

PitcherNet: Powering the Moneyball Evolution in Baseball Video Analytics

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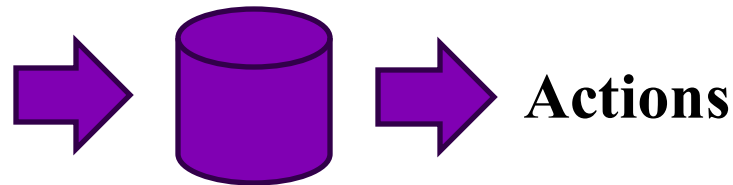
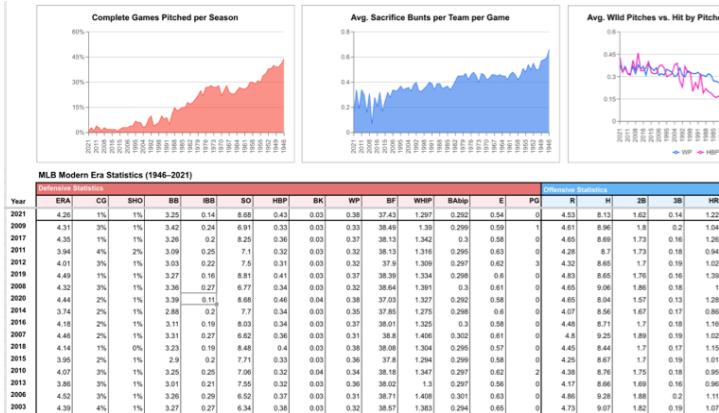
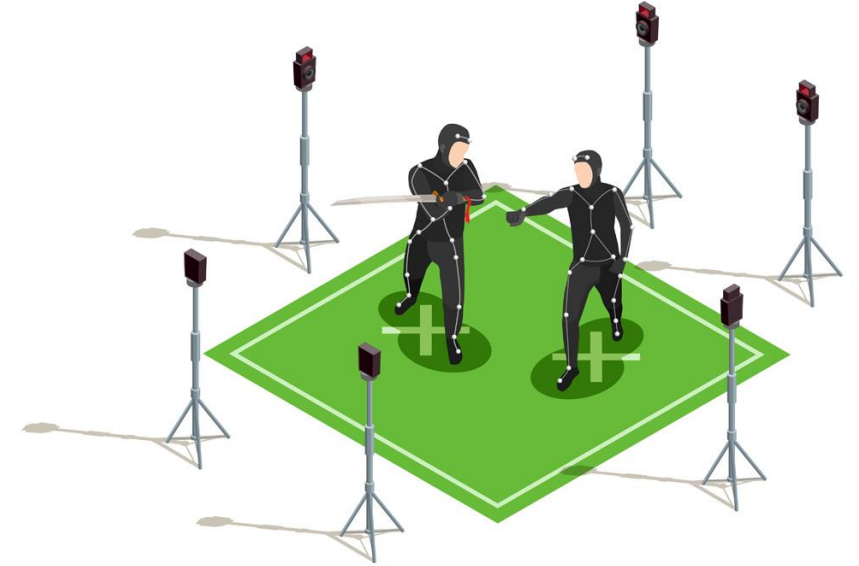
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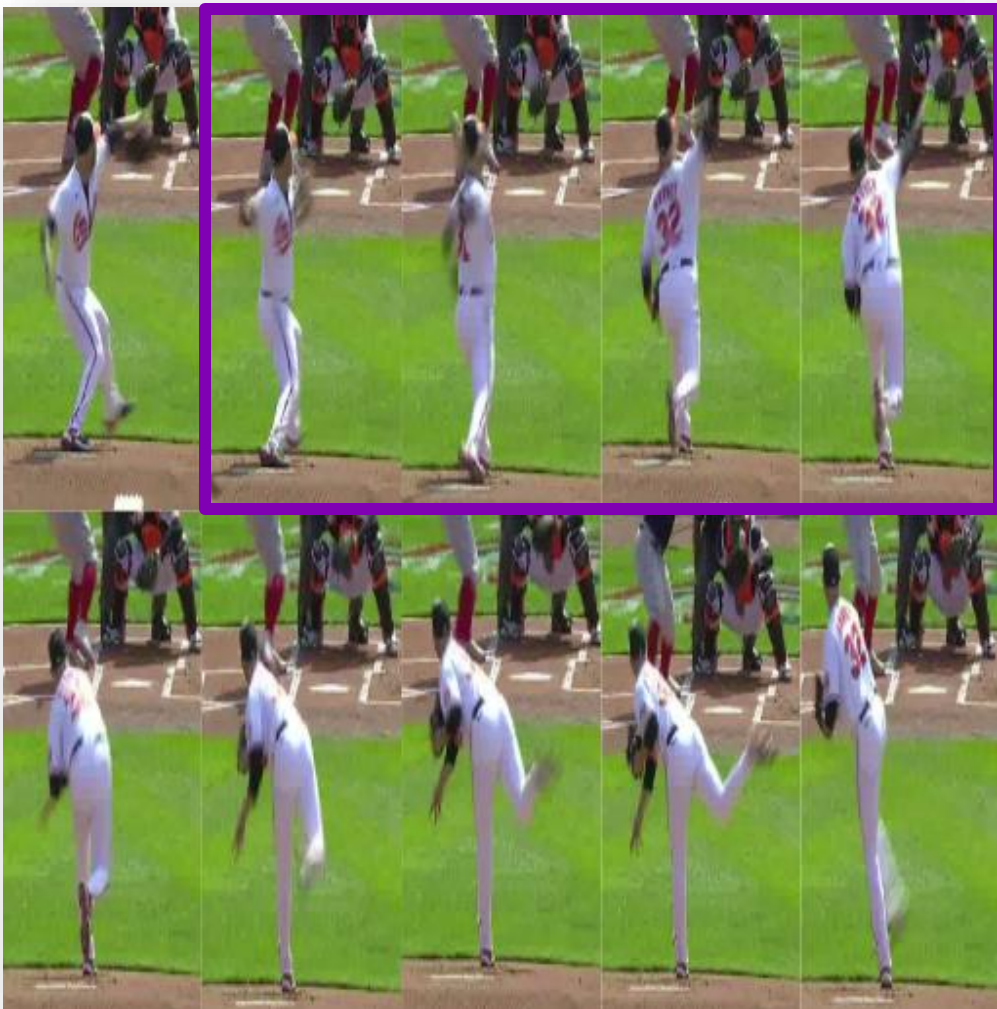
Prior Research on Baseball Analysis

