# 通用特征引导的零样本类别级物体姿态估计

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### Motivation

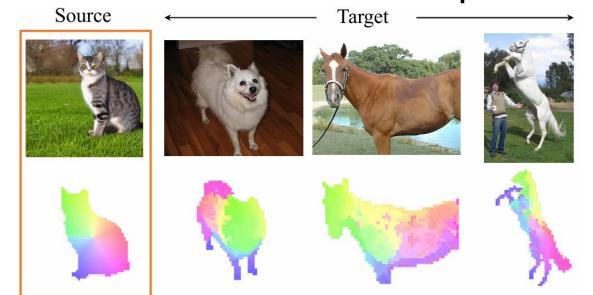
The diversity of object categories limits the generalization ability of pose estimation models.





Various Object Categories<sup>[1,2]</sup>

The universal features extracted by the foundation models can learn the semantic similarities between objects and thus establish correspondences.



Correspondence with Universal Features[3]

### Introduction

We propose a zero-shot method to achieve category-level 6-DOF object pose estimation, which exploits both 2D and 3D universal features of input RGB-D image to establish semantic similaritybased correspondences and can be extended to unseen categories without additional model fine-tuning:

#### **Our main contributions:**

- > A 2D/3D universal features guided zero-shot category-level object pose estimation with coarse-to-fine optimization.
- In order to handle pose ambiguity due to intra-category shape difference, we employ 3D universal features to refine the 6-DOF object and the shape of reference model by dense pixel-level registration.

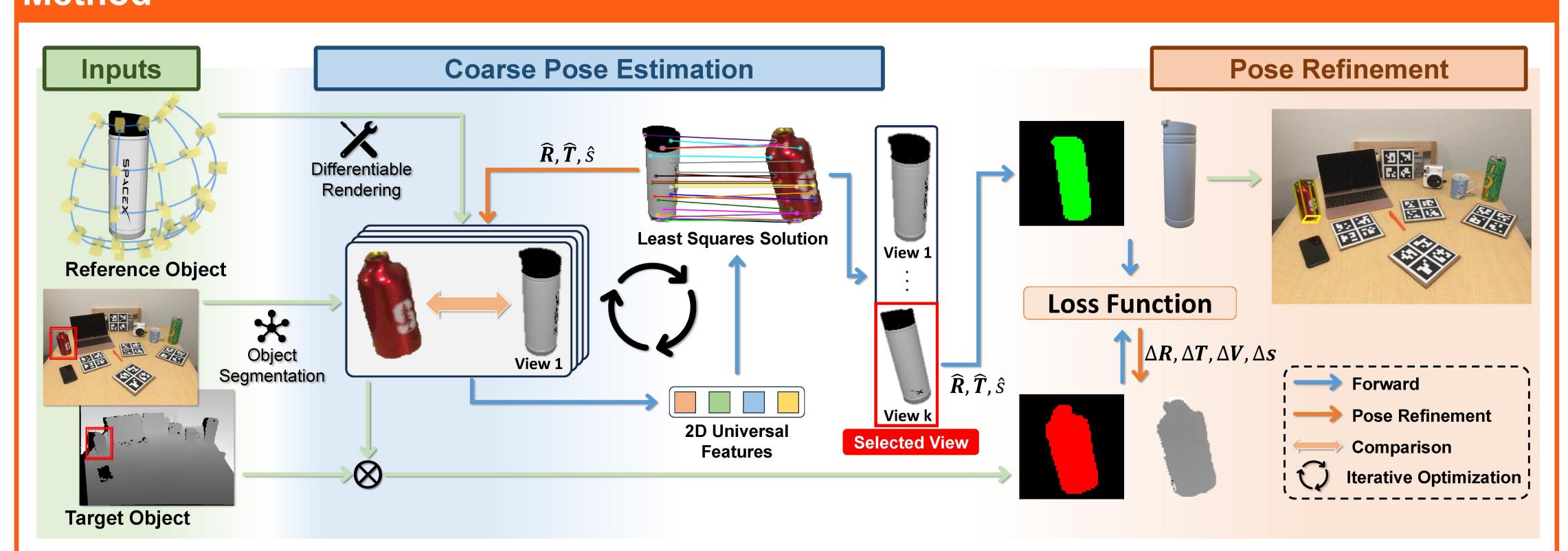
After the shape optimization, the reference object shape will become

closer to the target object shape, resulting in more accurate pose.

