DPOD: Dense 6D Pose Object Detector in RGB images

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Abstract

In this work we propose a new method for simultaneous object detection and 6DoF pose estimation. Unlike most recent techniques for CNN-based object detection and pose estimation, we do not base our approach on the common 2D counterparts, i.e., SSD and YOLO, but propose a new scheme. Instead of regressing 2D or 3D bounding boxes, we output full-sized 2D images containing multiclass object masks and dense 2D-3D correspondences. Having them at hand, a 6D pose is computed for each detected object using the PnP algorithm supplemented with RANSAC. This strategy allows for substantially better pose estimates due to a much higher number of relevant pose correspondences. Furthermore, the method is real-time capable, conceptually simple and not bound to any particular detection paradigms, such as R-CNN, SSD or YOLO. We test our method for single- and multiple-object pose estimation and compare the performance with the former state-of-the-art approaches. Moreover, we demonstrate how to use our pipeline when only synthetic renderings are available. In both cases, we outperform the former state-of-the-art by a large margin.

1. Introduction

Object detection has always been an important problem in computer vision and a large body of research has been dedicated to it in the past. This problem, like many other vision problems, witnessed a complete renaissance with the advent of deep learning. Detectors like R-CNN [7], and its follow-ups Fast-RCNN [6], Faster-RCNN [22], Mask-RCNN [8], then YOLO [21] and SSD [17] marked this research field with excellent performance. All these works localize objects of interest in images in terms of tight bounding boxes around them. However, in many applications, e.g., augmented reality, robotics, machine vision, etc., this is not enough and a full 6D pose is necessary. While this problem is easier to solve in depth images, in RGB images it is still quite challenging due to perspective ambiguities and significant appearance changes of the object when seen from different viewpoints.

Recent deep learning-based approaches, like SSD6D [13] and YOLO6D [26] are the current top performers for this task in RGB images. SSD6D, developed by Kehl et al., trains on synthetic renderings of reconstructed 3D models with texture and, thus, does not use real data. The approach extends the SSD detector by performing classification of discrete viewpoints and...
Detecting 3D objects and estimating their 6D pose has been addressed in many works in the past, but the majority of them used depth or RGB-D cameras [2, 4, 14, 15, 19, 24, 27]. Depth information disambiguates the object’s scale that is the most critical in RGB images due to perspective projection. Therefore, using only RGB images for detection and 6D pose estimation is quite a challenging problem. Recent solutions are mainly based on deep learning and automatically learned features, while older ones use hand-crafted features or image information like gradients or directly image pixel intensities.

Template matching approaches, e.g. [10, 11, 23], render synthetic image patches from different viewpoints distributed on a sphere around the 3D model of the object and store them as a database of templates. Then the input images are searched using this template database sequentially in a sliding window fashion. Efficient and robust template matching strategies have been presented for color, depth and RGB-D images. The most popular approach is arguably LineMOD [10], which also provided a first dataset with labeled poses. This dataset is still used as a benchmark for object detection and pose estimation. As an alternative to template matching approaches, learning approaches that employ random forests [2, 3] for solving this problem.

In the last two years deep learning approaches have shown that excellent results can be obtained for detection and pose estimation in RGB images. Here we review the four recent approaches: SSD6D [13], YOLO6D [26], BB8 [20], and AAE [25].

SSD6D (Single Shot Multibox Detector 6D) [13] is an approach that extends the ideas of a popular 2D object detector [17] in order to allow, not only for real-time object detection, but also for 6D pose estimation. The authors of SSD6D opted for a discrete viewpoint classification. It means that regression of the "continuous" pose is replaced with classification of the pose among one of the predefined discrete poses. All the poses are divided into a large number of discrete ones, represented by rotation matrices, and each of them is further divided into smaller number of discrete in-plane rotations. However, the resulting predicted pose is only a discrete approximation and must then be refined, otherwise results without refinement are not very encouraging.

