GAML: Geometry-Aware Meta-Learner for Cross-Category 6D Pose Estimation

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Abstract

We present a novel meta-learning approach for 6D pose estimation on unknown objects. In contrast to “instance-level” and “category-level” pose estimation methods, our algorithm learns object representation in a category-agnostic way, which endows it with strong generalization capabilities across object categories. Specifically, we employ a neural process-based meta-learning approach to train an encoder to capture texture and geometry of an object in a latent representation, based on very few RGB-D images and ground-truth keypoints. The latent representation is then used by a simultaneously meta-trained decoder to predict the 6D pose of the object in new images. Furthermore, we propose a novel geometry-aware decoder for the keypoint prediction using a Graph Neural Network (GNN), which explicitly takes geometric constraints specific to each object into consideration. To evaluate our algorithm, extensive experiments are conducted on the LineMOD dataset, and on our new fully-annotated synthetic datasets generated from Multiple Categories in Multiple Scenes (MCMS). Experimental results demonstrate that our model performs well on unseen objects with very different shapes and appearances. Remarkably, our model also shows robust performance on occluded scenes although trained fully on data without occlusion. To our knowledge, this is the first work exploring cross-category level 6D pose estimation.

1. Introduction

Estimating the 6D pose of an object is of practical interest for many real-world applications such as robotic grasping, autonomous driving and augmented reality (AR). Prior work has investigated instance-level 6D pose estimation [26, 27, 45, 63], where the objects are predefined. Although achieving satisfying performance, these methods are prone to overfit to specific objects and thus suffer from poor generalization. Due to the high variety of objects with different colors and shapes in the real-world, it is impractical to retrain the model every time new objects come in, which is time-consuming and data inefficient. Recently, this issue has raised increasing attention in the community and several approaches [4, 5, 7, 8, 62, 64] have been proposed for category-level 6D pose estimation. NOCS [64] and CASS [4], for example, map different instances of each category into a unified representational space based on RGB or RGB-D features. However, the assumption of a unified space potentially leads to a decrease in performance in case of strong object variations. FS-Net [7] proposes an orientation-aware autoencoder with 3D graph convolutions for latent feature extraction where translation and scale are estimated using a tiny PointNet [48]. Furthermore, Chen et al. [8] provide an alternative based on “analysis-by-synthesis” to train a pose-aware image generator, implicitly representing the appearance, shape and pose of the entire object categories. However, these methods require a pre-
In summary, the main contributions of this work are as follows:

- We introduce a novel meta-learning framework for 6D pose estimation with strong generalization ability on unseen objects within and across object categories.
- We propose a GNN-based keypoint prediction module that leverages geometric information from canonical keypoint coordinates and captures local spatial constraints among keypoints via message passing.
- We provide fully-annotated synthetic datasets with abundant diversity, which facilitate future research on intra- and cross-category level 6D pose estimation.

2. Related Work

6D Pose Estimation. For instance-level 6D pose estimation, methods can be categorized into three classes: correspondence-based, template-based and voting-based methods [11]. Correspondence-based methods aim to find 2D-3D correspondences [47, 54, 70] or 3D-3D correspondences [17]. Template-based methods, on the other hand, match the inputs to templates, which can be either explicit pose-aware images [28, 29] or templates learned implicitly by neural networks [56]. Voting-based approaches [26, 27, 45] generate voting candidates from feature representations, after which the RANSAC algorithm [18] or a clustering mechanism such as MeanShift [9] is applied for selecting the best candidates. Our feature extractor, FFB6D [26], falls into this latter category. FFB6D proposes a bidirectional fusion module to combine appearance and geometry information for feature learning. The extracted features are then used to predict per-point semantic labels and keypoint offsets, after which MeanShift is used to vote for 3D keypoints. Finally, the keypoints are used to predict the final 6D pose by Least-Squares Fitting [1].

Recently, category-level 6D object pose estimation has gained increasing attention [4, 7, 8, 62, 64]. Wang et al. [64] share a canonical representation for all possible object instances within a category using Normalized Object Coordinate Space (NOCS). However, inferring the object pose by predicting only the NOCS representation is not easy given large intra-category variations [14]. To tackle this problem, [58] accounts for intra-category shape variations by explicitly modeling the deformation from shape prior to object model while CASS [4] generates 3D point clouds in the canonical space using a variational autoencoder (VAE). FS-Net [7] proposes a shape-based model using 3D graph convolutions and a decoupled rotation mechanism to further reduce the sensitivity of RGB features to the color variations. However, these methods model the feature space explicitly on a category-level and therefore have a limited generalization ability across categories. By contrast, our

Figure 2. Schematic pipeline of our approach.

trained object detector on each specific category which limits their generalization ability across categories.

