





INTRODUCTION

SIEMENS

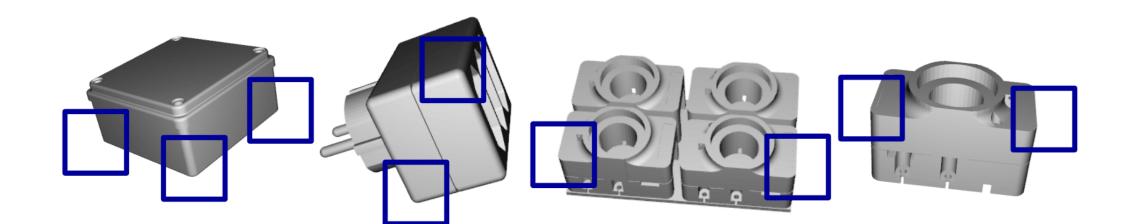
- ▶ Motivation: 3D pose estimation from color images state-of-the-art methods rely on the power of Deep Learning however:
 - ▷ these methods have to be retrained for each new object
 - ▷ many different images of these new objects need to be available
 - ▷ domain transfer methods for training with synthetic data can be used but they take time

► Goal & Contribution:

▷ 3D pose estimation of new objects without additional learning nor training images

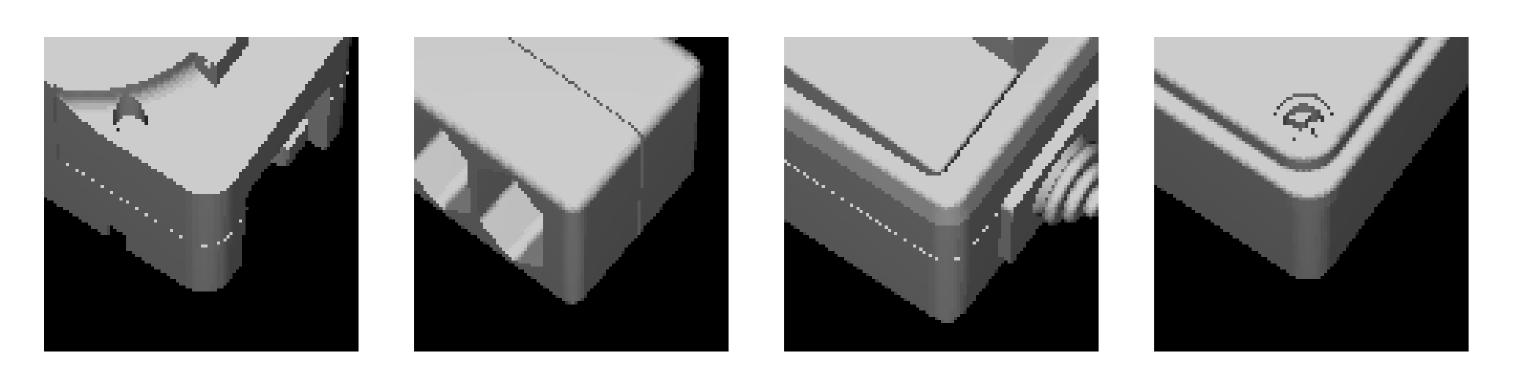
► Idea:

- \triangleright Industrial objects often share common parts \Rightarrow Estimate the object's 3D pose by learning to estimate the pose of its 3D parts
- ▷ Large number of industrial objects have prominent corners. Let's focus on corners!

