



## Task

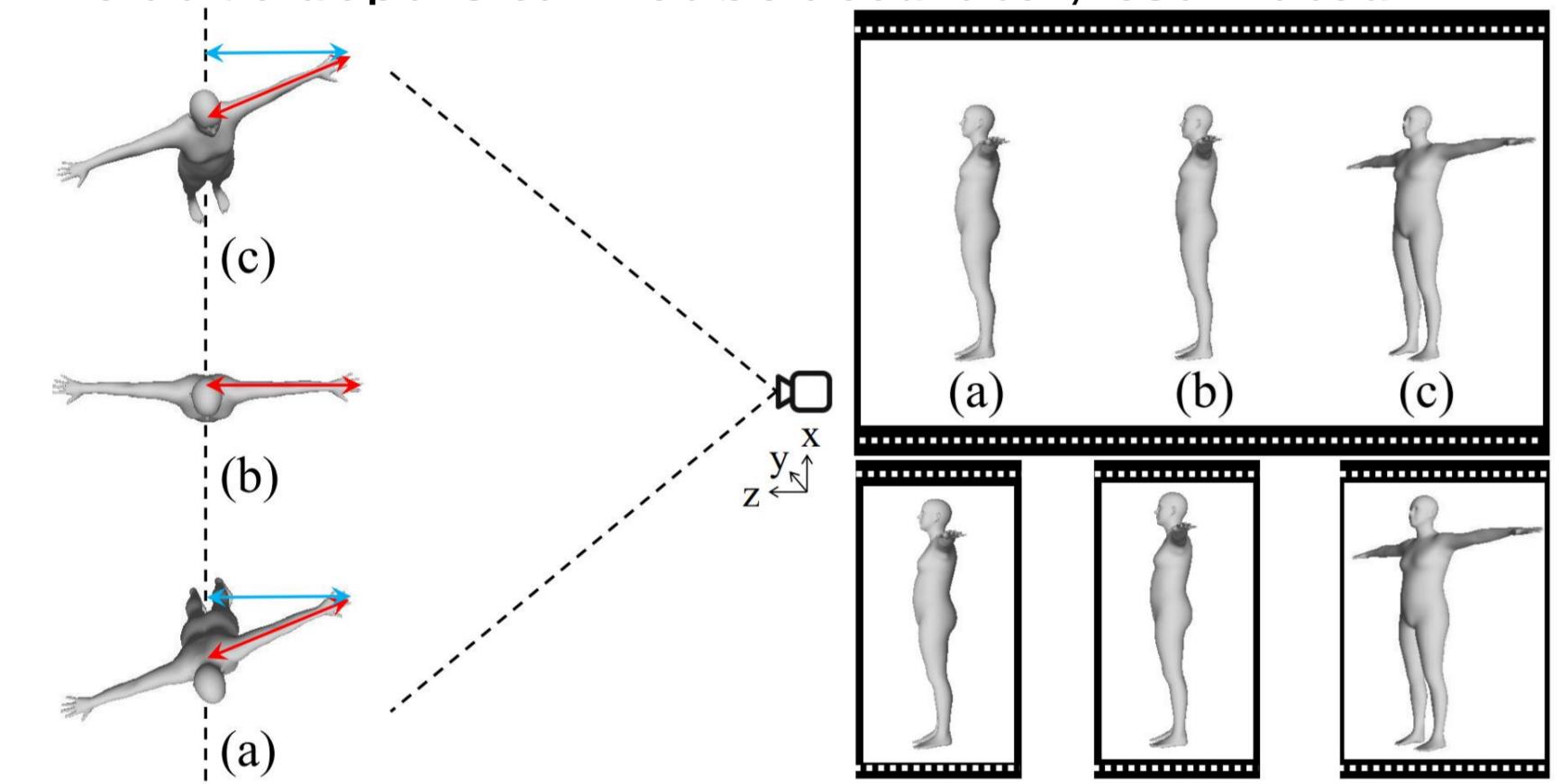
**3D Human Pose Estimation (HPE):** Estimate the 3D positions of human joints from individual images. Some 3D Human Pose and Shape Estimation (HPS) methods treat 3D HPE as a sub-task.

