CONCURRENT VALIDITY AND RELIABILITY OF IN-LAB MARKERLESS MOTION CAPTURE IN ESTIMATING JOINT KINEMATICS IN BASEBALL PITCHING

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Markerless motion capture systems allow for the estimation of 3D segmental pose of human movement without the encumbrance of markers. Therefore, the aim of this study is to measure the concurrent validity and reliability of baseball pitching kinematics estimated by an in-lab markerless motion capture system. This analysis is based of 100 pitches thrown by 18 collegiate baseball pitchers. Discrete kinematic variables varied in their equivalence and reliability between systems (mean bias range of 0.04 to -28.4). Kinematic variables in the sagittal plane had more agreement between systems than variables in the transverse plane. Segment lengths were also comparable between systems. Although markerless technology provides ease of collecting biomechanical data in a baseball setting, inter-system differences do still exist between marker-based systems and markerless systems.

KEYWORDS: machine learning, equivalence, segment length, statistical parametric mapping

INTRODUCTION: Kinematic analysis is an important foundation of clinical and research biomechanics. There are various ways in which technology can estimate the 3D segmental pose of human movement. However, marker-based motion capture has long been seen as one of the most accurate ways to measure joint kinematics and can provide kinematic measurements in various biomechanical applications (Windolf et al., 2008). Although marker-based motion capture is considered to be accurate, specialized training is needed to perform adequate kinematic analyses.

Markerless motion capture technology attempts to address the limitations of marker-based motion capture by utilizing trained neural networks to estimate 3D poses of body segments during human movement (Mathis et al., 2018). Utilizing markerless technology and solely relying on the neural networks to identify joint centres takes away any human error of having to place markers on skin. *Theia3D* (Theia Markerless Inc., Kingston, ON, Canada) is a video-based example of this type of novel technology and has started to be implemented into clinical and research biomechanics labs because of its feasibility (Kanko et al., 2021).

While *Theia3D* has started to be implemented into clinical practice, there have been limited studies assessing its accuracy when compared to marker-based motion capture. Evidence in the literature show that *Theia3D* has good to excellent agreement with marker-based motion capture in most spatiotemporal parameters of gait, but lower limb kinematics had lower agreement, especially in the transverse plane (Kanko et al., 2021).

Biomechanical analysis in high level sports is growing exponentially. Baseball specifically has adopted many biomechanical technologies in hopes to optimize performance and identify pathomechanics that increase risk of musculoskeletal injuries (Trasolini et al., 2022). While marker-based motion capture has historically been used to analyse throwing and hitting kinematics, machine-learning markerless technology is becoming more prevalent both in labs and on the field. The emergence of this new technology has made collecting data in high level environments practical, however, there is limited data in the literature showing the performance of these markerless technologies compared to marker-based systems. A recent study assessed the agreement between an in-game markerless motion capture system and marker-based technology in minor league baseball pitchers and showed fair agreement in kinematics with some exceptions (Aguinaldo, 2022). However, this analysis was limited to a sample of 3 players. Therefore, the purpose of this study is to compare the concurrent validity and reliability of baseball pitching kinematics estimated by in-lab markerless and marker-based motion capture system.

METHODS: Eighteen collegiate pitchers (height =1.83 ± 0.5 m, mass = 86 ± 18 kg) threw 10 fastball pitches off a regulation mound while 3D joint centre estimation and pose was concurrently recorded with a 10-camera markerless motion capture system (Qualisys, Goteborg, Sweden) utilizing Theia3D (Theia Markerless Inc., Kingston, ON, Canada) and with an 8-camera marker-based motion capture system (Qualisys, Goteborg, Sweden) at a sampling rate of 300 Hz and 540 p for both systems. Thirty-eight reflective markers were placed on the skin of each pitcher according to a link segment rigid-body model (Aguinaldo & Chambers, 2009). Positional data, from both systems, for a total of 100 pitches (n = 100, minimum of 5 pitches per subject) were smoothed with a fourth-order zero-lag Butterworth filter at a cut-off frequency of 18 Hz. Raw data from both systems were processed through the same Inverse Kinematic model (Aguinaldo & Chambers, 2009) in Visual3D (C-Motion, Germantown, MD) to estimate joint kinematics throughout the entire pitching motion. (C-Motion, Germantown, MD). Kinematic waveform data from both systems were statistically compared using statistical parametric mapping (SPM) t-tests. Random field theory (RFT) was used to define the threshold above which 5% of waveform differences would be produced by random data (Pataky et al., 2013). Variables of interest include stride length, stride knee flexion at stride foot contact (SFC), hip shoulder separation, max shoulder external rotation, pelvic width, femur length, and humerus length. All SPM t-tests were performed in Python utilizing the *spm1d* package. Analyses were performed over the entire pitching motion as well as at different phases defined by temporal instances within the pitching motion (Aguinaldo & Nicholson, 2021). A concordance correlation coefficient (CCC) (Carrasco et al., 2013) was used to assess the reliability and equivalence between the markerless and marker-based system at different discrete kinematic data points and average segment lengths. Additionally, to examine the agreement between both methods, a modified Bland-Altman analysis was performed with the limits of agreement (LoA) estimated using a method that accounts for the variance from repeated trials per subject. All data analyses were performed in *RStudio* at an a *priori* significance level of 0.05 with the *simplyagree* and *cccrm* packages.