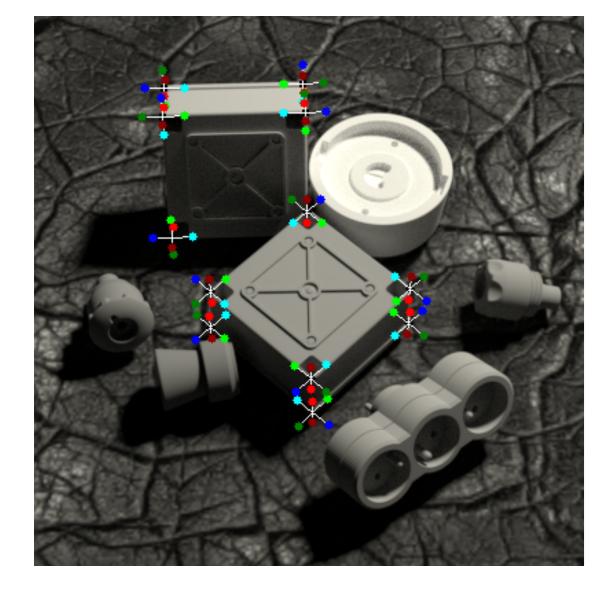


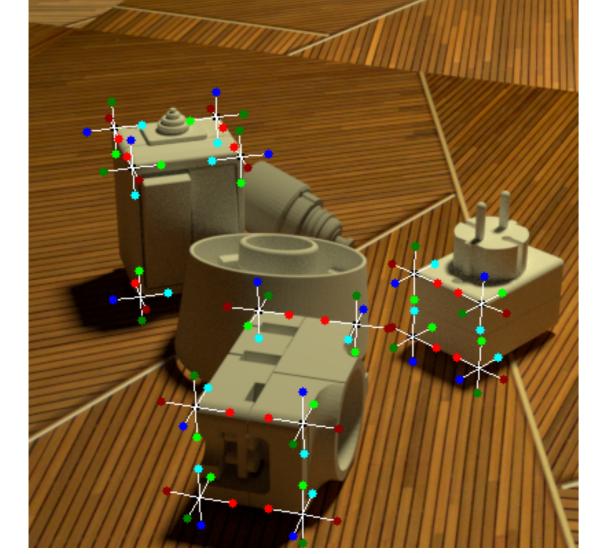
TRAINING DATA FOR CORNER DETECTION

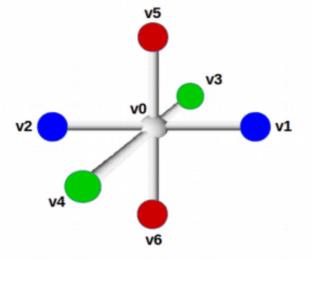
► Considering generic corners of various shapes and appearances to be able to deal with new objects without retraining

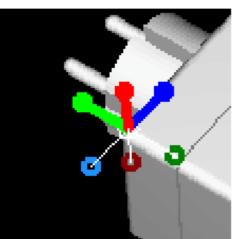


- ▶ Representing the 3D pose of a corner in terms of the 2D reprojections of a set of 3D virtual points. It makes it easy to compute the 3D pose of an object from several corners
- ► Examples of synthetic training images generated by rendering objects from the T-LESS dataset with annotated 2D reprojections of virtual points.