In this paper, we present a new meta-learning based approach to increase the generalization capability of 6D pose estimation. To our knowledge, this is the first work that allows generalization across object categories. The main idea of our method lies in meta-learning object-centric representations in a category-agnostic way. Meta-learning aims to adapt rapidly to new tasks based only on a few examples. More specifically, we employ Conditional Neural Processes (CNPs) [21] to learn a latent representation of objects, capturing the generic appearance and geometry. Inference on new objects then merely needs a few labeled examples as input to extract a respective representation. In particular, fine-tuning on new objects is not necessary. A comparison between traditional instance-level approaches and ours is illustrated in Fig. 1.

For feature extraction, we use FFB6D [26], which learns representative features through a fusion network based on RGB-D images. However, instead of directly using the extracted features for downstream applications, i.e., segmentation and keypoint offsets prediction, we add CNP on top of the fusion network to further meta-learn a latent representation for each object. CNP takes in the representative features from a set of context images of an object, together with their ground-truth labels, and yields a latent representation. The subsequent predictions for new target images are conditioned on this latent representation.

To further leverage the object geometry and improve the keypoint prediction, we propose a novel GNN-based decoder which takes predefined canonical keypoints in the object’s reference frame as an additional input and encodes local spatial constraints via message passing among the keypoints. Note that the additional input to the GNN does not require any further annotations on top of those existing datasets used by prior keypoint-based methods. The proposed pipeline is illustrated in Fig. 2.

Due to the lack of available data for cross-category level 6D pose estimation, we generate our own synthetic dataset for Multiple Categories in Multiple Scenes (MCMS) using objects from ShapeNet [3] and extending the open-source rendering pipeline [10] with online occlusion and truncation checks. This provides us with the flexibility to generate datasets with limited and considerable occlusion respectively.
method learns 6D pose estimation in a category-agnostic manner and can handle new objects from unseen categories.

Meta-Learning. Meta-learning, also known as learning to learn, aims to acquire meta knowledge that can help the model to quickly adapt to new tasks with very few samples. In general, meta-learning can be categorized into metric-based [53, 57, 60], optimization-based [15, 16, 43] and model-based [21, 22, 32, 50] methods. Many meta-learning approaches have been applied to computer vision applications, e.g., few-shot image classification [24, 39, 59, 71], vision regression [20], object detection [6, 12, 13, 46, 72], robotic grasping [19], semantic segmentation [36, 44, 52, 73] and 3D reconstruction [42, 61]. Our work is based on Neural Processes (NPs) [22, 25, 32, 34, 41], which fall into the category of model-based meta-learning approaches. NPs have shown promising performance on simple tasks like function regression and image completion. However, their application to 6D pose estimation has not yet been explored properly. We introduce CNP [21] to this problem in order to tackle the issue of poor generalization ability of existing methods on both intra- and cross-category level.

Graph Neural Networks. Graph neural networks (GNNs) have been widely applied on vision applications, such as image classification [31, 35, 40], semantic segmentation [33, 37, 49, 66], and object detection [30, 51, 67]. Recently, many works start using GNNs on human pose estimation [2, 65, 69]. Yang et al. [69] derive the pose dynamics from historical pose trajectories through a GNN which accounts for both spatio-temporal and visual information while PGCN [2] builds a directed graph over the keypoints of the human body to explicitly model their correlations. DEKR [23] adopts a pixel-wise spatial transformer to concentrate on information from pixels in the keypoint regions and dedicated adaptive convolutions to further disentangle the representation. Our approach is based on a similar idea as PGCN, where we take the keypoints in the canonical object coordinates as an additional input in order to leverage the spatial constraints between keypoints. We show that this drastically increases the performance on unseen objects and robustness on occluded scenes.

3. Preliminary - Conditional Neural Processes

Conditional Neural Processes (CNPs) [21] can be interpreted as conditional models that perform inference for some target inputs \( x_t \) conditioned on observations, called “contexts”. These contexts consist of inputs \( x_c \) and corresponding labels \( y_c \) originating from one specific task. Note that in our case, each distinct object is considered as a task.

The basic form of CNP comprises three core components: encoder, aggregator and decoder. The encoder takes a set of \( M_c \) context pairs from a given task \( C = \{ (x^i_c, y^i_c) \}_{i=1}^{M_c} \) and extracts embeddings from each context pair respectively, \( r_i = h_\theta (x^i_c, y^i_c), \forall (x^i_c, y^i_c) \in C \), where \( h \) is a neural network parameterized by \( \theta \). Afterwards, the aggregator \( a \) summarizes these embeddings using a permutation invariant operator \( \otimes \) and yields the global latent variable as task representation: \( z = a(r_1, r_2, ..., r_{M_C}) = r_1 \otimes r_2 \otimes ... \otimes r_{M_C} \). Since the size of context set \( M_c \) varies and the task representation has to be independent of the order of contexts, a permutation invariant mechanism is essential. Max aggregation is used in our model as we empirically find it outperforms mean aggregation, which is used in the original CNP. Finally, the decoder performs predictions for a set of target inputs \( T = \{ x^i_t \}_{i=1}^{M_t} \) conditioned on the corresponding task representation \( z \) extracted and aggregated before: \( \hat{y}^i_t = g_\phi (x^i_t, z), \forall x^i_t \in T \). \( M_t \) is the number of target inputs, \( g \) denotes the decoder, a neural network parametrized by \( \phi \).