BB8 [20] uses a three stage approach. In the first two stages the coarse-to-fine segmentation of the image is performed outputting the object location in the image. From there a third network is used, which is trained to output projections for the object’s bounding box points. Knowing the relation between bounding box 2D projections and their 3D counterparts, the 6D pose can be estimated with PnP. The main disadvantage of this pipeline is that it is multi-stage, resulting in very slow run times.

Building on YOLO and BB8 ideas, the YOLO6D [26] paper proposes a novel deep learning architecture capable of efficient and precise object detection and pose estimation. In the basic YOLO detector images are divided into a uniform S x S cell grid. For each cell the network predicts if there is an object within this cell, the class of the object, the confidence of classification, and sizes of the bounding box.
Therefore, the output of the net is a $S \times S \times D$ tensor, where $S \times S$ is the number of cells and $D$ is the number of values predicted for each cell. YOLO6D additionally regresses 18 values for each cell. For each object those 18 values correspond to the 2D image coordinates of 9 so-called control points. Control points are the 8 corners of the 3D object bounding box object plus the 3D center of the object. The advantages of this parametrization are its relative compactness and that it does not introduce a pose ambiguity as opposed to a direct regression of the rotation. Moreover, in contrast to SSD6D, it does not suffer from pose discretization resulting in much more accurate pose estimates.

Finally, the most recent approach, AAE (Augmented Auto Encoder) [25], actually concentrates on pose estimation and training from synthetic models, while using already computed SSD detection bounding boxes as input. Our work differs from AAE by being a complete end-to-end pipeline integrating a detector and a pose estimator based on dense correspondences. We demonstrate that we can train either from real or synthetic data and in both cases we outperform all related approaches by a large margin on the LINEMOD and OCCLUSION datasets.

3. Methodology

In this section we first discuss training data preparation steps, followed by neural network architecture and loss functions used, as well as pose estimation step from dense correspondences.

3.1. Data Preparation

Most recent RGB-based detectors can be divided in two groups based on the type of data they use for training: synthetic-based and real-based. The first group of methods, e.g. SSD6D [13] and AAE [25], makes use of textured 3D models, usually provided with the public 6D pose detection datasets. The objects are rendered from different viewpoints producing synthetic training set. The methods of the second group on the other hand, e.g. BB8 [20], YOLO6D [26], use the training split of the real dataset. They utilize ground truth poses provided with the dataset and compute object masks to crop the objects from real images and in that way form the training set.

Both types of data generation have their pros and cons. When real images sufficiently covering the object are available, it is more advantageous to use them for training. The reason is that their close resemblance to the actual objects allows for faster convergence and better results. When, however, no pose annotations are available, which can often be the case since acquiring pose annotations is an expensive process, we are left with 3D models of the objects. With synthetic renderings one can produce virtually infinite number of images from different viewpoints. Despite being advantageous in terms of the pose coverage, one has to deal with the domain gap problem severely hindering the performance if no additional data augmentation is applied. Since our pipeline is not data-specific, here we show how to generate the training data for both scenarios.

**Synthetic-based Data Generation:** Given 3D models of the objects of interest, the first step is to render them from different poses sufficiently covering the object. The poses are defined by the vertices of an icosahedron placed around the object. To achieve finer sampling, triangles are recursively subdivided into four smaller ones until the desired density is obtained. In our case, 4 subdivisions are used. Additionally, we rotate the view camera at each sampling vertex around its viewing direction from -30 to 30 degrees, with a stride of 5 degrees to model in-plane rotations. Then, for each of the camera poses, an object is rendered on a black background and both RGB and depth channels are stored.

Having the renderings at hand, we use a generated depth map as a mask to define a tight bounding box for each generated rendering. Cropping the image with this bounding box position, we store RGB patches, masks separating them from the background, and the camera poses. At this point, we have everything ready for the online augmentation stage, which is described in the later subsection.

**Real-based Data Generation:** In this case, an available dataset with pose annotations is divided into non-overlapping train and test subsets. Here, we follow the protocol defined by BB8 [20] and YOLO6D[26] and use 15% of data for training and the rest 85% for evaluation. Poses are selected such that the relative orientation between them is larger than a certain threshold. This approach guarantees that selected poses cover the object from all sides. Objects are then cut out from the original image using provided mask and stored as patches for the online augmentation stage.

