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Estimation of Upper Limb Kinematics in Baseball Pitching Using Sensor-embedded Ball

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***Abstract*— We estimated the kinematics of the upper limb during baseball pitching using a sensor-embedded ball. Twenty collegiate pitchers performed 24 trials each, throwing fastballs, curveballs, and sliders. Kinematic data were collected using motion capture system and a sensor-embedded baseball. Machine learning models, including Linear Regression, Lasso, Random Forest, Gradient Boosting, and Support Vector Regression (SVR), were used to estimate joint angles. The evaluation metric was the R^2 score from 10-fold cross-validation. Random Forest (R^2 score (the average of all joint movement) = 0.85) and Gradient Boosting showed high accuracy (R^2 score (the average of all joint movement) = 0.85), particularly for shoulder and elbow joints. The ensemble model further improved accuracy. The model demonstrated high accuracy in estimating joint angles for the shoulder joint (external/internal rotation) (R^2 score (the average of all time) = 0.97) and elbow joint (supination/pronation) (R^2 score (the average of all time) = 0.96). In the future, the application of this model is expected to facilitate the acquisition of kinematic data of the pitching arm in competitive environments.**

I. Introduction

Numerous studies have investigated the kinematics of baseball pitching, with the primary purposes of improving performance and preventing injuries. For example, one of the research projects has shown that shoulder abduction and horizontal abduction are crucial for ball control during the maximum external rotation phase [1]. Additionally, significant differences in elbow joint flexion/extension and shoulder joint abduction have been observed between major and minor league pitchers, highlighting the role of kinematics in performance levels [2]. These findings underscore the critical importance of understanding joint kinematics in optimizing performance and reducing the risk of injury among pitchers at different competitive levels.

In terms of injury prevention, one study has found that shoulder joint external rotation beyond 100 degrees increases the risk of elbow injuries [3]. While some studies reported no significant differences in upper limb kinematics between fatigued and non-fatigued athletes [4], another showed that overuse leads to shoulder and elbow injuries [5]. It has been reported that 32-35% of pitchers experience shoulder pain and 17-58% experience elbow pain, with these injuries occurring across all performance levels [6, 7]. Common injuries in pitching arm include rotator cuff injuries and medial collateral ligament injuries [8, 9]. Fatigue-induced changes in upper limb kinematics, such as increased elbow flexion and shoulder rotation, have been linked to higher injury risk [10, 11].

Collecting kinematic data on the pitching arm is vital for both injury prevention and performance enhancement. However, traditional studies often use motion capture systems in controlled environments, which are time-consuming and require specialized skills. This study aims to address these limitations by using a sensor-embedded ball to estimate the kinematics of the pitching arm in a more practical and accessible manner. The novelty of this study also lies not only in the posture estimation of the sensor itself but in the use of machine learning to estimate the distal joint angles from the ball's perspective using a single inertial sensor. This method offers an advantage by enabling more accessible kinematic estimation.

The purpose of this study is to estimate the kinematics of the upper limb during baseball pitching using a sensor-embedded ball. The significance of this research lies in its potential to easily obtain upper limb kinematics data and apply it in environment like baseball game.

II. Methods

A. Data Collection

Twenty pitchers (age : 19.8 ± 1.1 years, body height : 1.76 ± 0.05 m, body mass : 75.8 ± 8.1 kg, career : 13.1 ± 1.7 years) participated in this study. Each participant threw a sensor-embedded baseball 24 times. For the 24 trials, each participant was required to throw 8 fastballs (FB), 8 curveballs (CB), and 8 sliders (SL). These pitch types were chosen because they are the top three most frequently thrown in games by the X League, an affiliate of the All Japan University Baseball Federation [12].

During the measurements, retroreflective markers were attached to twelve anatomical landmarks (Fig. 1). This data was captured using eight dedicated cameras (MAC3D, Motion Analysis, USA) at a sampling frequency of 500 Hz.

