Multi-view Body Part Recognition with Random Forests

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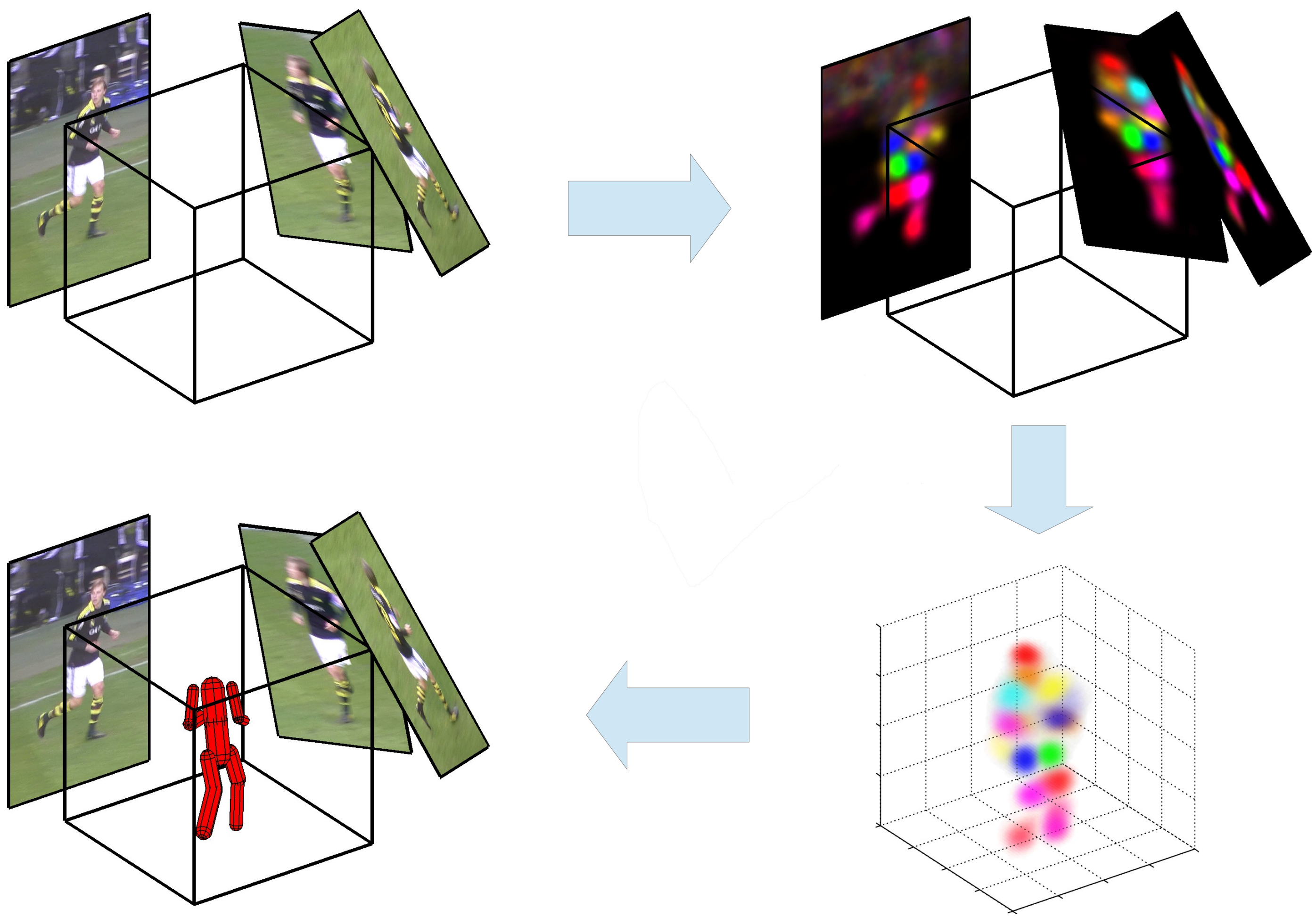
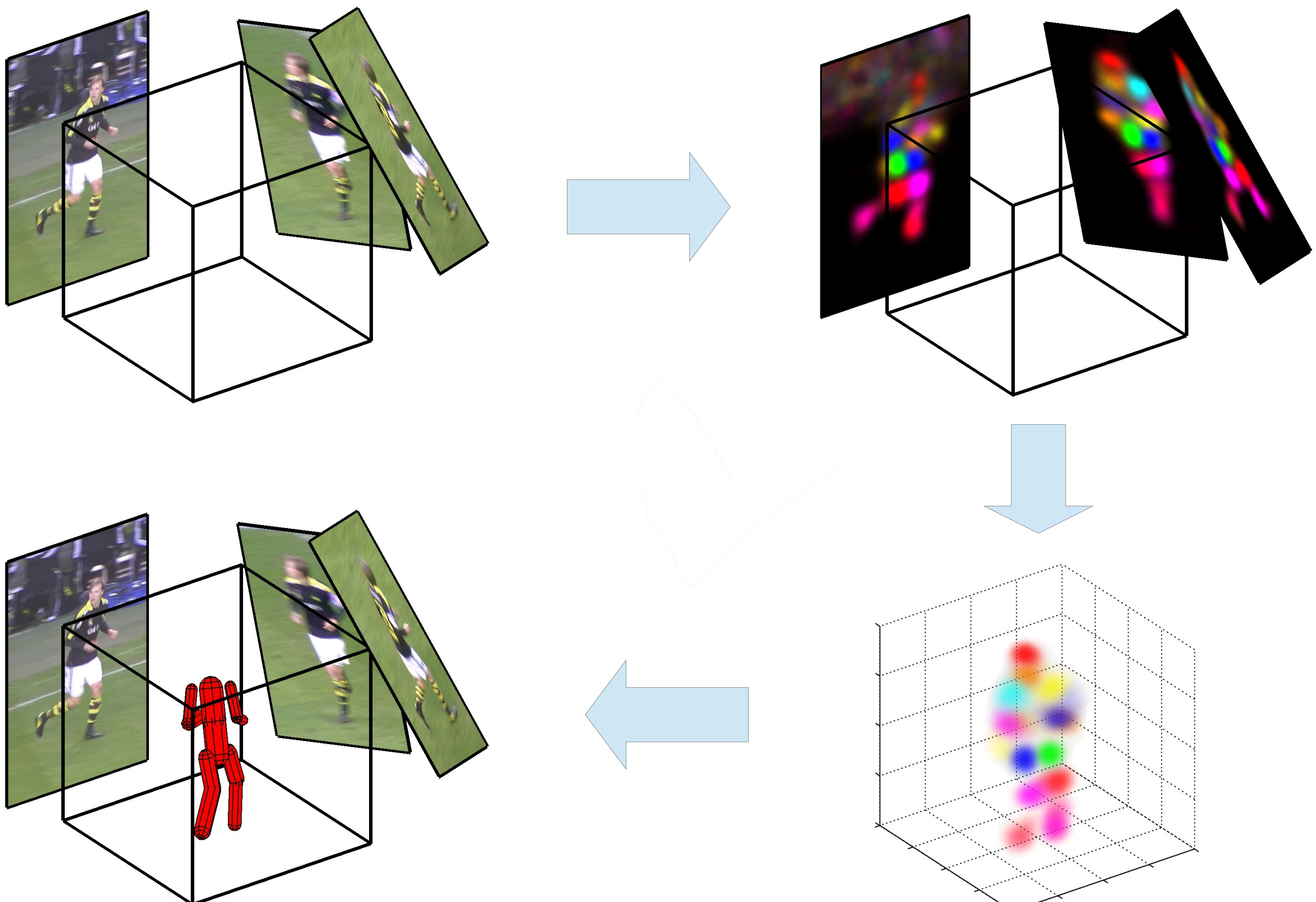
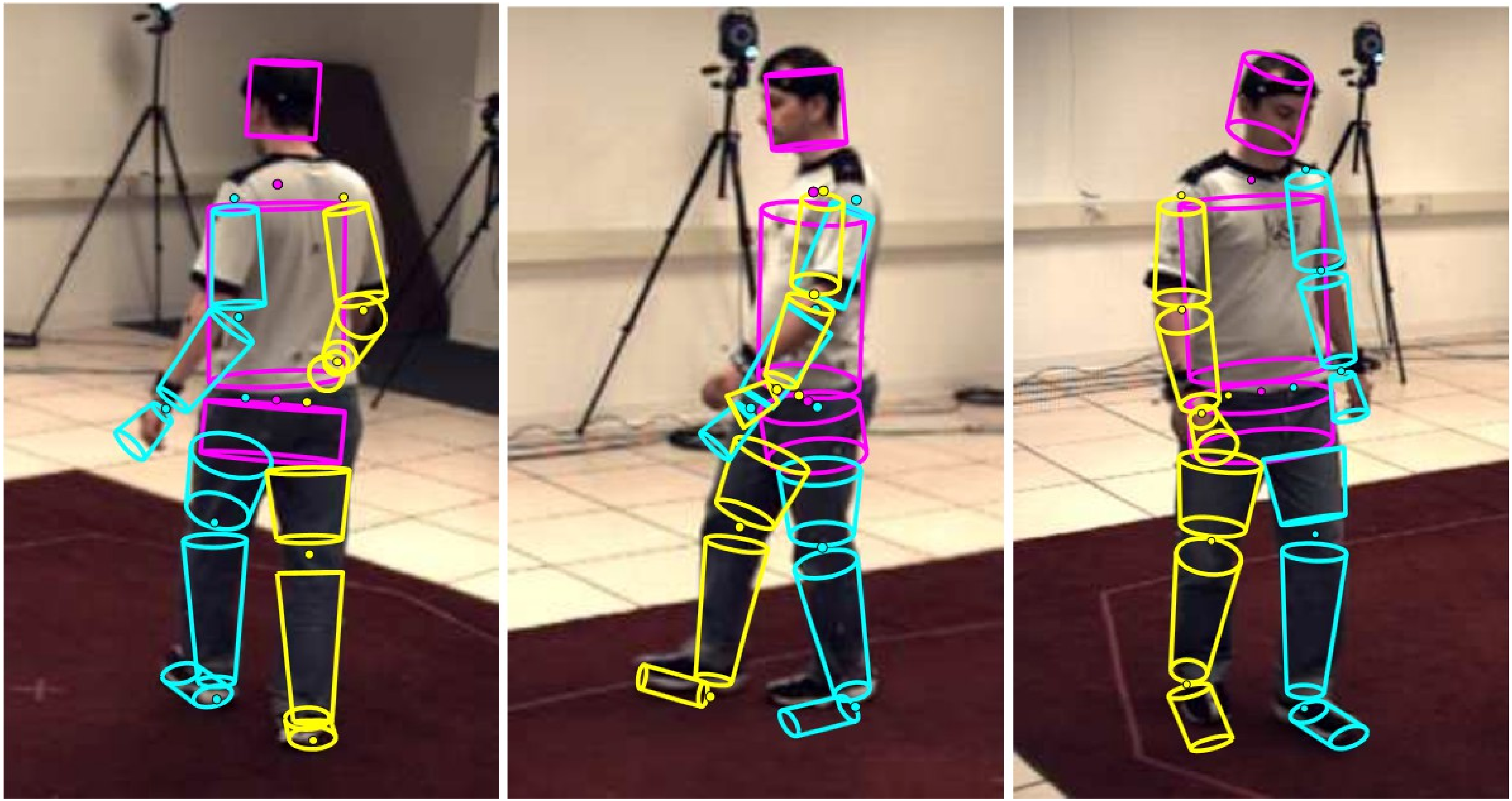