**Application:** AR/VR and human-computer interaction.

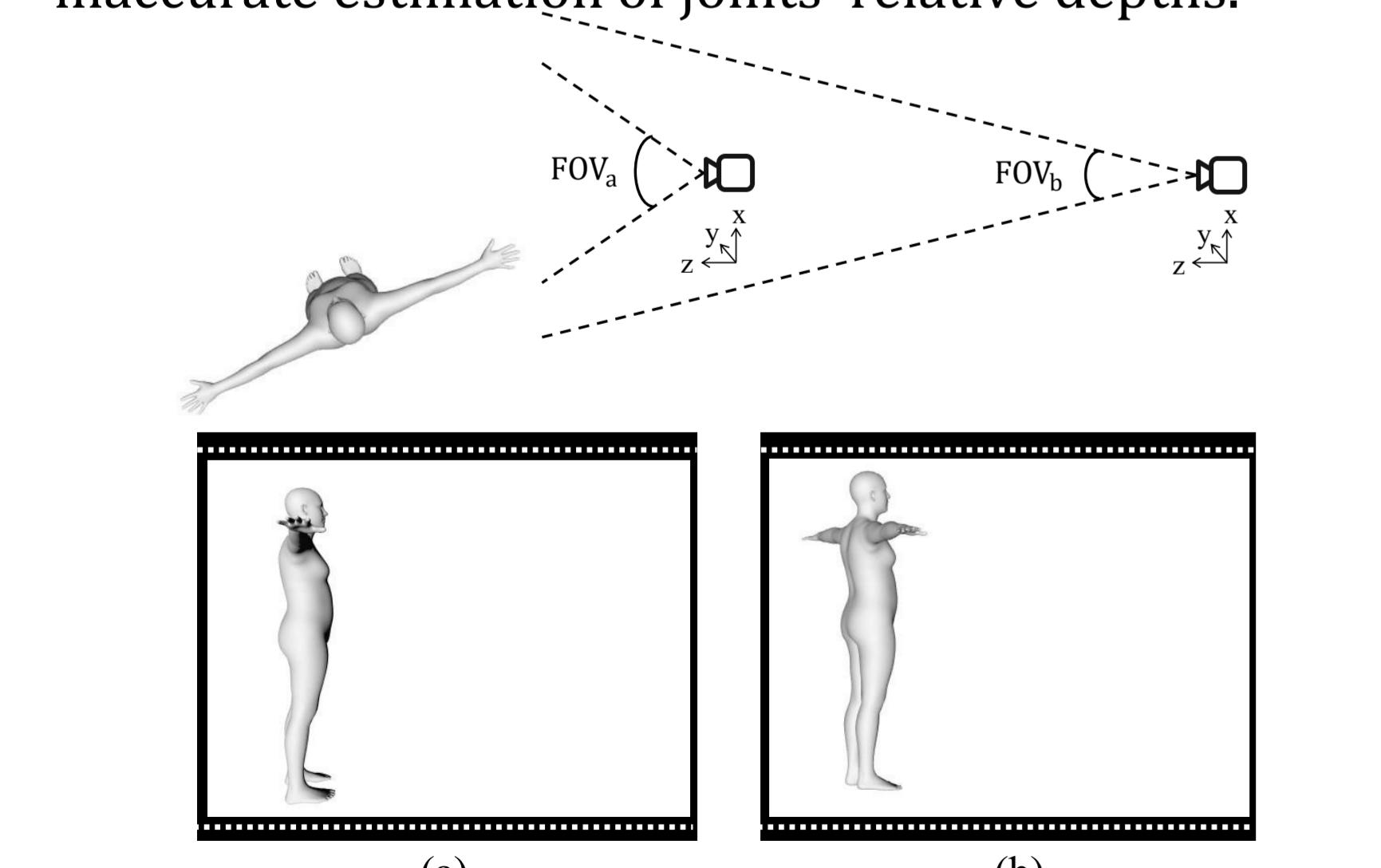
**Background:** Existing 3D HPE methods typically use **cropped images alone** as input. However, we found that without **camera intrinsics** information, the relative depths of joints cannot be accurately estimated.

## Importance of Camera Intrinsics in 3D HPE

- **Case 1:** When only input the **cropped image**, joints' relative depths cannot be accurately estimated.