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During the trials, the pitchers were instructed to throw the ball at a target 18.44 meters away. Sensor-embedded baseball (MA-Q, Mizuno Corp, Japan) was used in this study. This ball has the same mass, moment of inertia and material as the one used in the X League. However, the cork core at the center of the ball has been replaced with a capsule containing a sensor, allowing it to be thrown with the same feel as the ball used in the X League. Acceleration and angular velocity data were collected with the sensor-embedded baseball. These data were collected at a sampling frequency of 500 Hz.

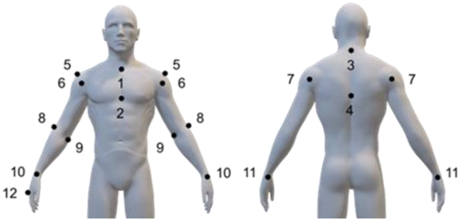


Figure 1 Anatomical landmarks

The target was designed according to the strike zone defined by a ballistic measurement and analysis device (Rapsodo Pitching 2.0, Rapsodo, Singapore). The strike zone dimensions were 0.457–1.067 meters in height and 0.508 meters in width (Fig. 2).

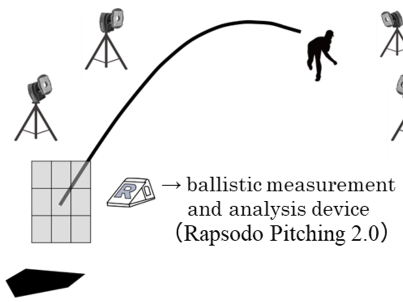


Figure 2 Experimental setup

B. Definition of coordinate system

The X_G axis of the global coordinate system was the unit vector pointing from the midpoint of pitching plate to the center of strike zone, the Z_G axis was the unit vector pointing vertically upward, and the Y_G axis was the cross product of Z_G and X_G. We then defined the coordinate system with X_G, Y_G, and Z_G as the global coordinate system (ΣG) (Fig. 3).

In this study, referring to previous research on the serving motion in volleyball (Horiuchi et al., 2019), we set up a local coordinate system (ΣUT, ΣUA, ΣFA, ΣHND) in which each axis was standardized and orthogonalized for the trunk (thorax) and the upper limbs (upper arm, forearm, and hand) on the throwing side [13].

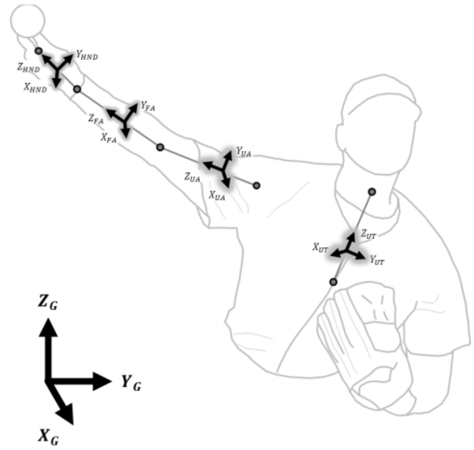


Figure 3 Definition of coordinate systems

C. Calculation of Joint Angle

The relative Euler angle of the upper arm coordinate system (ΣUA) to the thoracic coordinate system (ΣUT) was calculated as the shoulder joint angle. The postures in which X_{UT} and X_{UA}, Y_{UT} and Y_{UA}, and Z_{UT} and Z_{UA} were coincident were used as the reference coordinates, and the rotation order was $Z_{UA} - Y'_{UA} - X"_{UA}$. The rotation order was defined as external (+) / internal rotation (-), horizontal abduction (+) / horizontal adduction (-), and adduction (+) / abduction (-). The elbow joint angle was calculated using the relative Euler angles of the forearm coordinate system (ΣFA) to the upper arm coordinate system (ΣUA). The postures where X_{UA} and X_{FA}, Y_{UA} and Y_{FA}, and Z_{UA} and Z_{FA} were aligned were used as the reference coordinates, and the rotation order was Y_{FA}–Z'_{FA}–$X"_{FA}$. The rotation order was defined as flexion (+) / extension (-), supination (+) / pronation (-), and varus (+) / valgus (-). The terms varus (+) / valgus (-) were mentioned in the definition of the rotation order, but they were not used subsequently in the analysis. The wrist joint angle was calculated using the relative Euler angles of the hand coordinate system (ΣHND) to the forearm coordinate system (ΣFA). The postures where X_{FA} and X_{HND}, Y_{FA} and Y_{HND}, and Z_{FA} and Z_{HND} were aligned were used as the reference coordinates, and the rotation order was Z_{HND}–Y'_{HND}–$X"_{HND}$. The order of rotation was defined as medial (+) / lateral rotation (-), palmar (+) / dorsi flexion (-), and ulnar (+) / radial flexion (-). The terms medial (+) / lateral rotation (-) were mentioned in the definition of the rotation order, but they were not used subsequently in the analysis.