Problem

Multi-view human 3D pose estimation in the wild

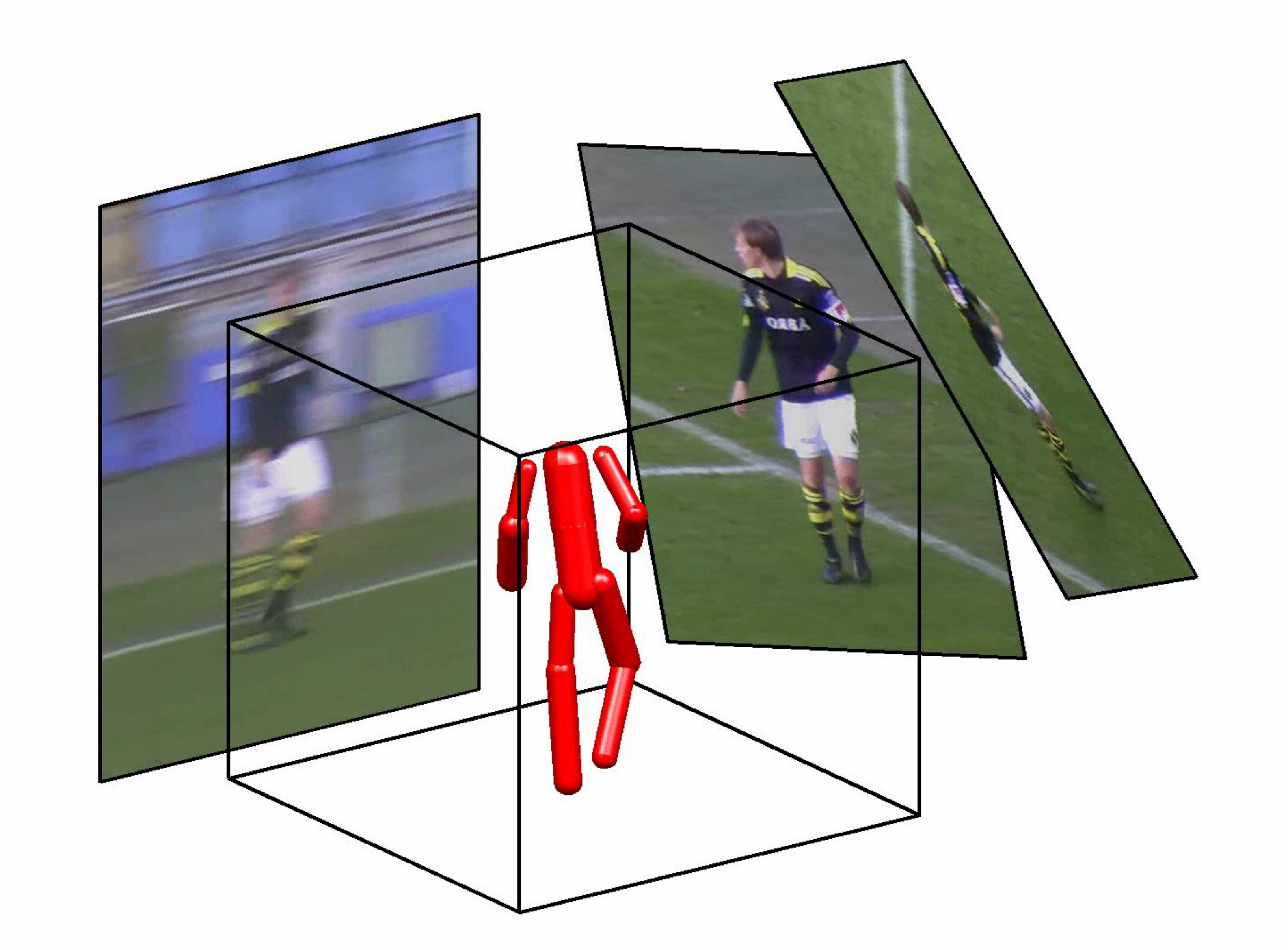


The Typical 3D Pose Data Set



HumanEva data set

Our New 3D Pose Data Set

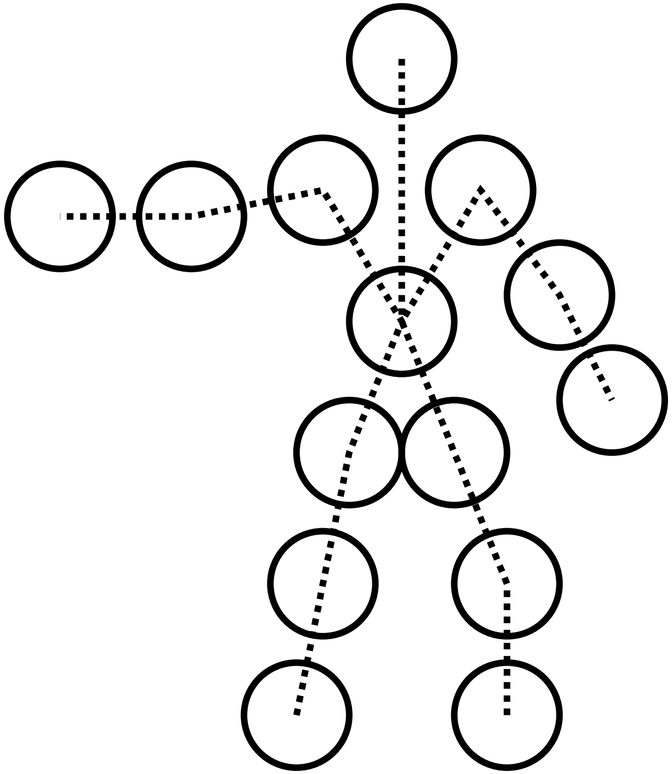


Challenges: moving cameras, dynamic backgrounds, motion blur, occlusion.

