

# Coarse-to-Fine Volumetric Prediction for Single-Image 3D Human Pose

Georgios Pavlakos, Xiaowei Zhou, Konstantinos G. Derpanis, Kostas Daniilidis



Training Code  
Testing Code

[tinyurl.com/PoseVolumetric](http://tinyurl.com/PoseVolumetric)

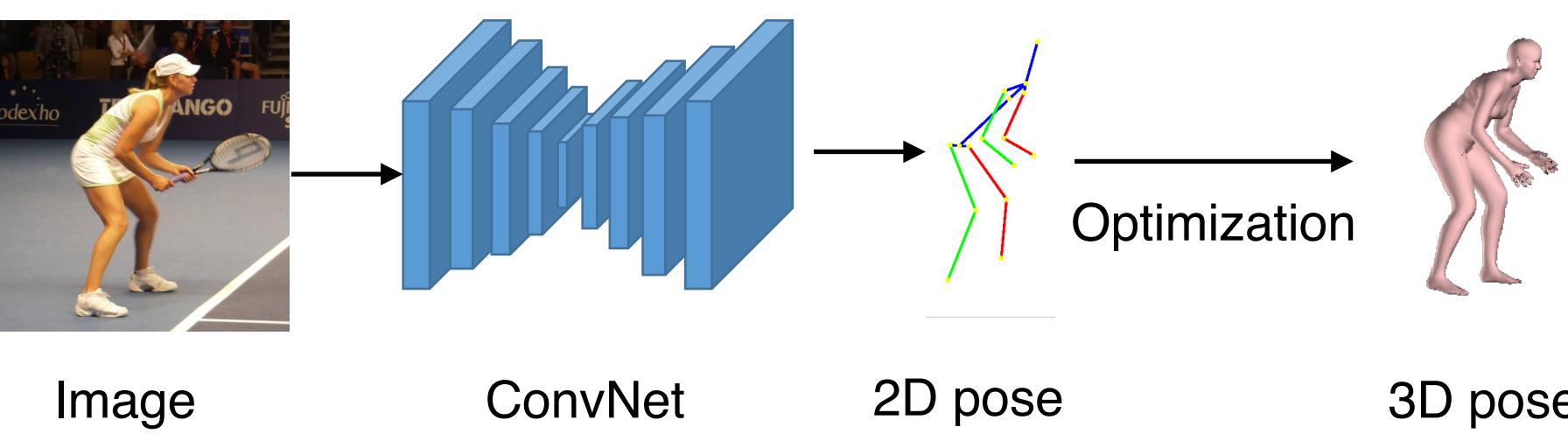
**Goal: Estimate 3D human pose from a single color image**

Two paradigms dominate this problem. Reconstruction and discriminative approaches.

