Zolly: Zoom Focal Length Correctly for Perspective-Distorted Human Mesh Reconstruction

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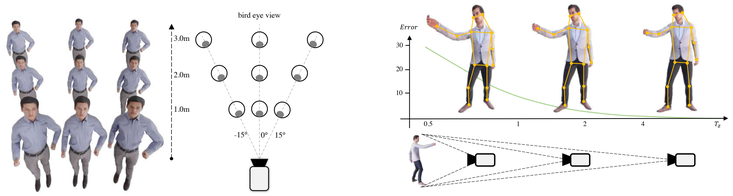
Introduction

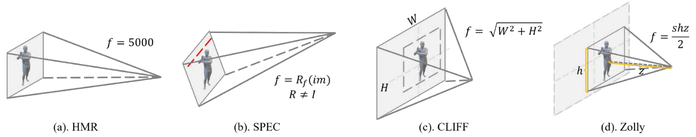
- **Motivation:** Existing 3D human mesh reconstruction methods either use a constant large focal length or estimate one based on the background environment context, which can not tackle the problem of the torso, limb, hand or face distortion caused by perspective camera projection when the camera is close to the human body. The naive focal length assumptions can harm this task with the incorrectly formulated projection matrices.
- **Distortion Analysis:** (a) The distortion is caused by the distance and the facing angle to the camera center. (b) Although the size in the whole image could be controlled by dolly zoom effect, the distortion varies a lot owing to the distance. The distortion could be neglected when the distance is farther than 8 meters.



(a) (b)

- **Contribution**
  A novel camera system tailored to the perspective-distorted 3DHMR task.
  A new neural model, and a hybrid re-projection loss.
  A new and the first synthetic dataset, PDHuman, for perspective-distorted 3D human pose estimation.

Camera System Design



(a). HMR (b). SPEC (c). CLIFF (d). Zolly

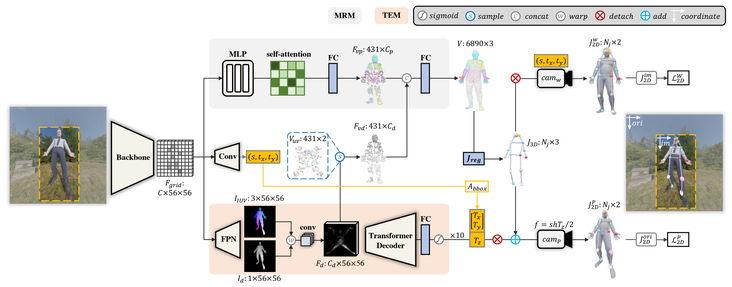
- **HMR**. The f is fixed as 5000 pixels. Most methods follow this setting.
- **SPEC**. The f is estimated by a network R_f pre-trained on other scene datasets.
- **CLIFF**. Use the length of diagonal length if no ground-truth f provided.
- **Zolly**. We use the estimated z-axis translation *z*, camera parameter *s*, and image height *h* to calculate f.

The weak-perspective camera parameters (s, t_x, t_y), which represent 2D orthographic transformation, could be used to approximate the projection:

$$\begin{bmatrix} f(x+T_x)/T_z \\ f(y+T_y)/T_z \end{bmatrix} = \begin{bmatrix} s(x+t_x) \\ s(y+t_y) \end{bmatrix}, s \times T_z = f, T_x = t_x, T_y = t_y. \quad (1)$$

In previous methods, they either use a constant or estimated f, and calculate distance by $T_z = f/s$. On contrary, we estimate T_z based on human body distortion clues and calculate f by $f = s \times T_z$.

Proposed Pipeline



- **Translation Estimation Module.** We regress the distortion image I_d and IUV image I_{IUV} and warp the distorted image into the continuous UV space to eliminate the 2D scale, shift, and rotation. We use a Transformer to regress the z-axis distance and use sigmoid then $\times 10$ to restrict T_z less than 10m.
- **Mesh Estimation Module.** We adopt an MLP structure to lift per-vertex position features F_{vp} from the spatial feature F_{grid}, and use fully connected layers to predict the coordinates of a coarse mesh of the body that is composed of 431 vertices. The coarse mesh is up-sampled using two fully connected layers to get the 6890 vertices.
- **Loss Functions.** The total loss function is the summation of mesh loss, translation loss, and re-projection loss.

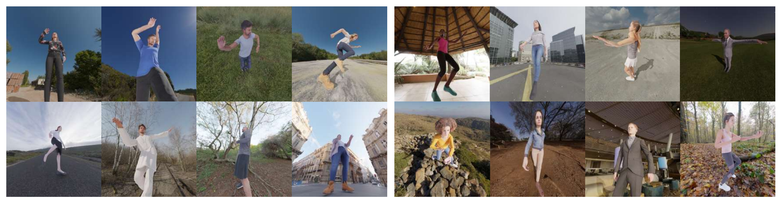
$$\mathcal{L}_{total} = \mathcal{L}_{Mesh} + \mathcal{L}_{Transl} + \mathcal{L}_{2D} \quad (2)$$

where the $\mathcal{L}_{2D}$ is the hybrid re-projection loss containing both weak-perspective and perspective projection.

$$\mathcal{L}_{2D} = \sum_{i=1}^{N_j} \frac{1}{d_{J[i]}} (\| \hat{J}^W_{2D}[i] - J^{im}_{2D}[i] \|^1_F + \| \hat{J}^P_{2D}[i] - J^P_{2D}[i] \|^1_F) \quad (3)$$

New Virtual Dataset: PDHuman

- **Amount**: 126,198 images in the training and 27,448 images in the testing
- **Annotations**: Camera intrinsic matrix, 2D/3D keypoints, SMPL parameters $\boldsymbol{\theta}$, $\boldsymbol{\beta}$, and translation.
- **Camera**: Use the dolly-zoom effect to generate random camera extrinsic and intrinsic matrices with random rotations, translations, and focal lengths.
- **Rendering**: Use human models from RenderPeople and body pose sequences from Mixamo, with 500 HDRi images with various lighting conditions as backgrounds. Then we use Blender to render the RGB images.



Experiments

- Results on 3DPW and Human3.6M.

Method	Backbone	3DPW			Human3.6M	
		PA-JPE	MPJPE	PVE	PA-JPE	MPJPE
HMR	Res50	72.6	116.5	-	56.8	88.0
SPEC	Res50	52.7	96.4	-		
CLIFF	HR48	43.0	69.0	81.2	32.7	47.1
Zolly	HR48	39.8	65.0	76.3	32.3	49.4

- Results on PDHuman and SPEC-MTP.

Method	Backbone	PDHuman (p5)			SPEC-MTP (p3)		
		PA-JPE	PVE	mIoU	PA-JPE	PVE	mIoU
HMR	Res50	62.5	106.7	21.7	73.9	145.6	16.0
SPEC	Res50	65.8	109.6	19.6	76.0	144.6	18.8
CLIFF	HR48	66.2	115.2	24.8	74.3	132.4	23.7
Zolly	HR48	49.9	82.0	26.5	67.4	126.7	30.4

Metric mIoU here is the mIoU between rendered mask and the ground-truth mask, which could vividly describe the re-projection quality.

Quality Results

Qualitative results of SOTA methods. Row 1: PDHuman test. Row 2, 3, 4: web images. Row 4: SPEC-MTP. Row 6: 3DPW. The number under each image represents predicted/ground-truth f, FoV angle, and T_z. The focal lengths here are all transformed to pixels in full image.