### PitcherNet: Powering the Moneyball Evolution in Baseball Video Analytics

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# Motivation

- Analysis from kinematic information.
- Performance optimization, injury prevention, quantitative analysis of the player mechanics.





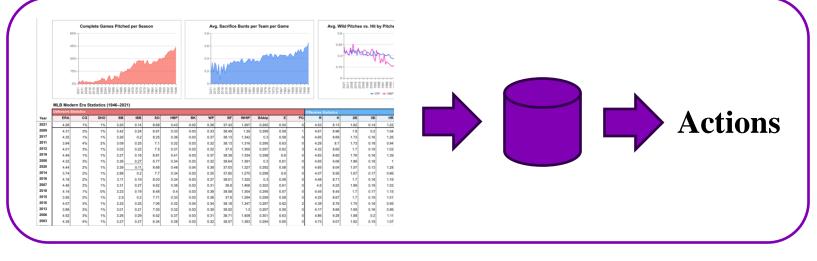




# **Prior Research on Baseball Analysis**

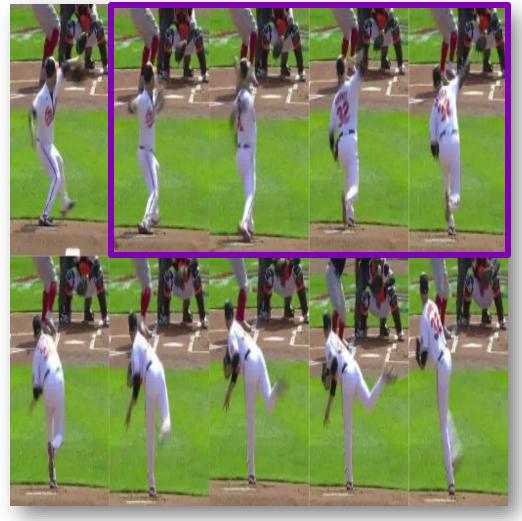
- Pre-recorded baseball databases (Pitch f/x).
- Controlled environments (MoCap Systems).







# **Challenges with Video Inputs**









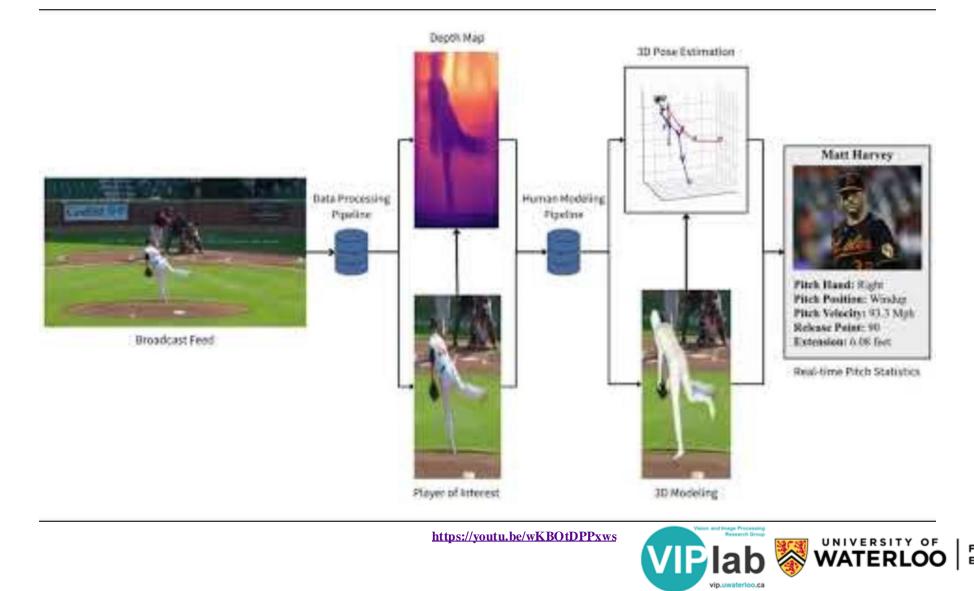
Motion Blur

### Objective

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



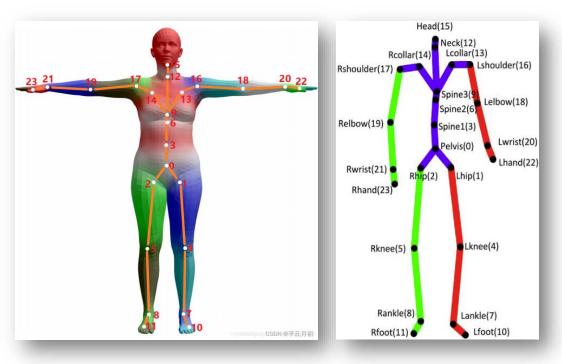
### **High-level Workflow of PitcherNet**