**Approach**

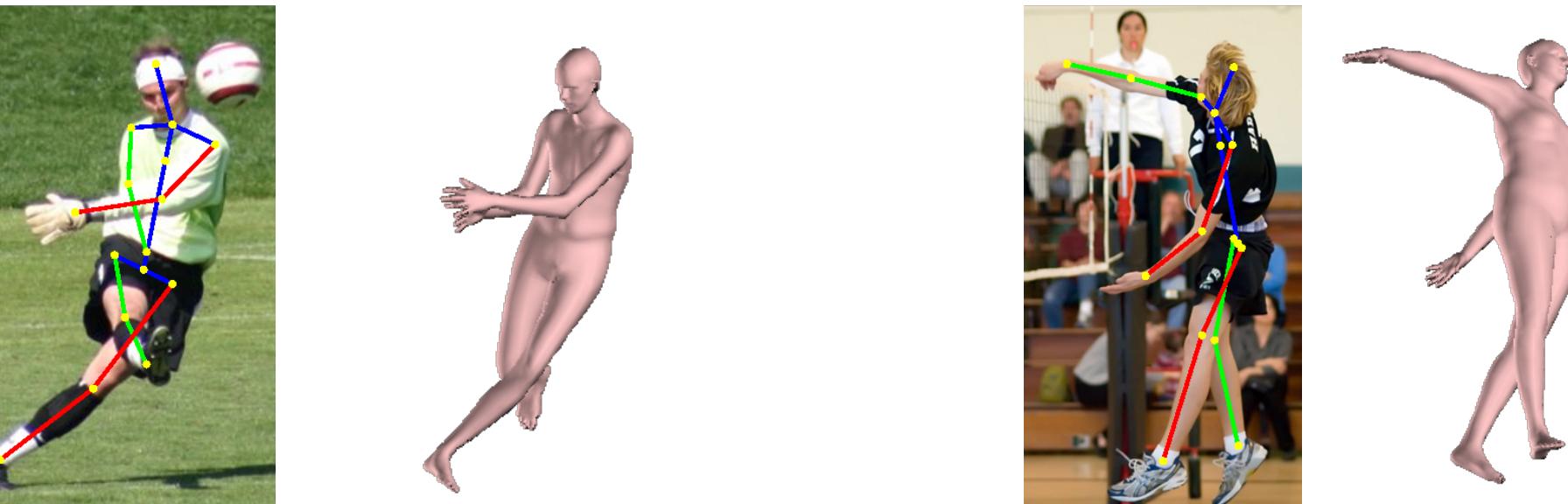
**Two-step Reconstruction Approaches**

2D pose estimation + optimization lifting 2D-to-3D



**Limitation**

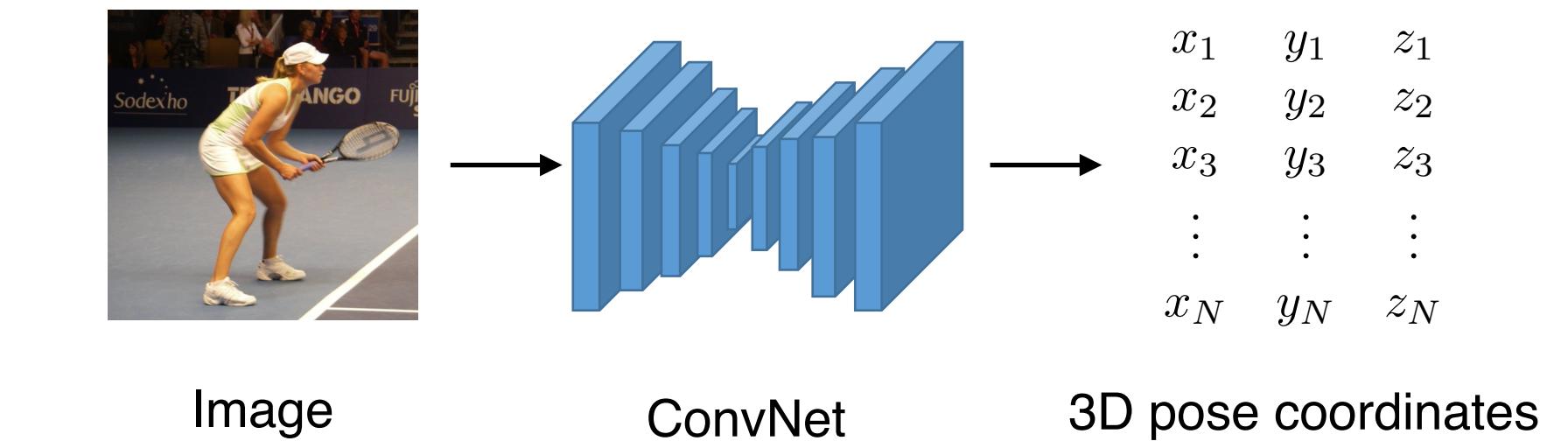
Reconstruction Ambiguity!



**Approach**

**Discriminative Approaches** e.g.: coordinate regression

Estimate the 3D pose directly from the image.



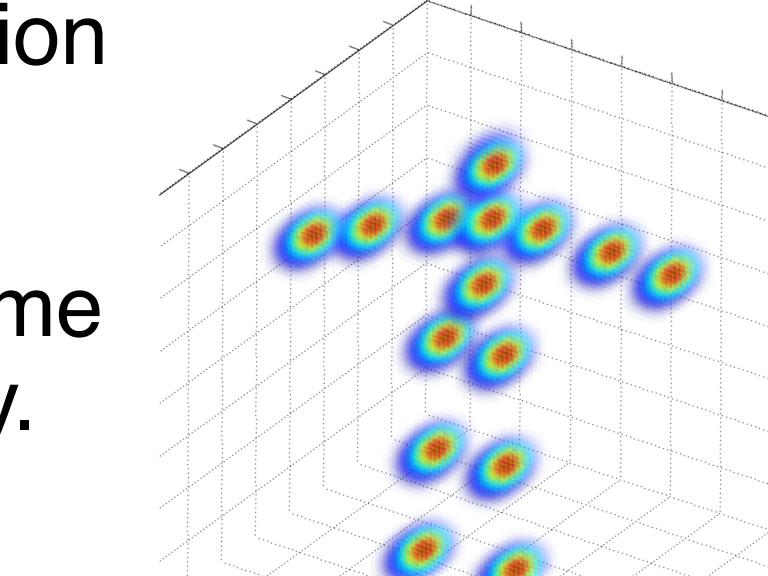
**Limitation**

Problem is highly non-linear.  
Mapping from images to 3D coordinates is hard to learn.  
Underperforms compared to two-step approaches.

**This work**

We attempt to bridge the gap!

We introduce the volumetric representation for 3D human pose.