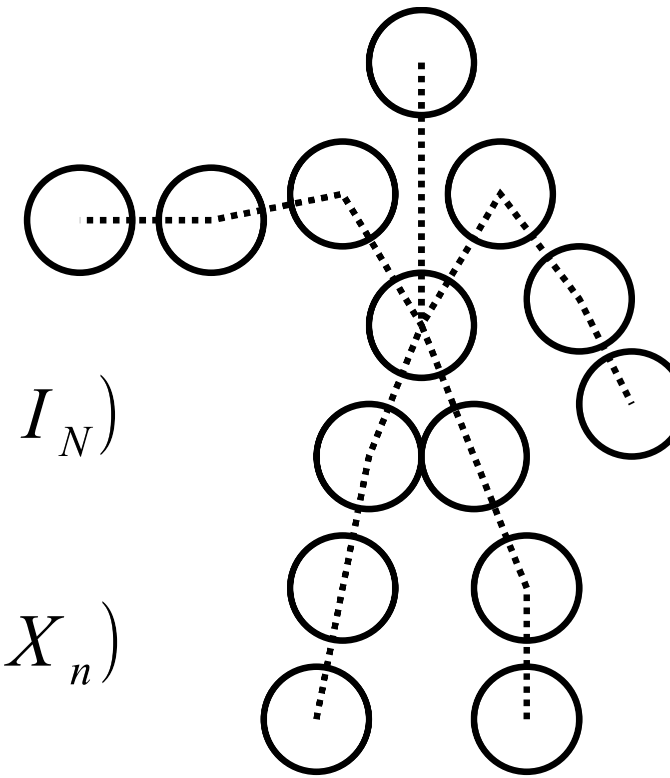
2D & 3D Pose Estimation using Pictorial Structures / Part-based Models

- Appearance model for each part

- Pose model connecting the parts

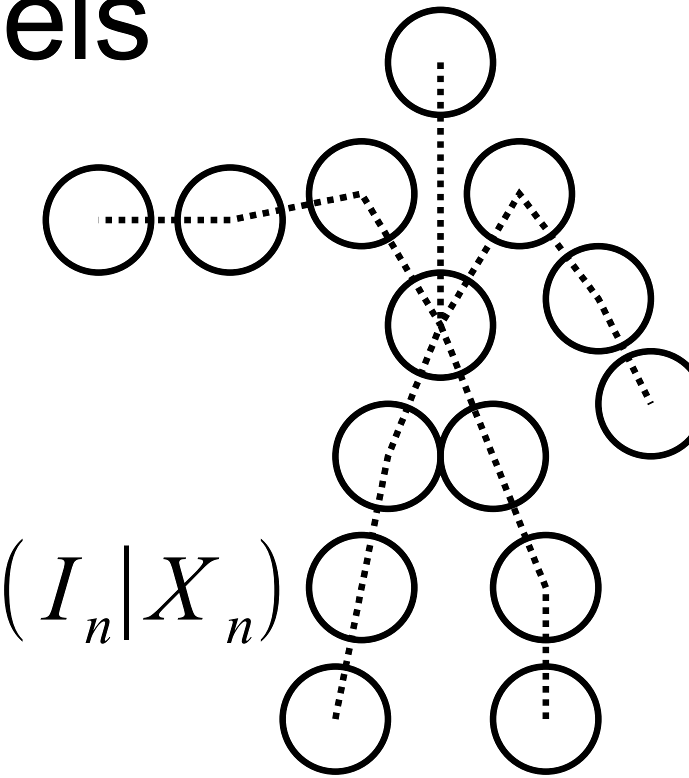


Pictorial Structures & Part-based Models



- Position of the parts $X = (X_1, \ldots, X_N)$
- Image evidence for the parts $I = (I_1, \ldots, I_N)$
- Appearance model for each part $P(I_n | X_n)$
- Pose model connecting the parts $P(X)$
- Joint distribution $$P(X, I) = P(X) \prod_{n=1}^{N} P(I_n | X_n)$$

Pictorial Structures & Part-based Models



$$P(X, I) = P(X) \prod_{n=1}^{N} P(I_n | X_n)$$

$$\log P(X, I) = \log P(X) + \sum_{n=1}^{N} \log P(I_n | X_n)$$

$$\underset{X}{argmax}\, P(X | I) = \underset{X}{argmax} \log P(X, I)$$

Can use dynamic programming to find global solution:

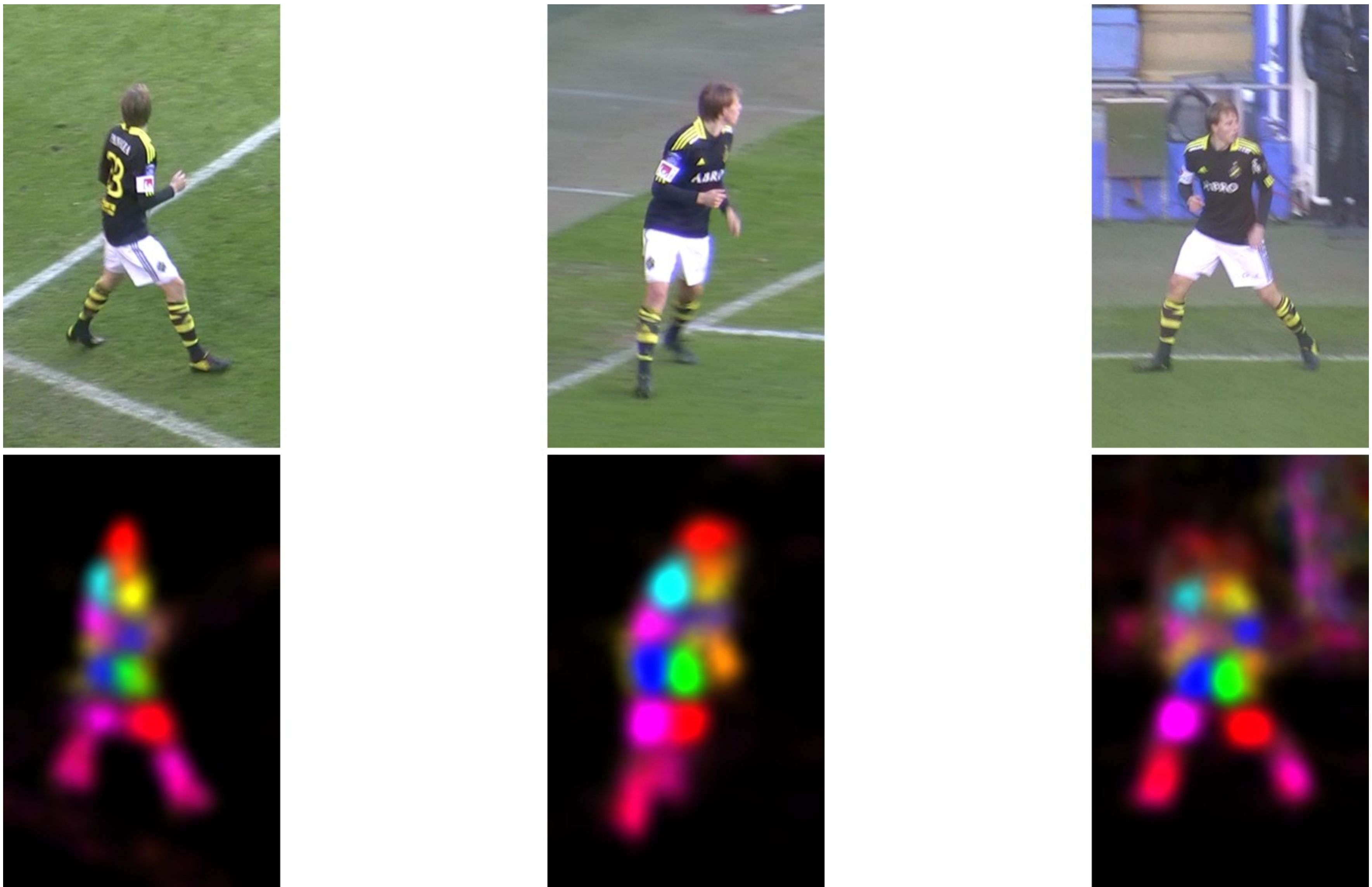
- For 2D pose estimation see Felzenszwalb et al. CVPR 2000.
- For 3D pose estimation see Burenius et al. CVPR 2013.

