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# Comparison of lower limb kinematics and kinetics estimation of basketball players during jumping with markerless and marker-based motion capture systems

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ABSTRACT

Background: Basketball requires high lower limb performance. Assessing jump biomechanics is vital for enhancing performance and injury prevention. Marker-based (MB) systems are common but limited. In recent years, Markerless (ML) motion capture systems have gradually become emerging tools in sports biomechanics research due to their characteristic of not requiring physical marker points. However, their specific application and verification in basketball events are still relatively limited. Purpose: This study compares lower limb kinematics and kinetics estimated by MB and ML motion capture systems during jumps.Methods: Twelve subjects performed the standing vertical jump (SVJ), standing long jump (SLJ) and running vertical jump (RVJ) tests.Data was collected using 10 infrared cameras, 6 high-resolution cameras, and two force platforms via Vicon Nexus software. Markerless motion capture calculates sagittal plane angles, torque and power of the Hip, Knee and Ankle joints via Theia3D software, with these parameters also collected by the marker-based Vicon system. Both systems' data are then processed in Visual3D. We analyzed the correlation coefficient (r), root mean square difference (RMSD), and maximum/minimum errors, as well as using statistical parametric mapping (SPM) to compare temporal patterns between groups and determine specific moments where significant differences occurred. Results: SLJ capture was slightly inferior in both systems. SPM analysis of the sagittal plane showed significant differences only at the hip joint. Joint angle RMSD was < 8.2°, torque RMSD < 0.41 N·M/kg, and power RMSD < 1.76 W/kg. Conclusion: The ML system accurately captures knee and ankle joints in the sagittal plane but shows significant differences in hip measurement and certain movements, requiring further validation.

Key words: Mark-based motion capture system; markerless motion capture system; Basketball; Jumping; Biomechanics



## 1 INTRODUCTION

Basketball is a sport characterized by high intensity physical exertion and complex movements, which puts forward extremely high demands on the lower limbs of athletes[4]. Understanding the kinematic and kinetics characteristics of these movements is essential for optimizing athlete performance, preventing sports injuries, and promoting rehabilitation[29]. Motion capture systems, as a powerful tool, have been widely used in human motion analysis, providing detailed insights into the mechanics of movement performance[27]. The traditional marker-based motion capture system has been extensively applied in sports biomechanics research, capable of delivering precise and dependable data, including joint angles, force, and power[16, 25]. Marker-based motion capture systems are limited by high costs, lab-use constraints and manual marker-placement errors. Controlling experimental conditions, calibrating the system, using multi-camera setups and advanced algorithms can enhance accuracy, but their application remains restricted. In recent years, markerless motion capture systems have gained popularity as a more efficient and user-friendly alternative, thanks to their ability to capture motion without the need for physical markers.

At present, MB systems are widely used in basketball. Athletes need various jumping abilities for actions like jockeying for position under the basket, fast - break layups, rebounding, and blocking. These impact scoring, defense, and injury risk control[4].

Although MB systems are effective tools for biomechanical analysis, they have limitations in practical applications[17]. These limitations drive researchers to seek more efficient and accurate motion capture technologies. The emergence of ML systems offers a new solution. By capturing 3D motion signals with high - resolution video cameras and using deep learning algorithms for automatic analysis, ML systems overcome the manual marker - placement errors, limited capture range, and complex data acquisition process of MB systems[6]. The ML system has been applied to gait analysis, running posture, and various daily motor movements. Kanko et al. found that the two systems are comparable during treadmill walking [14]. Ito et al. additionally stated that, in their comparative study of gait, squatting, and forward jumping kinematics, the kinematics of squatting and forward jumping are comparable in the sagittal plane but not in the frontal and transverse planes[13]. Hui Tang found that different running speeds affected the lower limb kinetics parameters estimated by both systems, with the ML system estimating increased lower limb joint kinetics and faster speeds during the swing phase[30]. Ke Song compared eight daily motor movements and found that the ankle and knee estimates from the ML and MB systems matched very well for most movements, while the differences between the systems were greater for hip estimates and faster movements[27]. However, there is no research comparing the application of ML and MB systems in basketball.In basketball, actions such as positioning under the basket to grab rebounds, fast break run-up layups, rebounding and blocking pose special biomechanical requirements for athletes' jumping ability to adapt to various jumping needs during the game. The accuracy and reliability of the ML system in estimating the kinematic and kinetics parameters of the lower limbs during basketball players' jumps need further validation.

To our knowledge, studies comparing basic MB and ML systems have primarily focused on gait and running, with limited research in specific sports. Therefore, this study compared the estimation of lower limb kinematics and kinetics parameters of MB and ML systems during the jumping process of basketball players to evaluate the performance differences between the two systems. Through comparative analysis, this study is expected to provide valuable insights into the field of sports science and offer guidance for future research and practice. As the application of ML technology in sports science becomes increasingly widespread, the findings of this study will help promote the further development and improvement of related technologies and provide a scientific basis for the training and competition of basketball players[14]. Through this study, we aim to offer a novel perspective on evaluating basketball players' jumping abilities, provide fresh insights for basketball training and scientific research, deepen the understanding of the biomechanical mechanisms underlying basketball players' jumps, and furnish a scientific basis for athletes' training, competition performance enhancement, and injury prevention.

The primary objective of this study is to compare the differences in lower extremity kinematics and kinetics estimates between markerless and marker-based motion capture systems for basketball players during jumping. Based on prior studies, we speculate that in most movements, the estimates of markerless motion capture will be highly consistent with those of marker-based systems at the ankle and knee joints. But in different motion phases or moments, differences between the two will be more pronounced at the hip joint.