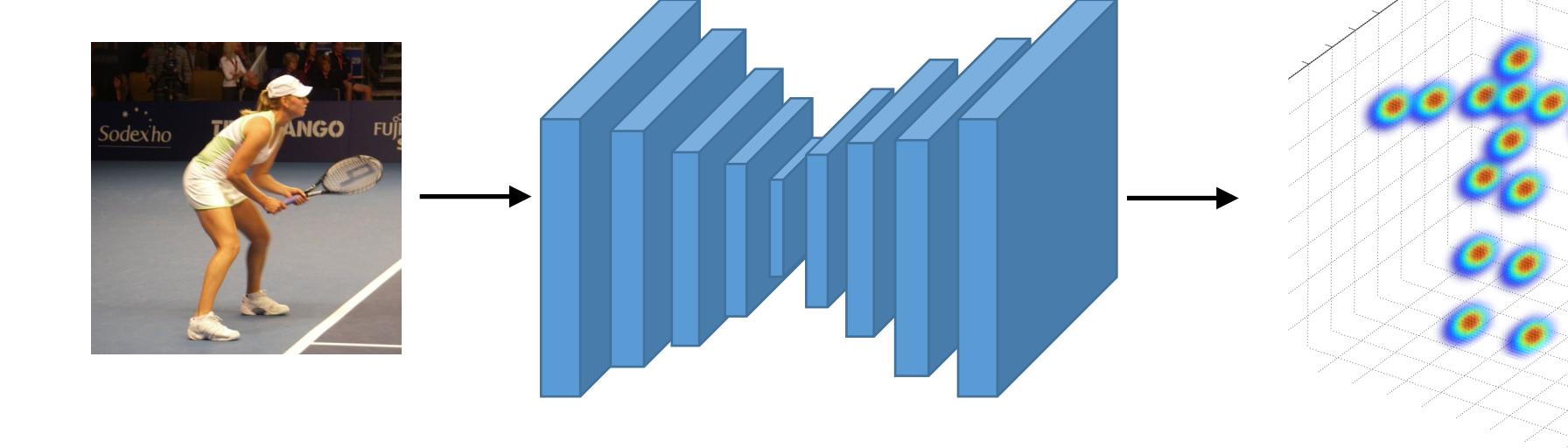


We use a coarse-to-fine prediction scheme to deal with the excessive dimensionality.

We employ a decoupled architecture for 3D human pose estimation "in-the-wild".

We achieve more than **30% relative error reduction** for standard benchmarks!

**Volumetric representation for 3D human pose**



We cast the problem as 3D keypoint localization.

We regress 3D heatmaps of dimensions 64x64x64 for each joint.

**Major advantages**

ConvNets can naturally map from 2D images to 3D volumes.  
The mapping can be achieved with a Fully Convolutional Network.  
Rich output (64x64x64 for each joint). Useful for other tasks/postprocessing.

**Approach**

	Average Error	Human3.6M (mm)
Coordinate Regression	112.41	
Volume Regression (depth = 32)	92.23	
Volume Regression (depth = 64)	85.82	

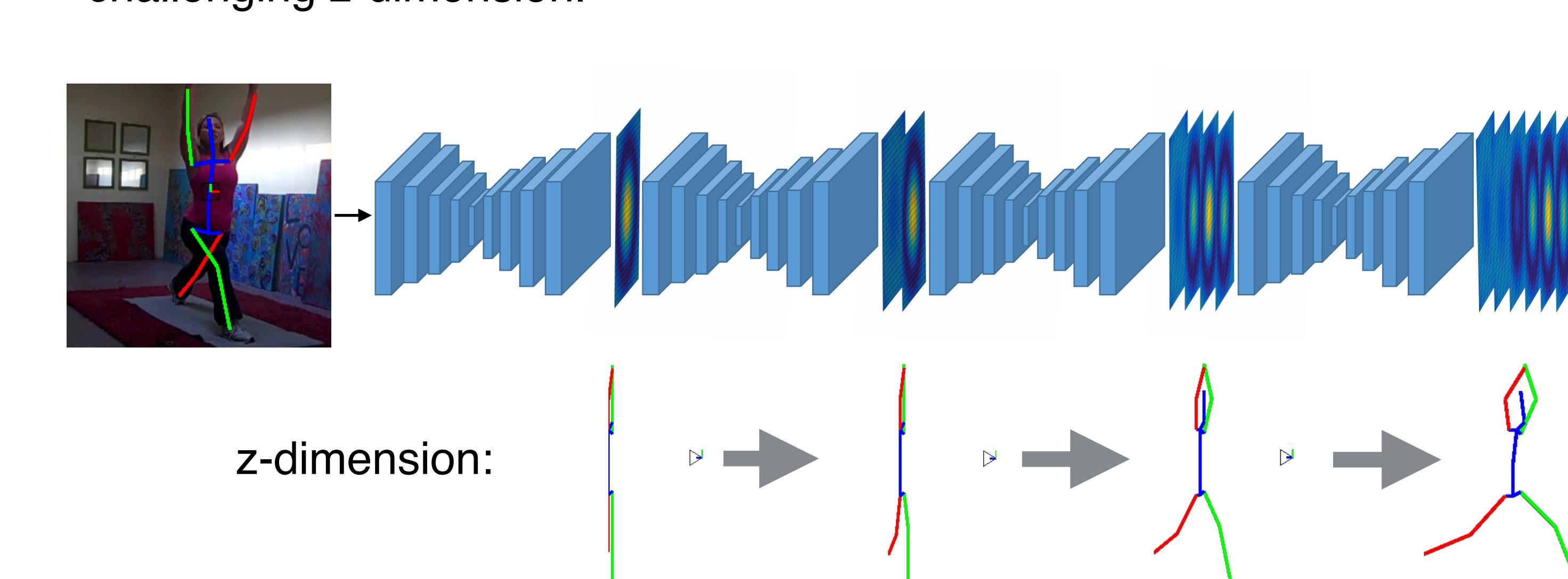
**Limitation**

**Coarse-to-Fine prediction**

Iterative estimation offers diminishing returns because of the excessive dimensionality of our representation.

**We do it in a coarse-to-fine way!**

The resolution of the supervision volume increases gradually for the most challenging z-dimension.



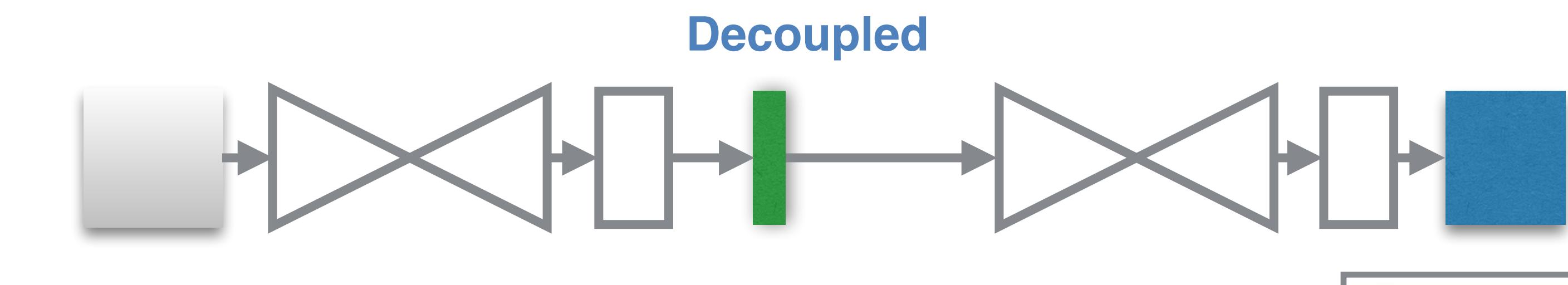
**Approach**

	Decoupled	Coarse-to-Fine
Average Error	78.10	69.77

**Versatility of volumetric representation**

Regress 3D heatmaps using 2D heatmaps as input.

**Decoupled**

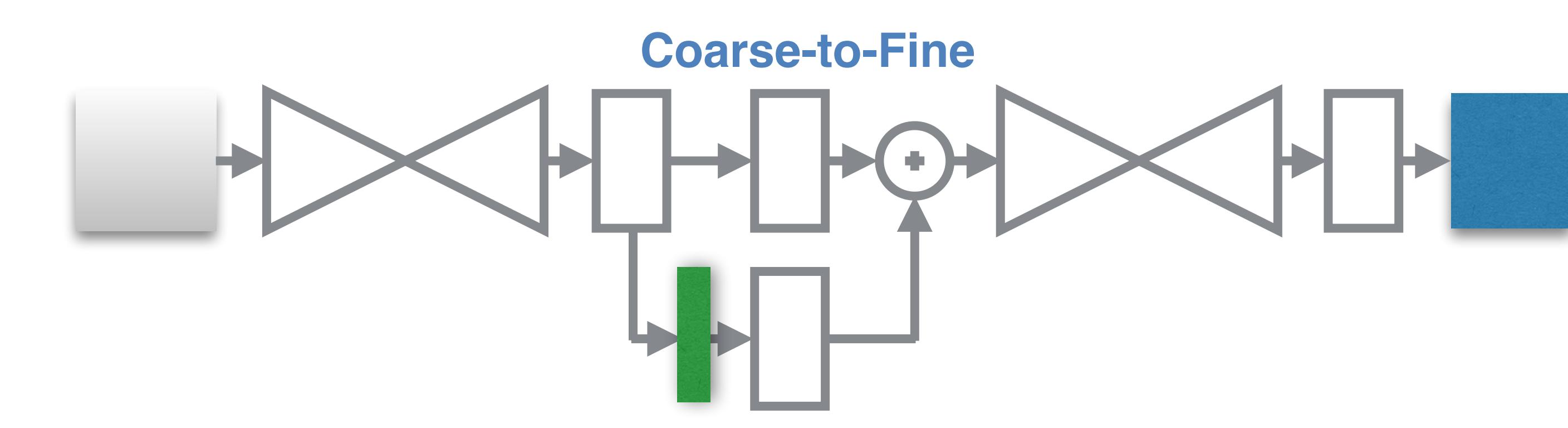


Allows us to train independently for the 2D and the 3D task.

We present compelling results for in-the-wild images.

- Uses only 2D joint locations and discards additional image evidence.
- When 2D estimates are wrong, 3D prediction can be lead astray.
- Underperforms compared to end-to-end approach.