Part Appearance Model

1. Single view 2D
2. Multiple view 3D

2D Part Appearance Model

$$P\left(I_n \middle| X_n\right)$$



Body Part Classification as 2D Appearance Model

- Inspired by Kinect approach:

  Real-Time Human Pose Recognition in Parts from a Single Depth Image. Shotton et al. CVPR 2011.

HOG image　　Position

- Input: $x = (h, p)$

- Output: $y \in \{0, 1, \ldots, N\}$

Background　　Body Parts

Joint-based
part representation

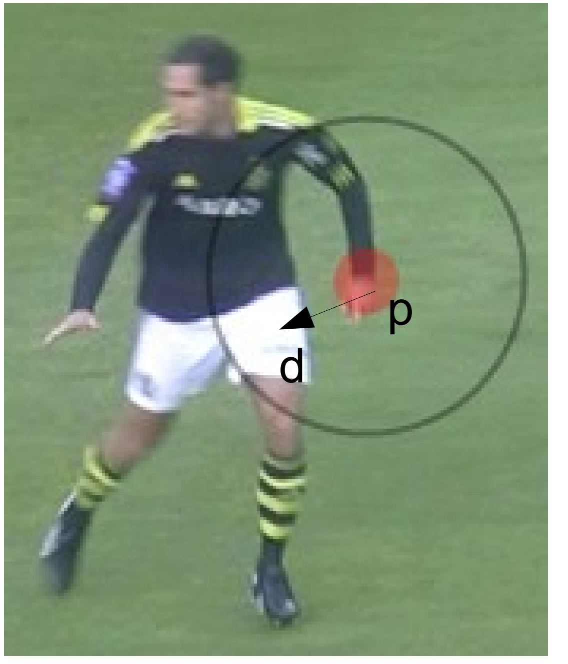
Decision Tree for Pixel Classification

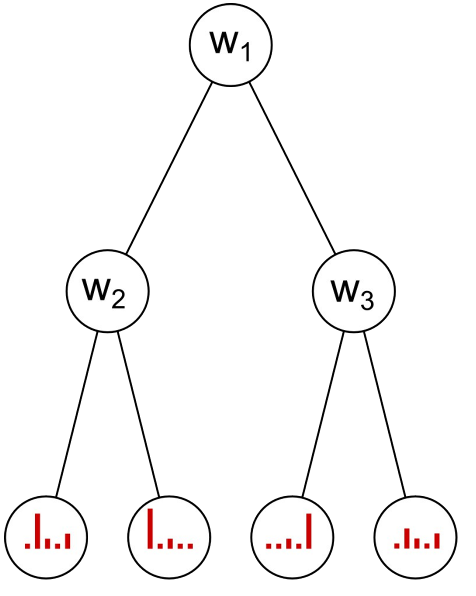
- Weak classifier: $w = (d, n, t)$

Position Offset — HOG-dimension — Threshold

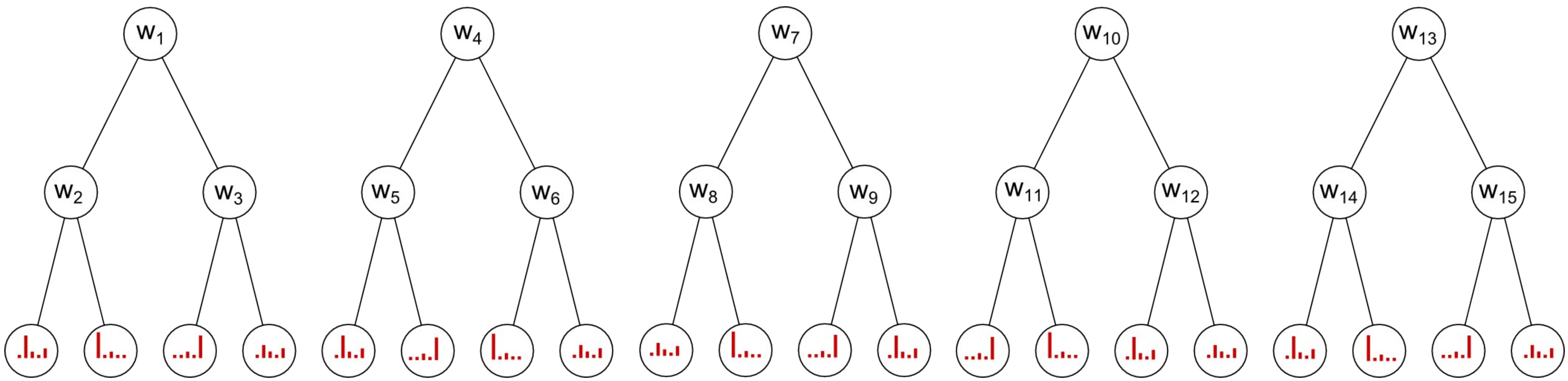
- Decision: $h(p+d, n) < t$

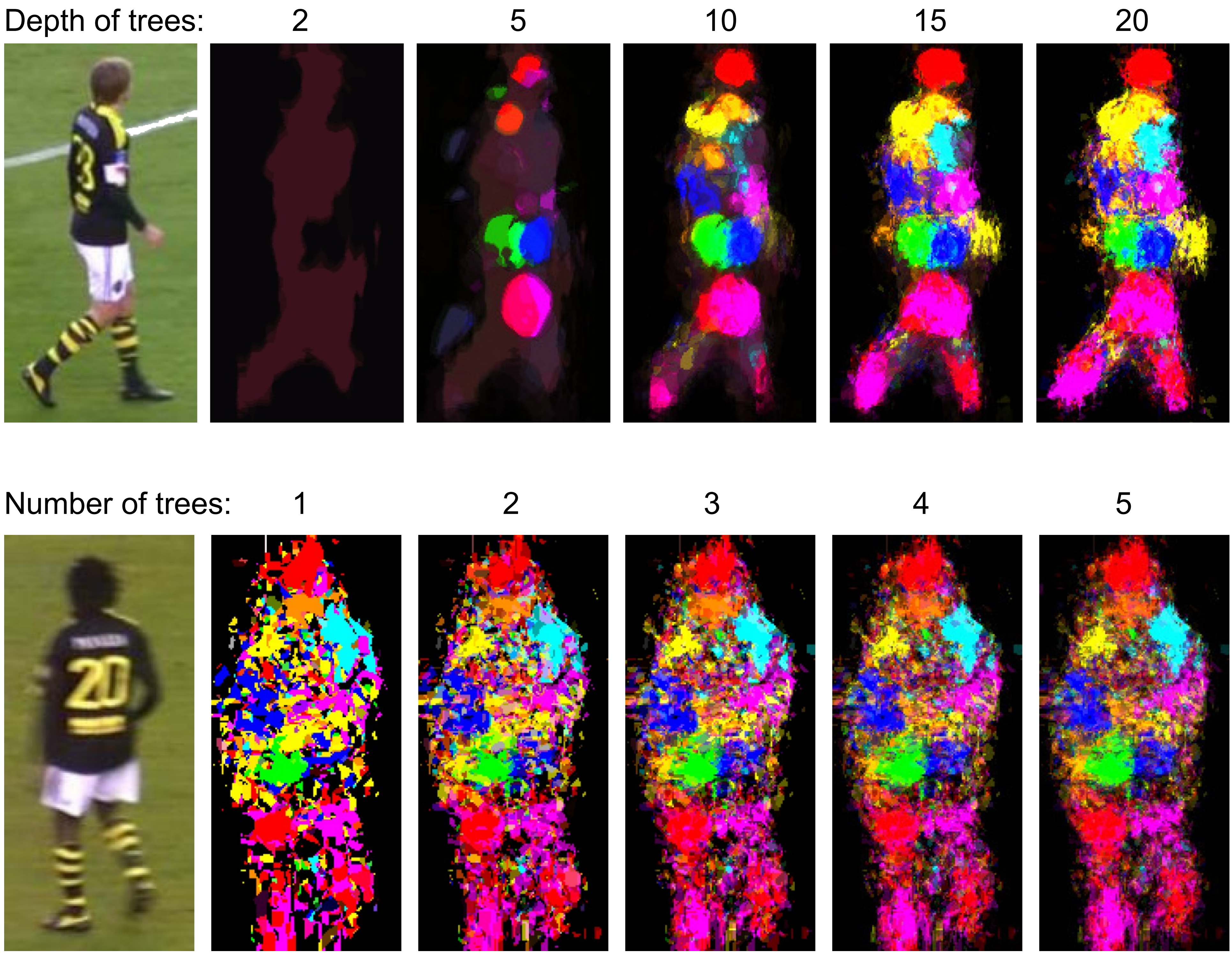
HOG image — Position





Random Forest



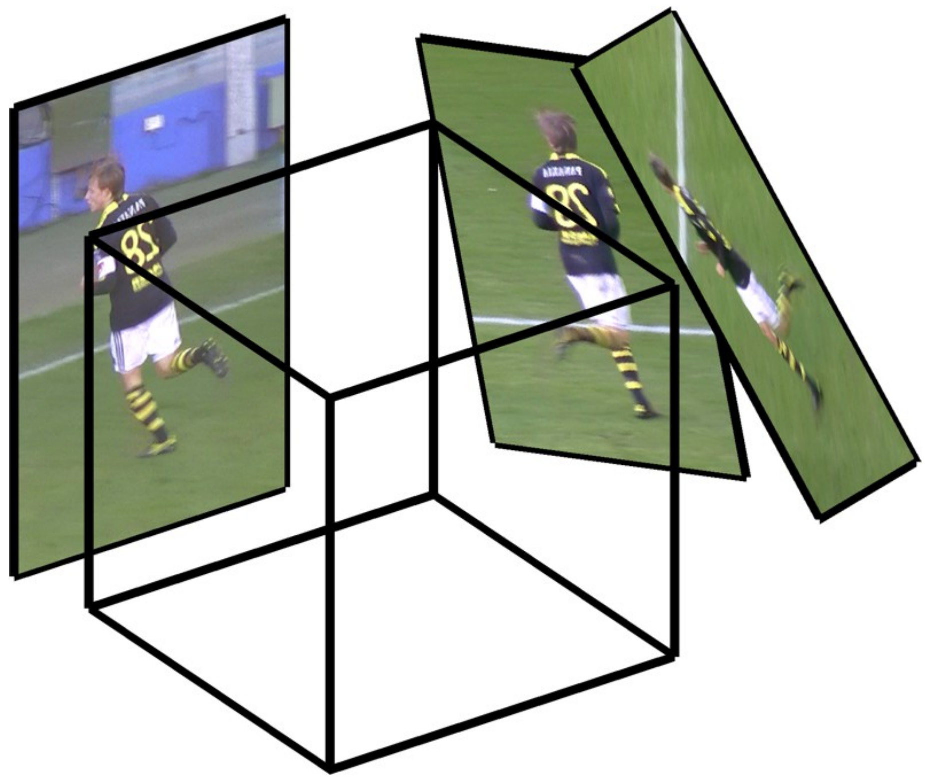


Depth of trees:
2
5
10
15
20
Number of trees:
1
2
3
4
5

2D Pose Estimation Demo Movie

