



Perspective Flow Aggregation for Data-Limited 6D Object Pose Estimation

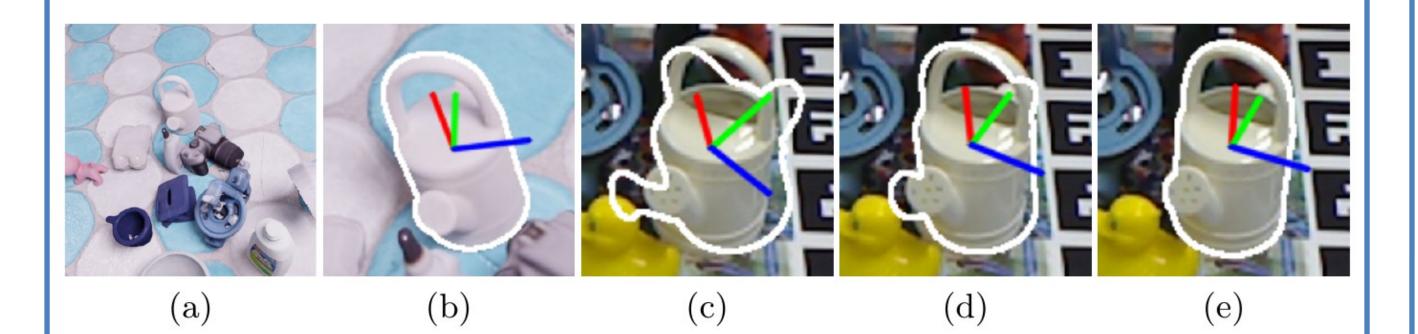




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Problems

- Most recent 6D object pose estimation methods, including unsupervised ones, require many real training images.
- Unfortunately, for some applications, such as those in space or deep under water, acquiring real images, even unannotated, is virtually impossible. These are the scenarios we refer to as data-limited.
- Although rendering-based synthetic techniques can help, the domain shift between the synthetic and real images is still a problem.



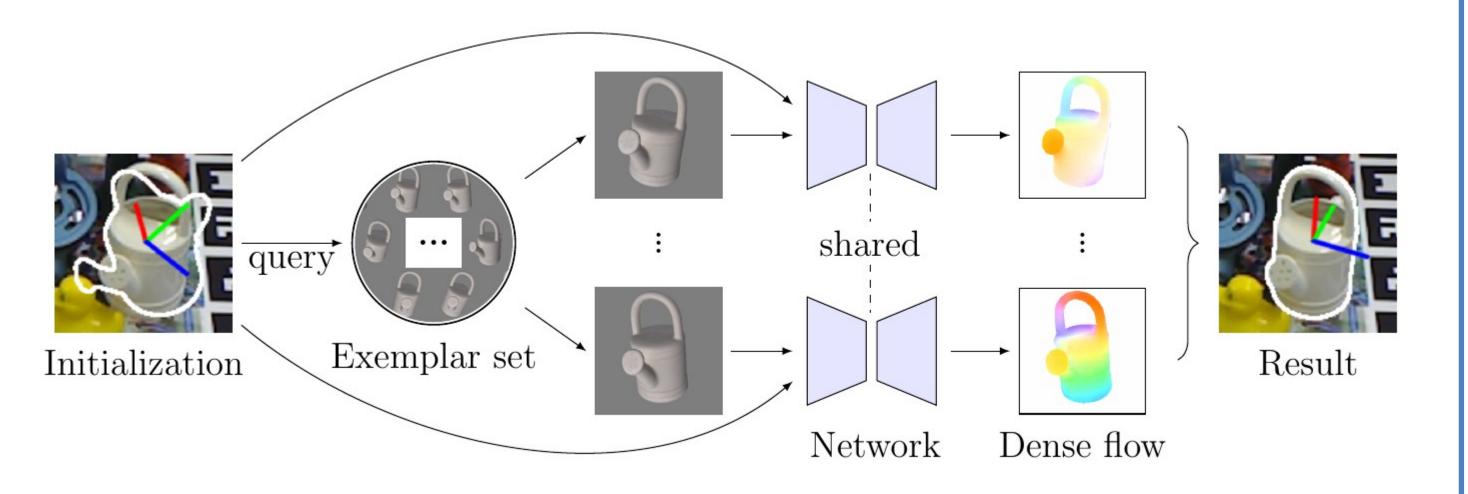
(a) Synthesized images. (b) Although the resulting accuracy on synthetic data is great, (c) that on real images is significantly worse. (d) While the common global-based refinement approach can help, it still suffers from the synthetic-to-real domain gap (DeepIM). (e) Our local-based strategy generalizes much better to real images.