## 2 MATERIALS AND METHODS

### *2.1 Participants*

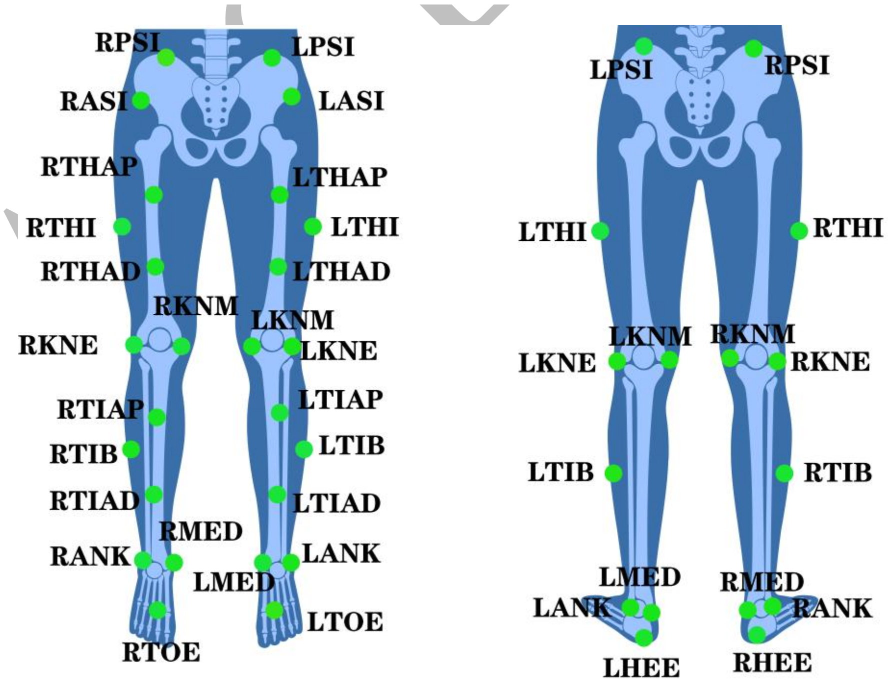
Based on the results of the pre-experiment, we calculated the effect size using the in-place reach at the peak hip joint angles (78.4±6.7 °, 87.6±7.9°) measured by the two systems, and the effect size was 1.26. We conducted a power analysis of the two systems using the paired t-test (power = 0.8, significance level $\alpha = 0.05$), and calculated that the required sample size was 11. To compensate for possible exits or poor data quality, we have increased the sample size by an additional one. Ultimately, this study recruited 12 professional basketball players from universities and professional teams to participate in the experiment. The age was 19.93±1.23 years old, the stature was 1.84±0.06m, the body mass was 78.38±8.51kg, and the BMI was 23.13±1.67kg/$m^2$. Inclusion criteria were: (1) no injury to the lower extremities or waist for at least 6 months prior to the formal study; (2) At least 6 years of training experience; (3) Participants were asked not to do any high-intensity exercise for 48 hours prior to the formal experiment.

### *2.2 Motion capture system and experimental setup*

In the experiment, we utilized 10 Vicon MX-F40 motion capture cameras (Vicon Corporation, Denver, Colorado, USA), with a resolution of 2352×1728 pixels, to track the 3D position of the markers at a frequency of 100Hz, generating a 3D bone model of the individual during walking. Concurrently, we employed the Theia3D system (Theia Markerless, Kingston, Ontario, Canada), a marker-free motion capture method based on deep learning algorithms. This system uses six Oryx10GigE cameras (Teldyne FLIR, Wilsonville, Oregon, USA) to acquire multi-view 2D pose information at 100Hz to calculate the three-dimensional human skeleton[14]. The camera is calibrated using the

Direct Linear Transformation (DLT) method, which maps three-dimensional spatial coordinates to two-dimensional image plane coordinates, thereby achieving three-dimensional scene reconstruction from a two-dimensional image[13, 30]. Two force-measuring platforms (Model BP600900, supplied by AMTI Corporation, Watertown, Massachusetts, USA) were embedded under the floor of the Capture Space Center to record the ground reaction force at 1000Hz. The force measuring platform and the two dynamic capture systems were recorded synchronously using a synchronization module via Vicon Nexus software (version 2.16, Vicon Motion Systems Ltd., Oxford, UK). The synchronization was achieved by connecting the force measuring platform and the two dynamic capture systems to a converter module via wired connections. The cameras were mounted on rails or tripods, distributed around the capture space, and tilted towards the force plate. A 3D spatial calibration of the cameras was performed before data collection, with the origin (reference point) of the two systems set at the intersection of the two force platforms, ensuring that the motion data recorded by the two systems were aligned in all concurrent captured trials[27].

Prior to the experiment, each participant was briefed on the test protocol and provided informed consent. They changed into lab-provided shorts and running shoes for the measurement of their stature and body mass. Before conducting the jump test, participants were required to attach 28 14mm reverse reflection spherical markers to specific anatomical landmarks. These markers included 12 placed on the left and right anterior superior iliac spines, posterior superior iliac spines, knee joints, and ankle joints; 12 positioned on the upper and lower middle thirds of the left and right shins and the middle halves of the left and right thighs; and four attached to the heels and second metatarsophalangeal joints of both feet. Subsequently, the participant stood at the center of the force-measuring platform with arms outstretched in an anatomical position to capture a static model. Thereafter, four non-tracking markers on the inner sides of the left and right knees and ankles were removed to alleviate the participant's movement burden[15](Seen figure 1 below). All participants performed the standing vertical jump (SVJ), standing long jump (SLJ), and running vertical jump (RVJ) in a fixed sequence. They were instructed to exert maximum effort on each jump, with natural arm swinging unrestricted. Rest periods of 60 - 90 seconds were provided between each exercise and different movements. Valid data for the three movements of each participant were collected at least three times.



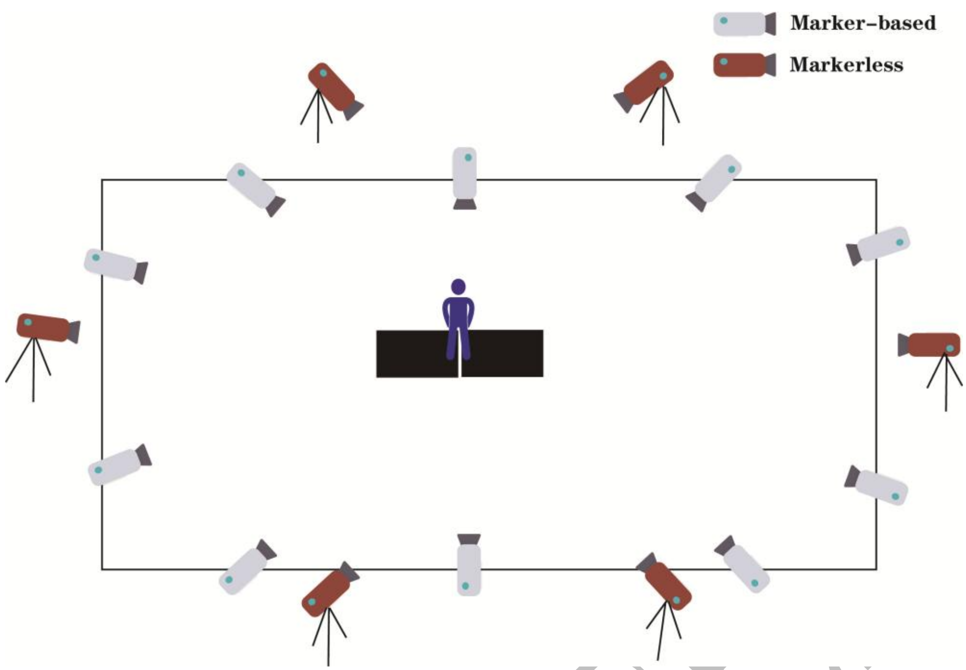



Figure 1: During marker-based motion capture, markers are set to track the position of the pelvis and lower limbs. In this example, the study participants are being captured in a static model.

