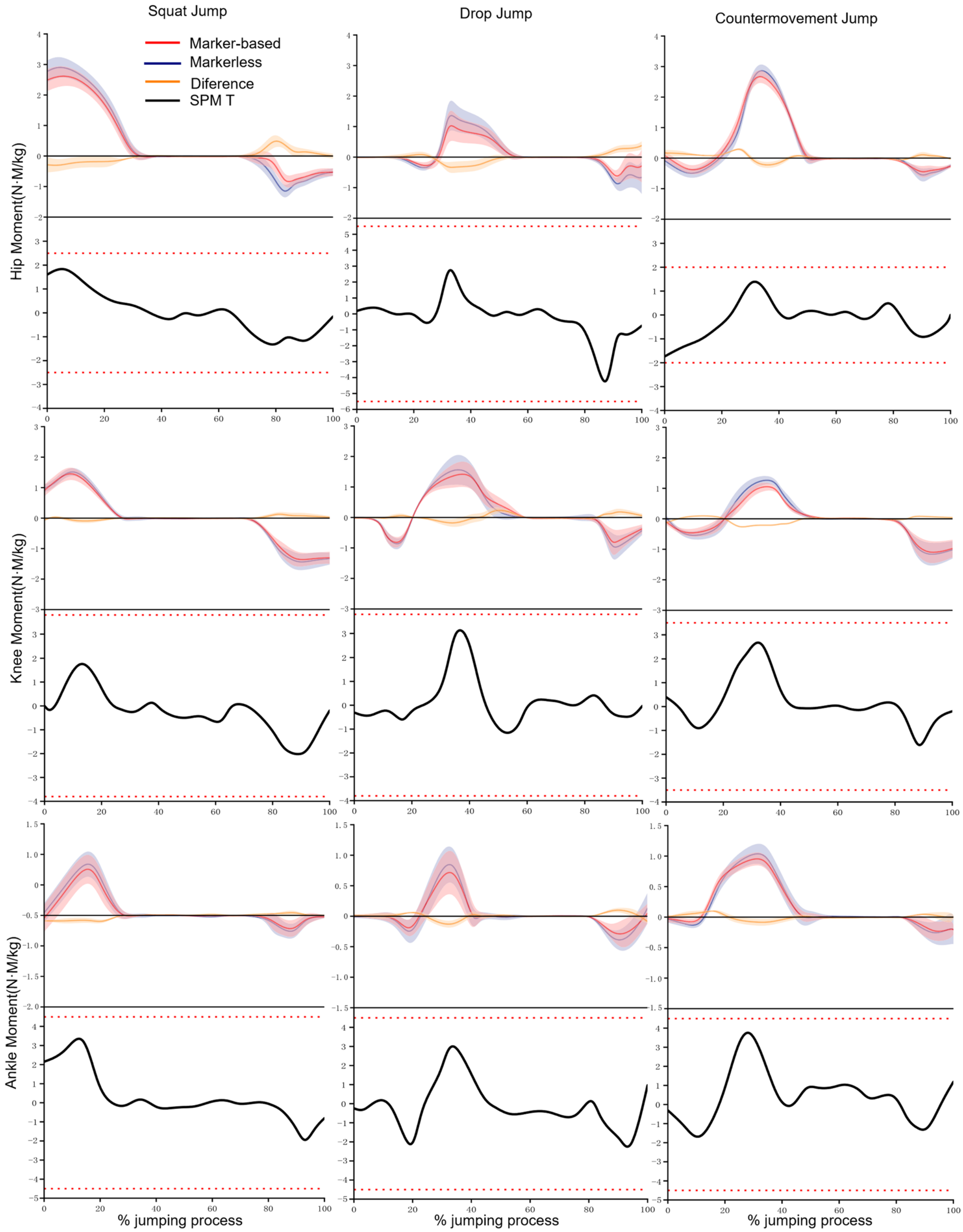

Fig. 5. Rows 1, 3, and 5 display the pooled curves of the differences in lower extremity joint moment between the marker-based (MB) and markerless (ML) motion capture systems for 12 participants completing Squat Jump, Drop Jump, and Countermovement Jump. Rows 2, 4, and 6, corresponding to rows 1, 3, and 5, respectively, show the results of the SPM paired t-test analysis. The horizontal red dashed line represents the critical random field theoretical threshold for significance ($p < 0.05$). The blue (MB) and red (ML) lines represent the combined curves of the systematically estimated joint angles, the yellow line shows the difference between MB and ML, and the black line depicts the SPM paired t-test trajectory.