![Figure 2: Illustration of patch generation depending on the available training data.](image) In case of using real data, we extract patches from the training images given the object masks. For synthetic data, we render the object from different view points. In both cases we generate the correspondence patch by rendering the correspondence models in the same poses.
### 3.1.1 Correspondence Mapping

To be able to learn dense 2D-3D correspondences, each model of the dataset is textured with a correspondence map (see Figure 4). A correspondence map is a 2-channel image with values ranging from 0 to 255. Objects are textured using either simple spherical or cylindrical projections. Once textured, we get a bijective mapping between the model's vertices and pixels on the correspondence map. This provides us with easy to read 2D-3D correspondences since knowing the color of the pixel we can instantaneously estimate its position on the model surface by selecting the vertex with the same color value. For convenience, we call the copies of the original models textured with correspondence map correspondence models. Given the predicted correspondence map, we estimate the object pose with respect to the camera using pose estimation block, which is described later. Similarly to synthetic or real data generation steps, we render the correspondence models under the same poses as in the generated training split and store the correspondence patches for each RGB patch (see Figure 2).

### 3.1.2 Online Data Generation and Augmentation

The final stage of data preparation is the online data generation pipeline, which is responsible for providing full-sized RGB images ready for training. Generated patches (real or synthetic) are rendered on top of images from MS COCO (Microsoft Common Objects in Context) dataset [16] producing training images containing multiple objects. It is an important trick which ensures the detector generalizes to different backgrounds and prevents it from overfitting to backgrounds seen during training. Moreover, it forces the network to learn model’s features needed for pose estimation rather than to learn contextual features which might not be present in images when the scene changes. This step is performed regardless of the training being done with synthetic or real patches. We additionally augment the RGB image by random changes in brightness, saturation, and contrast values, and by adding Gaussian noise. Moreover, object ID masks and correspondence patches are also rendered on top of the black background in order to generate the ground truth correspondence maps. The object ID mask is constructed by assigning to each pixel, which belongs to the object, its class ID number. The online data generator runs on multiple CPU threads and constantly puts prepared

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**Figure 3:** Pipeline Description: Given an input RGB image, the correspondence block, featuring an encoder-decoder neural network, regresses the object ID mask and the correspondence map. The latter one provides us with explicit 2D-3D correspondences, whereas the ID mask estimates which correspondences should be taken for each detected object. The respective 6D poses are then efficiently computed by the pose block based on PnP+RANSAC.

**Figure 4:** Correspondence model. Given a 3D model of interest (1), we apply a 2 channel correspondence texture (2) to it. The resulting correspondence model (3) is then used to generate GT maps and estimate poses.
batches in a queue, from which they are picked as inputs to the network.

4. Dense Object Detection Pipeline

Our inference pipeline is divided into two blocks: the correspondence block and the pose block (see Figure 3).

Correspondence block: The correspondence block consists of an encoder-decoder convolutional neural network with three decoder heads which regress the ID mask and dense 2D-3D correspondence map from an RGB image of size $320 \times 240 \times 3$. The encoder part is based on a 12-layer ResNet-like [9] architecture featuring residual layers which allow for faster convergence. The decoders upsample the feature up to its original size using a stack of bilinear interpolations followed by convolutional layers. However, in principle the proposed method is agnostic to a particular choice of encoder-decoder architecture. Any other backbone architectures can be used as well without any need to change the conceptual principles of the method. For the ID mask head the output is a $H \times W \times O$ tensor, where $H$ and $W$ are the height and width of the original input image and $O$ is the number of objects in the dataset plus one additional class for background. Similarly to the ID mask head, the two correspondence heads regress tensors with the following dimensions $H \times W \times C$, where $C$ stands for the number of unique colors of the correspondence map, i.e. 256. Each channel of the output tensors stores the probability values for the class corresponding to the channel number. Once tensors are regressed, we store them as single channel images where each pixel stores the class with the maximal estimated probability, forming the ID mask and U and V channels of the correspondence image.