### *2.3 Data analysis*

#### *2.3.1 Data pre-processing*

The raw video data from the markerless motion capture is pre-processed by Theia3D software. This involves extracting the two-dimensional positions of the learned features in all frames. Subsequently, these positions are converted into three-dimensional spatial coordinates based on the calculated camera position and orientation. Finally, an articulated multi-body model is scaled to fit the subject's specific landmark positions in three-dimensional space. Inverse kinematics (IK) methods are then utilized to estimate the subject's three-dimensional pose throughout the physical task, as determined by the Theia3D software's automatic analysis[6]. The data captured by the MB system is interpolated by Vicon Nexus software using

Woltring gap filling. This method is employed to estimate and fill in missing data points, ensuring a continuous and smooth dataset for further analysis[34].

*2.3.2 Visual3D processing*

The pre-processed lower limb data were further analyzed using Visual3D software (preview version v2022.06.02, provided by C-Motion, Germantown, Maryland, USA). We applied the same Visual3D 6 degrees of freedom (6DOF) algorithm and inter-segment inverse kinematics (IK) constraints as those used in the marker-based (MB) system. This approach automatically generated a model for the markerless (ML) data and produced corresponding segment attributes, such as segment mass, centroid position, and joint center position[14]. Visual3D models segments as cones, cylinders, spheres, and ellipsoids (geometric shapes) and calculates the segment mass for each segment based on Dempster's regression equation, which estimates mass based on segment length and other anthropometric data[19]. The Cardan sequence, also known as the Cardan angles or Euler angles, was employed to calculate the joint angles with reference to the proximal segment. This method involves decomposing the rotational movement of a segment into three sequential rotations around specific axes, typically following the order of flexion/extension, abduction/adduction, and internal/external rotation. By applying the Cardan sequence, the complex three-dimensional joint movements can be broken down into more manageable components, facilitating the calculation and interpretation of joint angles in the context of the proximal segment's orientation[10]. The Newton-Euler method was employed to compute the torque and power of each joint in the lower extremity relative to the proximal segment, providing a comprehensive analysis of the mechanical forces and energy involved in the movements[9, 24].The data is then normalized by the participant's weight, an effective strategy to minimize individual variations and enhance the comparability of results across different participants[1, 21]. The midpoint between the external markers of the corresponding segment was utilized to estimate the center of the knee and ankle joints. For the hip joint, its center was estimated using the method proposed by Bell et al., which predicts the hip joint center based on external landmarks[3]. The joint angle, torque, power, and cycle range of motion (as shown in Figure 2) were filtered from both the MB and ML models using a 4th-order bidirectional Butterworth low-pass filter with a cutoff frequency of 6 Hz. The duration of the action cycle was scaled to 101 data points.

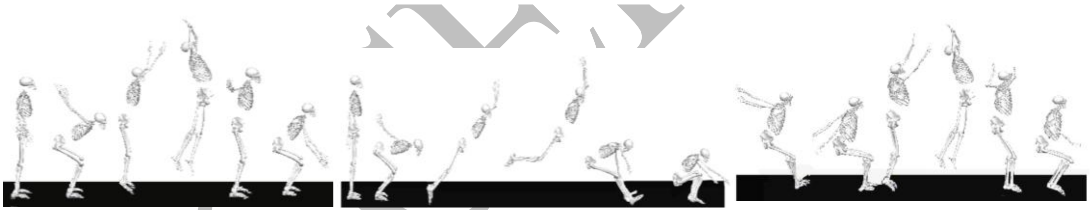


Figure 2: Panel 1, 2, and 3 respectively represent SVJ, SLJ, and RVJ. In Visual3D, truncation points for SVJ and SLJ include: pre-zero COM acceleration, max knee flexion, force platform zero, peak COM, force platform just over 0N, and repeat max knee flexion. For RVJ, from force platform just over 0N, time points 2-6 align with the first two jumps.

*2.3.3 Statistical analysis*

We calculated the joint angle, joint torque, and joint power for each measurement in the exercise test. The duration of the movement cycle was normalized to 101 data points proportionally. We calculated the Pearson correlation coefficient (Rxy) between the ML and MB system estimates for each measurement, measuring the degree of correlation between the two variables to quantify the consistency of the two waveforms. According to the guidelines by Schober et al., we defined that a coefficient of Rxy $\geq 0.7$ suggests a strong correlation between the two systems, and Rxy $\geq 0.9$ suggests a very strong correlation[26]. The root-mean-square difference (RMSD) between the ML and MB system estimates for each measurement is also calculated. As a measure of the difference between the measured values, RMSD quantifies the average magnitude of discrepancy by computing the square root of the mean of squared errors. It reflects overall errors and shows sensitivity to outliers and extreme values. The errors of maximum and minimum Angle, torque and power are also calculated separately. The Rxy, RMSD, and max-min errors for each of the 3 experiments were averaged, and the group mean and standard deviation for 12 participants were calculated to determine the overall level of agreement and magnitude differences between markerless and marker-based estimates. In addition, in order to evaluate every single time series, the difference between the system of kinematics and dynamics, we use the statistical parameter mapping (SPM) analysis, the function is embedded in the SPM (spm1d. Stats. Normality. Ex1d_ttest_paired. M) used to assess the normality of the data, For the data conforming to the normal distribution, the paired sample T-test was performed using the built-in function (spm1d.stats.ttest_paired.m). All SPM analysis was performed in MATLAB (The MathWorks,Natick,MA,USA) using the open source package SPM1d Version 0.4. The significance level $\alpha$ for all statistical tests was 0.05.