D. Machine Learning Models

The machine learning in this study was conducted using Python, with the code written in the Spyder integrated development environment (IDE). We used multiple machine learning models to estimate joint angles, with explanatory variables being the six components (acceleration (x, y, z) and angular velocity (x, y, z) data) of the ball kinematics data. The target variables included various shoulder, elbow, and wrist joint movements. Features were standardized using StandardScaler from sklearn.preprocessing. We used Linear Regression, Lasso Regression, Random Forest, Gradient

Boosting, and SVR. Scores were calculated over 100 frames by collecting corresponding rows from each dataframe. To improve performance of estimation, ensemble models using VotingRegressor were created, with weights calculated by ignoring negative scores.

In this study, hyperparameter tuning was performed for Random Forest, Gradient Boosting, and SVR. For Random Forest, the number of trees was set to 100, and the maximum depth was set to 10. For Gradient Boosting, the learning rate was set to 0.1, with the number of trees set to 100 and maximum depth set to 5. For SVR, the regularization parameter was set to 1.0 and epsilon to 0.1. Other parameters were set to the default values provided by sklearn.

The evaluation metric for each model was the R^2 score, which measures the proportion of variance explained by the model. The R^2 score ranges from 0 to 1, with values closer to 1 indicating a better fit of the model to the data. An R^2 score of 0 implies that the model fails to capture any variance in the data, whereas a score of 1 indicates that the model perfectly explains the observed variance. In practical applications, an R^2 value above 0.7 is typically considered a good fit, though this threshold may vary depending on the specific domain and dataset characteristics. Each model's score was derived from the average value obtained through 10-fold cross-validation, ensuring robust and reliable estimates.

Compared to other methods, the machine learning models used in this study require lower computational load and allow for faster estimation. Therefore, we chose to adopt these models for their efficiency and practicality.

III. RESULTS

A. Evaluation of Ensemble Model

The temporal changes in the R^2 scores are shown in Figure 4 to 6.

Referring to the results shown in these figures, the estimation scores by the ensemble model for shoulder joint (external/internal rotation) and elbow joint (supination/pronation) angles were consistently high across the entire evaluation period. However, for shoulder joint (abduction/adduction), there were intervals where the scores became negative, indicating poor estimation accuracy at certain times. Additionally, for wrist joint kinematics, the scores transitioned between 0.5 and 0.8, with a tendency to decline just before the release.

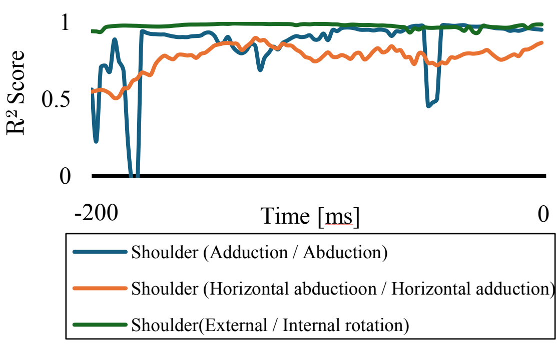


Figure 4 Ensemble Score (Shoulder)