### Background

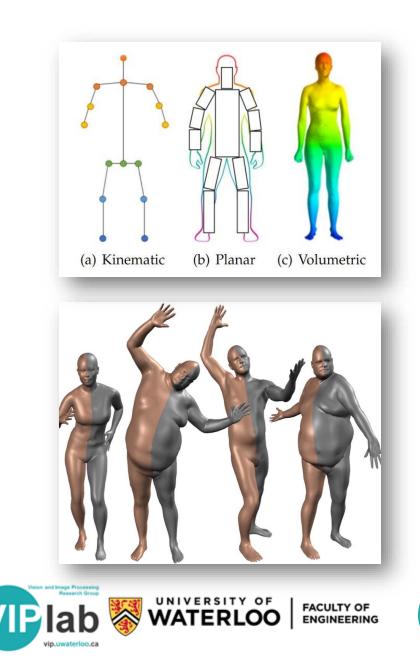
#### **3D Human Modeling - SMPL**

- Skinned Multi-Person Linear model<sup>[1]</sup>.
- 72 joint and 10 shape parameters -> 6890 vertices.

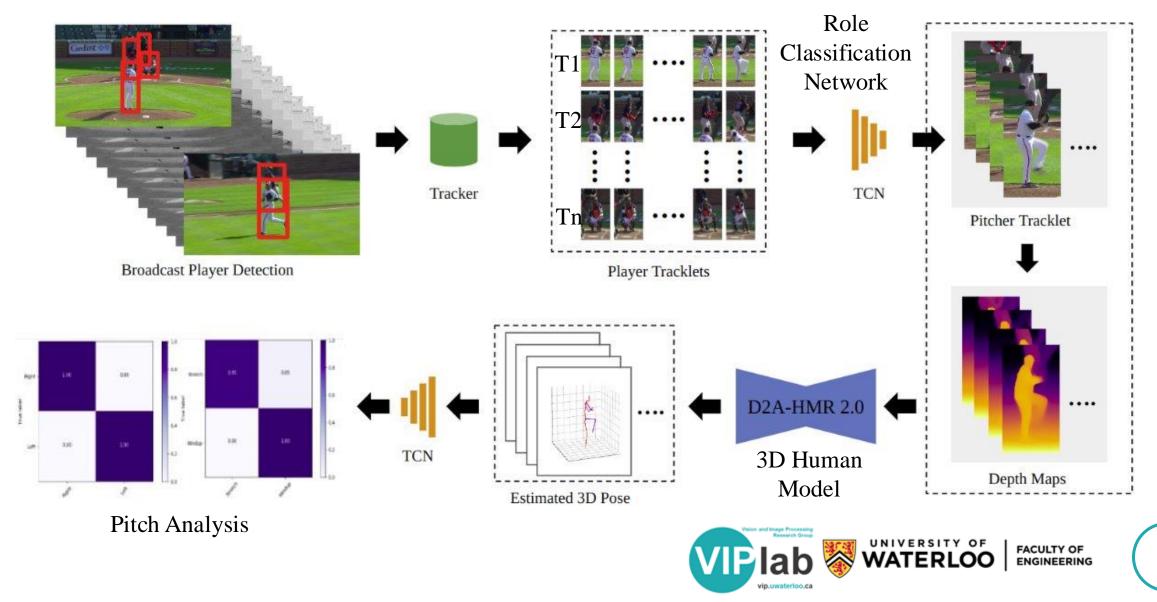


Credits:

[1] Matthew Loper, Naureen Mahmood, Javier Romero, Gerard Pons-Moll, and Michael J. Black. SMPL: a skinned multi-person linear model. ACM Transactions on Graphics, 2015.