Formulating color regression problem as discrete color class classification problem proved to be useful for much faster convergence and for the superior quality of 2D-3D matches. Initial experiments on direct coordinate regression showed very poor results in terms of correspondence quality. The main reason for the problem was the infinite continuous solution space, i.e. $[-1;1]^3$, where the number of dimensions and $[-1;1]$ is the normalized coordinate range of a 3D model. Classification of the discretized 2D correspondences allowed for a huge boost of the output quality by dramatically decreasing the output space (now $256^2$, where $256$ is the size of a single UV map dimension). Moreover, this parametrization also ensures that 3D points of the predicted correspondences always lie on the object surface.

The network parameters are optimized subject to the composite loss function:

$$L = \alpha L_m + \beta L_u + \gamma L_v,$$

where $L_m$ is the mask loss, and $L_u$ and $L_v$ are the losses responsible for the quality of the U and V channels of the correspondence image. $\alpha, \beta$, and $\gamma$ are weight factors set to 1 in our case.

Both $L_u$ and $L_v$ losses are defined as multi-class cross-entropy functions, whereas $L_m$ uses the weighted version of it:

$$L_m(x, c) = w_c \left( -x_c + \log \left( \sum_j e^{x_j} \right) \right),$$

where $x_c$ is the output score of the class $c$, and $w$ sets the rescaling weight for each class, which is set to 0.01 for the background class and to 1 for the object classes.

Pose block: The pose block is responsible for the pose prediction. Given the estimated ID mask, we can observe which objects were detected in the image and their 2D locations, whereas the correspondence maps each 2D point to a coordinate on an actual 3D model. The 6D pose is then estimated using the Perspective-n-Point (PnP) [28] pose estimation method that estimates the camera pose given correspondences and intrinsic parameters of the camera. Since we get a large set of correspondences for each model, the iterative Random sample consensus (RANSAC) method is used in conjunction with PnP to make the final camera pose more robust to possible outliers. For the results presented in the evaluation section, for each pose we run 150 RANSAC iterations with the threshold on reprojection error set to 1.

5. Training Details

Our pipeline is solely implemented in Python using the Pytorch deep learning framework. All the experiments were conducted on an Intel Core i7-6900K CPU 3.20GHz with NVIDIA TITAN X (Pascal) GPU. To train our method, we used the ADAM solver with a constant learning rate of $3 \times 10^{-4}$ and weight decay of $3 \times 10^{-5}$.

When training on synthetic data, the problem of domain adaptation becomes one of the main challenges. Training the network without any prior parameter initialization makes it impossible to generalize to the real data. The easy solution to this problem was proposed in several works, including [12, 18], where they freeze the first layers of the network trained on a large dataset of real images, e.g. ImageNET [5] or MS COCO [16], for the object classification task. The common observation that the authors conclude is that these layers, learning low-level features, very quickly overfit to the perfect object renderings. We follow this setup, and freeze the first five layers of our encoder initialized with the weights of the same network pretrained on ImageNET. Last but not least, we found it crucial for the performance of the detector to use various light sources during rendering of synthetic views to account for changing light conditions and shadows in the real data.
Table 1: Comparison of our approach to other RGB detectors on the LINEMOD dataset. The table reports percentages of correctly estimated poses w.r.t. the ADD score.

