Always Look on the Bright Side of the Field: Merging Pose and Contextual Data to Estimate Orientation of Soccer Players

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[1] Decomposing the Immeasurable Sport:a Deep Learning Expected PosessionValue Framework for Soccer [Fernández *et al.*]



(a) Dominant Regions

(b) Pass Distances



[2] A Winning Combination: Pairing Video and Movement Data to Enhance Sports Data Analysis [Stein *et al.*]





-Yesteryear soccer: 1 Control

<u>Source</u>: @toppng.com [Pinterest]









-Yesteryear soccer: 1 Control

- Today's faster soccer:

1) Orient

Source: @toppng.com [Pinterest]













Problem Statement: -Player Orientation: missing critical piece of information in soccer analytics.

Goal:

Soccer Video Feed

Player Pose and Position (+ ball)



Proposed Method
 Pipeline



Proposed Method Pipeline





Proposed Method Pipeline



Proposed Method















[3] Realtime Multi-Person 2D Pose Estimation using Part Affinity Fields [Cao et al.]

Up to 25 parts detected / person

Associated confidence value / part

Output: 1 heatmap / part + PAFs (limbs)







Full-HD Frame

Tiny Pixel Resolution / Player Not enough for OpenPose to produce a decent result







Original Crop

Upscaling by Bicubical Interpolation



Upscaling by Convolutional Networks







Original Crop

Upscaling by Upscaling by **Convolutional Networks Bicubical Interpolation** [4] Residual Dense Network for Image Super-Resolution [Cardinale et al.]

































Proposed Method Shoulder / Hip Orientation, Homography Estimation





[Field Domain]







































Image Domain









Image Domain Conf: 0.51

Output: (angle, confidence)











Main Open-Pose drawback at low-resolution







Main Open-Pose drawback at low-resolution

(a) Front



(b) Side





(c) Back

(d) Profile Orientations







Main Open-Pose drawback at low-resolution

(a) Front







Extract color (HSV) and geometrical features from the upper-torso

Annotate 14.000 instances with 3 possible labels: front / side / back

Train SVM model to perform a double-check













Bin N°	1	2	3	4	()	22	23	24
Included Angles	0-15°	15-30°	30-45°	45-60°	()	315-330°	330-345°	345-360°

Orientation Expressed with Probability Vectors (Gaussian Support)



Bin Nº	1	2	3	4	()	22	23	24		
Included Angles	0-15°	15-30°	30-45°	45-60°	()	315-330°	330-345°	345-360°		
Orientation Expressed with Probability Vectors (Gaussian Support)										

- Example 1: (angle, confidence) (50°, 0.8)
- Example 2: (angle, confidence) (155°, 0.4)



<u>16 17 18 19</u> 12 13 14 15 20 11 21 22 23 24 \bigcirc $\left(\right)$ $\left(\right)$ $\left(\right)$ \bigcap































Proposed Method Contextual Weighting





Proposed Method Contextual Weighting

 $H_{TOT} = w \bullet$



Pose Orientation H_P

Final orientation: central value of the bin in H_{TOT} with a higher weight

Ball Orientation H_B



Proposed Method Visualization









Content:

domains) and corners positions, eventing data. Ground-truth orientation.

Validation:

- Subsampling to 1/3 of original frame rate; 2000 frames, 30000 players.

-La Liga: video footage (25 fps, Full-HD), smoothed tracking data (image and field -Youth games: video footage, raw data from EPTS devices (100 samples/second).





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OpenPose + Super-Resolution



Detection Rate: 89.69%





OpenPose + Super-Resolution



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LR Accuracy: 92.43%







OpenPose + Super-Resolution



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LR Accuracy: 92.43%

Coarse Validation (80-20 train-test)



Accuracy: 85.91%





Results Parameter Adjustment

$OD_{i_t} = \min(|\alpha_{i_t} - \omega_{i_t}|, 360 - |\alpha_{i_t} - \omega_{i_t}|)$ Best Combination: $H_{TOT} = 0.7 \cdot H_P + 0.3 \cdot H_B$ Median: 27.66°

Mean: 29.78°



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Mean: 29.78°



Median: 27.66°









Practical Applications

Reaction Maps

On-Field Maps

Conclusions

Body orientation estimator for soccer scenarios through the combination of:

Pose Orientation

Detection Rate: 89.69%

Mean Error: 29.78°

Future Work: Quantify the relevance of body orientation [5] Using Player's Body Orientation to Model Pass Feasibility in Soccer [Arbués-Sangüesa et al.]

Ball Orientation

LR Accuracy: 92.43%

Median Error: 27.66°

References

[Fernández et al.] - MIT Sloan Sports Analytics Conference 2019 IEEE Digital Library 2018 [3] Realtime Multi-Person 2D Pose Estimation using Part Affinity Fields [Cao et al.] - CVPR 2016 [4] Residual Dense Network for Image Super-Resolution [Cardinale et al.] - CVPR 2018 Vision in Sports Workshop at CVPR 2020

- [1] Decomposing the Immeasurable Sport: a Deep Learning Expected Posesssion Value Framework for Soccer
- [2] A Winning Combination: Pairing Video and Movement Data to Enhance Sports Data Analysis [Stein et al.] -
- [5] Using Player's Body Orientation to Model Pass Feasibility in Soccer [Arbués-Sangüesa et al.] Computer

Thank you for your attention! adria.arbues@upf.edu