## 3 RESULT

Table 1 presents the comparison results between the markerless and marker-based systems, including the Pearson correlation coefficient (r), root mean square difference (RMSD), and absolute errors for minimum (min_error) and maximum (max_error) joint angles, torque, and powers, specifically for hip flexion, knee flexion, and ankle dorsiflexion and plantar flexion angles.

| Parament | Standing vertical jump | | | Standing long jump | | | Running vertical jump | | |
|---|---|---|---|---|---|---|---|---|---|
| | Hip | Knee | Ankle | Hip | Knee | Ankle | Hip | Knee | Ankle |
| Angle Correlaation(r) | 0.92±0.04 | 0.95±0.03 | 0.97±0.02 | 0.82±0.07 | 0.94±0.04 | 0.95±0.03 | 0.91±0.05 | 0.94±0.04 | 0.97±0.02 |
| Angle RMSD(°) | 5.7±2.3 | 3.7±1.3 | 2.6 ± 0.8 | 8.2±3.4 | 4.3±1.5 | 2.9±1.3 | 6.6±2.5 | 4.1±1.2 | 2.8±1.0 |
| Angle$_{max}$_error(°) | **9.6±2.7** | 9.5±3.3 | 3.4±1.4 | **9.8±4.6** | 10.6±3.1 | 4.3±1.4 | **7.1±1.8** | 10.1±3.2 | 2.6±1.1 |
| Angle$_{min}$_error(°) | 3.8±1.5 | 1.2±1.1 | 2.3±1.2 | 1.7±1.2 | 11.9±4.3 | 2.6±1.7 | 3.3±1.6 | 2.2±1.4 | 3.8±2.1 |
| Torque Correlaation(r) | 0.94±0.05 | 0.94±0.05 | 0.98±0.03 | 0.86±0.09 | 0.83±0.11 | 0.92±0.04 | 0.93±0.04 | 0.92±0.05 | 0.97±0.03 |
| Torque RMSD(N·M/kg) | 0.20±0.08 | 0.14±0.14 | 0.12±0.06 | 0.41±0.11 | 0.32±0.11 | 0.21±0.02 | 0.23±0.07 | 0.19±0.11 | 0.14±0.04 |
| Torque$_{max}$_error(N·M/kg) | **0.27±0.13** | 0.22±0.17 | 0.13±0.04 | **0.54±0.44** | 0.68±0.42 | 0.21±0.06 | **0.26±0.15** | 0.25±0.17 | 0.17±0.11 |
| Torque$_{min}$_error(N·M/kg) | 0.31±0.17 | 0.15±0.09 | 0.15±0.07 | 0.66±0.51 | 0.52±0.32 | 0.33±0.04 | 0.29±0.14 | 0.37±0.29 | 0.18±0.07 |
| Power Correlaation(r) | 0.96±0.03 | 0.95±0.03 | 0.98±0.02 | 0.89±0.06 | 0.92±0.04 | 0.95±0.03 | 0.95±0.03 | 0.91±0.04 | 0.98±0.02 |
| Power RMSD(W/kg) | 1.74±0.52 | 0.96±0.32 | 0.47±0.19 | 1.76±0.63 | 1.23±0.37 | 0.75±0.12 | 1.64±0.49 | 1.12±0.34 | 0.52±0.29 |
| Power$_{max}$_error(W/kg) | 2.05±0.54 | 1.63±0.36 | 0.34±0.29 | 2.74±0.77 | 1.52±0.27 | 1.12±0.31 | 2.51±0.62 | 3.20±1.76 | 0.91±0.43 |

Table 1: Pearson correlation coefficient (r), root-mean-square difference (RMSD), and absolute errors of minimum (min_error) and maximum (max_error) joint Angle, moment, and power between ML and MB system estimates.

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| $Power_{min}$_error(W/kg) | 2.18±1.07 | 1.20±0.62 | 0.71±0.34 | 2.92±1.26 | 0.81±0.38 | 1.08±0.42 | 2.24±1.11 | 0.57±0.41 | 0.50±0.42 |

### *3.1 Lower limb joint Angle*

According to the SPM paired sample T-test analysis, significant differences were found in the hip angles of the three movements between the systems, particularly in the SLJ, which showed significance at two consecutive time points, with significant regions ranging from 40% to 50% ($P < 0.05$) and 80% to 100% ($P < 0.001$). For the SVJ and RVJ, the hip angles were significant at 26% to 28% ($P < 0.05$) and 0% to 10% ($P < 0.05$), respectively (See the second row in Figure 3). During the entire exercise, the hip angle correlation coefficient ($Rxy \geq 0.82$) was slightly low. Yet, the ankle and knee angle correlation coefficients were $\geq 0.94$, showing a very strong correlation. In the three movements, the hip joint ($RMSD \leq 8.2°$) had the greatest variability among the three joints (See Row 1 in Table 1). The Angle max_error at maximum hip flexion for the three movements was 9.6°, 9.8°, and 7.1°, respectively, and all three moments showed significant differences in the significant regions (See the third row in Table 1).