2D part appearance likelihoods and pose estimation using a pose prior.
Estimation is done independently for each frame.

3D Part Appearance Model



Assume calibrated cameras
and bounding cube of player

3D Part Appearance Model

Back-project from 2D pixels to a 3D voxel grid (64x64x64) covering the bounding cube:

Camera projection

2D part position

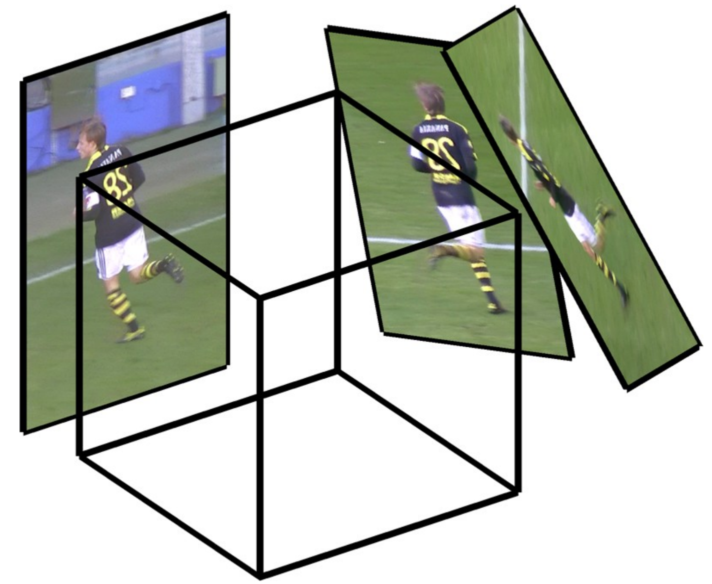
3D part position

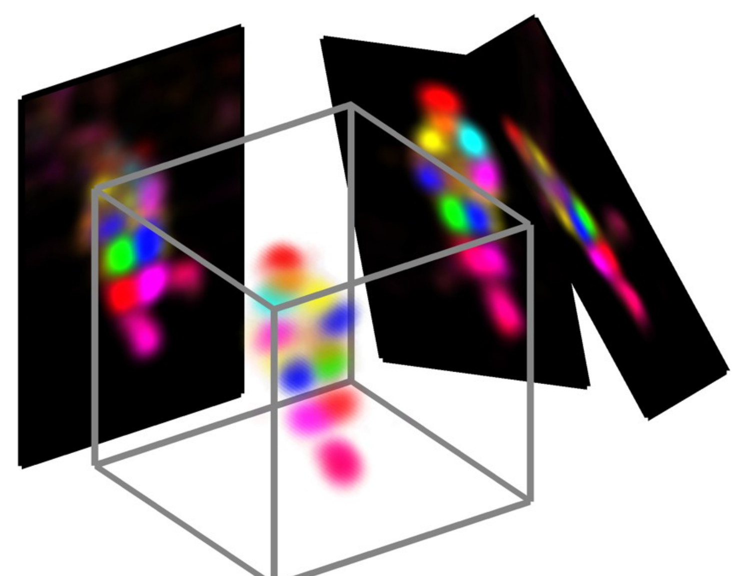
$$X_n^c = T^c(X_n)$$

Multi-view appearance model

$$P(I_n \mid X_n) = \prod_{c=1}^{C} P(I_n^c \mid X_n^c)$$

Single-view appearance model





The Problem of Symmetric Body Parts

Left and right parts look similar.

The Problem of Symmetric Body Parts

Approach 1:

Classify left/right parts of the person.

Disadvantage:

- Too Difficult

The Problem of Symmetric Body Parts

Approach 2:

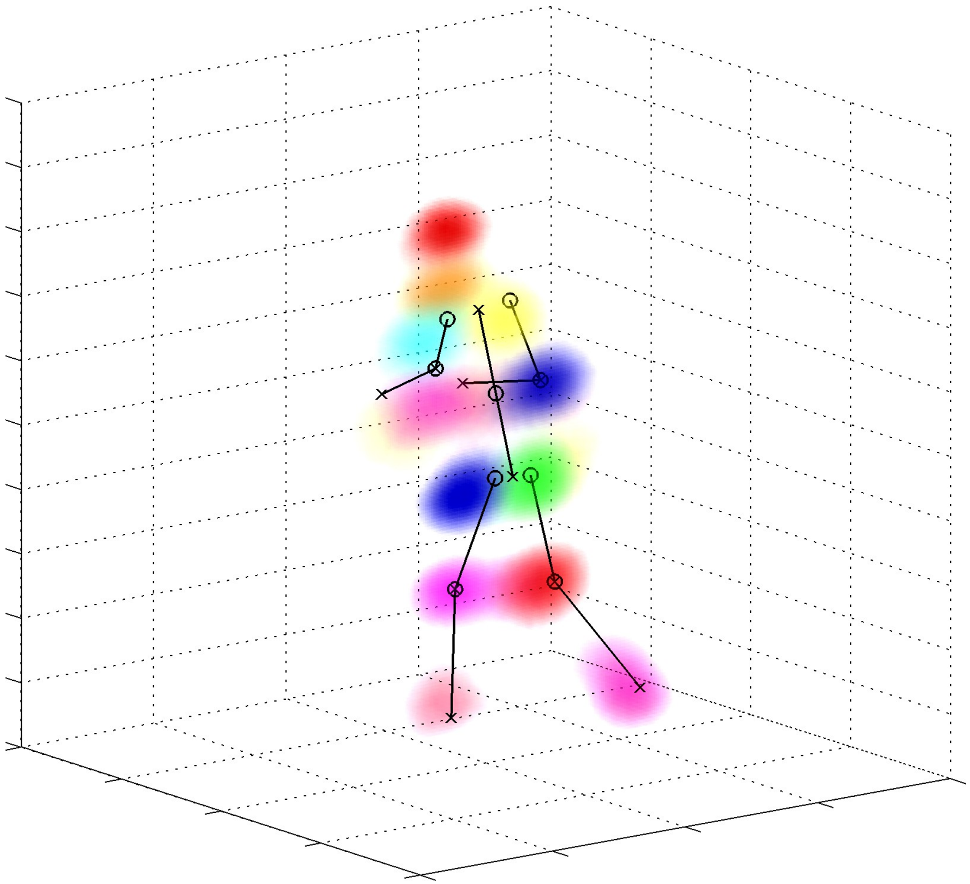
Ignore the left/right label of parts.