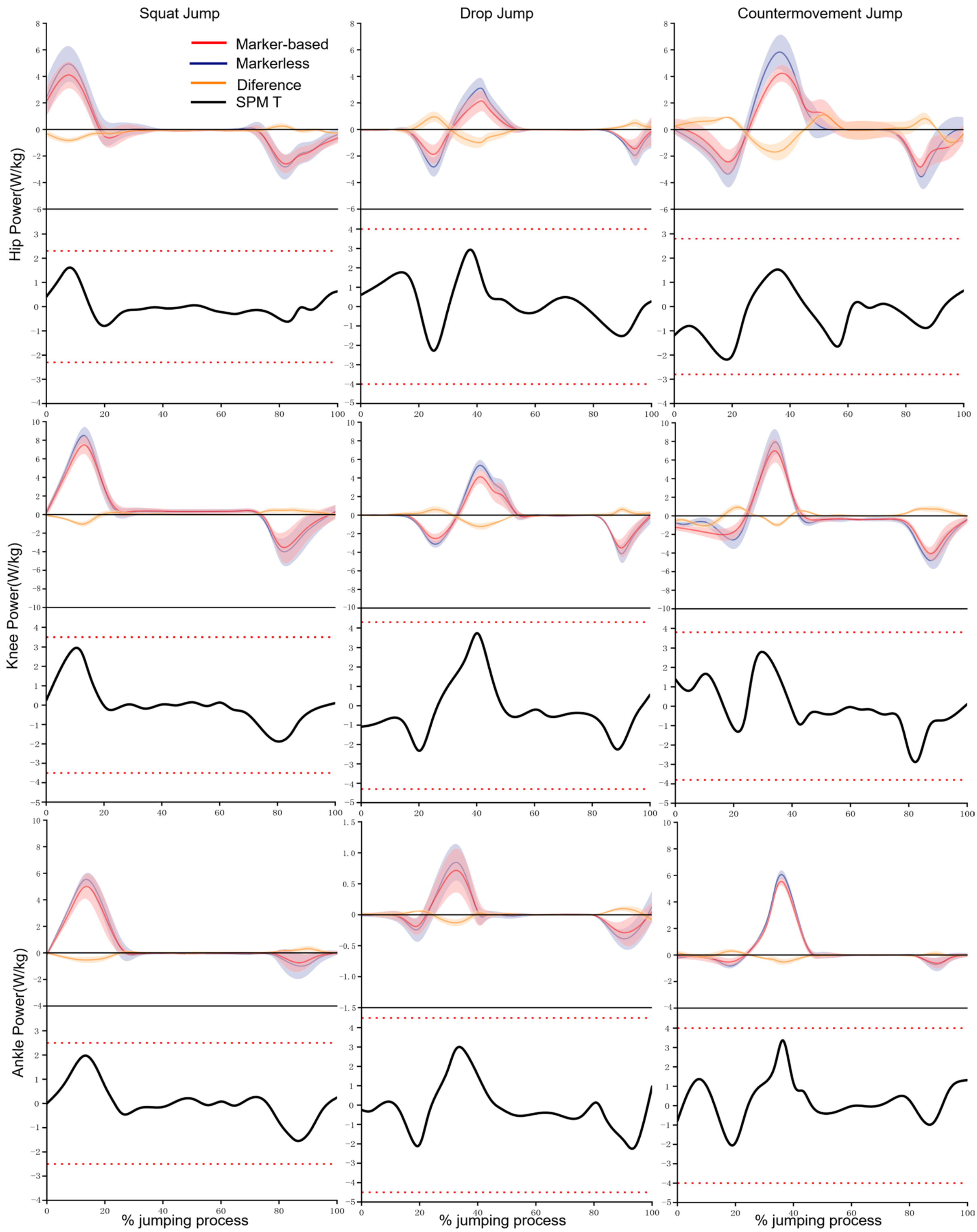

Fig. 6. Rows 1, 3, and 5 display the pooled curves of the differences in lower extremity joint power between the marker-based (MB) and markerless (ML) motion capture systems for 12 participants completing Squat Jump, Drop Jump, and Countermovement Jump. Rows 2, 4, and 6, corresponding to rows 1, 3, and 5, respectively, show the results of the SPM paired t-test analysis. The horizontal red dashed line represents the critical random field theoretical threshold for significance ($p < 0.05$). The blue (MB) and red (ML) lines represent the combined curves of the systematically estimated joint angles, the yellow line shows the difference between MB and ML, and the black line depicts the SPM paired t-test trajectory.