The ability to extract meaningful latent representation from very few samples renders CNP well-suited for our purposes. Due to the fact that each distinct object comes with different predefined keypoints, prior keypoint-based methods for 6D pose estimation do not generalize well to novel objects. Meta-training CNP to extract latent keypoint representations from object features, however, allows us to overcome this difficulty.

4. Approach

In this paper, we propose a keypoint-based meta-learning approach for 6D pose estimation on unseen objects. Given an RGB-D image, the goal of 6D pose estimation is to calculate the rigid transformation \( [R; t] \) from the object coordinates to the camera coordinates, where \( R \in SO(3) \) represents the rotation matrix and \( t \in \mathbb{R}^3 \) represents the translation vector. We build on keypoint-based methods, that first predict the location of keypoints in camera coordinates from input RGB-D images and then regress the transformation between these and predefined keypoints in the object coordinates. The predefined keypoints in canonical object coordinates are thereby fixed beforehand, e.g., using the Farthest Point Sampling (FPS) algorithm on the object mesh.

4.1. Overview

We consider 6D pose estimation in three stages: feature extraction, keypoint detection and pose fitting. At the first stage, we employ the feature extractor FFB6D [26] to extract representative features from RGB-D images. For the second stage we use a CNP-based meta-learning approach. The flow of context and target samples through our model is shown in Fig. 3, where the context inputs for each task \( x_c \), i.e., the features extracted from the context RGB-D images, and the corresponding labels \( y_c \), are used jointly to distill a task representation. This representation serves as prior
knowledge for the subsequent prediction on target inputs $x_t$. We use two decoders in our meta-learning framework, predicting semantic labels and 3D keypoint offsets respectively. Furthermore, we propose a novel geometry-aware decoder using a GNN for the keypoint offsets prediction, which explicitly models the spatial constraints between the keypoints. Finally, the 6D pose parameters are regressed by least-squares fitting at the third stage.

4.2. Feature Extraction

For feature extraction we rely on the fusion network FFB6D [26] which combines appearance and geometry information from RGB-D images and extracts representative features for a subset of seed points sampled from the input depth images. Therefore, the output is a set of per-point features corresponding to the sampled seed points.

4.3. Meta-Learner for Keypoint Detection

Two steps are involved in the keypoint estimation procedure: segmentation of the queried object and keypoint detection, which both rely on a preceding extraction of latent representations.

**Extraction of latent representations.** Identifying and distinguishing a novel object from a multi-object scene and extracting its keypoints requires modules, which are conditioned on the latent representation of the queried object. In order to obtain such a latent representation, we need a set of context samples $\{(x_{c,i}, y_{c,i})\}_{i=1}^{M_c}$. Here $x_{c,i}$ denotes the per-point features extracted in the first stage from context images and $y_{c,i} = \{y_{u}^{c,i}\}_{u=1}^{M_K}$ is the ground-truth label where $y_{u}^{c,i} = \{y_{u}^{c,i}, y_{seg}^{c,i}\}$ includes the 3D keypoint offsets $y_{u}^{c,i}$ between the seed point and predefined keypoint $p_u$, and semantic label $y_{seg} \in \{0, 1\}$ indicating whether the seed point belongs to the queried object. Given a context sample as input, an encoder generates per-seed-point embeddings for each of the $M_k$ keypoints to be predicted:

$$r_{i}^{u} = h_\theta(x_{c,i} \oplus y_{c,i}^{u}), \ i = 1, ..., M_c, \ u = 1, ..., M_k, \ (1)$$

where $M_c$ denotes the number of seed points selected from each context image; $M_k$ is the number of selected keypoints which in our case is 9. $\oplus$ stands for the concatenation operation, where the inputs are first broadcast to the same shape, if necessary. The obtained embeddings are next aggregated by max aggregation to first obtain a latent representation $z_{kp}^u$ for each keypoint. A second aggregation over these keypoint representations is then applied in order to extract a representation $z_{seg}$ for the segmentation task:

$$z_{kp}^u = \max_{i=1}^{M_c} (r_{i}^{u}), \ u = 1, ..., M_k, \ (2)$$

$$z_{seg} = \max_{u=1}^{M_k} (z_{kp}^u). \ (3)$$

**Conditional Segmentation.** In the step described above, the model encapsulates relevant information (e.g., shape
and texture attributes) into the latent variable $z_{seg}$. This can then be used to identify and locate the queried object in the target images. The segmentation decoder $g_S$ takes the latent variable $z_{seg}$ and features $x_t$ extracted from the target images (see Fig. 3) and predicts a semantic label for each seed point via a multi-layer perceptron (MLP):

$$y_{seg,t,i} = g_S(x_{t,i} \oplus z_{seg}), \quad i = 1, \ldots, M_t,$$

where $M_t$ is the number of seed points sampled from each target image, $x_{t,i}$ denotes the corresponding extracted features. These per-point segmentation predictions $y_{seg}$ are then used to select only the seed point features $x_{obj}$ belonging to the queried object from $x_t$ for the subsequent keypoint prediction.