<table>
<thead>
<tr>
<th>Object</th>
<th>Synthetic</th>
<th>+Refinement</th>
<th>Real</th>
<th>+Refinement</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ape</td>
<td>2.6</td>
<td>3.96</td>
<td>21.79</td>
<td>65</td>
</tr>
<tr>
<td>Benchvise</td>
<td>15.1</td>
<td>20.92</td>
<td>71.25</td>
<td>80</td>
</tr>
<tr>
<td>Cam</td>
<td>6.1</td>
<td>30.47</td>
<td>29.82</td>
<td>78</td>
</tr>
<tr>
<td>Can</td>
<td>27.3</td>
<td>35.87</td>
<td>56.65</td>
<td>86</td>
</tr>
<tr>
<td>Cat</td>
<td>9.3</td>
<td>17.90</td>
<td>24.92</td>
<td>70</td>
</tr>
<tr>
<td>Driller</td>
<td>12.0</td>
<td>23.99</td>
<td>67.46</td>
<td>73</td>
</tr>
<tr>
<td>Duck</td>
<td>1.3</td>
<td>4.86</td>
<td>23.29</td>
<td>66</td>
</tr>
<tr>
<td>Eggbox</td>
<td>2.8</td>
<td>81.01</td>
<td>75.28</td>
<td>100</td>
</tr>
<tr>
<td>Glue</td>
<td>3.4</td>
<td>45.49</td>
<td>79.29</td>
<td>100</td>
</tr>
<tr>
<td>Holepuncher</td>
<td>3.1</td>
<td>17.60</td>
<td>18</td>
<td>49</td>
</tr>
<tr>
<td>Iron</td>
<td>14.6</td>
<td>32.03</td>
<td>87.59</td>
<td>78</td>
</tr>
<tr>
<td>Lamp</td>
<td>11.4</td>
<td>60.47</td>
<td>66.67</td>
<td>73</td>
</tr>
<tr>
<td>Phone</td>
<td>9.7</td>
<td>33.79</td>
<td>27.73</td>
<td>79</td>
</tr>
<tr>
<td>Mean</td>
<td>9.1</td>
<td>28.65</td>
<td>49.98</td>
<td>79</td>
</tr>
</tbody>
</table>

6. Evaluation

In this section we evaluate our algorithm in terms of its pose and detection performance, as well as its runtime. and compare it with the state-of-the-art RGB detector solutions available.

6.1. Datasets

All experiments were conducted on LINEMOD [11] and OCCLUSION [2] datasets, as they are the standard datasets used to evaluate performance of object detection and pose estimation methods. The LINEMOD dataset consists of 13 sequences, each of which contains ground truth poses for one object of interest in cluttered environment. CAD models for all the objects are provided as well. The OCCLUSION dataset is an extension of LINEMOD, suitable for testing how well detectors can deal with occlusions. Although it has only one sequence, all visible objects from the LINEMOD dataset are supplied with their poses.

6.2. Evaluation Metrics

Following the example of SSD6D [13] we evaluate the quality of 6 DoF pose estimation only for objects which were correctly detected in 2D. Correct detection is defined as a detection whose predicted bounding box has an intersection over union (IoU) with a ground truth bounding box not lower than 0.5.

Analogously to other related papers [20, 26, 13], we measure the accuracy of pose estimation using the ADD score [11]. ADD is defined as an average Euclidean distance between model vertices transformed with the predicted and the ground truth pose. More formally it is defined as follows:

\[
m = \frac{1}{|M|} \sum_{x \in M} \| (Rx + T) - (\hat{R}x + \hat{T}) \|_2,
\]

where \( M \) is a set of vertices of a particular model, \( R \) and \( T \) are the rotation and translation of a ground truth transformation whereas \( \hat{R} \) and \( \hat{T} \) correspond to those of an estimated transformation. This formulation is not suitable for symmetric objects since there exist transformations which do not visually change such objects. Nevertheless, the ADD metric can be extended in order to handle symmetric objects as in [11]. Instead of measuring distance from a predicted location of each particular model’s vertex to its ground truth location, it suggests to take the closest vertex of the model.

6.3. Single Object Pose Estimation

Results of pose estimation experiments on the LINEMOD dataset are reported in Table 1. We separately compared our method trained either on real data and the ground truth poses. More formally it is defined as follows:

\[
m = \min_{x_1 \in M, x_2 \in M} \| (Rx_1 + T) - (R\hat{x}_2 + \hat{T}) \|_2.
\]
Figure 5: Qualitative results. Poses predicted with the proposed approach on (a) the LINEMOD dataset and (b) the Occlusion dataset. Green bounding boxes correspond to ground truth poses, bounding boxes of other colors to predicted poses. On both datasets predicted poses are very close to correct poses.

or on purely synthetic data. The left-hand side of the table reports accuracy of pose estimation as percentages of poses which are correct according to ADD measure for training done on synthetic data. If no refinement is used, our approach outperforms all other approaches by a significant margin on the majority of the objects. Moreover, the average percentage of correctly estimated poses (49.98%) is significantly higher than 28.65% of the second best approach. The accuracy gap is more prominent on small objects such as ape and duck. The availability of a large number of 2D-3D correspondences ensures that the performance of our method is 5 times better than SSD6D and almost 2 times better than AAE. In contrast to AAE, which uses ICP refinement, we do not use any depth information.