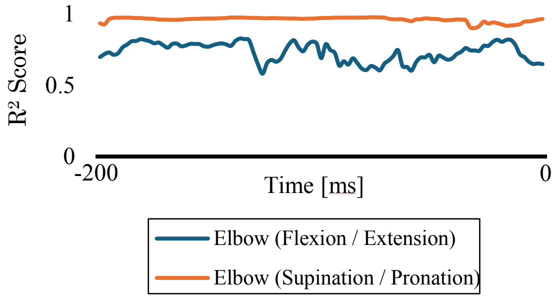


Figure 5 Ensemble Score (Elbow)

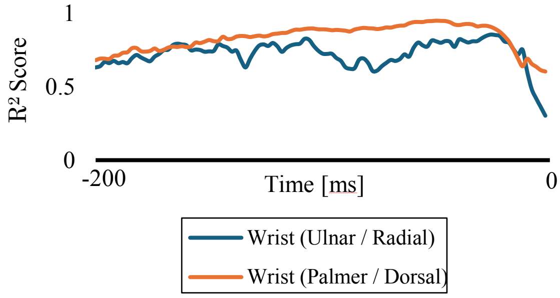


Figure 6 Ensemble Score (Wrist)

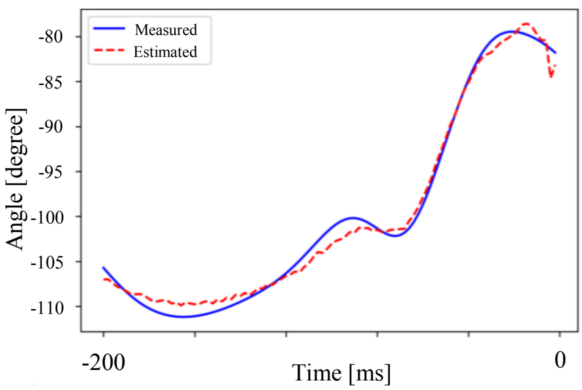
B. Estimation of Joint Angle

In this study, we utilized an ensemble model to determine the differences between the measured values and the estimated values for each of the 100 frames, ranging from -200ms. The mean absolute differences for each of the 100 frames were calculated and defined as the error for each movement. In Table 1, the errors which were the average and standard deviation of all trials were shown. Notably, the shoulder joint (external/internal rotation) and the elbow joint (supination/pronation), which showed high R^2 scores in the ensemble model, exhibited smaller errors.

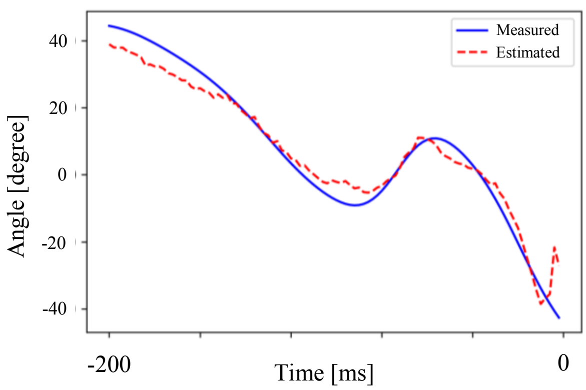
Table 1. The average error of each joint movement (ensemble model)

Joint Movement		**Error (degree)**
Shoulder Joint	Adduction / Abduction	9.46 ± 6.29
	Horizontal adduction / abduction	2.89 ± 1.31
	External / Internal Rotation	1.98 ± 1.38
Elbow Joint	Flexion / Extension	2.93 ± 1.64
	Supination / Pronation	2.11 ± 1.58
Wrist Joint	Palmar / Dorsal Flexion	2.13 ± 1.08
	Ulnar / Radial Flexion	1.06 ± 0.44