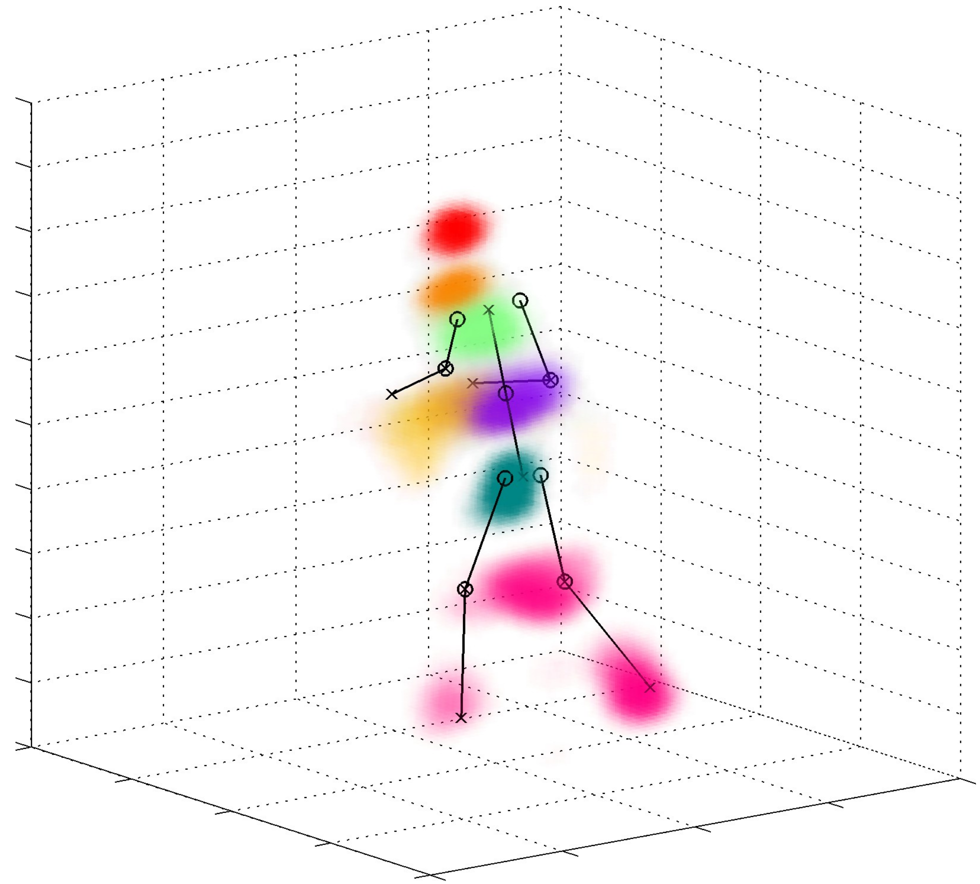
Disadvantages:

- Double counting
- Correspondences across views

Aggregating Scores Across Views

$$P(I_n | X_n)$$

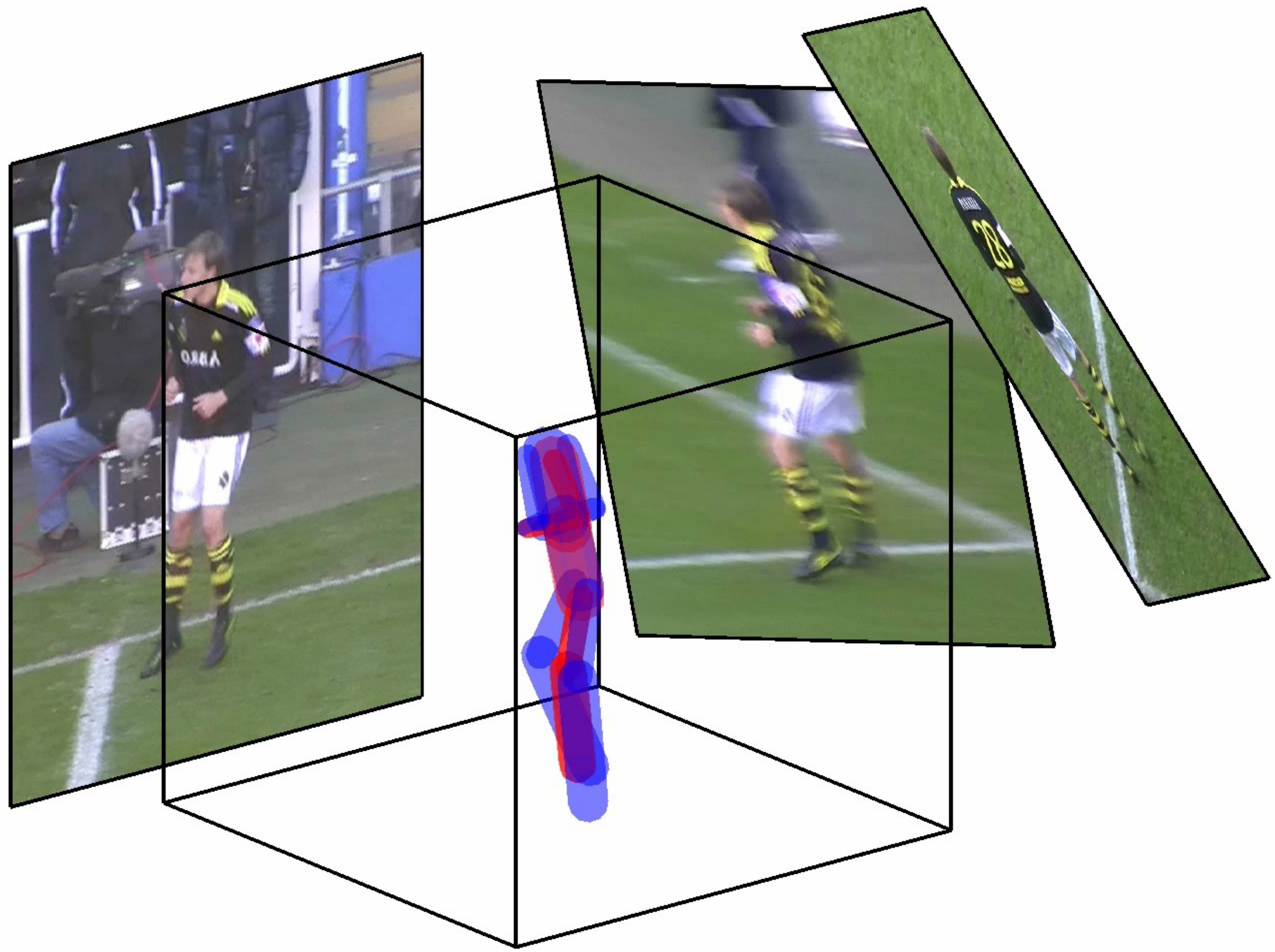




Approach1:
Assuming we know the left/right label, relative the person, for each view.

Approach 2:
Ignoring left/right label of parts.

Naive Multi-view Pose Estimation



Ground truth **Estimation**

The Problem of Symmetric Body Parts

Approach 3:

Classify the left/right parts <u>of the image</u>.