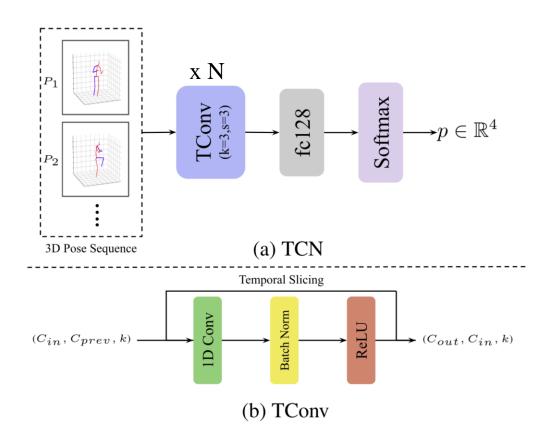
### **PitcherNet System**



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## **Role Classification**

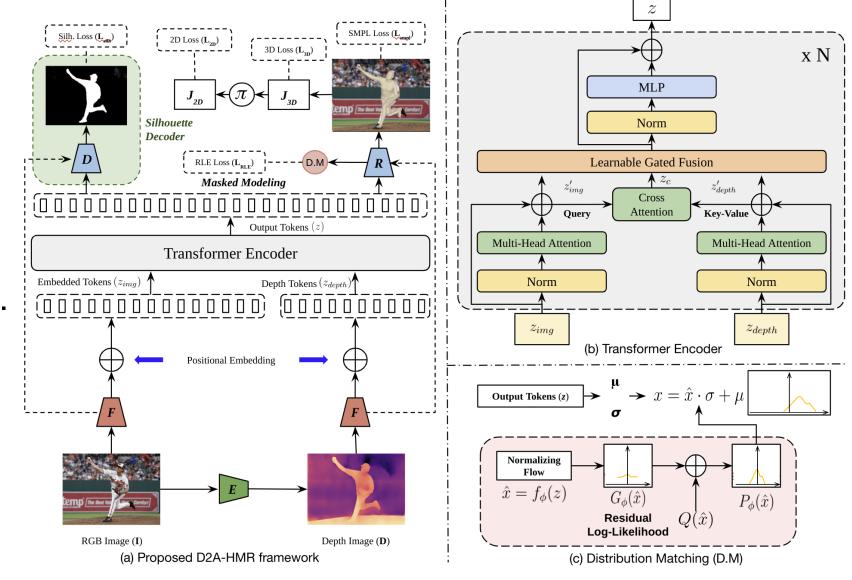
- Decouples action from player kinematics.
  - Input: Pseudo-pose from estimated tracklets.
  - Output: Player role.
- Invariant to viewpoint/ facial features/ player jersey numbers.





# **3D Human Model**

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



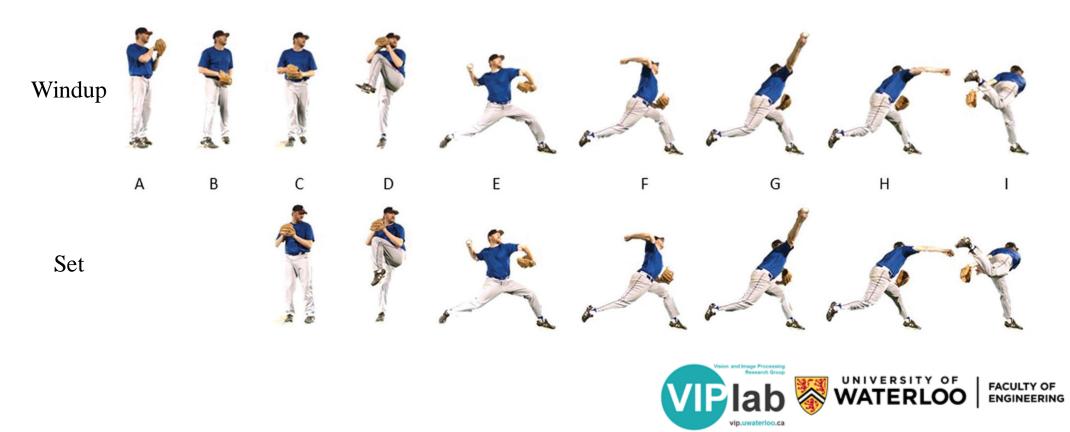
[2] **Jerrin Bright**, Bavesh Balaji, Harish Prakash, Yuhao Chen, David A Clausi, and John Zelek. 2024. Distribution and Depth-Aware Transformers for 3D Human Mesh Recovery. In 21st Conference on Robots and Vision - ORAL

