

Generalizable Object Re-Identification via Visual In-Context Prompting

Supplementary Material

6. Additional Experiments

Robustness to occlusions: Robustness to pose/lighting has been validated through MVImageNet and CUTE datasets, which offer rich pose variations via multi-view videos or lab-controlled pose/lighting variations. While ShopID10K is visually observed with occlusion variations, there are no explicit occlusion labels, making it difficult to quantitatively evaluate occlusion robustness. To address this, we leverage SAM segmentation model to generate object segmentation maps for ShopID10K and perform connected components analysis to construct a subset of occluded objects based on the disjoint regions. We then use this subset as the query to evaluate VICP and baseline methods. As shown in Tab. 7, our method consistently outperforms baselines under occluded conditions with strong robustness to occlusions.

| | DINOv2 | Triplet | Triplet+ | VICP |
|--------|--------|---------|----------|-------------|
| mAP | 25.7 | 40.5 | 46.8 | 50.2 |
| Rank-1 | 36.1 | 52.4 | 59.2 | 61.4 |

Table 7. Results on occluded ShopID10K subset.

Cross-Domain evaluation: We performed cross-domain evaluation by using the models trained on PetFace/MVImageNet/CUTE to evaluate directly on ShopID10K in Tab. 8. Despite the inherent difficulty of this setting, our method consistently outperforms Triplet+, demonstrating its ability to generalize across significantly different domains. The smaller gains of VICP on PetFace compared to other two datasets suggest that large domain gaps constrain its generalization ability.

| | PetFace | MVImageNet | CUTE |
|----------|-------------|-------------|-------------|
| Triplet+ | 40.2 | 51.6 | 47.9 |
| VICP | 41.6 | 54.2 | 52.1 |

Table 8. Cross-domain mAP.

Comparisons with few-shot learning techniques: Few-shot methods like prototypical or matching networks target coarse-grained tasks, *e.g.*, classification. In contrast, ReID requires fine-grained, identity-level discrimination, limiting their utility. We therefore evaluate the most relevant alternative—model-agnostic meta-learning (MAML) [23]. We train MAML on base categories and fine-tune it on the few-shot examples from unseen categories (same setup as Triplet+). As Tab. 9 shows, MAML marginally outperforms Triplet+, yet still falls short of VICP, which requires no additional fine-tuning.

| | Triplet | Triplet+ | MAML | VICP |
|--------|---------|----------|------|-------------|
| mAP | 50.3 | 54.8 | 55.9 | 58.5 |
| Rank-1 | 63.1 | 67.4 | 68.1 | 68.4 |

Table 9. Results of MAML on ShopID10K.