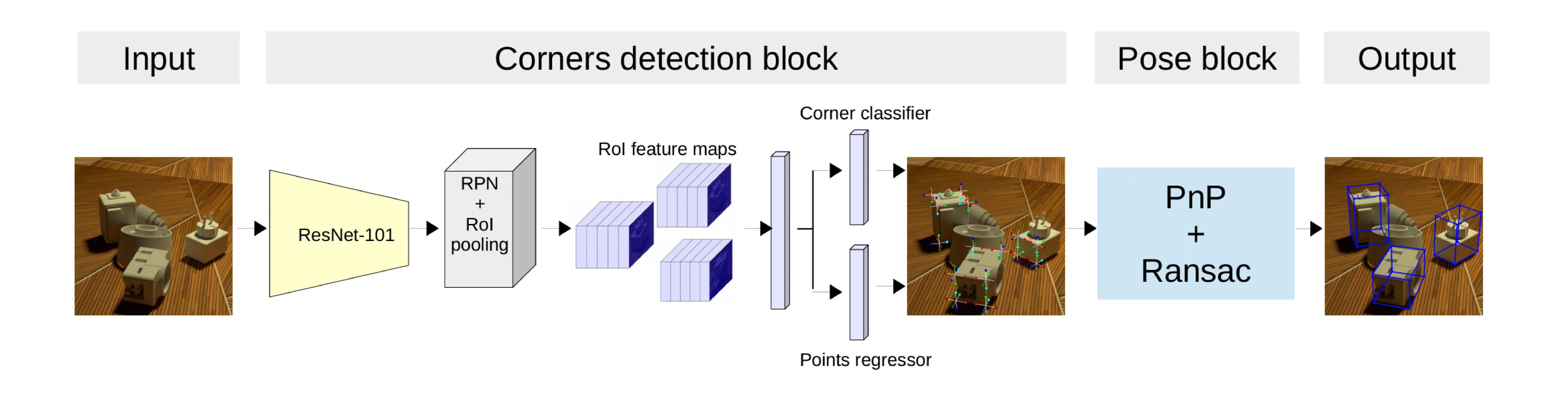


CORNET: GENERIC 3D CORNERS FOR 6D POSE ESTIMATION OF NEW OBJECTS WITHOUT RETRAINING

Slobodan $\text{Ilic}^{3,4}$ Giorgia Pitteri¹ Vincent Lepetit² ¹ Laboratoire Bordelais de Recherche Informatique, Université de Bordeaux, ² LIGM (UMR 8049), École des Ponts, UPE, ³ Technische Universät München, ⁴ Siemens AG Corporate Technology

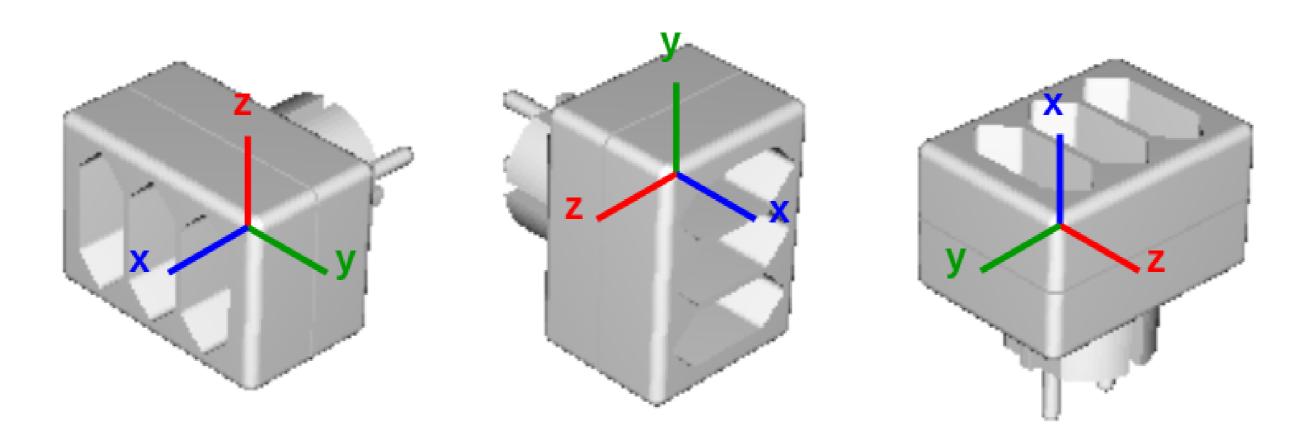
METHOD

- ► Corners detection and 2D reprojections of 3D virtual points prediction by adding specific branches to Faster R-CNN
- ▶ RANSAC-like pose estimation computation by solving a PnP agorithm from 2D-3D correspondences



DEALING WITH CORNER POSE AMBIGUITIES

► The same corner can look identical under different 3D poses. This implies that it is possible to predict the 3D pose of a corner up to some rigid motion \Rightarrow three possible arrangements of 3D virtual points