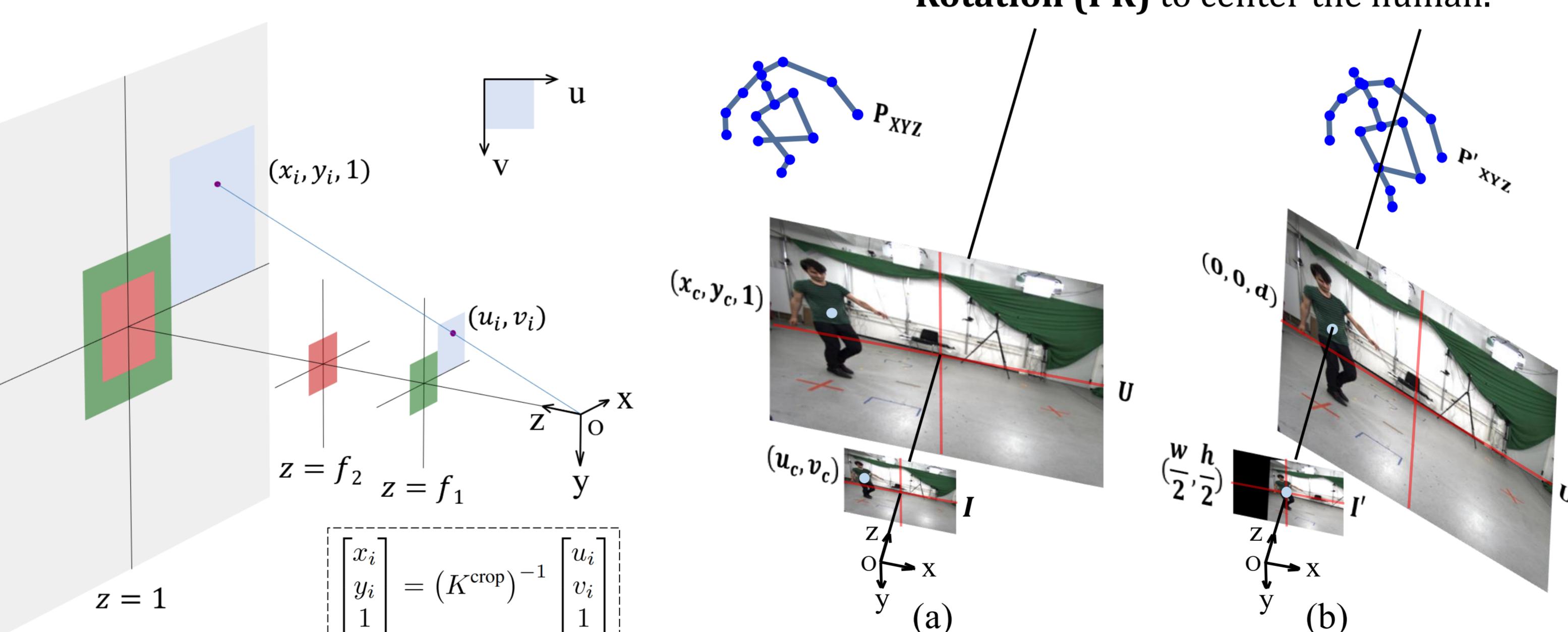
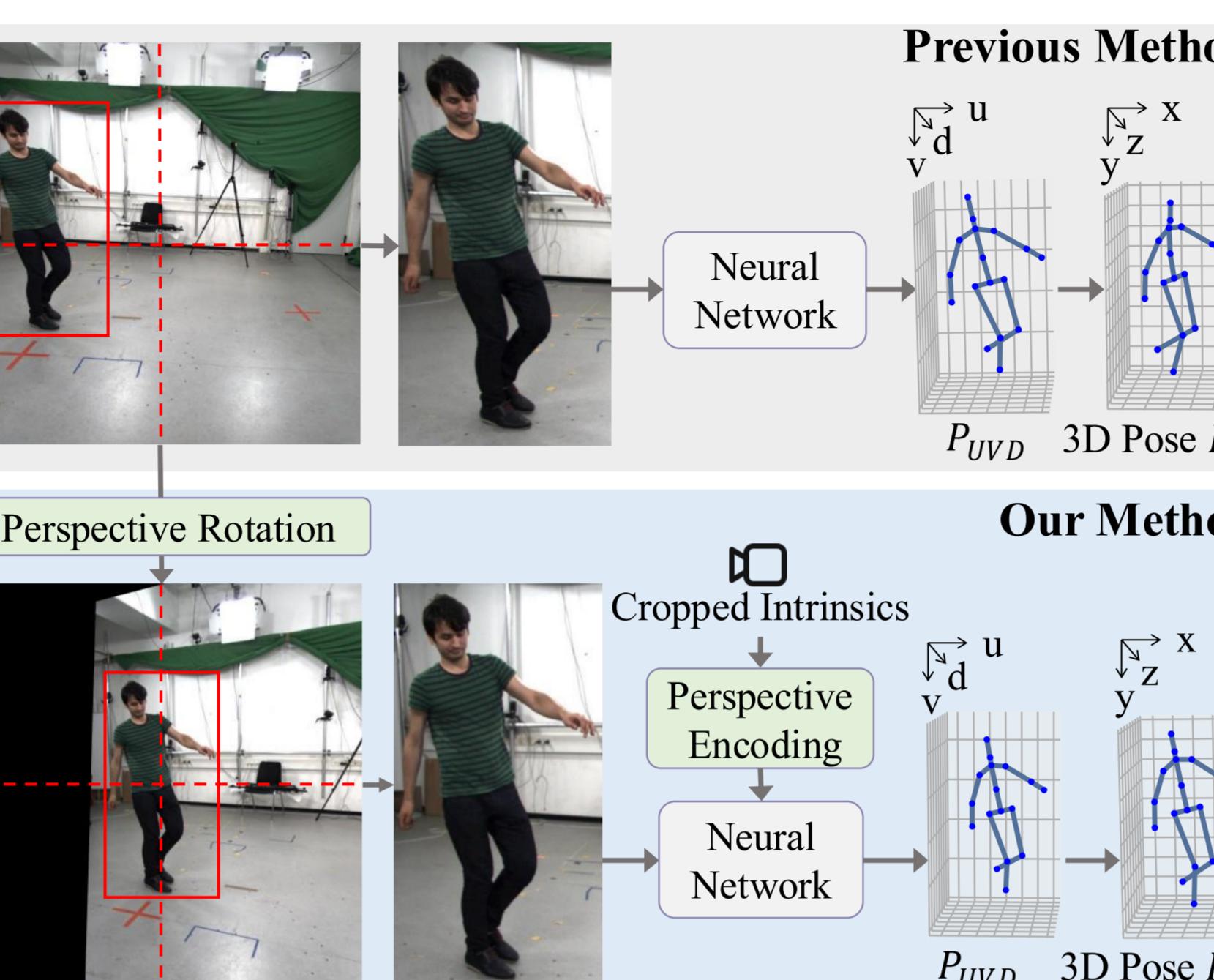