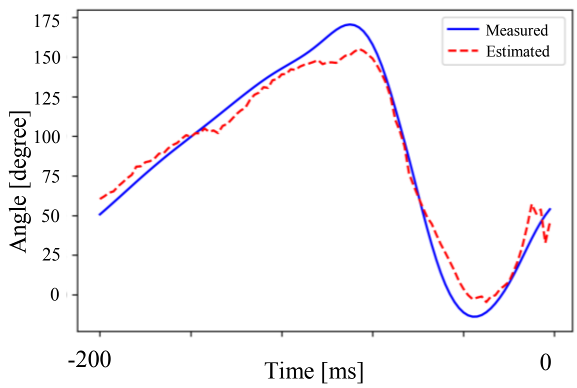
Figure 7 to 9 present the comparison between the measured and estimated time-series data using the model adopted in this study. These are based on the trials in which the discrepancy between the measured and estimated values was closest to the average value of the discrepancy among 480 trials. The average difference for the shoulder joint (adduction/abduction) was 8.58 degrees, for the shoulder joint (horizontal adduction/abduction) it was 3.57 degrees, and for the shoulder joint (external/internal rotation) it was 0.87 degrees. The average difference for the elbow joint (flexion/extension) was 3.01 degrees, and for the elbow joint (supination/pronation) it was 2.37 degrees. For the wrist joint (ulnar/radial), the average difference was 0.57 degrees, for the wrist joint (palmar/dorsal flexion) it was 2.22 degrees, and for the wrist joint (supination/pronation) it was 1.92 degrees. In all cases, the measured and estimated values exhibited similar waveforms from -200 ms to -40 ms; however, the difference between the measured and estimated values increased significantly from -40 ms to 0 ms.



(a) Adduction (+) / Abduction (-)

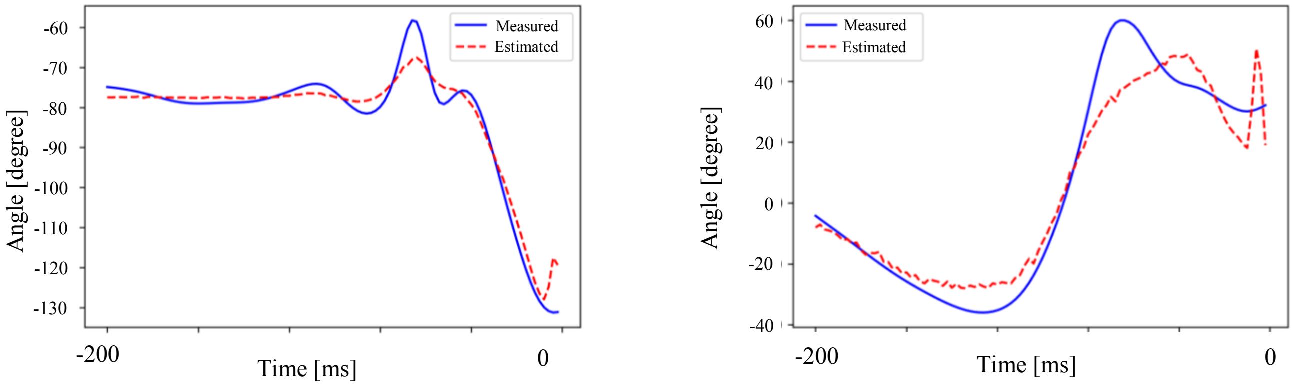


(b) Horizontal Abduction (+) / Adduction (-)