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# **Pitch Analysis**

Pitch Position

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

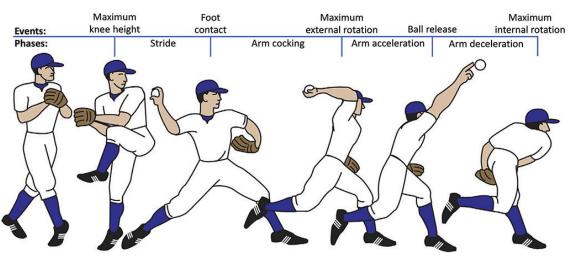


# **Pitch Analysis**

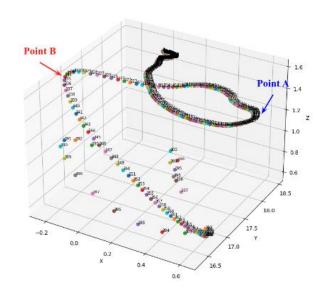
Release Point

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

#### **Point A-** Arm Cocking **Point B-** Arm Deceleration



6 phases of pitching action







Trajectory of the right wrist joint in 3D space



# **Pitch Analysis**

Pitch Velocity

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

Release Extension

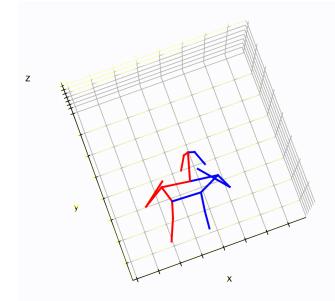
$$E_{rel} = \sqrt{(w_x - a_x)^2 + (w_y - a_y)^2 + (w_z - a_z)^2}$$



### **MLBPitchDB Dataset**

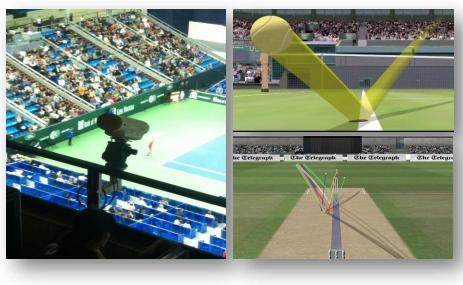
#### What we have?

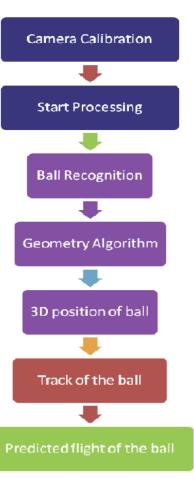
- 1000+ games
- 3D Hawk-Eye pose data
- Various pitch metrics



#### What is Hawk-Eye Camera System?

- Triangulation with many cameras around the playing area
- Applications include pose estimation, tracking, etc.







## **Quantitative Results of Role Classification**

Table I. Comp	arison with baselines		Test Accuracy ↑
1	Test Accuracy ↑	Gerke <i>et al</i> . [21] Li <i>et al</i> . [30]	64.47 88.29
M sformer	85.55 91.11	Vats $et al. [50]$ Balaji $et al. [2]$	89.46 93.68
5	96.66	Balaji <i>et al</i> . [3]	94.70
		Ours	96.82

Table II. Comparison with jersey identification techniques



Ours	96.66
Transformer	91.11
LSTM	85.55
	Test Accuracy ↑

## **Quantitative Results of 3D Human Modeling**

Method	Hun	nan3.6M	3DPW		
	mPJPE	mPJPE PA-mPJPE		PA-mPJPE	
HMMR'19	-	58.1	116.5	72.6	
TCMR'21	62.3	41.1	95.0	55.8	
VIBE'20	65.6	41.4	93.5	56.5	
SPIN'21	62.5	41.1	96.9	59.2	
PyMAF'21	57.7	40.5	92.8	58.9	
ROMP'21	-	-	105.6	53.5	
HMREFT'20	63.2	43.8	85.1	52.2	
PARE'21	76.8	50.6	82.0	50.9	
ProHMR'21	-	41.2	95.1	59.5	
P2M'20	64.9	47.0	89.2	58.9	
METRO'21	54.0	36.7	77.1	47.9	
Ours	53.2	35.9	78.7	46.9	