- **Case 2:** Use the full image but without **FOV** info → still inaccurate estimation of joints' relative depths.



Cropping an image is equivalent to capturing the same scene with different camera intrinsics, so this new **cropped intrinsics** encapsulate both cropping and FOV information.

## Method



- **Perspective Encoding (PE):** We project virtual sensors onto a fixed reference plane at  $z = 1$ . For each sensor, the corresponding projected area geometrically represents its unique view frustum. So, we employ this projected area as the encoded representation of the cropped intrinsics.

We design **Perspective Encoding (PE)** to encode cropped intrinsics (including  $f^{crop}, c_x^{crop}, c_y^{crop}$ ) as a 2D PE map, which is then jointly fed into the CNN with the cropped image.

$$\begin{aligned} \text{--} f_\theta : (I^{crop}, f^{crop}, c_x^{crop}, c_y^{crop}) &\rightarrow P_{XYZ} \\ \text{PR} \quad \text{--} \tilde{f}_\theta : (I^{crop}, f^{crop}) &\rightarrow P_{XYZ} \end{aligned}$$

As the human subject can appear anywhere within the original image, the principal point of the cropped images may differ significantly, which complicates model fitting. And the further the human deviates from the image center, the greater the perspective distortions. To address these issues, we propose **Perspective Rotation (PR)** to center the human.