If trained on real data, our approach performs the best to the extent of our knowledge. The right-hand side of Table 1 compares the proposed approach to previous deep learning based ones. If no refinement is used, the proposed approach outperforms all other methods by a significant margin. On average, we are better than YOLO6D by 21%. Moreover, unrefined poses estimated with our approach are better than refined poses of Brachmann on all the objects, and better than BB8 with refinement on all the objects apart from cat. Last but not the least, even if poses predicted of SSD6D are refined, the accuracy of our unrefined poses is only 1.33% worse. Again, our approach uses exclusively RGB data and does not rely on depth data. Figure 5a provides visual comparison of ground truth poses versus predicted poses. Poses are visualized as projections of 3D bounding boxes of models in given poses onto an image plane.

In conclusion, the proposed detector achieves state-of-the-art results surpassing other detectors by a large margin without any need in additional pose refinement. Pose quality varies from object to object, but in general poses are significantly better on larger objects since there more 2D-3D correspondences are available. On the other hand, simplicity of the proposed approach also makes it quick. On average, it performs at 31 FPS. Table 2 summarizes frame efficiency of our approach with respect to previous state-of-the-art approaches.

<table>
<thead>
<tr>
<th>Method</th>
<th>Frames per second</th>
<th>Refinement</th>
</tr>
</thead>
<tbody>
<tr>
<td>Brachmann [3]</td>
<td>2</td>
<td>100 ms/object</td>
</tr>
<tr>
<td>BB8 [20]</td>
<td>3</td>
<td>21 ms/object</td>
</tr>
<tr>
<td>AAE [25]</td>
<td>4</td>
<td>200 ms/object</td>
</tr>
<tr>
<td>SSD6D [13]</td>
<td>10</td>
<td>24 ms/object</td>
</tr>
<tr>
<td>Ours</td>
<td>31</td>
<td>-</td>
</tr>
<tr>
<td>YOLO6D [26]</td>
<td>50</td>
<td>-</td>
</tr>
</tbody>
</table>
Figure 6: Performance on the OCCLUSION dataset. (a) Percentage of correctly estimated poses as a function of the distance threshold on 2D projection error. (b) Percentage of correctly estimated poses as a function of model’s diameter threshold on ADD. (c) Comparison of the proposed approach to YOLO6D in terms of average percentage of correctly estimated poses among all models as a function of the distance threshold on projection error.

Table 3: Computational times of the pipeline execution stages in milliseconds.

<table>
<thead>
<tr>
<th>Execution stage</th>
<th>Milliseconds</th>
</tr>
</thead>
<tbody>
<tr>
<td>Encoder + Decoder Inference</td>
<td>11</td>
</tr>
<tr>
<td>Finding 2D-3D correspondences</td>
<td>3</td>
</tr>
<tr>
<td>PnP + RANSAC</td>
<td>26</td>
</tr>
<tr>
<td>Total</td>
<td>40</td>
</tr>
</tbody>
</table>

rate of the proposed approach in comparison to other detectors. As it is seen from Table 3, PnP and RANSAC take the largest part of the runtime, which is sensitive to particular settings of RANSAC, number of 2D-3D correspondences as well as their quality. Phone is the object on which the approach runs at the lowest frame rate of 10 FPS. The fastest detection is on duck with 57 FPS.