**Coarse-to-Fine**

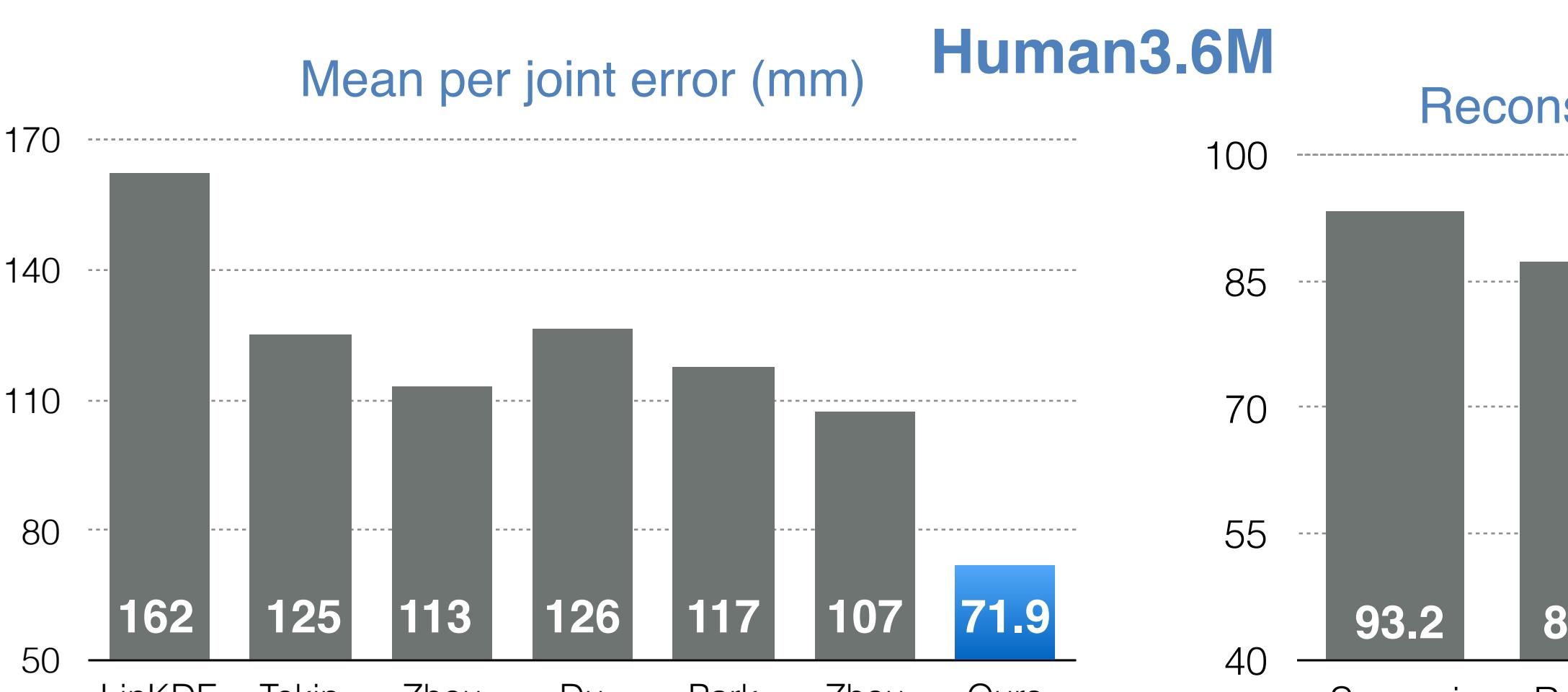


**Approach**

	Decoupled	Coarse-to-Fine
Average Error	78.10	69.77

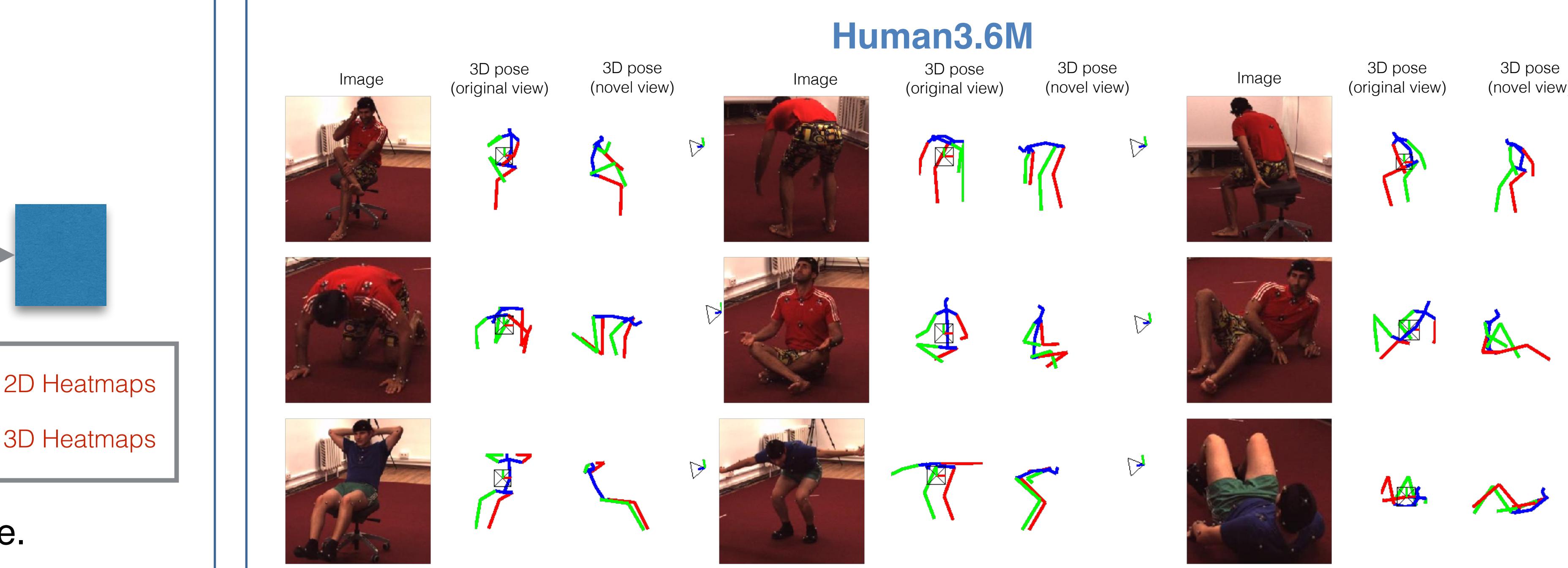
**Quantitative results**

**Human3.6M**

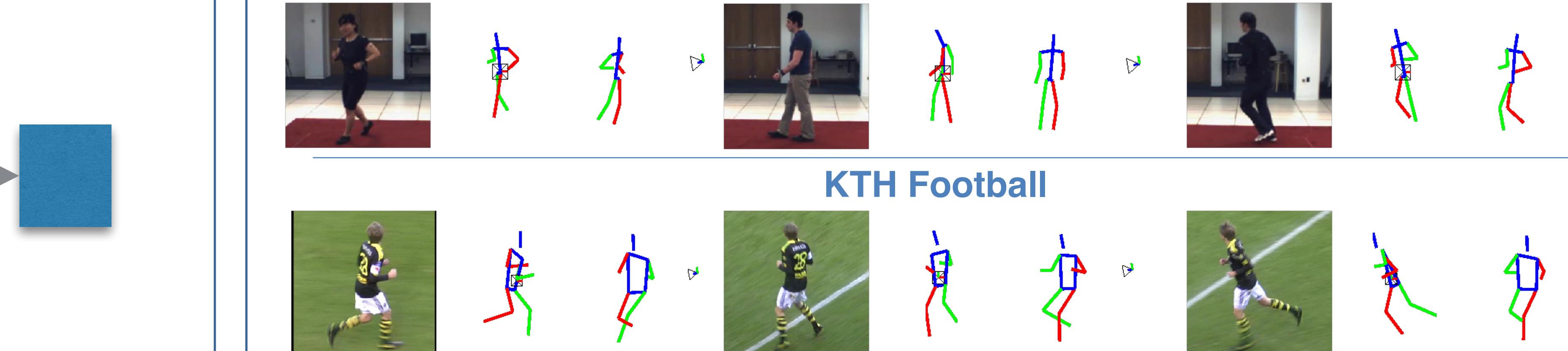


Method	Mean per joint error (mm)
LinKDE (PAMI 2014)	162
Tekin (CVPR 2016)	125
Zhou (CVPR 2016)	113
Du (ECCV 2016)	126
Park (ECCV 2016)	117
Zhou (ECCV 2016)	107
Ours	71.9

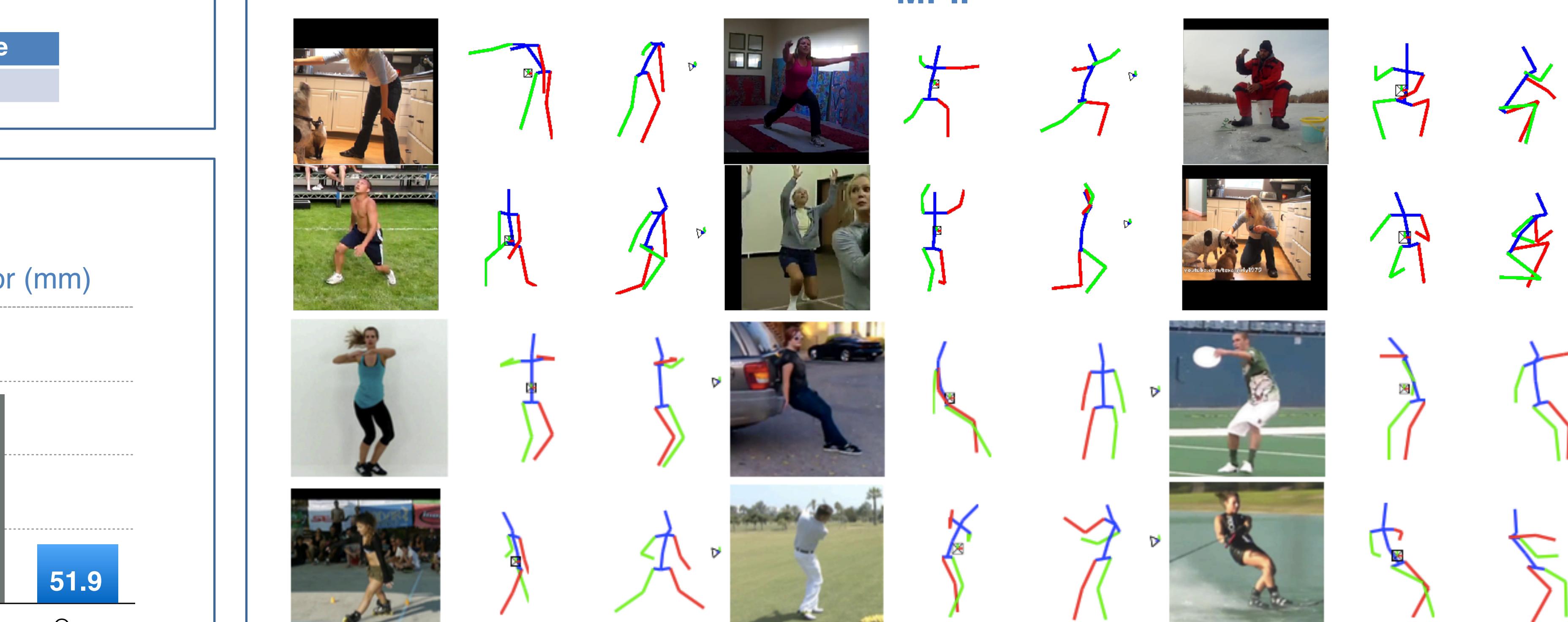
**HumanEva**



**KTH Football**



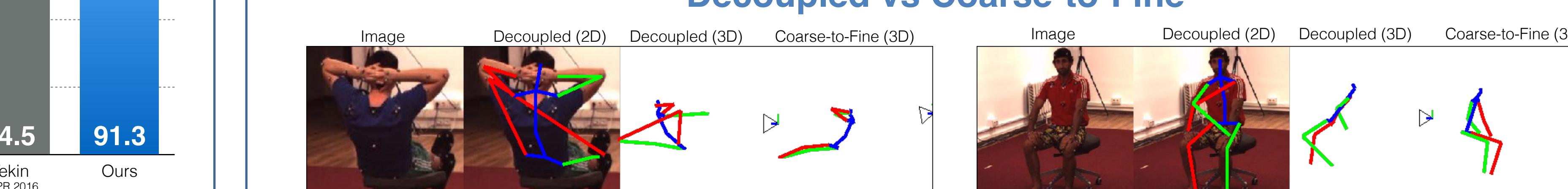
**MPII**



**Failure cases**

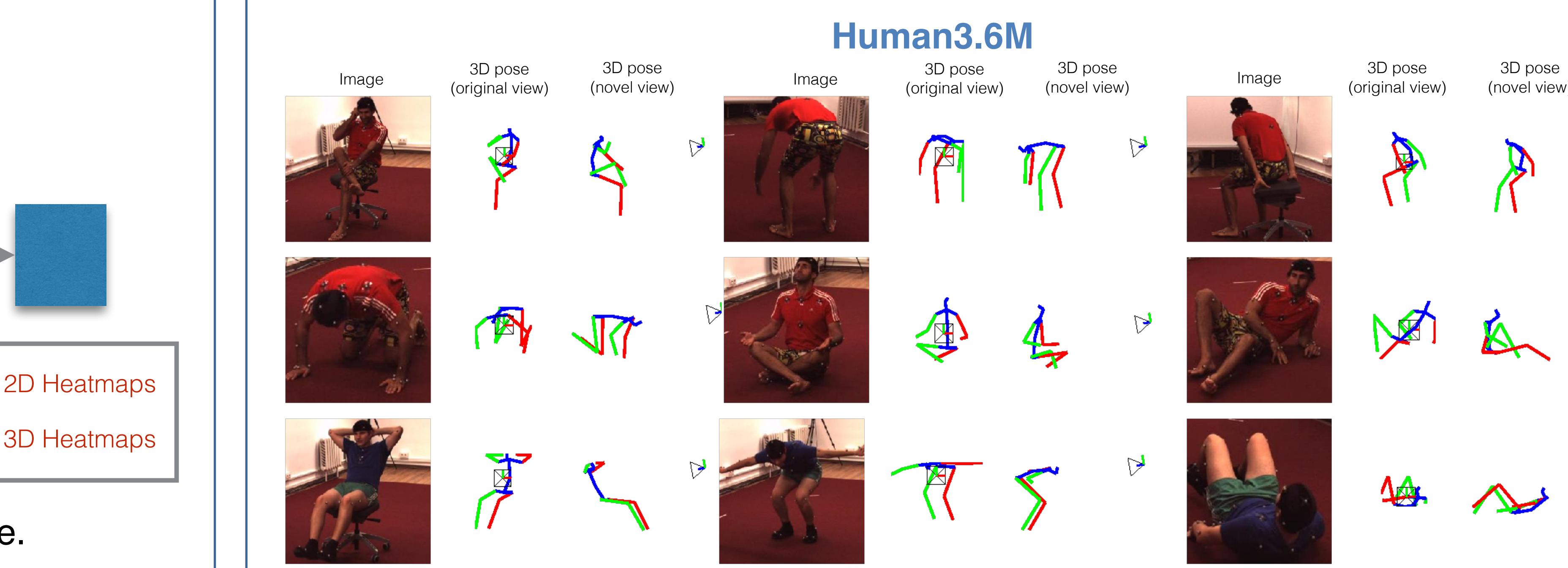


**Decoupled vs Coarse-to-Fine**

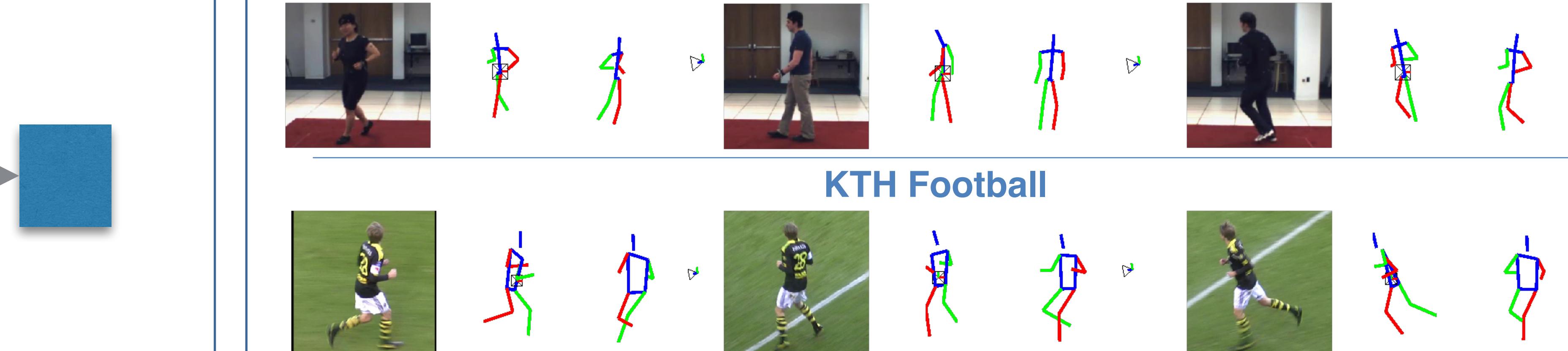


