NeRF-Pose: A First-Reconstruct-Then-Regress Approach for Weakly-supervised 6D Object Pose Estimation

Supplementary

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We add some additional training details and results in the following sections.

1. Implementation and Runtime Analysis

We implement our object-centric NeRF network based on the original version of NeRF in\textsuperscript{[15]}, and train the network from scratch. For the 2D detector, we use the standard YOLOv3 \textsuperscript{[4]} detector in stage two. An ImageNet \textsuperscript{[12]} pre-trained ResNet34 \textsuperscript{[6]} network is leveraged as the backbone of our pose regression network. All networks are trained until convergence.

The training is done on a machine with a Titan RTX GPU with 24GB Memory, an Intel(R) i7-8700K CPU and 24GB RAM. During inference, for a single image with $640 \times 480$ resolution, our approach takes about 0.25s for one object, including about 0.03s for YOLOV3 2D detector, 0.01s for pose regression and 0.21s for our pose solver.

2. Limitations

Though we present NeRF-Pose in a weakly-supervised way, considering the training difference in OBJ-NeRF network and our pose regression net, failing to enable end-to-end optimization sometimes leads to local minima.

As indicated in Tab. \textsuperscript{[1]} when trained on pbr images rendered by Blender with high quality from BOP \textsuperscript{[10, 9]}, GDR \textsuperscript{[19]} and SO-Pose\textsuperscript{[2]} gain about 10\% improvement on ADD(-S) metric. Those fully-supervised methods benefit from pbr images that cover more poses and have more realistic occlusion under various light conditions. It inspires us to generate more synthetic training data using our well-trained OBJ-NeRF for better performance.

3. Experiments

We add object-wise results in this section for the Linemod dataset(LM) in Table \textsuperscript{[2]} and Linemod Occlusion(LMO) datasets in Table \textsuperscript{[1]}. We also present additional results on T-Less \textsuperscript{[8]} dataset in Table \textsuperscript{[3]} T-Less. We evaluate our pipeline on T-Less dataset. The T-Less dataset comprises 30 objects with real training images. We train our model using relative camera poses and real training images. In Tab. \textsuperscript{[3]} we report the AR of VSD, MSSD, MSPD metrics on the BOP challenge test set. We achieve closer to benchmark accuracy despite not using a CAD model. It shows that Nerf can learn accurate geometry and render correspondences which are usually extracted from the CAD model. SurfEmb performs better than our approach as their approach is tailored for symmetric objects and also employs an inference pipeline with 2.2s. However, the results compared to other regression-based, Dpod and DpodV2, show that our approach can perform equally better employing NeRF.

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Table 1. Comparisons with state-of-the-art methods on LMO. We report the Average Recall(%) of ADD(-S) without refinement. * real denotes the same real data as LM. syn denotes self-generated synthetic data, and pbr denotes blender rendered synthetic data from BOP[9]. * denotes the symmetric objects. Our-pose denotes our results with accurate pose labels and Our-weak is with relative pose labels. w/o NeRF denotes our results using original PnP+RANSAC and w/ NeRF is our method with our NeRF-enabled PnP+RANSAC.

| Object | PVNet | Single-Stage | HybridPose | GDR SO-Net | Cai. | Our-pose | Our-weak | Our-weak |
|--------|--------|--------------|------------|------------|-----|----------|----------|----------|
| CAD w/ CAD | real+syn | real | real | real | real | real | real | real |
| Ape | 15.8 | 19.2 | 20.9 | 39.3 | 46.3 | 46.8 | 48.4 | 7.10 | 46.8 | 46.9 | 48.3 | 49.7 |
| Can | 63.3 | 65.1 | 75.3 | 79.2 | 81.1 | 90.8 | 85.8 | 40.6 | 79.1 | 86.2 | 81.4 | 86.4 |
| Cat | 16.7 | 18.9 | 24.9 | 23.5 | 18.7 | 40.5 | 32.7 | 15.6 | 20.7 | 27.1 | 28.8 | 26.9 |
| Driller | 65.7 | 69.0 | 70.2 | 71.3 | 71.3 | 82.6 | 77.4 | 43.9 | 58.9 | 65.8 | 60.4 | 66.2 |
| Duck | 25.2 | 25.3 | 27.9 | 44.4 | 43.9 | 46.9 | 48.9 | 12.9 | 25.3 | 29.9 | 32.8 | 36.9 |
| Eggbox | 50.2 | 52.0 | 52.4 | 58.2 | 46.6 | 46.6 | 49.7 | 49.7 |
| Glue | 49.6 | 51.4 | 53.8 | 49.3 | 63.3 | 75.8 | 78.3 | 51.7 | 61.0 | 66.3 | 69.8 | 70.9 |
| Holey | 36.1 | 45.6 | 54.2 | 58.7 | 62.9 | 60.1 | 75.3 | 41.8 | 49.8 |
| Mean | 40.8 | 43.3 | 47.5 | 53.0 | 54.3 | 62.2 | 62.3 | 50.3 | 49.2 | 48.2 | 51.4(↑ 21.1) |

Table 2. LM results in on ADD-10 metric. * denotes that the objects is symmetric and is evaluated in ADD-S. Our-pose denotes our results trained on 6D pose labels, and Our-weak denotes training on camera relative pose labels. Ours-sam denotes our results trained on 6D pose labels and segmentation masks extracted using SegmentAnything. w/o NeRF denotes our results using original PnP+RANSAC and w/ NeRF is our method with our NeRF-enabled PnP+RANSAC.

| Object | PVNet | CDPN | GDR SO-Pose | LieNet | Cai. | Ours-sam | Ours-pose | Our-pose | Our-weak |
|--------|--------|------|------------|--------|-----|----------|----------|----------|----------|
| CAD w/ CAD | w/ CAD | w/ CAD | w/ CAD | w/ CAD | w/ CAD | w/ CAD | w/ CAD | w/ CAD |
| Ape | 43.6 | 64.4 | - | - | 38.8 | 52.9 | 50.1 | 69.4 | 89.1 | 93.1 |
| Bvise | 99.9 | 97.8 | - | - | 71.2 | 96.5 | 99.4 | 99.4 | 99.3 | 99.6 |
| Cam | 86.9 | 91.7 | - | - | 52.5 | 87.8 | 97.7 | 98.3 | 98.7 | 98.9 |
| Can | 95.5 | 95.9 | - | - | 86.1 | 86.8 | 98.7 | 97.8 | 99.1 | 99.7 |
| Cat | 79.3 | 83.8 | - | - | 66.2 | 67.3 | 77.2 | 77.8 | 97.1 | 98.1 |
| Drill | 96.4 | 96.2 | - | - | 82.3 | 88.7 | 99.1 | 99.6 | 97.4 | 98.7 |
| Duck | 52.6 | 66.8 | - | - | 32.5 | 54.7 | 57.4 | 69.7 | 90.3 | 94.2 |
| Eggbox* | 99.2 | 99.7 | - | - | 79.4 | 94.7 | 89.1 | 99.9 | 99.6 | 99.9 |
| Glue* | 95.7 | 99.6 | - | - | 63.7 | 100 | 98.9 | 91.9 | 98.1 | 99.3 |
| Holey | 81.9 | 88.5 | - | - | 56.4 | 75.4 | 90.3 | 89.4 | 94.3 | 96.5 |
| Iron. | 98.9 | 97.9 | - | - | 65.1 | 94.5 | 100 | 99.89 | 98.1 | 97.8 |
| Lamp | 99.3 | 97.9 | - | - | 89.4 | 96.6 | 98.7 | 99.8 | 97.9 | 98.7 |
| Phone | 92.4 | 90.8 | - | - | 65.0 | 89.2 | 90.2 | 94.8 | 96.4 | 97.3 |
| Mean | 86.3 | 89.9 | 93.7 | 96.0 | 65.2 | 82.9 | 88.3(↑ 5.4) | 91.8(↑ 8.9) | 96.6(↑ 13.7) | 97.8(↑ 14.9) |

Table 3. Comparisons with state-of-the-art methods on T-Less. We report the VSD, MSPD, MSSD, AR metrics as described in the BOP challenge without refinement. CAD refers to the approaches assuming that the CAD model is available for training.

| Approach | Dv2 | SurfEmb | EP | CP | Dv2 | CDPN | Ours |
|----------|-----|---------|----|----|-----|------|------|
| CAD Y Y Y Y N N N |
| VSD 0.57 0.5 0.57 0.46 0.49 0.45 |
| MSSD 0.62 0.53 0.59 0.49 0.67 0.49 |
| MSPD 0.76 0.83 0.63 0.76 0.59 0.41 0.66 |
| AR 0.65 0.62 0.47 0.64 0.51 0.37 0.54 |
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