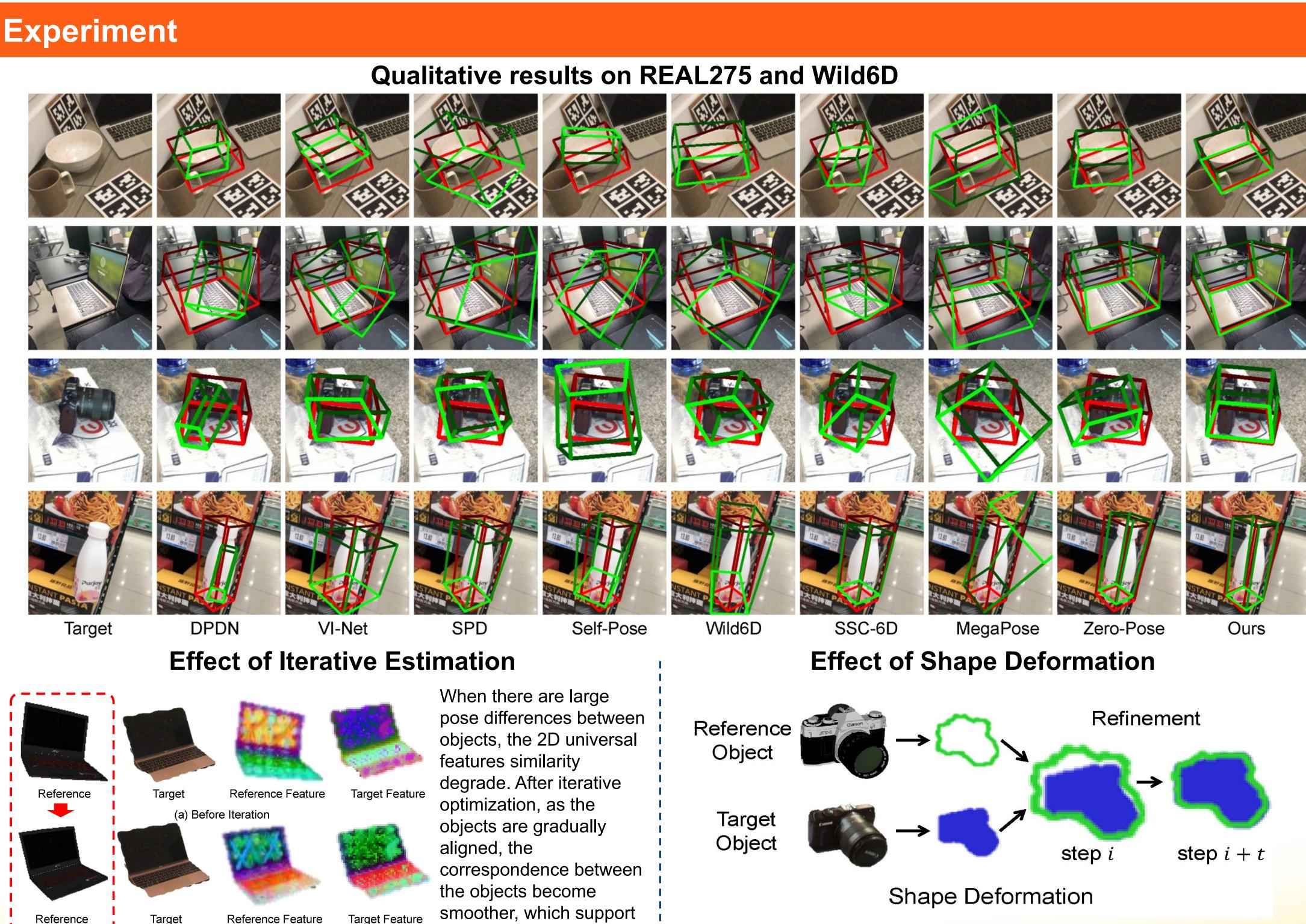


Project Webpage: https://iscas3dv.github.io/univers al6dpose/

## Method



Our framework includes a coarse pose estimation module and a pose refinement module. In the first module, we establish the correspondences between image pairs based on the 2D universal features and calculate the coarse pose using least squares in an iterative manner. In the second module, we use pixel-level optimization combined with 3D universal features to refine the pose and shape of reference model to obtain the fine pose.



Reference: [1] Wang H, Sridhar S, Huang J, et al. Normalized object coordinate space for category-level 6d object pose and size estimation[C]//Proceedings of the IEEE/CVF conference on computer vision and pattern recognition. 2019: 2642-2651. [2] Jung H J, Wu S C, Ruhkamp P, et al. Housecat6d-a large-scale multi-modal category level 6d object perception dataset with household objects in realistic scenarios[C]//Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. 2024: 22498-22508. [3] Zhang J. Herrmann C. Hur J. et al. A tale of two features: Stable diffusion complements dino for zero-shot semantic correspondence[J]. Advances in Neural Information Processing Systems, 2023, 36: 45533-45547. [4] Fu Y, Wang X. Category-level 6d object pose estimation in the wild: A semi-supervised learning approach and a new dataset[J]. Advances in Neural Information Processing Systems, 2022, 35: 27469-27483.

to calculate an accurate

[5] Caron M, Touvron H, Misra I, et al. Emerging properties in self-supervised vision transformers[C]//Proceedings of the IEEE/CVF international conference on computer vision. 2021: 9650-9660. [6] Oquab M, Darcet T, Moutakanni T, et al. Dinov2: Learning robust visual features without supervision[J]. arXiv preprint arXiv:2304.07193, 2023. [7] Rombach R, Blattmann A, Lorenz D, et al. High-resolution image synthesis with latent diffusion models[C]//Proceedings of the IEEE/CVF conference on computer vision and pattern recognition. 2022: 10684-10695. [8] Goodwin W, Vaze S, Havoutis I, et al. Zero-shot category-level object pose estimation[C]//European Conference on Computer Vision. Cham: Springer Nature Switzerland, 2022: 516-532.

pose.

(b) After Iteration