## Experimental Results

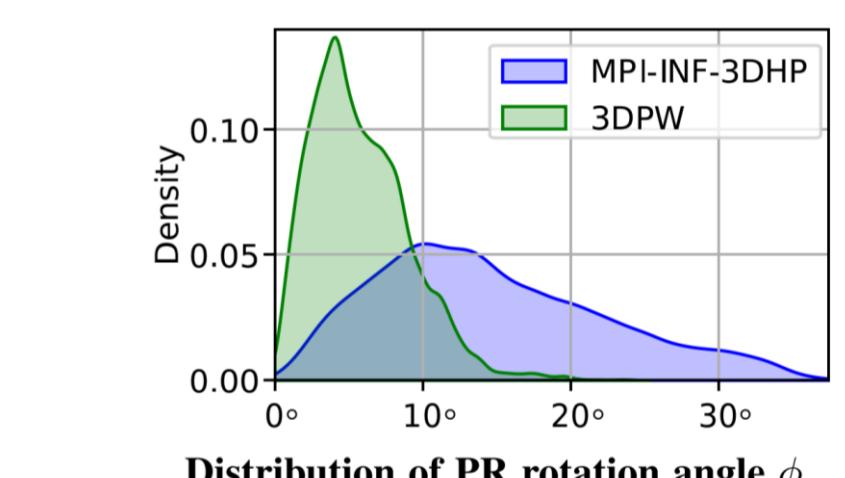
- PersPose achieves SOTA performance on several datasets.

		3DPW			Human3.6M			MPI-INF-3DHP		
		PA-MPJPE↓	MPJPE↓	PVE↓	PA-MPJPE↓	MPJPE↓	PVE↓	PCK↑	AUC↑	MPJPE↓
HMR [8] †	CVPR'18	81.3	130.0	152.7	56.8	88.0	96.1	72.9	36.5	124.2
SPIN [14] †	ICCV'19	59.2	96.9	116.4	41.1	-	-	76.4	37.1	105.2
I2L-MeshNet [26] †	ECCV'20	57.7	93.2	110.1	41.1	55.7	65.1	-	-	-
Pose2Mesh [3] †	ECCV'20	58.3	88.9	106.3	46.3	64.9	85.3	-	-	-
Mesh Graphomer [19]	ICCV'21	45.6	74.7	87.7	34.5	51.2	-	-	-	-
HybrIK [16] ‡	CVPR'21	45.0	74.1	86.5	34.5	54.4	65.7	87.5	46.9	93.9
CLIFF [18]	ECCV'22	43.0	69.0	81.2	32.7	47.1	-	-	-	-
FastMETRO [2]	ECCV'22	44.6	73.5	84.1	33.7	52.2	-	-	-	-
IKOL [42] ‡	AAAI'23	45.5	73.3	86.4	-	-	-	87.9	48.1	88.8
VirtualMarker [24] ‡	CVPR'23	41.3	67.5	77.9	32.0	47.3	58.0	-	-	-
ProPose [4] ‡	CVPR'23	40.6	68.3	79.4	29.1	45.7	-	-	-	-
PLIKS [29] ‡	CVPR'23	42.8	66.9	82.6	34.7	49.3	-	91.8	52.3	72.3
Zolly [35]	ICCV'23	39.8	65.0	76.3	32.3	49.4	-	-	-	-
Gwon et al. [6]	CVPR'24	44.3	73.2	80.3	-	-	-	-	-	-
GLNet-W48 [37]	ECCV'24	39.5	66.9	77.9	29.4	48.8	-	-	-	-
PostoMETRO [38]	WACV'25	39.8	67.7	76.8	-	-	-	-	-	-
<b>PersPose</b> ‡		<b>39.1</b>	<b>60.1</b>	<b>72.4</b>	<b>28.3</b>	<b>43.0</b>	<b>52.7</b>	<b>94.0</b>	<b>55.2</b>	<b>72.1</b>



- Ablations show larger gains as perspective complexity increases.

PR	PE	Dataset	3DPW			MPI-INF-3DHP		
			Depth error↓	PA-MPJPE↓	MPJPE↓	Depth error↓	PA-MPJPE↓	MPJPE↓
-	-	R	45.1	39.8	62.4	57.3	57.3	80.1
-	✓	R	44.5	39.7	62.2	53.7	56.3	76.6
✓	✓	R	<b>43.8</b>	<b>39.1</b>	<b>60.1</b>	<b>51.0</b>	<b>54.4</b>	<b>71.9</b>
-	-	R+B	41.5	37.8	58.4	54.2	55.5	76.8
-	✓	R+B	41.2	37.8	58.1	51.0	55.1	73.4
✓	✓	R+B	<b>40.0</b>	<b>37.3</b>	<b>57.2</b>	<b>48.6</b>	<b>53.7</b>	<b>70.2</b>



MPI-INF-3DHP spans a wider PR rotation angle range than 3DPW, indicating greater scene-crop perspective change; in such cases, PE/PR help more.

- Visualization.