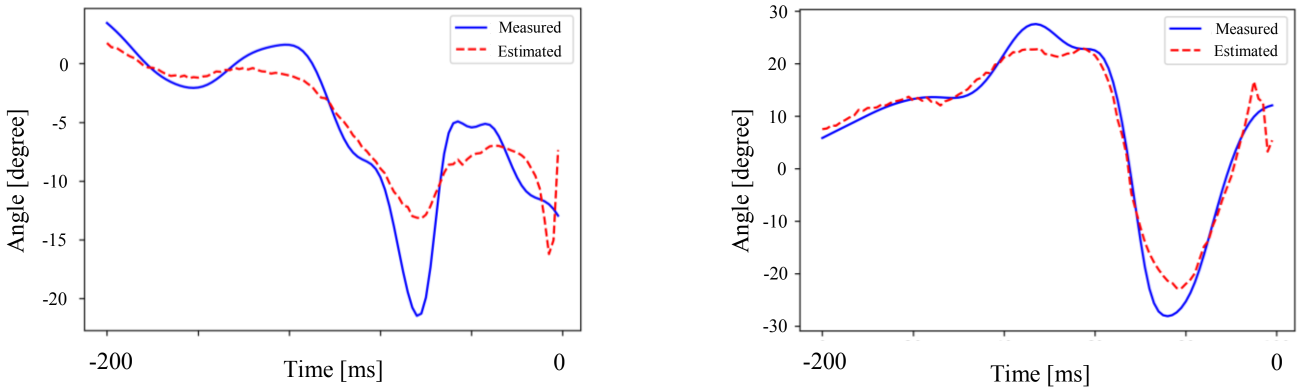
(c) External (+) / Internal Rotation (-)

Figure 7 Measured vs Estimated Shoulder Joint Angle (the trial in which the discrepancy between the measured and estimated values was closest to the average value of the discrepancy among 480 trials).



(a) Flexion (+) / Extension (-) (b) Supination (+) / Pronation (-)

Figure 8 Measured vs Estimated Elbow Joint Angle (the trial in which the discrepancy between the measured and estimated values was closest to the average value of the discrepancy among 480 trials).



(a) Ulnar (+) / Radial (-) (b) Palmer (+) / Dorsi (-)

Figure 9 Measured vs Estimated Wist Joint Angle (the trial in which the discrepancy between the measured and estimated values was closest to the average value of the discrepancy among 480 trials).

IV. Discussion

A. Machine Learning Models

Hyperparameter tuning as wrote in methods resulted in higher scores for Random Forest and Gradient Boosting compared to the other models. In addition, of course, ensemble model was the best way to estimate kinematics of upper limb in pitching side.

B. Estimated Kinematics

The time-series changes in each joint angle were verified to be within reasonable values by referencing previous studies [14, 15]. This study analyzed the phases of pitching including the arm acceleration phase and the ball release phase. It has been shown that an increase in the external rotation range of motion of the shoulder joint during arm acceleration raises the risk of glenohumeral cartilage damage and medial collateral ligament injuries [16]. Additionally, the pronation angle of the forearm at ball release has been shown to affect the direction and accuracy of the pitch [17]. These two joint movements obtained high scores in this study, suggesting the utility of our model.

C. Limitation

The difference between the measured and estimated angles observed in the -40ms to 0ms is likely due to the angular velocity data reaching the upper limit of the equipment during this time. To address this issue, expanding the sample size to include data from pitchers with diverse throwing styles would not only increase the amount of training data for machine learning but also enhance the model's ability to more accurately estimate angles from acceleration data, thereby improving the overall performance.

In this study, the sample size was 480 trials. These 480 trials were collected from 20 pitchers, including both right-handed and left-handed pitchers, and incorporated three different pitch types. However, this sample size is not necessarily sufficient for machine learning. By increasing the number of participants or adding more pitch types, it is expected that the R^2 score could be further improved. Moreover, constructing a machine learning model with this method would allow for broader applicability across pitchers with various throwing forms, making the model more robust and versatile.

V. CONCLUSION

This study demonstrated the effectiveness of using a sensor-embedded baseball to estimate the kinematics of the upper limb during baseball pitching. The machine learning models, particularly Random Forest and Gradient Boosting, showed high accuracy in estimating joint movements such as shoulder joint (external/internal rotation) and elbow joint (supination/pronation). The ensemble model further enhanced the accuracy of these estimates, confirming its superiority in this context. The ensemble model adopted in this study were expected to improve the accuracy as the sample size increases. By using these models with data from the sensor-embedded baseball, reliable acquisition of kinematic data of the pitching arm will become possible in competitive environments.

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