**Conditional Keypoint Offset Prediction.** The keypoint offsets decoder $g_K$ takes the features extracted by the segmentation module along with the latent variables $z_{kp}$ as input and predicts translation offsets $y_{of}$ for each keypoint:

$$y_{of,t,i}^u = g_K(x_{obj,i} \oplus z_{kp}^u), \quad i = 1, \ldots, M_{obj}, \quad u = 1, \ldots, M_k,$$

where $M_{obj}$ denotes the number of selected seed points on the queried object, $x_{obj,i}$ denotes the object features of $i$-th seed point. The decoder $g_K$ can be any appropriate module in Eq. (5). In the vanilla version of our framework, it is given by a trivial MLP. However, we use a GNN for $g_K$ in our final version, the details of which will be given in Sec. 4.4.

**Pose Fitting.** Similar as in [26], we adopt MeanShift [9] to obtain the final keypoint prediction $\{p_i^v\}_{i=1}^{M_k}$ in the camera coordinates, based on keypoint candidates output by the keypoint decoder. Given predefined 3D keypoints in object coordinates $\{p_i\}_{i=1}^{M_k}$, 6D pose estimation can be converted into a least-squares fitting problem [1] where the optimized pose parameters $[R; t]$ are calculated by minimizing the squared loss using singular value decomposition (SVD):

$$L_{lsf} = \sum_{i=1}^{M_k} ||p_i^v - (R \cdot p_i + t)||^2.$$

**4.4. Geometry-Aware Keypoint Decoder**

Similar to prior methods [26, 27], we rely on predefined object keypoints for the final pose fitting. However, we also utilize them as an additional input to the keypoint decoder. Since they contain useful prior knowledge of the object’s geometric structure, they can significantly improve keypoint detection. In order to highlight the additional input to our decoder, we rewrite Eq. (5) as follows:

$$y_{of,t,i}^u = g_K(x_{obj,i}, z_{kp}^u, p_v), \quad v \in \mathcal{N}(u),$$

where $\mathcal{N}(u)$ denotes the neighbor set of keypoint $u$ including $u$ itself and $p_v$ are the 3D object coordinates of keypoint $v$. To leverage the geometric information contained in the relation among the keypoints, we propose a GNN-based decoder $g_K$ instead of the trivial MLP in Eq. (5). For this purpose, we create a graph over the keypoints of each object. The nodes are given by the keypoints which share edges with their $k$ nearest neighbours. Fig. 4 illustrates an example with $k = 3$. Internally, Eq. (7) is split into the following two steps involved in message passing along the graph:

$$\alpha_{i}^{u,v} = f^l(x_{obj,i} \oplus z_{kp}^v, p_u - p_v), \forall v \in \mathcal{N}(u),$$

$$y_{of,t,i}^u = f^g(\max_{v \in \mathcal{N}(u)} \alpha_{i}^{u,v}).$$

$g_K$ is correspondingly composed of two sub-networks, $f^l$ and $f^g$. These correspond to updating the messages $\alpha_{i}^{u,v}$ sent along all edges, aggregating the messages arriving at each node $u$ to update the corresponding node features and decoding them into keypoint offsets $y_{of,t,i}^u$.

**5. Experiments**

**5.1. Datasets**

**LineMOD.** LineMOD [29] is a widely used dataset for 6D pose estimation which comprises 13 different objects in 13 scenes. Each scene contains multiple objects, but only one of them is annotated with a 6D pose and instance mask.
MCMS dataset. Due to the unavailability of datasets for cross-category level 6D pose estimation, we generate two fully-annotated synthetic datasets using objects from ShapeNet [3], which contain various objects from Multiple Categories in Multiple Scenes (MCMS). The simple version of MCMS, named Toy-MCMS, is composed of images containing a single object with backgrounds randomly sampled from the real-world image dataset SUN [55]. Our second dataset can be further divided into a non-occluded and an occluded version, called PBR-MCMS and Occlusion-MCMS. To create these datasets, we extend the open-source physics-based rendering (PBR) pipeline [10] with functionalities such as online truncation and occlusion checks. For each image, five objects are placed in a random scene with textured planes and varying lighting conditions. Images are then photographed with a rotating camera from a range of distances. PBR-MCMS contains images without occlusion while Occlusion-MCMS contains images with 5% - 20% occlusion of the queried object. Fig. 5 shows an example for each dataset using an object from the car category as the queried object.