- Pre-recorded baseball databases (Pitch f/x).
- Controlled environments (MoCap Systems).



Challenges with Video Inputs

Motion Blur



Self-Occlusion



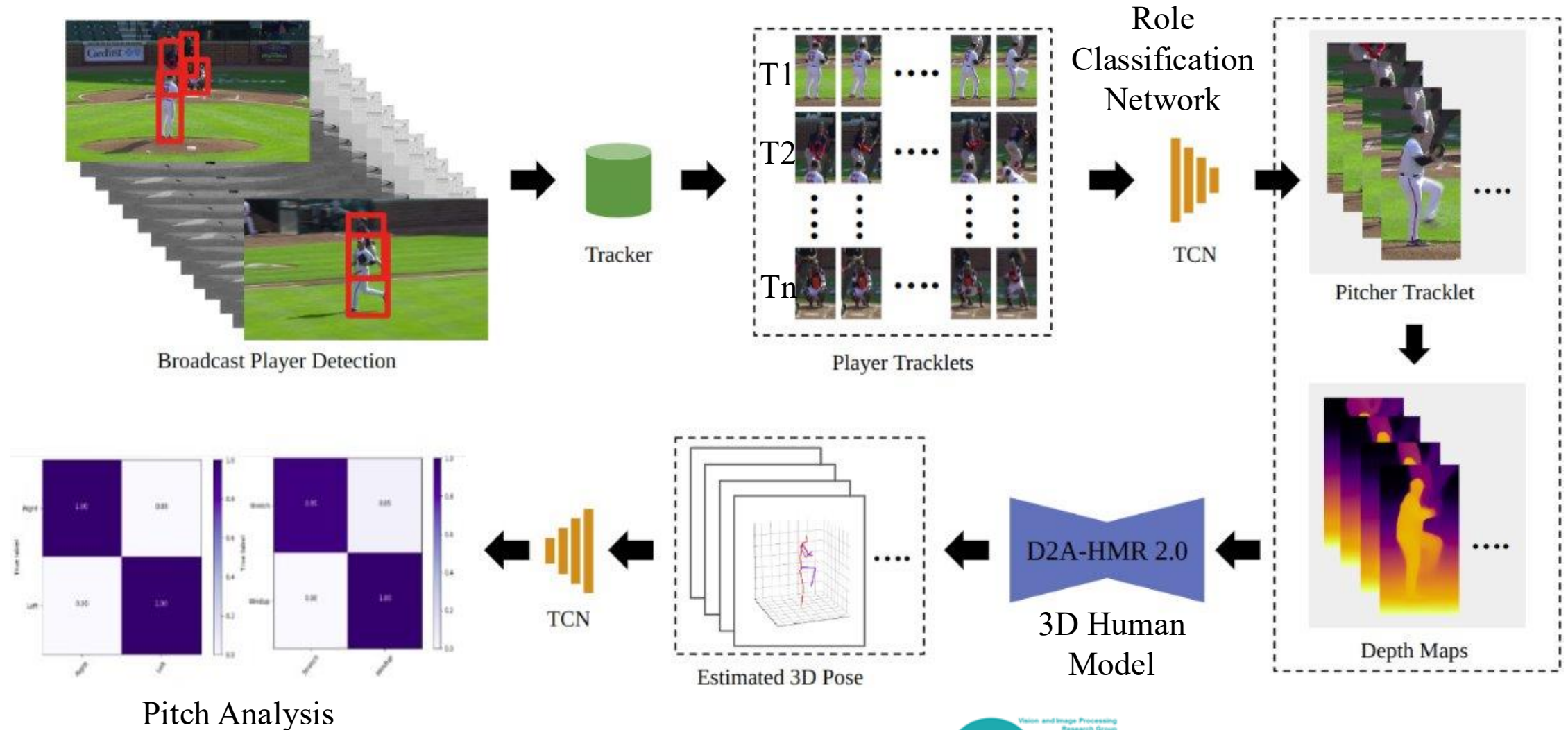
Out-of-distribution