Disadvantage:

- Correspondences across views

Handle Left-Right Correspondences with a Latent Variable

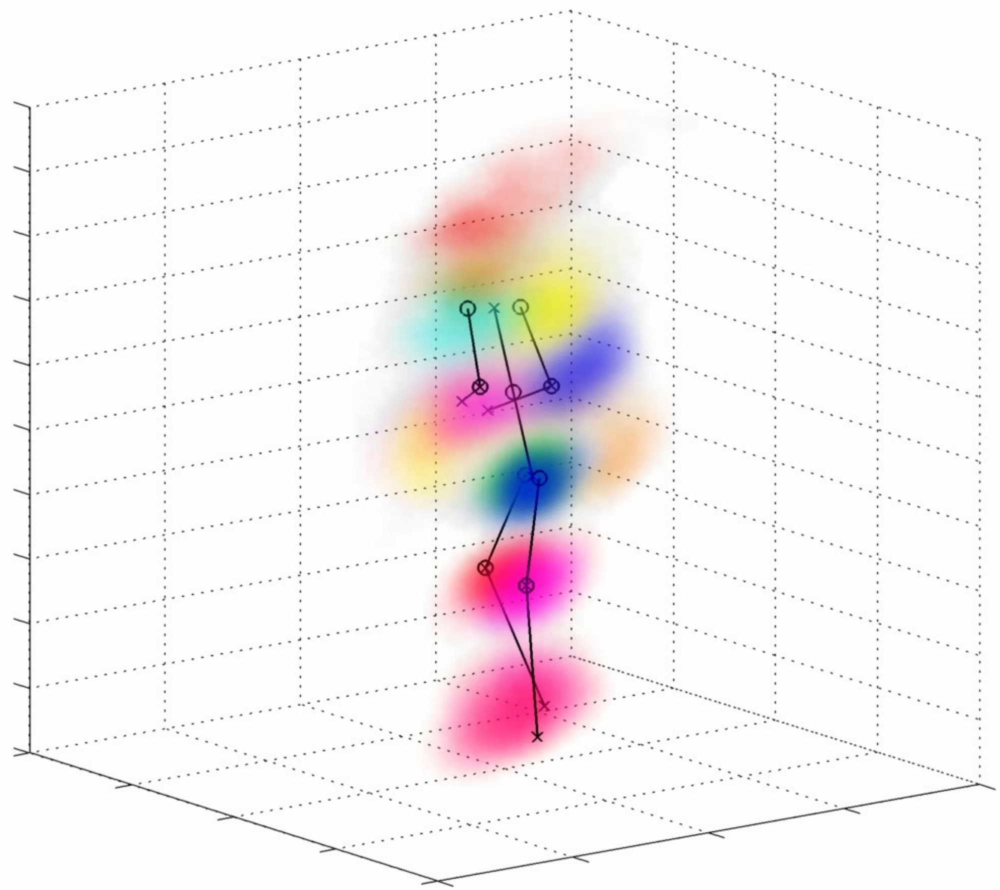
- Match left and right leg of the image with left and right leg of the person.
- For each view we have 2 choices for the legs and 2 for the arms.
- For C views we have 4^C choices.
- Let the latent random variable S describe this unknown mapping.

Multi-view Inference

$$P(X, I, S) = P(X)\,P(S)\prod_{n=1}^{N} P(I_n | X_n, S)$$

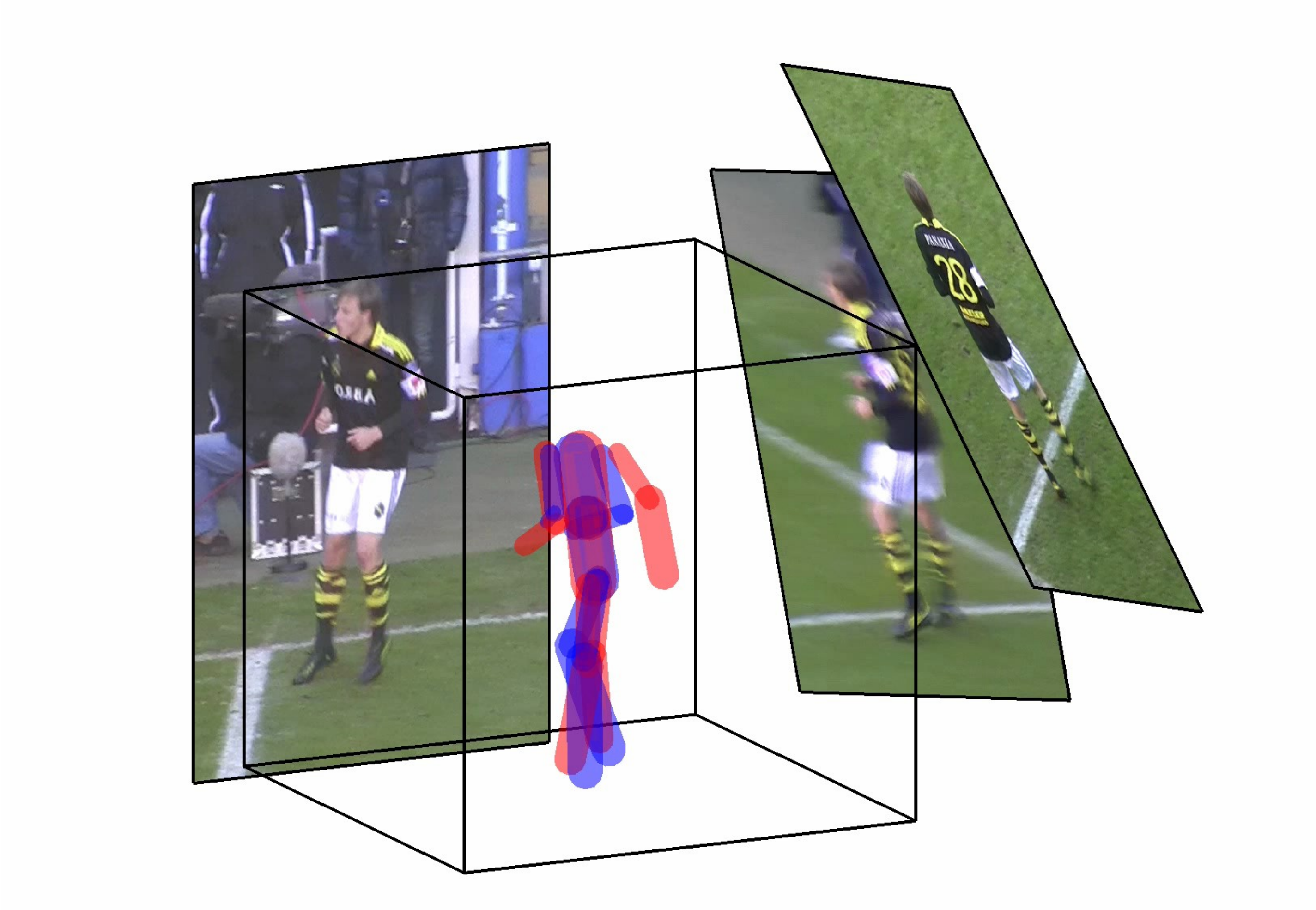
$$\max_{X,S} P(X, S | I) = \max_{S} \max_{X} \log P(X, I, S)$$