5.2. Evaluation Metrics

We use the average distance metrics ADD [29] for evaluation. Given the predicted 6D pose \([R; t]\) and the ground-truth pose \([R^*; t^*]\), the ADD metric is defined as:

\[
ADD = \frac{1}{m} \sum_{x \in O} \| (Rx + t) - (R^*x + t^*) \| ,
\]

where \(O\) denotes the object mesh and \(m\) is the total number of vertices on the object mesh. This metric calculates the mean distance between the two point sets transformed by predicted pose and ground-truth pose respectively. Similar to other works [26, 45, 68], we report the ADD-0.1d accuracy, which indicates the ratio of test samples, where the ADD is less than 10% of the object’s diameter.

5.3. Implementation and Training Details

For each object, we define 9 keypoints, where 8 keypoints are sampled from the 3D object model using FPS, and the other one is the object center. The nearest neighbors used for each keypoint is set to \(k = 8\) in our geometry-aware decoder. To train the meta-learner, we use the Focal Loss [38] to supervise the segmentation module and a L1 loss for per-point translation offset prediction. The overall loss is weighted sum of both terms, with a weight 2.5 for segmentation and 1.0 for keypoint offsets. During training, for each iteration, we arbitrarily sample 18 objects and 12 images per object. The number of context images is randomly chosen between 2 and 8 per object while the remaining images are used as target set.

Training setup. For the LineMOD dataset, we use iron, lamp, and phone as novel objects for testing and the 10 remaining objects for training. Since LineMOD contains only a very limited number of objects, we only evaluate the keypoint offset prediction module using the ground-truth segmentation for selecting the points belonging to the queried object. For Toy- and PBR-MCMS, we use 20 and 19 categories for training respectively, with 30 objects per category and 50 images per object. During evaluation, 30 novel objects of each training category are tested for intra-categorical performance and 5 novel categories for cross-category performance. All experiments are conducted on NVIDIA V100-32GB GPU.
### 5.4. Evaluation Results

We evaluate our approach using the LineMOD and MCMS datasets at intra- and cross-category levels. More quantitative and qualitative results are provided in Appendix A.

**LineMOD.** Tab. 3 shows training and test results following [26]. Note that the segmentation ground-truth is used for these results and we only evaluate the performance and generalization ability of the keypoint offset prediction module. Our model not only performs better on training objects, but also generalizes well to new objects even though it is trained on a limited number of objects and tested on new objects with large variations in appearance and geometry.

**Toy- & PBR-MCMS.** Tab. 1 shows test results on the Toy-MCMS dataset, which demonstrate that our proposed GNN decoder (GAML) consistently outperforms the Vanilla Meta Learner (Vanilla-ML) using classic MLP decoder on all categories. Fig. 6 visualizes some test examples for qualitative comparison. Next, we compare our meta-learner to FFB6D on the PBR dataset. Tab. 2 shows that our model generalizes well while FFB6D cannot directly transfer to novel objects. For a fair comparison, we further train FFB6D on the PBR dataset and fine-tune the pretrained model on each specific novel object with the same context images as given to GAML. Tab. 4 shows that our model still outperforms the fine-tuned FFB6D reliably and requires no trade-off between new and preceding tasks, whereas fine-tuning normally leads to a performance decrease on the previous tasks.

**Occlusion-MCMS.** Quantitative and qualitative results on Occlusion-MCMS are presented in Tab. 2 and Fig. 7. Strikingly, our approach achieves consistent and robust performance on occluded scenes even though training is conducted on non-occluded PBR-MCMS.

### 5.5. Ablation Study

**Effect of K Neighbors in GNN.** In Tab. 5, we study the effect of the $k$ neighbors in the GNN. We run tests using five seeds and calculate the mean. Compared to $k = 3$, using all keypoints as neighbors improves the robustness. We find this to be more crucial when training on a single category with limited object variations, where involving all keypoints gives more expressive spatial representation. Full statistics are presented in Appendix B.1.

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Table 1. Multi-category evaluation on Toy-MCMS dataset. Novel objects are marked with *.

| Category   | Vanilla-ML | GAML |
|------------|------------|------|
| ADD        | ADD        |      |
| Airplane   | 80.6       | 87.2 |
| Bench      | 56.7       | 72.3 |
| Chair      | 62.8       | 80.9 |
| Motorcycle | 92.6       | 94.7 |
| Washer     | 85.4       | 91.4 |
| Bus*       | 83.0       | 85.4 |
| Cap*       | 46.6       | 54.2 |
| Laptop*    | 18.8       | 48.8 |
| Piano*     | 47.1       | 50.7 |
| Remote*    | 53.5       | 56.1 |
| Intra-Categ.| 74.2       | 81.9 |
| Cross-Categ.| 50.3       | 59.0 |
| All        | 69.4       | 77.2 |

Table 2. Multi-category evaluation on PBR- and Occlusion-MCMS datasets. $\Delta$ represents the performance gap between PBR- and Occlusion-MCMS.