Table III. Comparison of D2AHMR 3D model



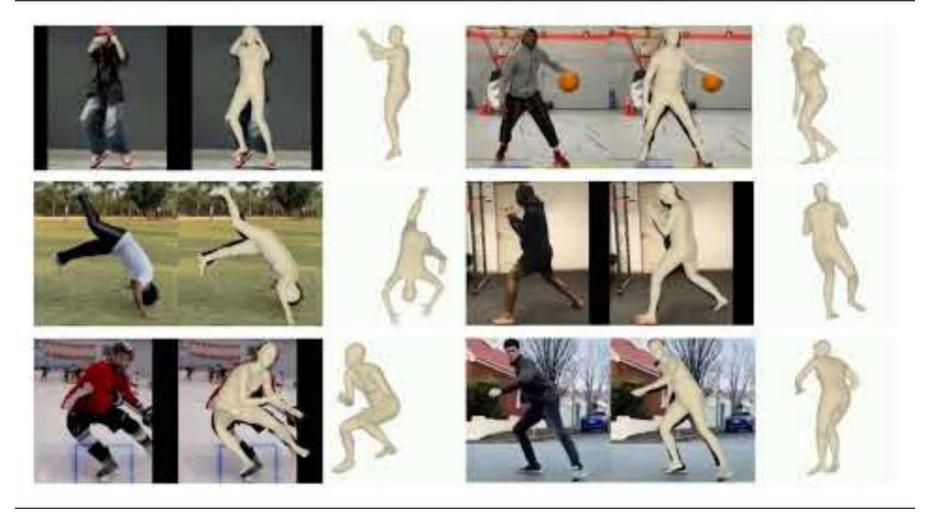
## **Quantitative Results of Pitch Analysis**

	(a) Handedness					(b) Pitch Position						
		Acc	uracy $\uparrow$	F1 Score ↑	Precisio	$n\uparrow$		Accuracy ↑	F1 Sco	ore $\uparrow$ F	Precision $\uparrow$	
	LSTM 85.0 Ours (TCN) 100.0			85.790.0100.0100.0			STM Durs (TCN)	81.3 97.5	82.5 <b>97.4</b>		85.0 <b>95.0</b>	
	(c) Releas	e Point			(d) Pitch	Velocity	7		(e) Releas	se Extensi	on	
	$A_1 \uparrow$	$A_2 \uparrow$	$A_5 \uparrow$		$A_{1\%}\uparrow$	$A_{2\%}$ ?	$\uparrow  A_{5\%} \uparrow$		$A_{5\%}\uparrow$	$A_{8\%}$ 1	$A_{10\%}\uparrow$	
LSTM TCN <b>Ours</b>	31.3 43.4 <b>80.8</b>	46.4 51.5 <b>85.8</b>	63.5 77.6 <b>97.9</b>	LSTM TCN <b>Ours</b>	5.1 10.1 <b>43.4</b>	13.1 18.1 <b>68.6</b>	22.2 48.4 <b>94.9</b>	LSTM TCN <b>Ours</b>	4.0 14.1 <b>24.2</b>	7.1 19.1 <b>31.3</b>	11.1 25.2 <b>37.3</b>	

 Table IV. Performance of our pitch statistics modules



### **Qualitative Results (3D Human Model)**



https://www.youtube.com/watch?v=TsA6bOcaaiU



## **Qualitative Results (Pitch Analysis)**



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itch Position	Pred: Stretch	GT: Stretch
itch Velocity	Pred: 90.48 Mph	GT: 87.58 Mph
Release Point	<b>Pred</b> : 90	<b>GT</b> : 90
Extension	Pred: 5.85 feet	GT: 6.13 feet
Pitch Hand	Pred: Left	GT: Left
Pitch Position	Pred: Windup	GT: Windup

|GT Left

Pred: Left	GT: Left
Pred: Windup	GT: Windup
Pred: 85.76 Mph	GT: 89.17 Mph
Pred: 88	<b>GT</b> : 89
Pred: 6.01 feet	GT: 6.16 feet
	Pred: Windup   Pred: 85.76 Mph   Pred: 88

Pitch Hand	Pred: Right	GT: Right
<b>Pitch Position</b>	Pred: Windup	GT: Windup
Pitch Velocity	Pred: 85.46 Mph	GT: 85.65 Mph
Release Point	Pred: 87	<b>GT</b> : 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.



# Thank you!

Supported by:



