Ki-Pode: Keypoint-based Implicit Pose Distribution Estimation of Rigid Objects

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1. Motivation

Pose estimation is the task of recovering an object’s 3D rotation and 3D translation. Prior work has primarily been concerned with the estimation of a single best estimate. However, object poses are often ambiguous e.g. due to symmetry or occlusion. Since pose ambiguity cannot be expressed by a single pose estimate, we estimate an entire probability distribution over object poses. As our primary concern was reliability, our method provides distribution estimates which are expressive, conservative, and interpretable.

Expressive: We express the pose distribution using an implicit formulation since this allows our method to model distributions of arbitrary complexity.

Conservative: Estimates must be conservative since overconfident estimates can lead to false positives, resulting in an unreliable system.

Interpretable: Since our method is trained on synthetic data, it is valuable to have interpretable estimates, to aid in identifying if the sim-to-real domain transfer is successful.

2. Method

Pose from keypoints

The probability distribution over the pose \( \theta \) can be expressed in terms of a joint distribution over projected keypoints \( k_0 \). Since the projected keypoints uniquely define a pose, it can be derived that:

\[
p(\theta|I) = \int p(\theta|k_0)p(k_0|I)dk_0
\]

Joint to marginals

The joint keypoint distribution is approximated from the marginal distributions, using the assumption of strong correlation \((p(k_i, k_j) = p(k_i)\)) This approximation is conservative since error introduced by the approximation will overestimate regions of low probability:

\[
p(k_0|I) \approx C \prod_{i=1}^{N} p(k_{0,i}|I)
\]

Heatmap estimation

The marginal distributions, referred to as a heatmap, are estimated using a U-Net [1]. The problem is formulated as spatial classification and the network is trained using cross-entropy loss with the target distributions being isotropic Gaussians.

\[
L = -\sum_{i=1}^{N} N(k_{i}, \sigma) \log p(k_i|I)
\]

Normalization

SO(3) is sampled in an equivolumetric grid using the Healpix-based method in [2]. The unnormalized likelihood is estimated for the \( M \) samples, interpreted as probability, and normalized such that the normalized likelihood can be computed as:

\[
\hat{p}(\theta|I) \approx \hat{P}(\theta|I)/(\sigma^2/M)
\]

3. Results

Our method has been applied to orientation estimation, so it can be compared to existing works. The figure shows our method applied to three objects. With 5 HEALPix recursions (1.8 million samples) the computation time was \(~125\)ms. The mean log-likelihood of the ground truth pose is used as a metric for comparison. Our method achieves state-of-the-art results on the YCB-V dataset and modest results on the T-LESS dataset. Furthermore, our method performs reliably on all objects.

4. Conclusion

We have presented a novel pose distribution estimation method, which provides estimates that:

- rely on conservative approximations to ensure reliability
- are highly expressive due to being formulated implicitly
- have high interpretability due to the intermediary keypoint representation

5. Acknowledgement

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6. References