| Category   | FFB6D | Vanilla-ML | GAML |
|------------|-------|------------|------|
| ADD        | ADD   | ADD        |      |
| Airplane   | 9.1   | 90.4       | 43.2 |
| Bench      | 2.9   | 52.1       | 40.4 |
| Chair      | 1.1   | 80.0       | 25.6 |
| Motorcycle | 12.7  | 90.2       | 64.8 |
| Washer     | 4.1   | 54.8       | 37.7 |
| Birdhouse* | 0.8   | 35.6       | 23.5 |
| Car*       | 2.4   | 52.5       | 42.9 |
| Laptop*    | 1.3   | 54.0       | 26.0 |
| Piano*     | 2.0   | 45.8       | 27.3 |
| Sofa*      | 2.6   | 68.1       | 45.4 |
| Intra-Categ.| 4.5   | 58.2       | 38.7 |
| Cross-Categ.| 1.8   | 51.2       | 33.0 |
| All        | 3.9   | 67.6       | 37.6 |

Table 3. Evaluation results on LineMOD dataset.

| Object   | FFB6D | Ours |
|----------|-------|------|
| ADD      | ADD   |      |
| Ape      | 0.06  | 100  |
| Holepuncher | 0.07 | 100  |
| Iron*    | 1.39  | 0.26 | 36.2 |
| Lamp*    | 1.52  | 0.38 | 22.4 |
| Phone*   | 0.89  | 0.17 | 17.8 |

Table 4. Comparison between GAML and fine-tuned FFB6D on PBR-MCMS using ADD metric.

| Airplane | Chair | Car | Laptop | Sofa |
|----------|-------|-----|--------|------|
| FFB6D    | 60.0  | 52.0| 36.7   | 48.0 |
| GAML     | 89.8  | 80.0| 56.9   | 85.0 |
|          |       |     |        | 69.8 |
Figure 7. Qualitative results on PBR- and Occlusion-MCMS datasets. Triangles and circles are the projections of ground-truth and predicted keypoints respectively. Note that our model is trained only on PBR-MCMS but shows robust performance on Occlusion-MCMS.

|                  | k = 3 | k = 8 |
|------------------|-------|-------|
| Multi-Categ.     | 60.1  | 61.9  |
| Single-Categ.    | 77.9  | 83.3  |

Table 5. ADD Results on PBR-MCMS using different number k of neighbors in GNN decoder.

|   | Intra-Categ. | Cross-Categ. | All  |
|---|--------------|--------------|------|
| CNP | 81.9         | 59.0         | 77.2 |
| ANP | 80.8         | 58.1         | 76.3 |

Table 6. ADD Results of CNP and ANP on Toy dataset.

Effect of the Aggregation Module in CNP. In our work, CNP uses max aggregation instead of mean as used in the original paper [21]. We further compare max aggregation with the cross-attention module proposed in Attentive Neural Processes (ANPs) [32] removing the self-attention part. The training curves (see Appendix B.2) show that both methods achieve similar training performance, though ANP converges faster at the beginning. Nevertheless, Tab. 6 illustrates that CNP generalizes slightly better to novel tasks on both intra- and cross-category levels.

Robustness to Occlusion. To further illustrate the benefits coming from the geometry-aware estimator, we compare GAML with Vanilla-ML. The results in Tab. 2 show that our purposed GNN decoder significantly improves the performance and robustness on occluded scenes.

Limitations. We find two limitations of our method. First, we observe that in rare cases, our model suffers from Feature Ambiguity by struggling to disentangle feature variations, e.g., textures, shapes and lighting conditions. Sometimes it can be fooled by two similar objects which results in inaccurate segmentation (see Fig. 8a). Second, keypoint-based approaches suffer from Symmetry Ambiguity, especially on novel objects where the symmetric axis is unknown. Consequently, keypoint predictions around the symmetric axis can be mismatched and hamper the training (see Fig. 8b). Accounting for the symmetry ambiguity, we also provide evaluations with the ADD-S metric in Appendix A.3 following prior work [26, 27, 63].

6. Conclusion

In this paper, we present a CNP-based meta-learner for cross-category level 6D pose estimation, which is capable of extracting and transferring latent representation on unseen objects from only a few samples. Besides, we propose a simple yet effective geometry-aware keypoint detection module using GNN, which leverages the spatial connections between keypoints and improves generalization on unseen objects and robustness on occluded scenes. Furthermore, we create fully-annotated synthetic datasets called MCMS with various objects and categories, aiming to fill the vacancy for cross-category pose estimation.
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A. Evaluation Results

We present evaluation results on both LineMOD and MCMS datasets. More results and code are available at https://github.com/Cvpr2022ID5164/CVPR2022-ID5164.