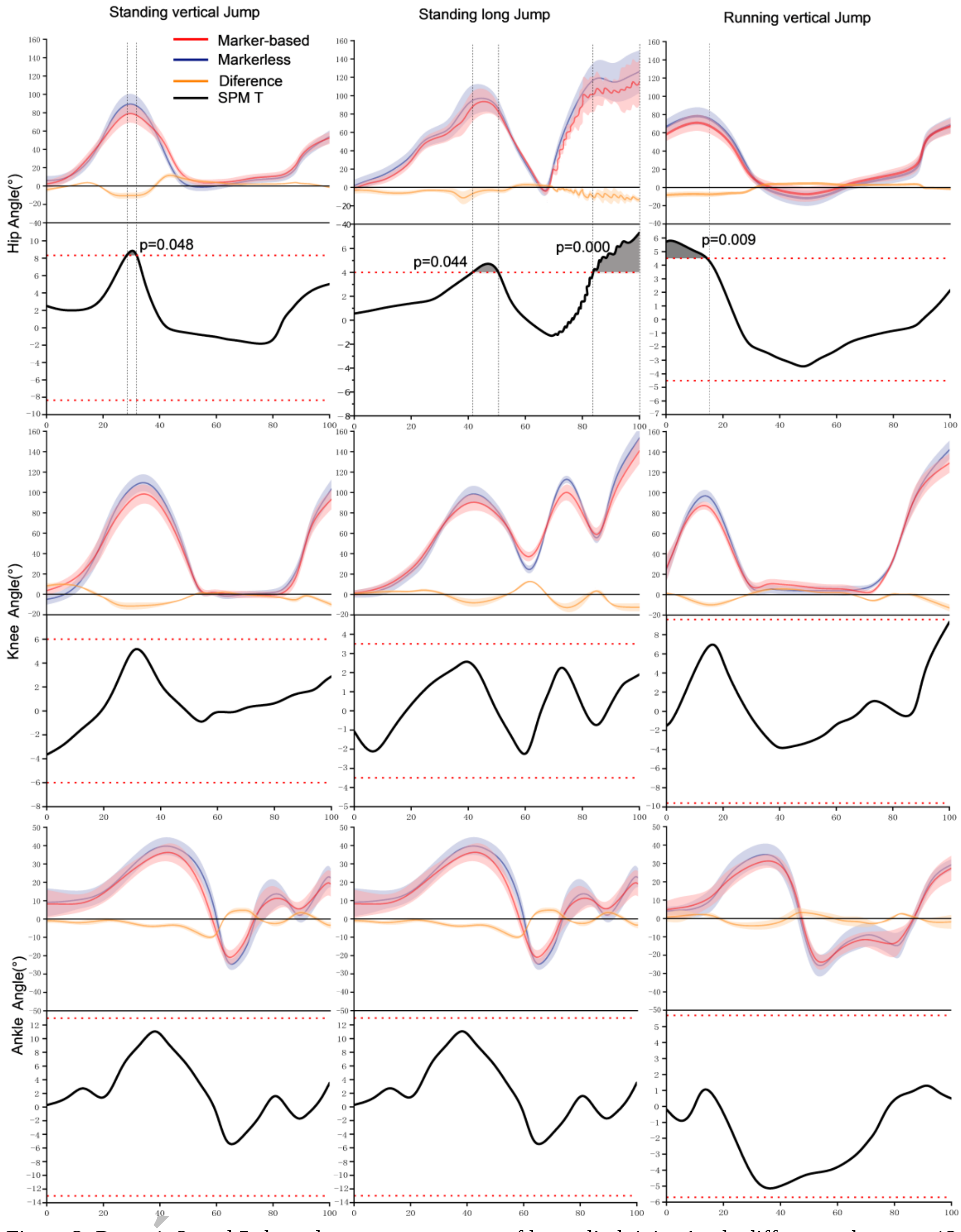



Figure 3: Rows 1, 3, and 5 show the aggregate curves of lower limb joint Angle differences between 12 participants who completed Standing vertical jump, Standing long jump, and Running vertical jump with marked and unmarked motion capture systems. The second, fourth, and sixth rows of figures corresponding to 1, 3, and 5 show the analysis results of SPM paired T-test. Where the horizontal red dotted line represents the critical random field theoretical threshold of the significance level ($p<0.05$), and the dashed rectangle represents the significant region. The blue line (ML) and red line (MB) represent the combined curve of the joint Angle estimated by the system, the yellow line represents the difference between MB and ML, and the black line shows the SPM paired T-test trajectory.

### *3.2 Lower limb joint torque*

According to the SPM paired sample T-test analysis, the hip torque in the three movements showed significant differences between the systems. For the SLJ, the significant regions were from 58% to 60% ($P < 0.05$) and 66% to 100% ($P < 0.001$). For the SVJ, the significant region was from 37% to 42% ($P < 0.05$). The significant range for the RVJ was 14% to 20% ($P < 0.05$) (See the second row in Figure 4). The correlation coefficient for hip and knee torque ($Rxy \geq 0.83$) was slightly lower in SLJ, while the correlation for other joint torques ($Rxy \geq 0.92$) was very strong (See Row 5 in Table 1). During SLJ, the hip and knee joint ($RMSD \leq 0.32$ N·M/kg) showed greater variability compared to other movement measurements (See Row 6 in Table 1). In the hip extension phase of SVJ and RVJ, the Torque max_error of the hip joint was 0.54 N·M/kg and 0.26 N·M/kg respectively, both occurring in the significant region (See Row 7 in Table 1).