Objective

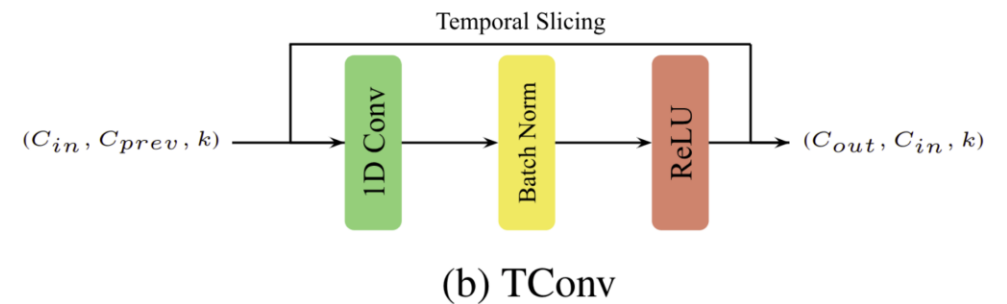
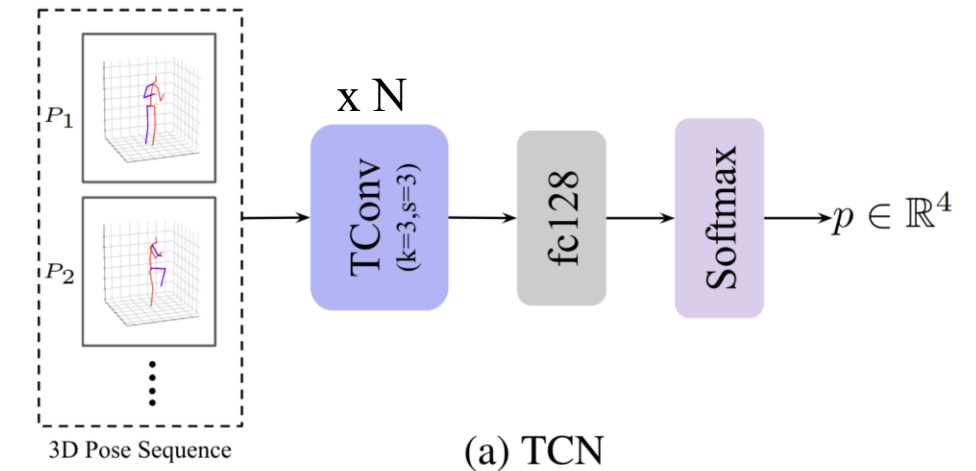
"Enable detailed analysis of pitcher dynamics from human models in 3D extracted solely from monocular broadcast feeds"

PitcherNet System



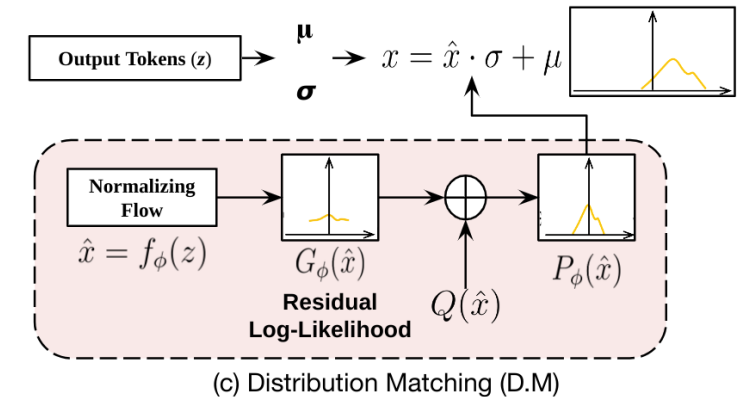
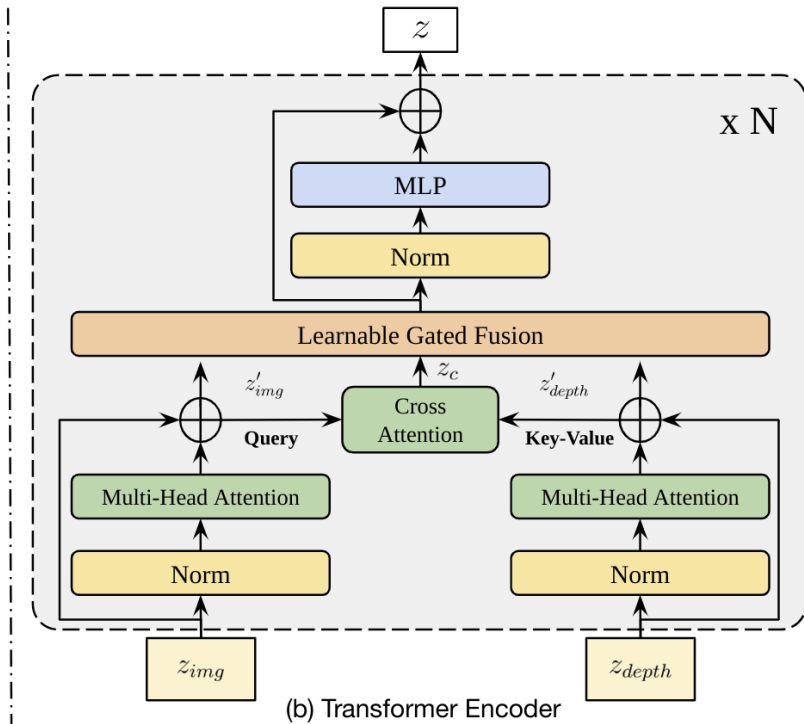
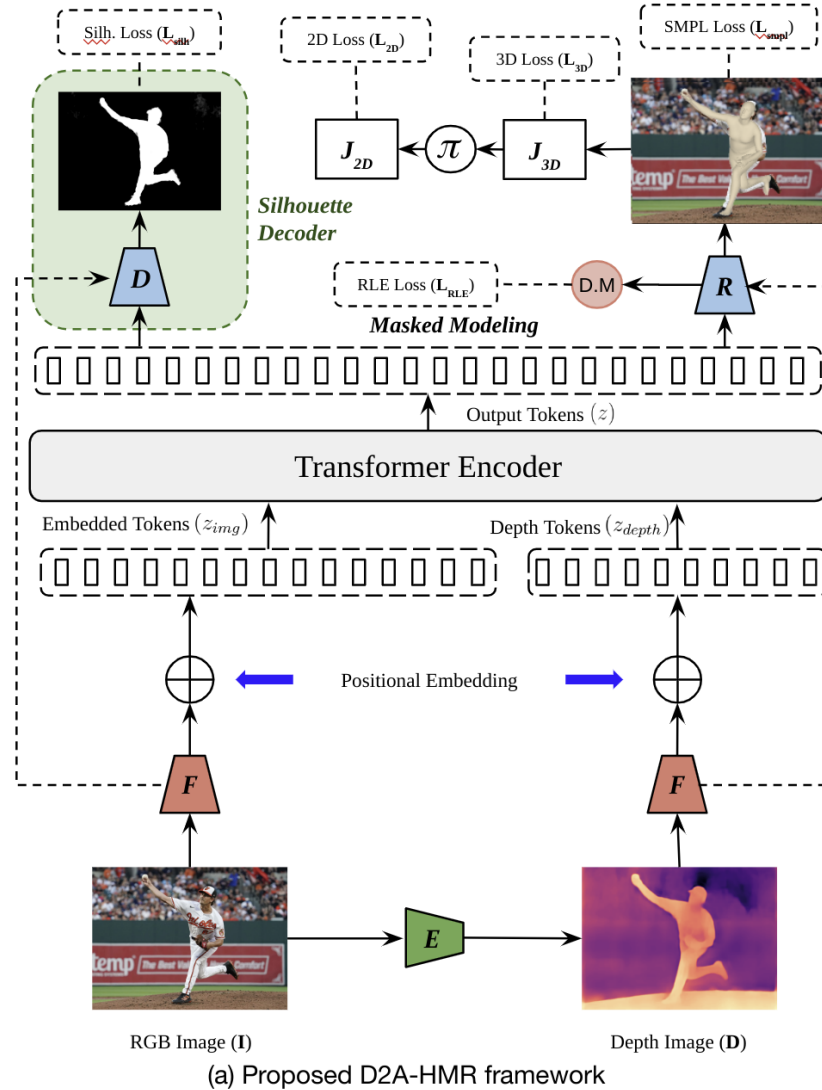
Role Classification

- Decouples action from player kinematics.
 - Input: Pseudo-pose from estimated tracklets.
 - Output: Player role.
- Invariant to viewpoint/ facial features/ player jersey numbers.



3D Human Model

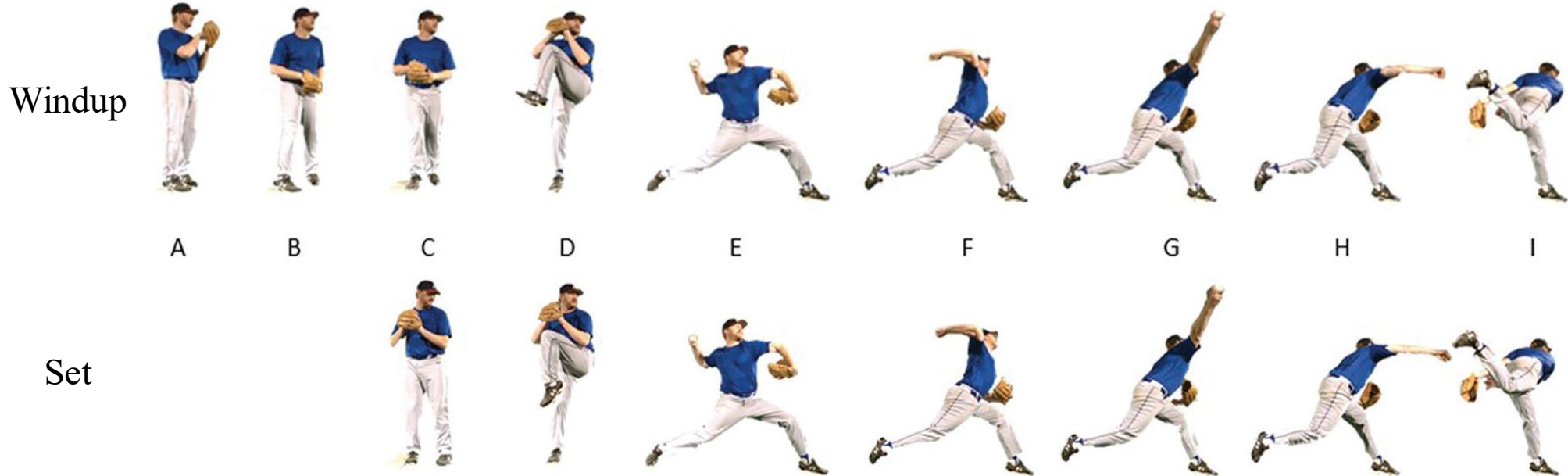
- Distribution and depth aware 3D modeling [2].
- Motion blur and in-the-wild data augmentation.
- Generalizable, reliable 3D human models.