Code is available at:

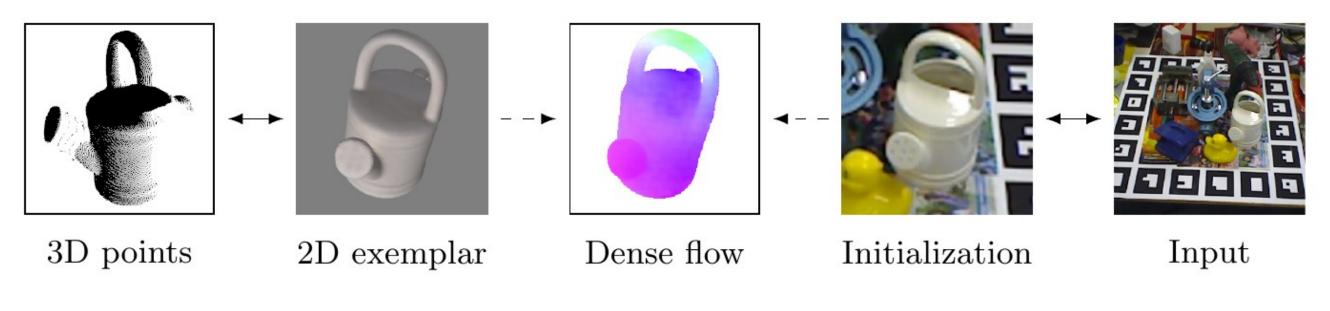
https://github.com/cvlab-epfl/perspective-flow-aggregation

Solution

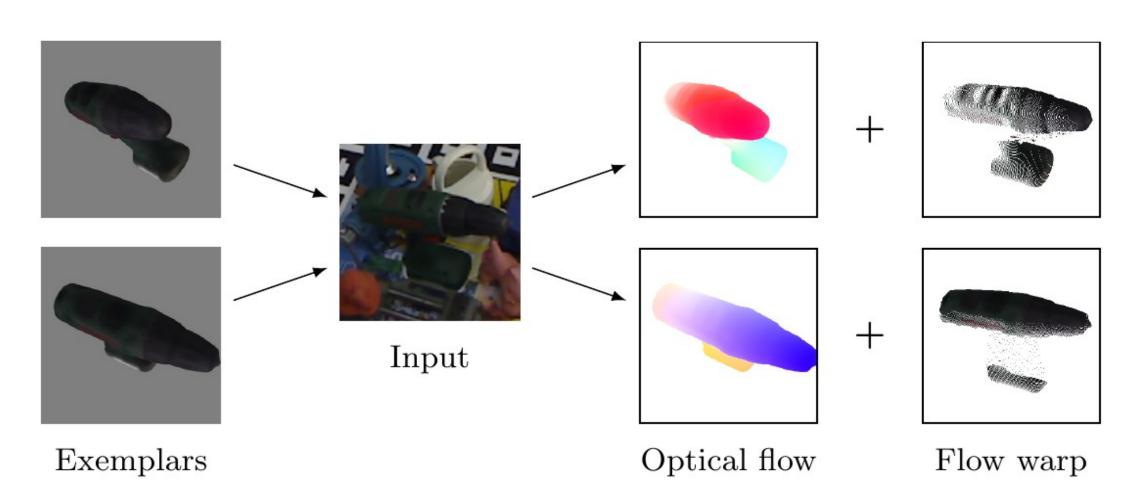
 We propose estimating dense 2D-to-2D local correspondences between input images to force the supervision of our training to occur at the pixel-level, making our DNN learn to extract features that contain lower-level information and thus generalize across domains:



From optical flow to pose refinement:

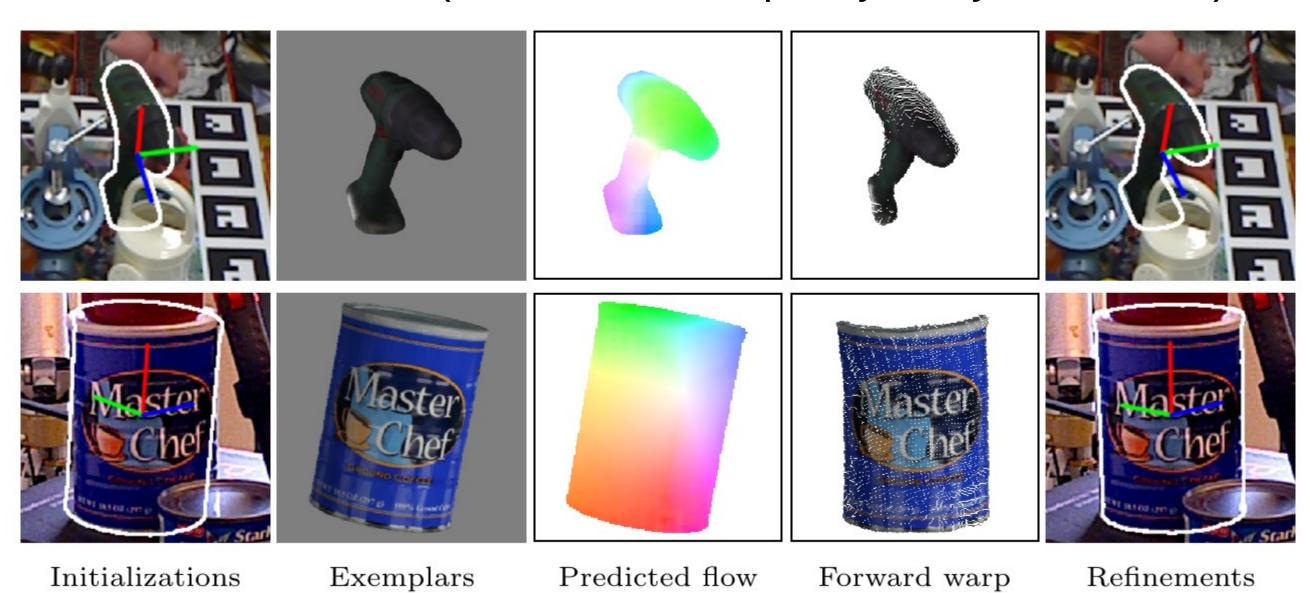


Multi-view flow aggregation:



Experiments

Cross-domain refinement (model is trained purely on synthetic data):



Even more accurate than annotations sometimes:



Annotation

Reprojection

Difference

Our result

Comparing against the SoTA:

| Data | Metrics | ${\bf PoseCNN}$ | SegDriven | PVNet | GDR-Net | DeepIM | CosyPose | Ours (+0) | Ours (+20) |
|------|-----------------|-----------------|-----------|-------|---------|--------|----------|-----------|------------|
| LM | ADD-0.1d | 62.7 | _ | 86.3 | 93.7 | 88.6 | _ | 84.5 | 94.4 |
| OLM | ADD-0.1d | 24.9 | 27.0 | 40.8 | 62.2 | 55.5 | - | 48.2 | 64.1 |
| VCD | ADD-0.1d AUC | 21.3 | 39.0 | _ | 60.1 | - | - | 56.4 | 62.8 |
| ICB | AUC | 61.3 | - | 73.4 | 84.4 | 81.9 | 84.5 | 76.8 | $\bf 84.9$ |

Training with some real images on OLM:

| | 0 | 10 | 20 | 90 | 180 |
|----------|-------------|------|------|------|------|
| DeepIM | 41.1 | 45.6 | 48.2 | 58.1 | 61.4 |
| CosyPose | 42.4 | 46.8 | 48.9 | 58.8 | 61.9 |
| Ours | 48.2 | 59.5 | 64.1 | 64.9 | 65.3 |

Multi-view flow aggregation:

| tion | N=1 | N=2 | N=4 | N=8 |
|------|----------------------|-------------------------------------|--|---|
| 54.1 | 82.0 | 82.7 | 84.3 | 84.1 |
| 52.7 | 81.1 | 81.2 | 83.3 | 83.9 |
| 60.2 | 82.0 | 83.4 | 84.5 | 84.9 |
| S | ~32 | ~ 25 | ~20 | ~14 |
| | 54.1 52.7 60.2 | 54.1 82.0 52.7 81.1 60.2 82.0 | 54.1 82.0 82.7 52.7 81.1 81.2 60.2 82.0 83.4 | 54.1 82.0 82.7 84.3 52.7 81.1 81.2 83.3 60.2 82.0 83.4 84.5 |