3D Part Appearance Model



$P\left(I_n \middle| X_n, \tilde{S}\right)$ & ground truth pose

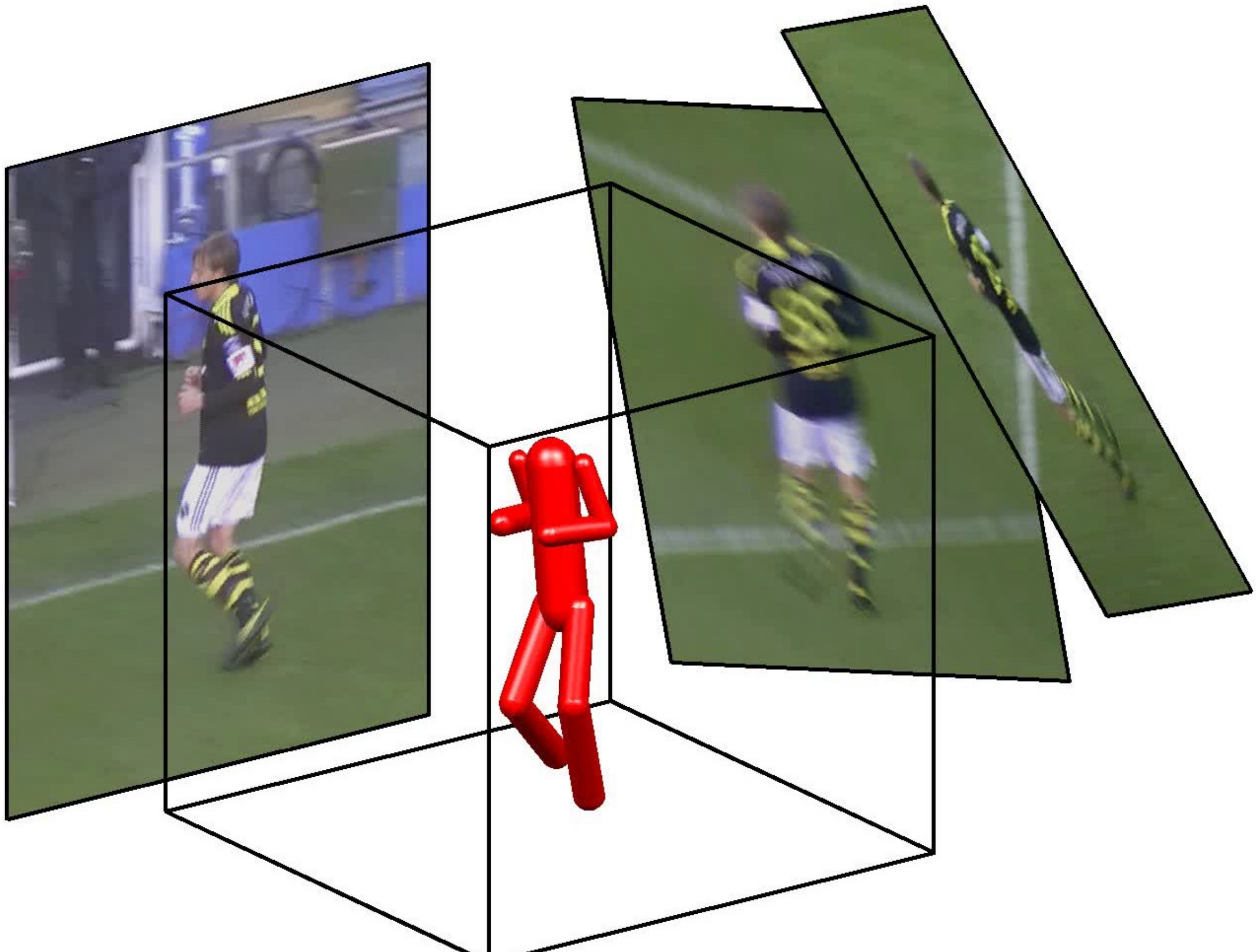
Multi-view Pose Estimation



- Just using 3D part appearance model.
- No 3D pose model. No motion model.
- Latent variable handles mirror symmetry.

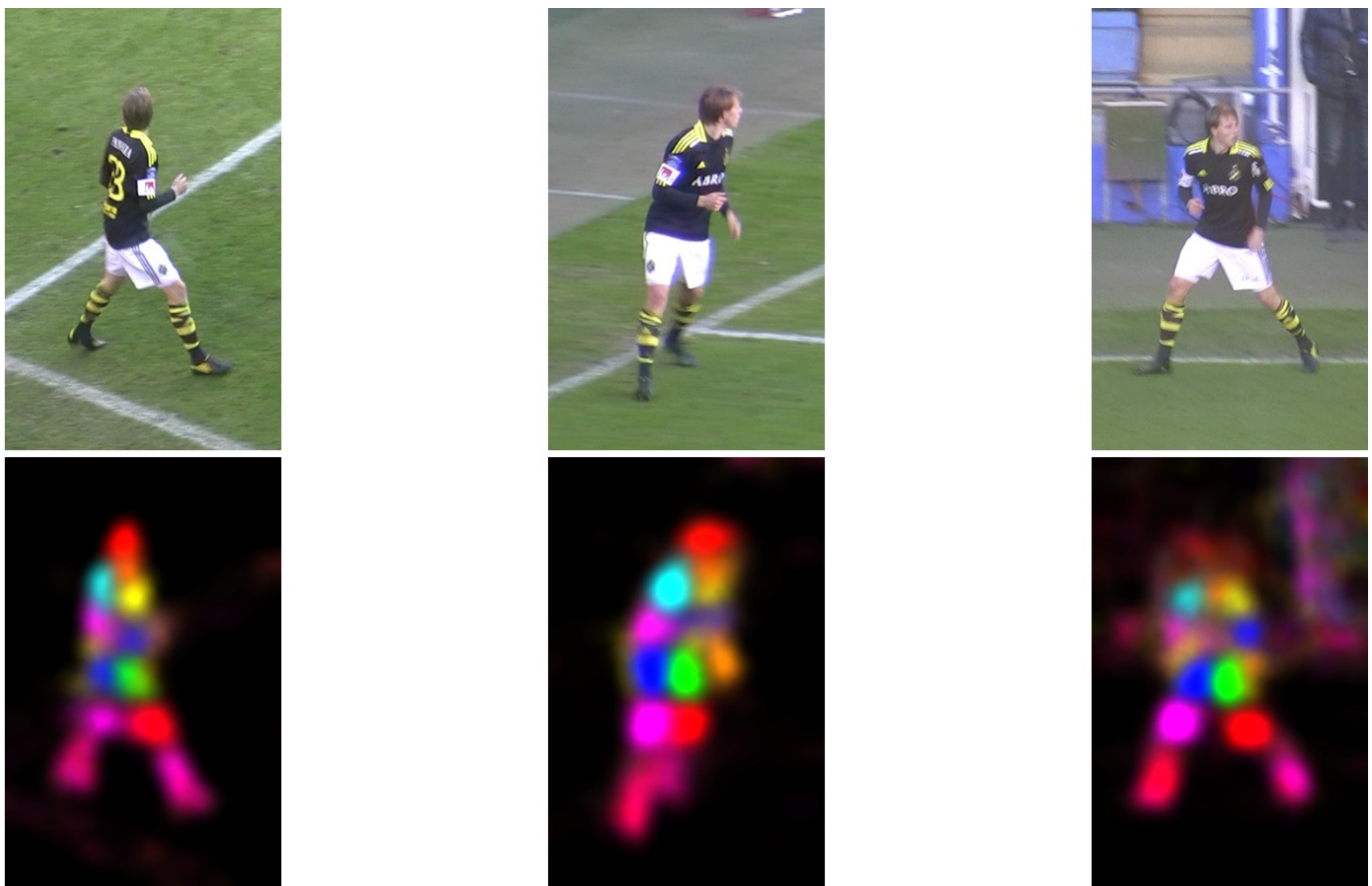
Conclusions

- New data set available at our web-page.



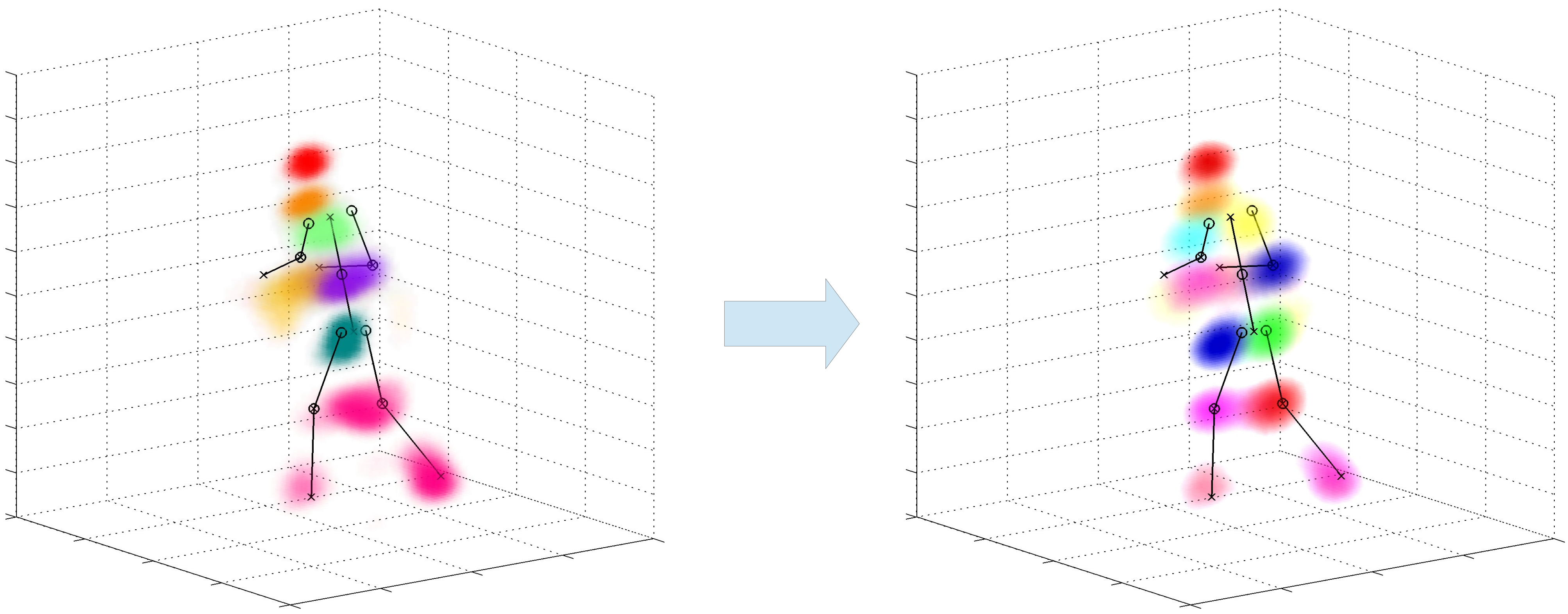
Conclusions

- Random forest classification works well for body part recognition in ordinary images.



Conclusions

- Problem of symmetric body parts, for multi-view part-based models.
- Latent variable solution.



Thank you!