**Qualitative results**

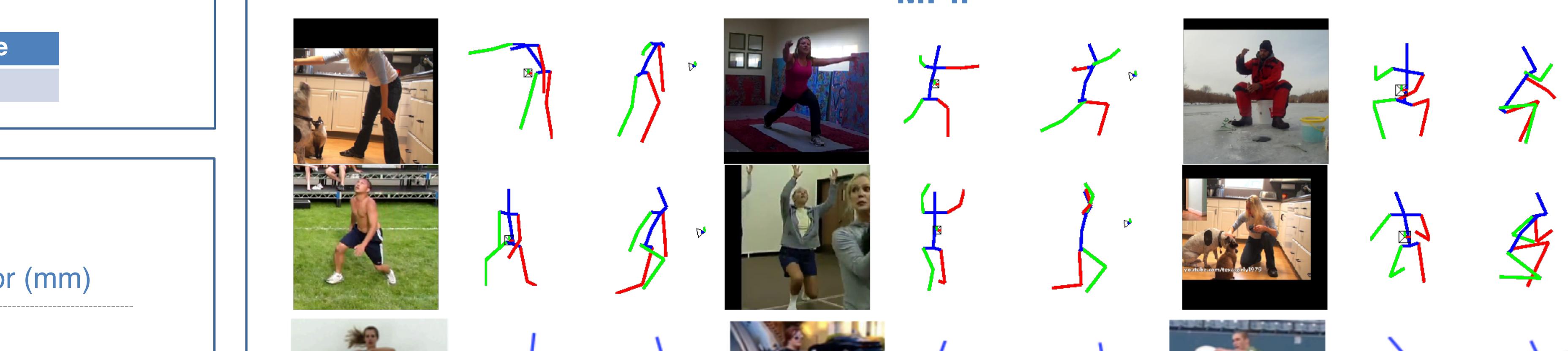
**Human3.6M**



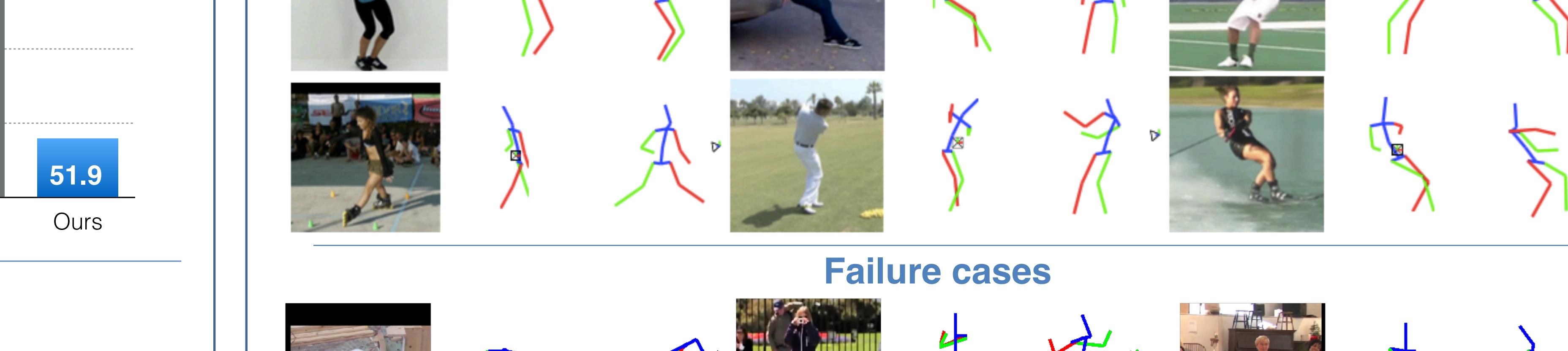
**HumanEva**



**KTH Football**



**MPII**



**Failure cases**



**Decoupled vs Coarse-to-Fine**