Pitch Analysis

- Pitch Position

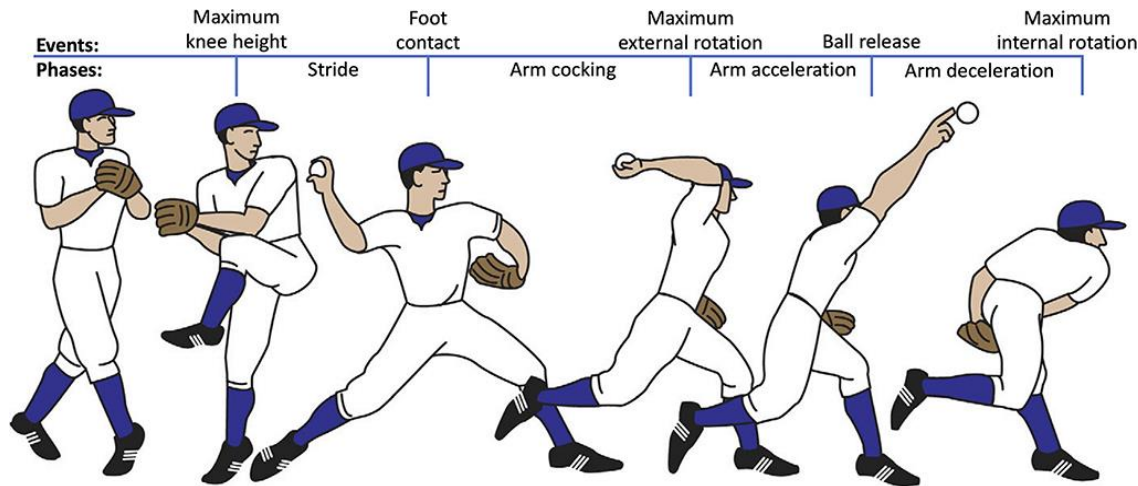
$$PP(windup, set) = \sigma(TCN(X))$$



Pitch Analysis

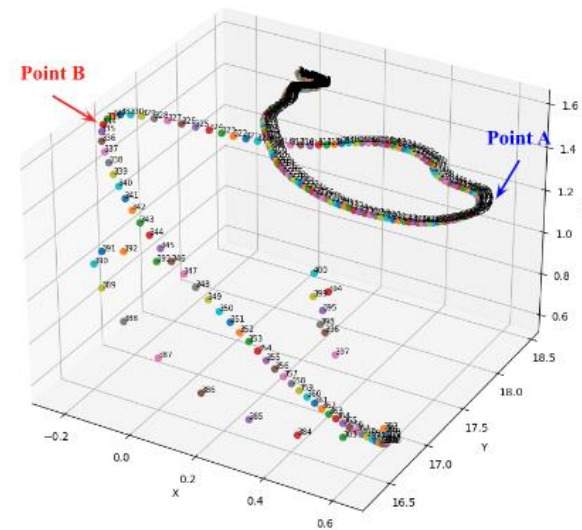
- Release Point

$$P_{rel} = \operatorname{argmax}(v(i) | i \in [P_b - n/2, P_b + n/2])$$



6 phases of pitching action

Point A- Arm Cocking
Point B- Arm Deceleration



Trajectory of the right wrist joint in 3D space

Pitch Analysis

- Pitch Velocity

$$v_p = \omega \times l = \{(\text{atan}(w_y^r, w_x^r) - \text{atan}(w_y^{r-1}, w_x^{r-1})) \times T\} \times l$$

- Release Extension

$$E_{rel} = \sqrt{(w_x - a_x)^2 + (w_y - a_y)^2 + (w_z - a_z)^2}$$

Quantitative Results of Role Classification

Table I. Comparison with baselines

	Test Accuracy ↑
LSTM	85.55
Transformer	91.11
Ours	96.66

Table II. Comparison with jersey identification techniques

	Test Accuracy ↑
Gerke <i>et al.</i> [21]	64.47
Li <i>et al.</i> [30]	88.29
Vats <i>et al.</i> [48]	89.46
Balaji <i>et al.</i> [2]	93.68
Balaji <i>et al.</i> [3]	94.70
Ours	96.82

Quantitative Results of Pitch Analysis

Table III. Performance of our pitch statistics modules

(a) Handedness				(b) Pitch Position			
	Accuracy \uparrow	F1 Score \uparrow	Precision \uparrow		Accuracy \uparrow	F1 Score \uparrow	Precision \uparrow
LSTM	85.0	85.7	90.0	LSTM	81.3	82.5	85.0
Ours (TCN)	100.0	100.0	100.0	Ours (TCN)	97.5	97.4	95.0