6.4. Multiple Object Pose Estimation

Performance evaluation of the proposed detector in cases when the number of objects to detect increases and when severe occlusions are present was conducted on the OCCLUSION dataset [2]. Accuracy of object detection on the OCCLUSION dataset is conventionally reported in terms of mean average precision (MAP). The confidence score is computed based on the RANSAC inlier count as confidence, rendering the final score of 0.5072, which is on par with the best result on this dataset (see Table 4).

Figure 6 provides evaluation of quality of pose estimation on the OCCLUSION dataset in terms of 2D projection error and ADD. Moreover, Figure 6 shows comparison of our detector to YOLO6D [26], which is the only detector that has good results without refinement. Figure 6a demonstrates percentage of correctly estimated poses as a function of pixel threshold on the 2D projection error. Figure 6b provides percentage of correctly estimated poses as a function of more strict ADD measure for various thresholds. In Figure 6c we compare our mean percentages of correctly estimated poses to those of YOLO6D [26]. To sum up, the figure shows that we consistently outperform YOLO6D [26] by a large margin. Figure 5b demonstrates an example result of detection and pose estimation of multiple objects on one image from the OCCLUSION dataset.

7. Conclusion

In this paper we proposed a Dense Pose Object Detector (DPOD) method that regresses multi-class object masks and dense 2D-3D correspondences between image pixels and corresponding 3D models. Unlike the best performing methods that regress projections of the object’s bounding boxes [20, 26] or formulate pose estimation as a discrete pose classification problem [13], dense correspondences computed by our method allow for more robust and accurate 6D pose estimation. We demonstrated that for both, real and synthetic training data, our detector outperforms other related works by a large margin. The accuracy of our results is generally better than the accuracy of refined poses from the related approaches, indicating the high fidelity of the proposed detector while remaining real-time capable.
References


Supplementary Material

8. Implementation Details

The architecture of our network is visualized in Figure 1. It is a standard ResNet-like (Resnet18 in PyTorch) model with a reduced number of layers and pooling operations in comparison to the original ResNet. Upsampling is implemented as bilinear interpolation rather than deconvolution in order to decrease the number of parameters and not to increase the required amount of computations. Each upsampling is followed by stacking, i.e. concatenating the output feature map with the feature map from the previous level, and one convolutional layer.

9. RANSAC Iterations

Number of RANSAC iterations crucially influences the quality of predicted poses. We ended up using 150 iterations as it yielded the best trade off between quality and runtime. The larger amount of iterations generally did not improve the results significantly, but resulted in longer execution times (see Table 1).

Table 1: Effect of the number of RANSAC iterations on the ADD metric.

<table>
<thead>
<tr>
<th>RANSAC #</th>
<th>5</th>
<th>25</th>
<th>50</th>
<th>75</th>
<th>100</th>
<th>150</th>
<th>250</th>
<th>500</th>
</tr>
</thead>
<tbody>
<tr>
<td>ADD</td>
<td>55.91</td>
<td>71.26</td>
<td>74.27</td>
<td>76.27</td>
<td>77.67</td>
<td>78.08</td>
<td>79.05</td>
<td></td>
</tr>
<tr>
<td>Exec. Time</td>
<td>2.38</td>
<td>6.15</td>
<td>10.69</td>
<td>14.15</td>
<td>17.62</td>
<td>25.74</td>
<td>34.31</td>
<td>56.54</td>
</tr>
</tbody>
</table>

10. Runtime analysis

In Table 2 we provide the runtimes of the proposed approach for all models from the LINEMOD dataset. The total runtime consists of the time needed for PnP and approximately 15 ms for the network’s forward pass and computation of 2D-3D correspondences. All the experiments were conducted on an Intel Core i7-6900K CPU 3.20GHz with NVIDIA TITAN X (Pascal) GPU.

Table 2: Runtime of the proposed approach for all models from the LINEMOD dataset.