A.1. LineMOD Dataset

The LineMOD dataset [29] is split into 10 training objects and 3 unseen test objects, where iron, lamp and phone are the novel test objects. Fig. 2 show the qualitative comparison between FFB6D [26] and the proposed model on training objects. It can be observed that our model can predict keypoints more accurately. From Fig. 3, we can see that our model achieves better performance on novel objects. It should be noted that we only train one model for all objects, rather than train one model for each object respectively.

A.2. Toy-MCMS Dataset

Tab. 1 provides the quantitative results of inter-category 6D pose estimation on the car category. We use 50 images per object for training and vary the number of training objects. From the experimental results, 80 car objects can achieve a similar ADD accuracy as 1100 objects, while the training time is reduced evidently. Overall, this represents a good comprise between prediction performance and training overhead. Fig. 4 shows the qualitative results on novel test objects using the model trained with 80 objects. Note that even within the car category, the colors and shapes of novel objects still vary a lot.

| Category       | Vanilla-ML | GAML  |
|----------------|------------|-------|
|                | L1 Loss    | ADD-0.1d | L1 Loss    | ADD-0.1d |
| Airplane       | 0.41       | 80.6     | 0.33       | 87.2     |
| Bag            | 0.34       | 85.2     | 0.30       | 87.1     |
| Basket         | 0.83       | 49.7     | 0.62       | 65.1     |
| Bathtub        | 0.46       | 79.3     | 0.34       | 88.6     |
| Bed            | 0.72       | 60.1     | 0.57       | 72.0     |
| Bench          | 0.95       | 56.7     | 0.63       | 72.3     |
| Birdhouse      | 0.35       | 83.2     | 0.28       | 89.7     |
| Bookshelf      | 0.48       | 79.5     | 0.42       | 80.9     |
| Cabinet        | 0.39       | 83.5     | 0.31       | 89.7     |
| Car            | 0.31       | 92.9     | 0.28       | 92.9     |
| Camera         | 0.57       | 65.0     | 0.46       | 73.4     |
| Chair          | 0.57       | 62.8     | 0.42       | 80.9     |
| Helmet         | 0.46       | 69.8     | 0.43       | 80.9     |
| Motorcycle     | 0.29       | 92.6     | 0.25       | 94.7     |
| Mug            | 0.25       | 91.9     | 0.24       | 93.3     |
| Pillow         | 0.76       | 54.7     | 0.58       | 81.5     |
| Table          | 0.80       | 61.1     | 0.54       | 76.2     |
| Train          | 0.41       | 80.6     | 0.36       | 86.2     |
| Vessel         | 0.62       | 66.9     | 0.53       | 70.9     |
| Washer         | 0.36       | 85.4     | 0.28       | 91.4     |
| Bus*           | 0.46       | 83.0     | 0.42       | 85.4     |
| Cap*           | 0.71       | 46.6     | 0.64       | 54.2     |
| Laptop*        | 1.02       | 18.8     | 0.73       | 48.8     |
| Piano*         | 0.86       | 47.1     | 0.75       | 50.7     |
| Remote*        | 0.53       | 53.5     | 0.52       | 56.1     |
| Intra-Categ.   | 0.52       | 74.2     | 0.41       | 81.9     |
| Cross-Categ.   | 0.72       | 50.3     | 0.62       | 59.0     |
| All            | 0.56       | 69.4     | 0.45       | 77.2     |

Table 2. Multi-category evaluation on Toy-MCMS dataset

on the minimum point distance:

\[
ADD - S = \frac{1}{m} \sum_{x_1 \in O} \min_{x_2 \in O} \| (Rx + t) - (R^*x + t^*) \|.
\]

A.4. Occlusion-MCMS Dataset

Comparison between Vanilla-ML and GAML on Occlusion-MCMS is given in Tab. 3.

B. Ablation Study

B.1. Effect of K Neighbors in GNN

We measure the ADD-0.1d accuracy of multi-category and single-category training with \( k = 3 \) and \( k = 8 \) in the GNN decoder. Tab. 4 presents the quantitative results.
B.2. Effect of Aggregation Module in CNP

Fig. 1 shows that both CNP and ANP methods achieve similar training performance in the end, even though ANP converges faster at the beginning.

C. Network Architecture

The detailed architecture model is shown in Tab. 5. We use ReLU as activation function after each FC layer except the output layer of segmentation decoder and global GNN decoder for keypoint offset prediction.
| Component   | Layer | Output Size |
|-------------|-------|-------------|
| Encoder     | FC    | 128         |
|             | FC    | 128         |
|             | FC    | 128         |
| Seg. Decoder| FC    | 128         |
|             | FC    | 128         |
|             | FC    | 128         |
|             | FC    | 2           |
| Local GNN   | FC    | 128         |
|             | FC    | 128         |
|             | FC    | 128         |
| Global GNN  | FC    | 128         |
|             | FC    | 128         |
|             | FC    | 3           |