(c) Release Point				(d) Pitch Velocity				(e) Release Extension			
	$A_1 \uparrow$	$A_2 \uparrow$	$A_5 \uparrow$		$A_{1\%} \uparrow$	$A_{2\%} \uparrow$	$A_{5\%} \uparrow$		$A_{5\%} \uparrow$	$A_{8\%} \uparrow$	$A_{10\%} \uparrow$
LSTM	31.3	46.4	63.5	LSTM	5.1	13.1	22.2	LSTM	4.0	7.1	11.1
TCN	43.4	51.5	77.6	TCN	10.1	18.1	48.4	TCN	14.1	19.1	25.2
Ours	80.8	85.8	97.9	Ours	43.4	68.6	94.9	Ours	24.2	31.3	37.3

Qualitative Results (Pitch Analysis)

	Pitch Hand	Pred: Left	GT: Left
	Pitch Position	Pred: Stretch	GT: Stretch
	Pitch Velocity	Pred: 90.48 Mph	GT: 87.58 Mph
	Release Point	Pred: 90	GT: 90
	Extension	Pred: 5.85 feet	GT: 6.13 feet
	Pitch Hand	Pred: Left	GT: Left
	Pitch Position	Pred: Windup	GT: Windup
	Pitch Velocity	Pred: 85.76 Mph	GT: 89.17 Mph
	Release Point	Pred: 88	GT: 89
	Extension	Pred: 6.01 feet	GT: 6.16 feet
	Pitch Hand	Pred: Right	GT: Right
	Pitch Position	Pred: Windup	GT: Windup
	Pitch Velocity	Pred: 85.46 Mph	GT: 85.65 Mph
	Release Point	Pred: 87	GT: 87
	Extension	Pred: 6.17 feet	GT: 6.11 feet

Summary

- Reliable pitch analysis driven by player kinematics and human model priors.
- Role classification aiming to classify players by decoupling actions.
- D2A-HMR v2 which improves 3D human modeling in degraded image quality.

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Figure 1. 3D player reconstruction and kinematic-driven pitch statistics from monocular video. We introduce PitcherNet, a pioneering deep learning system that tackles low-resolution video limitations through efficient 3D human modeling for robust player alignment (left) and reliable pitch statistics analysis from estimated kinematic data (right).

Abstract

In the high-stakes world of baseball, every ounce of a pitcher's mechanics holds the key to maximizing performance and minimizing runs. Traditional analysis methods often rely on pre-recorded offline numerical data, hindering their application in the dynamic environment of live games. Broadcast video analysis, while seemingly ideal, faces significant challenges due to factors like motion blur and low resolution. To address these challenges, we introduce PitcherNet, an end-to-end automated system that analyzes pitcher kinematics directly from live broadcast video, thereby extracting valuable pitch statistics including velocity, release point, pitch position, and release extension. This system leverages three key components: (1) Player tracking and identification by decoupling actions from player kinematics; (2) Distribution and depth-aware 3D human modeling; and (3) Kinematic-driven pitch statistics. Experimental validation demonstrates that PitcherNet achieves robust analysis results with 96.82% accuracy in pitcher tracker identification, reduced joint position error by 1.8mm and superior analytics compared to baseline methods. By enabling performance-critical kinematic analysis from broadcast video, PitcherNet paves the way for the future of baseball analytics by optimizing pitching strategies, preventing injuries, and unlocking a deeper understanding of pitcher mechanics, forever transforming the game.

3420

1. Introduction

Driven by sabermetrics, pioneered by the Society of American Baseball Research (SABR) [17], baseball analytics has transformed the sport into a data-driven powerhouse, revolutionizing player evaluation, strategic decision-making, and the pursuit of victory [35]. One crucial aspect of this transformation is the analysis of pitch mechanics, where subtle movements such as strides, arm angles, and ball release points significantly affect performance [24, 25]. Analyzing these intricate actions goes beyond traditional pitch type classification (fastball, curveball, etc.), delving into metrics that contribute to strategic deception, such as windup styles, varying velocities, induced ball movement, and ball release point.

Current research on baseball game analysis often rely on numerical databases containing pre-recorded offline data [8, 21, 43, 48]. These methods typically focus on predicting actions or game statistics based on these historical records. While some approaches utilize real-time data, they are often limited to controlled laboratory environments with expensive motion-capture setups [34, 39, 41]. This restricts the generalizability of their findings to the dynamic and complex situations encountered during live games. Live game broadcasts, however, offer a more holistic perspective by capturing the entirety of a pitcher's motion within the game's natural environment. This approach overcomes the limitations of controlled settings. However, analyzing



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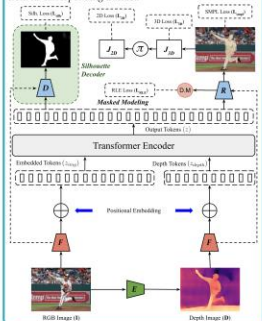
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KEY CONTRIBUTIONS

- Accurate baseball pitch statistics prediction from low-quality videos (PitcherNet).
- Classifying players based on their role by decoupling actions from player kinematics.
- 3D human modeling that addresses motion blur.