<table>
<thead>
<tr>
<th>Model</th>
<th>PnP (ms)</th>
<th>Total (ms)</th>
<th>FPS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ape</td>
<td>12</td>
<td>27</td>
<td>38</td>
</tr>
<tr>
<td>Benchvise</td>
<td>38</td>
<td>53</td>
<td>19</td>
</tr>
<tr>
<td>Cam</td>
<td>30</td>
<td>44</td>
<td>23</td>
</tr>
<tr>
<td>Can</td>
<td>25</td>
<td>39</td>
<td>26</td>
</tr>
<tr>
<td>Cat</td>
<td>17</td>
<td>32</td>
<td>32</td>
</tr>
<tr>
<td>Driller</td>
<td>21</td>
<td>35</td>
<td>28</td>
</tr>
<tr>
<td>Duck</td>
<td>4</td>
<td>17</td>
<td>57</td>
</tr>
<tr>
<td>Eggbox</td>
<td>11</td>
<td>25</td>
<td>41</td>
</tr>
<tr>
<td>Glue</td>
<td>7</td>
<td>21</td>
<td>48</td>
</tr>
<tr>
<td>Holepuncher</td>
<td>17</td>
<td>31</td>
<td>33</td>
</tr>
<tr>
<td>Iron</td>
<td>27</td>
<td>42</td>
<td>24</td>
</tr>
<tr>
<td>Lamp</td>
<td>34</td>
<td>48</td>
<td>21</td>
</tr>
<tr>
<td>Phone</td>
<td>90</td>
<td>105</td>
<td>10</td>
</tr>
<tr>
<td>Average</td>
<td>26</td>
<td>40</td>
<td>31</td>
</tr>
</tbody>
</table>

Figure 1: Network architecture: Encoder-decoder architecture based on ResNet.

11. Refinement

DeepIM\* presents an iterative refinement routine that takes an initial pose estimate from any external detector and iteratively improves it. Since DeepIM is not bound to any particular detector, we also tested it (GIT repository) on the output of our detector with the results outperforming PoseCNN+DeepIM presented in the paper:

<table>
<thead>
<tr>
<th>Model</th>
<th>Ape</th>
<th>Bv</th>
<th>Cam</th>
<th>Can</th>
<th>Cat</th>
<th>Drill</th>
<th>Duck</th>
<th>Eggbox</th>
<th>Glue</th>
<th>Holepuncher</th>
<th>Iron</th>
<th>Lamp</th>
<th>Phone</th>
<th>Avg.</th>
</tr>
</thead>
<tbody>
<tr>
<td>78.70</td>
<td>98.43</td>
<td>97.75</td>
<td>97.57</td>
<td>85.16</td>
<td>91.55</td>
<td>80.24</td>
<td>99.68</td>
<td>99.48</td>
<td>75.66</td>
<td>99.74</td>
<td>98.20</td>
<td>91.38</td>
<td>91.81</td>
<td></td>
</tr>
</tbody>
</table>

12. Additional Qualitative Results on the LINEMOD dataset

Figure 2: **Poses predicted with the proposed approach on the LINEMOD dataset**: ape (left), benchvise (middle), cam (right). Green bounding boxes correspond to ground truth poses, blue bounding boxes correspond to predicted poses.
Figure 3: **Example results on the LINEMOD dataset:** can (left), cat (middle), driller (right). Green bounding boxes correspond to ground truth poses, blue bounding boxes correspond to predicted poses.
Figure 4: Example results on the LINEMOD dataset: duck (left), eggbox (middle), glue (right). Green bounding boxes correspond to ground truth poses, blue bounding boxes correspond to predicted poses.
Figure 5: **Example results on the LINEMOD dataset:** holepuncher (left), iron (middle), lamp (right). Green bounding boxes correspond to ground truth poses, blue bounding boxes correspond to predicted poses.
Figure 6: **Example results on the LINEMOD dataset**: phone. Green bounding boxes correspond to ground truth poses, blue bounding boxes correspond to predicted poses.
13. Additional Qualitative Results on the OCCLUSION dataset

Figure 7: Example results on the OCCLUSION dataset: phone. Green bounding boxes correspond to ground truth poses, bounding boxes of other colors correspond to predicted poses.
Figure 8: Example results on the OCCLUSION dataset: phone. Green bounding boxes correspond to ground truth poses, bounding boxes of other colors correspond to predicted poses.