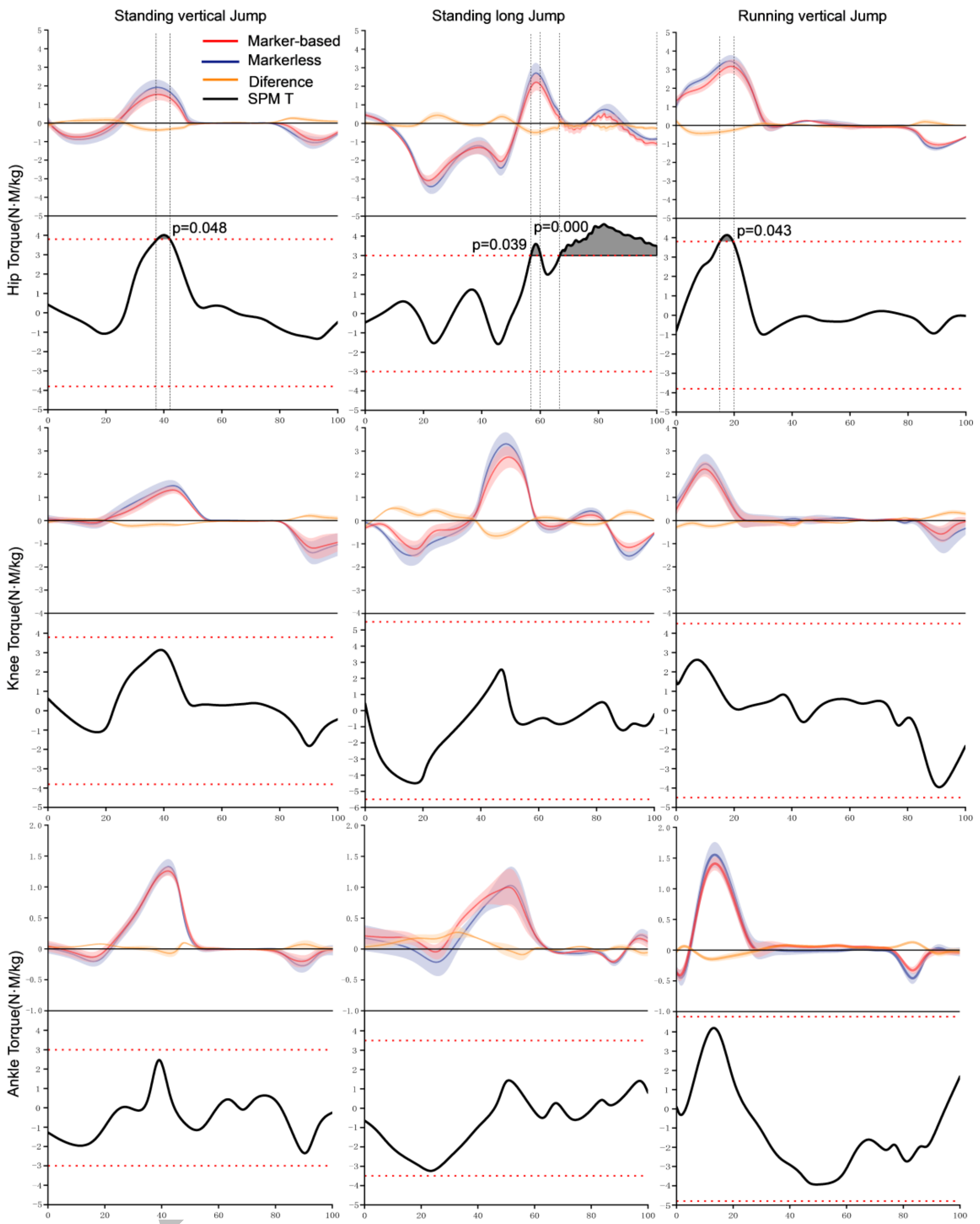



Figure 4: Rows 1, 3, and 5 show the aggregate curves of the difference in joint torque of the lower limbs of 12 participants when they complete the Standing vertical jump, Standing long jump, and Running vertical jump based on marked and unmarked motion capture systems. The second, fourth, and sixth rows of figures corresponding to 1, 3, and 5 show the analysis results of SPM paired T-test. Where the horizontal red dotted line represents the critical random field theoretical threshold of the significance level ($p<0.05$), and the dashed rectangle represents the significant region. The blue line (ML) and red line (MB) represent the combined curve of the joint Angle estimated by the system, the yellow line represents the difference between MB and ML, and the black line shows the SPM paired T-test trajectory.

### *3.3 Lower limb joint power*

According to the SPM paired sample T-test analysis, only the hip joints of the SLJ showed significant joint power ($P < 0.05$), with the significant region ranging from 69% to 80% (See the middle of the second row in Figure 5). Throughout the entire exercise process, except for the SLJ hip joint power correlation coefficient ($Rxy = 0.89$) being lower than 0.9, the correlation coefficients for other movements and joint power ($Rxy \geq 0.91$) indicated a very strong correlation (See Row 9 in Table 1). Among the three joints, the ankle exhibited the best performance with an RMSD of ≤0.75 W/kg, while the hip and knee showed stable results (1.64 W/kg ≤ RMSD ≤ 1.76 W/kg and 0.96 W/kg ≤ RMSD ≤ 1.23 W/kg, respectively)(See Row 10 in Table 1). The maximum joint power error (Power max_error) of the RVJ was 3.20 W/kg, which was significantly higher than that of other movements and joint power but did not reach a significant level (See Row 11 in Table 1).

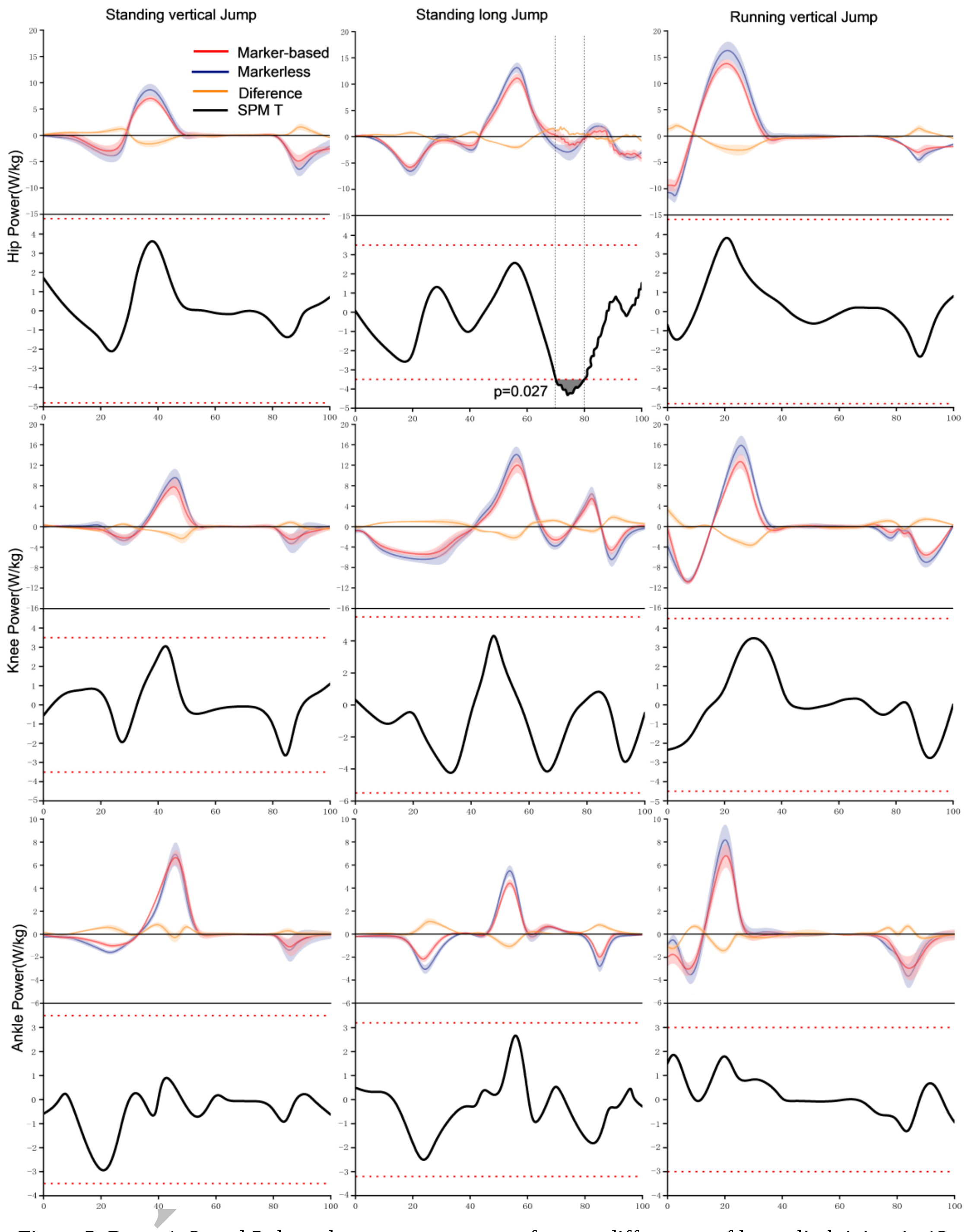



Figure 5: Rows 1, 3, and 5 show the aggregate curves of power differences of lower limb joints in 12 participants who completed Standing vertical jump, Standing long jump, and Running vertical jump with marked and unmarked motion capture systems. The second, fourth, and sixth rows of figures corresponding to 1, 3, and 5 show the analysis results of SPM paired T-test. Where the horizontal red dotted line represents the critical random field theoretical threshold of the significance level ($p<0.05$), and the dashed rectangle represents the significant region. The blue line (ML) and red line (MB) represent the combined curve of the joint Angle estimated by the system, the yellow line represents the difference between MB and ML, and the black line shows the SPM paired T-test trajectory.