Mercadal-Baudart[47] et al. evaluated hip and knee flexion, as well as ankle plantarflexion during the CMJ (reverse jump), using a single-camera markerless 3D human posture estimation model (Strided Transformer). The results showed that the root mean square error (RMSE) was smaller for the hip. However, the authors noted that a multi-camera system could yield more accurate results.Tylan[31] et al. evaluated the performance of the novel markerless motion capture system (ENABLE) for measuring lower limb kinematics during the drop vertical jump (DVJ). Their comparison with a conventional MB system revealed good agreement for sagittal plane kinematic measurements of the hip, knee, and ankle. Our study found significant differences in the hip joint, which could be due to the small sample size and greater movement variability between individuals. A larger sample size would improve the generalizability of the findings. However, the Tylan study cohort consisted solely of adolescent female athletes, and the system's performance for other demographics remains unknown. Gerda[48] et al. compared a 2D markerless motion capture system based on deep learning algorithms (Miqus) with a conventional MB system (Oqus) during CMJ testing. Their results showed high agreement for ankle and knee angles, but a deviation of approximately 21° was observed in hip angle measurements. In our study, the deviation was 5.6° for the hip joint, which may be due to differences in how the systems track pelvic points. Many ML systems struggle to track pelvic points due to sparse labeling in commonly used datasets. Furthermore, since Theia3D is not open-source, the reason for this discrepancy remains uncertain. When comparing the kinematics of the CMJ using an OpenSim-based unlabeled model and a labeled-based system (Oqus, Qualisys AB), Needham[12] et al. observed a mean difference of ≤ 3° in hip, knee, and ankle angles. However, they did not perform an SPM analysis and only included one jumping movement for the CMJ. Song[10] et al. compared lower limb kinematics estimated by both MB and ML capture across eight movements and found that ML were highly consistent with marker-based systems for ankle and knee kinematics in the CMJ. However, differences were more pronounced for the hip joint and faster movements, which aligns with our findings.

Regarding moment and power measurements, the SPM results showed that the marker-based and markerless systems were highly consistent in tracking moment and power variations across most joints. However, the difference in the estimation of joint moments during the DJ was significantly greater than in the other two movements, especially at the peak moment estimation (Momentmax-error = 0.23 N·M/kg). This discrepancy may be due to the rapid eccentric-concentric transition required at the hip, knee, and ankle joints during DJ touchdown[17]. The high rate of change in joint kinematics and the magnification of marker-induced kinematic errors from increased skin-to-bone motion can significantly affect kinetic calculations[46]. Additionally, ML can introduce inter-system variance due to blurred video images during fast movements[34]. Although we optimized video clarity by adjusting system parameters (e.g., camera resolution, illumination, shutter speed, and capture rate) prior to the experiments, such variance remains unavoidable during fast motion[10,34]. Tylan[31] et al. reported correlation coefficients of 0.90 or higher for all three joints in their study comparing unlabelled versus MB systems for sagittal joint moments during the drop vertical jump (DVJ), which is consistent with our findings. The differences in hip moments were relatively larger than those in the knee and ankle joints across all three movements, particularly at the peak extension moment (SJ Momentmax-error = 0.19 N·M/kg, DJ Momentmax-error = 0.27 N·M/kg, CMJ Momentmax-error = 0.23 N·M/kg). Song[10] et al. also found that while differences in hip moments were smaller, they were still greater than those for the knee and ankle joints during the CMJ, likely due to the complex motion of the hip relative to the pelvis and challenges in identifying anatomical landmarks and fixation markers on the pelvis[33]. Previous studies have also highlighted the hip as the most error-prone joint in MB biomechanical analyses[49]. Our results showed that the difference in sagittal plane power of the ankle measured by both systems was the smallest. The ankle's range of motion is relatively limited, and the power calculation based on the MB system depends more directly on the ground reaction force, requiring fewer inverse dynamics projections, thus reducing error. This finding aligns with D'Souza[27] et al., who observed high consistency in sagittal plane power measurements (RMSE < 0.37 W/kg, correlation ≥ 0.76) between MMB and ML systems during walking gait. However, their study showed greater variation at the ankle joint, possibly due to differences in the analyzed movements, such as ground walking versus jumping, which should be interpreted with caution. The difference in hip power, however, was notably higher between the two systems, particularly at the peak power moment of the CMJ. This cross-system difference may be attributed to Theia3D's underestimation of the anterior pelvic tilt angle[27], a bias that could amplify differences in hip moments through inverse dynamics calculations, which would, in turn, affect power estimates. These findings partially align with those of Tang[26] et al., who noted that the ML system tended to overestimate hip and knee moments and power at high speeds, with the discrepancy increasing as speed rose, especially during the swing phase. While MB has its limitations, it is also susceptible to soft tissue artifacts, which can cause errors. The MB relies on skin markers to define joint centers, and soft tissue artifacts can lead to a forward shift of the joint center during fast motion, overestimating the moment arm and ultimately increasing the error in power calculations[50].