3D HUMAN MODELING

Designed to extract kinematic information about the pitcher from its corresponding tracklet.

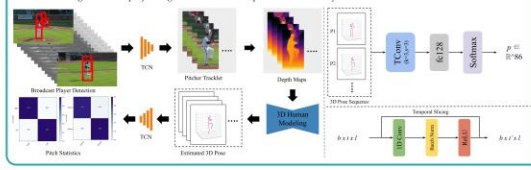


QUALITATIVE RESULTS



METHODOLOGY

We introduce PitcherNet, a pioneering deep learning system that tackles low-resolution video limitations through efficient 3D human modeling for robust player alignment and reliable pitch statistics analysis from estimated kinematic data.



PITCH STATISTICS

Pitch Position (PP):

$$PP(windup, set) = \sigma(TCN(X)), \text{ where } X \in \mathbb{R}^{100 \times 18 \times 3} \quad (1)$$

Release Point (P_{rel}):

$$P_{rel} = \arg\max(v(t)) \in [P_x - n/2, P_x + n/2] \quad (2)$$

Pitch velocity (v_p):

$$v_p = \omega \times t = \{(\tan(w_p^x, w_p^y) - \tan(w_p^{x-1}, w_p^{y-1})) \times T\} \times t \quad (3)$$

Release Extension (E_{rel}):

$$E_{rel} = \sqrt{(w_p - a_p)^2 + (w_p - a_p)^2 + (w_p - a_p)^2} \quad (4)$$

LOSS FUNCTIONS

Overall objective function for the 3D model:

$$\mathcal{L}_{model} = \lambda_{L1} \mathcal{L}_{L1} + \lambda_{SMPL} \mathcal{L}_{SMPL} + \lambda_{2D} \mathcal{L}_{2D} + \lambda_{vel} \mathcal{L}_{vel} + \lambda_{rel} \mathcal{L}_{rel} \quad (5)$$

Objective function for the TCN model:

$$L(p_i) = \sum_{t=1}^T a_t \times (1 - p_i)^t + \log(p_i) \quad (6)$$



QUANTITATIVE RESULTS

3D Human Modeling

Method	Human3.6M		3DPW	
	mPJPE	PA-mPJPE	mPJPE	PA-mPJPE
HMMR19	-	58.1	116.5	72.6
TCMR21	62.5	41.1	95.0	55.8
VIBE20	65.6	41.4	93.5	56.5
SPIN21	62.5	41.1	96.9	59.2
PymAF21	57.7	40.5	92.8	58.9
ROMP21	-	105.6	105.6	53.5
HMRFT20	63.2	43.8	85.1	52.2
PARE21	76.8	50.6	82.0	50.9
ProHMR21	-	41.2	95.1	59.5
PM20	64.9	47.0	89.2	58.9
METRO21	54.0	36.7	77.1	47.9
Ours	53.2	35.9	78.7	46.9

Handedness and Pitch Position Prediction

Method	Handedness			Pitch Position		
	A _T ↑	F1 ↑	Prece. ↑	A _T ↑	F1 ↑	Prece. ↑
LSTM	85.0	85.7	90.0	81.3	82.5	85.0
Ours	100.0	100.0	100.0	97.5	97.4	95.0

Release Point and Pitch Velocity Prediction

Method	Release Point			Pitch Velocity		
	A _T ↑	A ₂ ↑	A ₃ ↑	A _T ↑	A ₂ ↑	A ₃ ↑
LSTM	31.3	48.4	63.5	5.1	13.1	22.2
TCN	43.4	51.5	77.6	10.1	18.1	48.4
Ours	80.8	85.8	97.9	43.4	68.6	94.9

Release Extension Prediction

Method	Release Extension		
	A _T ↑	A ₂ ↑	A ₃ ↑
LSTM	4.0	7.1	11.1
TCN	14.1	19.1	25.2
Ours	24.2	31.3	37.3

ACKNOWLEDGEMENT



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Thank you!

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