## 4 DISCUSSION

The objective of this study was to compare the ability of marker-based and markerless motion capture systems to estimate lower limb kinematics and kinetics when basketball players perform the standing long jump, running vertical jump, and standing vertical jump. We confirmed our hypothesis that, in most movements, the estimates from markerless motion capture closely matched those from the marker-based system at the ankle and knee joints, and that the differences between the systems would be greater in faster hip movements.We focused particularly on the joint angle, torque, and power in the sagittal plane, as these parameters are essential for evaluating athletic performance[9]. The results indicate that the ML system demonstrates high validity, as evidenced by the Pearson correlation coefficient, and the RMSD between the two systems suggests that the ML system achieves high accuracy. The SPM results reveal that significant differences between the systems only occur in the hip joint angle and torque, and these differences may increase as the joint flexion angle increases. The absolute error moments for the minimum (min_error) and maximum (max_error) joint angle,torque, and power generally correspond to the moments when the difference between the systems is the largest, although the actual difference may not always be at the moment of the largest discrepancy.

We found that the two systems showed a high degree of similarity in the relative timing of peak estimation(See the positive and negative maximum values of all the small figures in Figure 3-5). At the peak, both joint extension and flexion were estimated to be higher by the ML system than by the MB system. This finding, reported in previous studies, may be attributed to the greater sensitivity of ML systems in estimating moment of inertia parameters or to the effects of soft tissue artifacts during rapid movement[5, 33]。

For the estimation of joint angles, the ML system was higher than the MB system at the moment when the flexion angles of the hip, knee and ankle joints were at their maximum, and significant differences were observed at the moment when the hip joint flexion was at its maximum. This trend is partially consistent with the research results of Barzyk,P et al.[2] That is, during the Countermovement Jump, the ML system estimates for hip and knee joints at maximum flexion were higher than those from the MB system. When the dorsiflexion of the ankle joint was at its maximum, the MB system was greater than the estimated value of the ML system, and significance was observed when the toe flexion of the ankle joint was at its maximum[2]. Compared to his study, the ankle joint in our research showed better performance with no significant differences. The reason for the different ankle joint results in the two experiments might be that he used only one camera with a small shooting range and a single perspective, which could have caused abnormal ankle joint data. However, in our experiment, we used six high-resolution cameras to capture the ML system's data, making the ankle joint data more reliable. Additionally, the estimated difference in the hip joint angle was greater than that of the knee and ankle joints, but the difference remained less than 8.2°. This finding aligns with the research results of Song K, who examined 8 different movements[27]. In the Countermovement Jump (CMJ), it was reported that the sagittal plane ankle and knee joint angles were highly consistent

(RMSD: 3.4°-5.3°), while the hip joint angle consistency was poor (RMSD ≥ 12.1°)[27]. In this study, the differences in joint angles were smaller for the ankle, knee (RMSD: 2.6°-4.3°), and hip joints (RMSD ≤ 5.7°). In a study by Needham et al., which compared OpenSIM-based unlabeled models with labeling systems (Oqus, Qualisys AB) in jump kinematics, the reported hip, knee, and ankle angles had an RMSD of less than or equal to 3°[22]. Although our hip, knee, and ankle angles (RMSD ≤ 8.2°) showed more variability compared to his study, the fact that he didn't perform SPM analysis or check for statistical differences at specific moments in the motion sequence means it can't be said that one system's joint angle estimates were superior to the other's at any moment or interval. SPM allows for the analysis of differences between datasets across 101 time nodes, pinpointing exact moments where significant discrepancies occur, which highlights its advantage in terms of temporal resolution. In the studies by Horsak et al. and Van Hooren et al., fixed-perspective single-camera markerless motion capture systems were compared with marker-based systems during walking or running. They reported differences in hip, knee, and ankle joint angles, with an RMSD of ≥5.0° [11, 32]. In contrast, our study showed more optimal results for the knee (RMSD ≤4.3°) and ankle (RMSD ≤2.9°) joint angles, while the hip joint (RMSD ≤8.2°) exhibited greater variability (See the second row of Table 1). They did not perform SPM analysis or check for statistical differences at specific moments. Our SPM analysis revealed significant differences in the hip joint at maximum squatting (see line 1 of Figure 3). The fixed-perspective single-camera system relies on a deep learning model trained on specific data, which may produce inaccurate estimates for unfamiliar movements.

Since the training data mainly consisted of slow motions, the system's attempts to estimate keypoints and sagittal plane angles from front-view videos might have reduced the amplitude of the angle curves, particularly for rapid movements. In the kinematics study of the Countermovement Jump (CMJ) conducted by Mercadal-Baudart et al., the root mean square difference (RMSD) of joint angles was found to be ≤5° for the ankle and knee, and ≤6° for the hip[20]. In this study, for SVJ with the same movement pattern as CMJ, the knee and ankle joint angles (RMSD: 2.6°-3.7°) and the hip joint (RMSD≤5.7°) performed better. SPM analysis revealed that during the movement, there were certain times or periods where significant differences in the estimation of knee and ankle joints between systems were observed (see rows 1, 3, and 5 in Figure 3). Moreover, significant differences in the hip joint were found at the maximum squatting moment (see row 1 in Figure 3). These specific times or intervals are crucial for assessing jumping movements.

