Supplementary Material for Holistic++ Scene Understanding: Single-view 3D Holistic Scene Parsing and Human Pose Estimation with Human-Object Interaction and Physical Commonsense

Yixin Chen*1, Siyuan Huang*1, Tao Yuan1, Siyuan Qi1,2, Yixin Zhu1,2, and Song-Chun Zhu1,2

* Equal Contributors

1 University of California, Los Angeles (UCLA)
2 International Center for AI and Robot Autonomy (CARA)

{ethanchen,huangsiyuan,taoyuan,syqi,yixin.zhu}@ucla.edu,sczhu@stat.ucla.edu

1. Parametrization

We represent the objects and room layout for each scene as 3D bounding boxes. Each 3D bounding box is parametrized by its 3D size $S \in \mathbb{R}^3$, center $C \in \mathbb{R}^3$, and orientation $Rot(\theta) \in \mathbb{R}^{3 \times 3}$, all in world coordinates. The 3D boxes can be reconstructed by first computing the 8 bounding box corners with center and size, and then rotate all the corners in x-y plane with $\theta$. Our parametrization is similar to [2, 1].

2. Baseline Model

As mentioned in Section 6.1 in the paper, we design a baseline model for multi-person 3D pose estimation in world coordinate.

We first extract a 2048-D image feature vector using the Global Geometry Network (GGN) [1] to capture the global geometry of the scene. Then we concatenate GGN image feature, 2D pose, 3D pose in the local coordinate, together with the camera intrinsic matrix as a feature vector, which is then fed into a 5-layer fully connected network to predict the global 3D pose. The fully-connected layers are trained using the mean squared error loss. The network structure of the baseline model is shown in Figure 1.

As described in Section 6.2, we augment SUN RGB-D dataset [3] by projecting sampled 3D poses back onto the image plane, which gives us the ground-truth global 3D poses and their corresponding 2D poses. We then train the proposed baseline on the training set of the synthetic SUN RGB-D dataset, which has 21234 pose pairs under 2666 different scenes.

3. Additional Qualitative Results

Figure 2 to Figure 22 show additional qualitative results.

References


Figure 2. Qualitative results of the proposed method on Watch-n-Patch and PiGraphs dataset.
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