RESULTS AND DISCUSSION: Discrete kinematic variables varied in their equivalence and reliability between systems (Table 1). Both stride length and stride knee flexion showed high equivalence and reliability between systems. Stride length had a mean bias of 4 cm and strong reliability with a CCC value of 0.93. Similarly, stride knee flexion at SFC had a mean bias of 5.3 º and a CCC value of 0.86. Consistent with previous literature, the Theia system was both equivalent and reliable in the sagittal plane (Figure 1). However, kinematic variables in the transverse plane exhibited lower equivalence. Hip shoulder separation had a mean bias of 14.9 º and lower reliability between systems with a CCC value of 0.27. Maximum shoulder external rotation (MER) had the most bias between systems (mean bias = -28.3 º) and low reliability (CCC = -0.034). The disagreement between systems in the transverse plane further illustrates the results of previous validity studies (Aguinaldo, 2022). The bias between systems in the transverse plane should be considered in performance and injury prevention decisions.

Variable	Marker Mean (SD)	Theia Mean (SD)	Mean Bias (CI)	CCC (CI)
Stride Length (m)	1.54 (0.13)	1.51 (0.13)	0.04 (0.03 to 0.04)	0.93 (0.87 to 0.96)
Stride Knee Flexion at SFC (deg)	50.1 (9.0)	46.5 (8.0)	5.27 (3.8 to 6.7)	0.86 (0.81 to 0.89)
Hip Shoulder Separation (deg)	48.1 (10.1)	31.5 (7.2)	14.9 (11.1 to 18.7)	0.27 (0.16 to 0.37)
MER (deg)	151.9 (16.4)	177.9 (10.4)	-28.3 (-37.6 to -19.0)	-0.03 (-0.17 to 0.10)
Pelvic Width (m)	0.17 (0.01)	0.22 (0.01)	-0.04 (-0.01 to -0.04)	0.03 (-0.02 to 0.09)
Femur Length (m)	0.46 (0.03)	0.44 (0.02)	0.01 (-0.01 to 0.02)	-0.24 (-0.48 to 0.04)
Humerus Length (m)	0.30 (0.02)	0.29 (0.02)	0.01 (-0.03 to 0.03)	-0.02 (-0.17 to 0.14)

Table 1: System means, mean bias, and CCC values for selected kinematic values and segment lengths

SPM{t} scalar fields further reveal discrepancies between systems in the kinematic variables of interest, measured throughout the entire pitching motion (Figure 2). Further analysis of the pitching motion highlights phases that might cause additional bias between markerless and marker-based systems. A suprathreshold region ($p<.05$) in the SPM{t} field showed significant differences in shoulder rotation of the pitching arm throughout the whole motion ($p<0.001$). Peak differences occurred during the arm-cocking and acceleration phases. While both systems showed agreement in the early stride phase and follow-through, peak differences in hip shoulder separation also occurred during the arm-cocking and acceleration phases. Greater bias during these phases is likely due to the high angular velocities of the movements, suggesting that markerless technology might struggle to accurately estimate upper-body kinematics during high-velocity movements such as pitching. Therefore, the phase of the pitching motion should be considered when evaluating performance and injury risk based on markerless motion capture data.
Mean segment lengths were within 2 cm when estimating femur and humerus length, indicating high equivalence between systems (Figure 3). However, although system means were similar and mean bias was low, CCC values were extremely low (CCC = -0.24 and -0.02 respectively) indicating low reliability. Therefore, system bias varied greatly depending on segment length magnitude. Similarly, pelvic width had a very low CCC value (CCC = 0.034) and a higher mean bias (mean bias = 4 cm) compared to both femur and humerus length. Discrepancies in pelvic width between marker-based and markerless systems could influence lower body kinematics in various movements.