Table 5. GAML network architecture.
| Category  | FFB6D L1 Loss | ADD | ADD-S | Vanilla-ML L1 Loss | ADD | ADD-S | GAML L1 Loss | ADD | ADD-S |
|-----------|---------------|-----|-------|---------------------|-----|-------|--------------|-----|-------|
| Airplane  | 1.51          | 9.1 | 85.7  | 0.11                | 90.4| 96.8  | 0.11         | 89.8| 98.8  |
| Bag       | 1.98          | 5.1 | 48.1  | 0.41                | 40.0| 85.0  | 0.47         | 42.7| 87.1  |
| Bathtub   | 2.22          | 2.7 | 41.4  | 0.55                | 43.3| 86.7  | 0.60         | 45.2| 90.8  |
| Bed       | 2.31          | 2.9 | 33.3  | 0.31                | 72.3| 90.4  | 0.41         | 58.5| 90.8  |
| Bench     | 2.26          | 2.9 | 43.0  | 0.39                | 62.1| 91.4  | 0.35         | 69.8| 91.7  |
| Bookshelf | 2.28          | 2.4 | 32.6  | 0.36                | 55.0| 85.4  | 0.41         | 50.2| 77.9  |
| Bus       | 1.94          | 3.5 | 56.5  | 0.51                | 41.5| 89.6  | 0.36         | 69.8| 92.7  |
| Cabinet   | 2.38          | 2.2 | 24.0  | 0.43                | 53.5| 73.7  | 0.34         | 67.7| 83.5  |
| Camera    | 1.93          | 2.1 | 51.5  | 0.38                | 46.3| 86.3  | 0.34         | 54.8| 85.8  |
| Cap       | 1.75          | 3.1 | 68.5  | 0.19                | 79.2| 98.5  | 0.19         | 80.8| 98.8  |
| Chair     | 2.27          | 1.1 | 26.1  | 0.18                | 80.0| 93.1  | 0.19         | 80.0| 89.6  |
| Earphone  | 1.79          | 4.2 | 62.8  | 0.38                | 34.0| 86.2  | 0.43         | 49.2| 97.1  |
| Motorcycle| 1.65          | 12.7| 85.1  | 0.16                | 90.2| 98.5  | 0.21         | 85.6| 98.1  |
| Mug       | 2.08          | 0.9 | 43.7  | 0.12                | 86.8| 97.9  | 0.14         | 84.2| 94.4  |
| Table     | 2.38          | 2.0 | 19.2  | 0.61                | 33.1| 73.5  | 0.65         | 39.2| 93.1  |
| Train     | 1.67          | 12.9| 71.9  | 0.46                | 38.5| 85.8  | 0.49         | 47.7| 90.6  |
| Vessel    | 1.64          | 11.0| 68.9  | 0.35                | 57.7| 94.1  | 0.37         | 56.0| 90.4  |
| Washer    | 2.48          | 4.1 | 29.1  | 0.33                | 54.8| 85.4  | 0.30         | 68.1| 89.0  |
| Printer   | 2.21          | 1.0 | 33.1  | 0.41                | 47.9| 83.9  | 0.43         | 55.2| 80.0  |
| Birdhouse*| 2.09          | 0.8 | 21.0  | 0.39                | 35.6| 59.4  | 0.43         | 35.4| 64.6  |
| Car*      | 1.79          | 2.4 | 70.5  | 0.44                | 52.5| 97.1  | 0.43         | 56.9| 96.7  |
| Laptop*   | 2.22          | 1.3 | 10.5  | 0.32                | 54.0| 82.9  | 0.20         | 85.0| 93.1  |
| Piano*    | 2.04          | 2.0 | 39.3  | 0.43                | 45.8| 77.5  | 0.44         | 45.8| 80.0  |
| Sofa*     | 2.17          | 2.6 | 27.1  | 0.34                | 68.1| 84.6  | 0.34         | 69.8| 79.0  |
| Intra-Categ.| 2.03          | 4.53| 48.7  | 0.35                | 58.2| 88.5  | 0.36         | 62.9| 90.0  |
| Cross-Categ.| 2.06         | 1.81| 33.7  | 0.38                | 51.2| 80.2  | 0.37         | 58.6| 82.7  |
| All       | 2.04          | 3.96| 45.5  | 0.36                | 56.7| 86.8  | 0.36         | 62.0| 88.4  |

Table 6. Multi-category evaluation on PBR-MCMS dataset

Figure 2. **Qualitative comparison on trained LineMOD objects.** Triangles and circles are the projections of ground-truth and predicted keypoints respectively. It can be observed that keypoint predictions of our method are more accurate.
Figure 3. **Qualitative comparison on new LineMOD objects.** Compared with FFB6D, the pose estimation on new objects of our GAML model is more accurate.

Figure 4. **Qualitative results on Toy-MCMS.** Our model can handle large intra-category variations. The car category is illustrated as an example.
Figure 5. Qualitative comparison between GNN and MLP decoder on Occlusion-MCM. Triangles and circles are the projected ground-truth and predicted keypoints respectively.