The estimation of joint torque and power by the two systems showed that the ankle joint (with RMSD of ≤0.21 N·M/kg and ≤0.75 W/kg) had smaller estimation differences compared to the hip (0.41 N·M/kg) and knee joints (1.76 W/kg). SPM analysis also revealed significant differeThe estimation of joint torque and power by the two systems showed that the ankle joint (with RMSD of ≤0.21 N·M/kg and ≤0.75 W/kg) had smaller estimation differences compared to the hip (0.41 N·M/kg) and knee joints (1.76 W/kg). SPM analysis also revealed significant differences in the maximum hip joint torque estimates (see the first row of Figure 5). T. Huang et al., in gait studies, found similar results. They compared ML and MB systems and reported RMSD values for hip, knee, and ankle joints in the sagittal plane as 17.1 N·M, 11.1 N·M, and 4 N·M, respectively, with significant differences at peak hip and knee torque moments ($P<0.01$), in the maximum hip joint torque estimates (see the first row of Figure 5). T. Huang et al., in gait studies, found similar results. They compared ML and MB systems and reported RMSD values for hip, knee, and ankle joints in the sagittal plane as 17.1 N·M, 11.1 N·M, and 4 N·M, respectively, with significant differences at peak hip and knee torque moments ($P<0.01$)[12]. but they didn't standardize joint torque. Similarly, K. Song et al. investigated the Countermovement Jump and reported RMSD values for hip, knee, and ankle joint torque as 0.92%, 0.56%, and 0.29% of height (H) times weight (W), respectively. They also found greater estimation differences for hip joint moment than for knee and ankle joints,[4]. aligning with our results. Although K. Song et al. standardized the joint moment, in terms of variability, the hip, knee, and ankle joint torque (RMSD: 0.12-0.20 N·M/kg) in our study performed better during the SVJ movement. Unlike T. Huang and K. Song et al., who didn't conduct kinematic analysis, we found that in our experiment, the significant differences in kinetics estimates (see the first row of Figure 4) corresponded to the intervals where significant differences in kinematic estimates occurred (as seen in the joint angle plots, Figure 3, first row). This suggests that the significant differences in kinetics estimates from the two systems in our study might stem from differences in kinematic estimates. Kinematic estimates are usually conducted prior to dynamic estimates, as kinetics calculations rely on key information from kinematic data, such as joint angles, angular velocity, and angular acceleration. This sequence and dependency can affect the accuracy and variability of the estimated parameters. In a study comparing the impact of different running speeds on the estimation differences between ML and MB systems, T Huang et al. observed that, compared with the MB system, the ML system estimated higher lower limb joint torque and power in most cases during the swing phase as speed increased, and the peak times of joint torque and power during the swing phase were significantly observable[12]. Similar to our study, T Huang et al. found that, in most cases, the ML system estimated higher joint torque and power than the MB system at the peak moment of joint torque and power during the motion extension phase. Additionally, a significant difference in hip joint power was observed at the peak moment of hip joint torque, and this significant difference in hip joint power was only observed during the flexion phase after the push and extension of the SLJ. We speculate that the significance of joint power in SLJ may be due to the fact that, compared with vertical jumps, horizontal jumps in the hip flexion phase are more likely to be obstructed by the lower arms, which can interfere with the camera's ability to capture the joint markers. This obstruction can affect the system's estimation accuracy. In our study, when comparing the three joints across the three movements, we found that the differences in hip torque and power between the two systems were greater during faster hip movements than those observed for the knee and ankle. Specifically, the differences were more than twice as large as those for the ankle. This trend is consistent with the findings of Song K, who studied eight movements and reported greater differences in hip torque between the two systems, particularly during fast movements[27]. The magnification of differences in hip torque and power estimates between the two systems can be attributed to the increased skin-to-bone motion, which amplifies kinematic errors and affects the calculation of dynamics. This is particularly evident when there is an instantaneous change in the direction of motion speed, such as during the maximum amplitude of hip flexion or a sudden stop. The inertia of the skin and the marking point can cause the system's estimation error to increase if the velocity direction is not changed in a timely manner[5, 33]. The ML system has the potential to reduce this error by adjusting system parameters, such as camera resolution, lighting, shutter speed, and capture rate, to optimize video sharpness. We made these relevant adjustments before the experiment. However, the experimental results show that these adjustments only slightly reduced the difference, especially during fast motion, the system error still exists[14, 27].The differences in the research results may also be caused by a variety of factors, including different ground conditions, kinetics calculation methods, moment normalization techniques, and the video image blur that may occur during fast motion in a markerless motion capture system, and differences in the marking position and marker-based model definition may also affect the accuracy of the system[21, 23].

This study has certain limitations. In the biomechanical analysis using the marker-based system, the hip joint has the largest estimation error. The joint centers of the hip have large displacements in the vertical and anterior-posterior directions. Different joint center positions can affect the moment arms, and the segmental center of mass (COM)can influence the moment of inertia estimation. These factors collectively affect the accuracy of torque arms and torque of inertia estimation, potentially leading to an amplification of differences in the estimation of torque and power. Previous studies have demonstrated that errors in the central position of the hip joint can significantly impact the kinematics and kinetics of both the hip and knee joints, particularly the flexion and extension torque of the hip joint[28]. Moreover, the thicker skin around the pelvis, the relative movement between the skin and the underlying bone, and the occlusion of marker points by the camera during hip flexion all contribute to the practical challenges of identifying anatomic landmarks and securely attaching pelvic markers[7, 16]. Therefore, it is difficult to know the absolute accuracy of the hip movement in this case.

Future studies should further compare the accuracy of ML and MB techniques in hip kinetics assessment by employing gold standard measurement methods, such as biplanar fluoroscopy. This approach will aid in validating the accuracy of both the ML and MB systems[18, 31]. Furthermore, the differences in biomechanical models between the ML and MB systems may also impact the results, which is a limitation that is difficult to eliminate. This is often hampered by different model definitions when conducting different motion analyses. For instance, factors such as pelvic tilt and the neutral angle of the ankle joint may lead to a shift in the hip angle[35]. Although there are existing model definition criteria, in the analysis of different sports or movements, it is still necessary to consider the actual limitations of the MB system. The ML system is able to overcome this obstacle by using the same joint model and segment definition in different experiments, helping to eliminate sources of kinematic offset[8, 35, 36].

## 5 CONCLUSION

In the analysis of basketball jumping motions, markerless motion capture system significant potential to overcome the limitations of traditional marker-based systems, particularly in enhancing player performance and biomechanical evaluation. Our findings indicate that the markerless system is highly consistent with the marker-based system in estimating the kinematics and kinetics of the knee and ankle joints in the lower extremity. However, further experiments are required to validate the measurements of the hip joint and certain movements. Consequently, ML systems hold promise for enabling biomechanical assessments in large-scale and real-world scenarios that were previously challenging with MB systems. The biomechanics community should continue to validate and expand the application of ML technology to enhance its accuracy and reliability in complex motions.



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