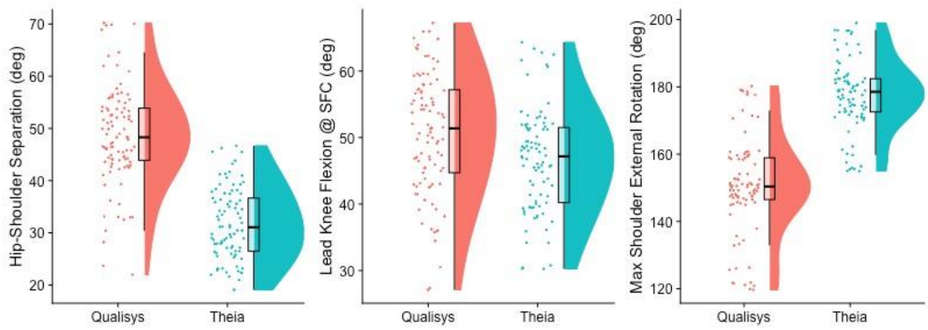

Figure 1: Hip shoulder separation, lead knee flexion, max shoulder external rotation rain plots for each system: markered (left) and markerless (right)

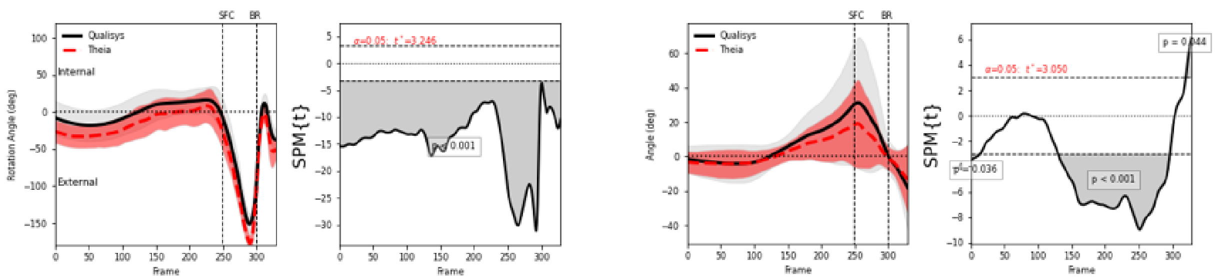

Figure 2: Mean ensemble shoulder rotation angle (left) and mean ensemble hip shoulder separation angle (right) measured by Theia and marker-based systems throughout pitching motion. SPM{t} fields show inter-system differences.

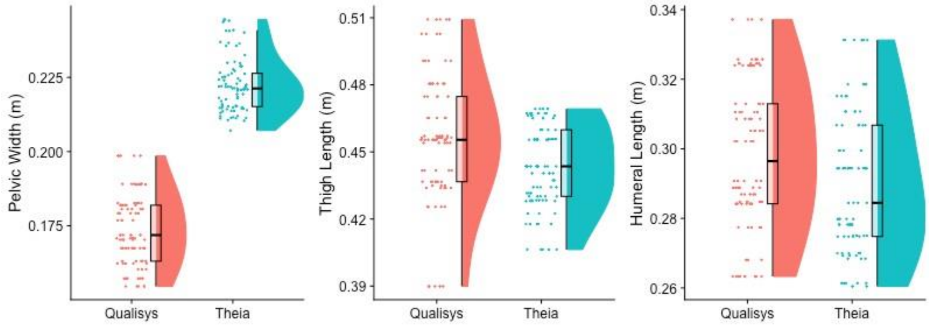

Figure 3: Pelvic Width, thigh length, and humeral length for each system: markered (left) and markerless (right).

CONCLUSION: These findings suggest that markerless motion capture technology can provide pitching kinematic and segment length measures that are equivalent to those measured by a marker-based system depending on the variable being examined and the temporal phases of the pitching motion. However, variables in the transverse plane showed less equivalence between systems. Segment length means were similar between systems, but some inter-system reliability was low. The range of inter-system differences and their implications should be accounted for when biomechanically assessing performance and injury risk in baseball pitching. Feasibility of markerlessly capturing the pitching motion has important implications for progressing the game of baseball from a player performance and health standpoint, however, further equivalence analyses and high sampled research are still needed.

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