There are several limitations in our study. First, the measured hip metrics were overestimated in the markerless biomechanical analysis. The ML system relies on its built-in deep learning algorithm for key point identification, which introduces bias in the pelvic coordinate system localization or the identification of anatomical landmarks[27]. This bias leads to errors in pelvic stance reconstruction, particularly underestimating the anterior pelvic tilt angle, which then affects hip measurements. Moreover, because Theia3D is not open-source, it is not possible to trace its pelvic marker point definitions, limiting the ability to precisely localize the sources of error. It is important to note that the marker-based methods commonly used in motion analysis have several limitations, including the time-consuming and labor-intensive process of affixing marker points, the risk of markers becoming dislodged or occluded, the restriction of natural motion, and limited applicability to certain scenarios[3,4,32,33]. Gold-standard measurement techniques, such as biplane hip dynamoscopy[51,52], can help validate the accuracy of both the ML and MB systems for hip joint measurements.Future development of the ML system could include improvements in neural network architectures for more accurate anatomical point predictions, better human models based on these predictions, and exploration of alternative neural network approaches, such as predicting segmental poses rather than individual anatomical points[53]. On the other hand, studies focused on vertical jumping movements, particularly during the touchdown phase involving high-speed eccentric contraction, face challenges with image blurring in the ML system due to transient high acceleration. Even with adjustments to camera parameters (e.g., resolution, shutter speed)[10,34] and higher resolution or more sensitive cameras, image quality could still be impacted. To address this, improvements in camera sensitivity to light and ambient lighting conditions could help improve image clarity and tracking accuracy[34]. Additionally, there are limitations in the selection of planes of motion in this study. We primarily focused on the biomechanics of the sagittal plane, but biomechanical parameters in the coronal plane, such as knee valgus moments, are closely associated with the risk of ACL injury[11]. Templin[23] et al. found that when comparing MB and ML systems for studying the drop vertical jump (DVJ) across non-sagittal degrees of freedom, the correlation of joint moments was more significant than that of joint angles. Future studies will need to establish a multiplanar validation framework, particularly in scenarios involving multidimensional coupled motions. ML systems have the potential to greatly expand 3D motion analysis, particularly in large populations of athletes.

Conclusion

Our results demonstrate that the ML system shows a high degree of agreement with the MB system in estimating sagittal plane kinematics and kinetics of the knee and ankle joints during standardized jumping tasks, including SJ, DJ, and CMJ. However, its accuracy in assessing hip biomechanics remains a limitation and warrants further investigation. Additionally, the study was conducted in a relatively controlled environment with a specific population, which may constrain the generalizability of the findings.

Data availability

The data that support the findings of this study are available on request from the corresponding author.

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Author contributions
Conceptualization, L.W. and C.Y.; methodology, X.H. and L.T.; software, L.W., C.Y., Y.X. and L.T.; validation, C.Y. and L.W.; formal analysis, C.Y., L.W., X.H., L.T. and Z.H.; investigation, Y.Z. and Z.H.; data curation, C.Y., L.W., X.L. and Z.H.; writing—original draft preparation, C.Y. and L.W.; writing—review and editing, Z.H. and X.L.; visualization, C.Y.; supervision, Z.H.; project administration, Y.H. All authors have read and agreed to the published version of the manuscript.

Declarations

Competing interests
The authors declare no competing interests.

Additional information
Correspondence and requests for materials should be addressed to X.L. or Z.H.

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