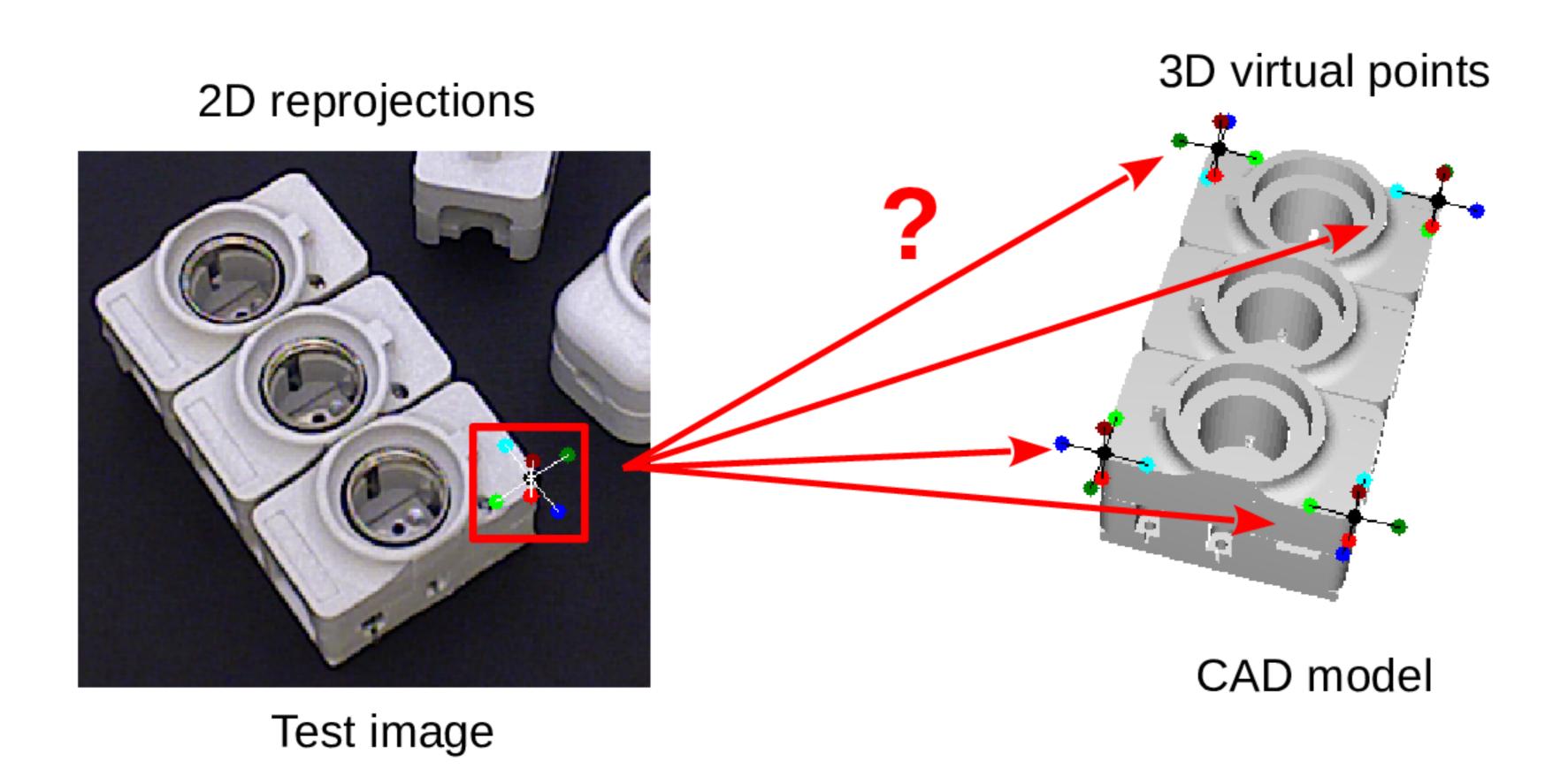


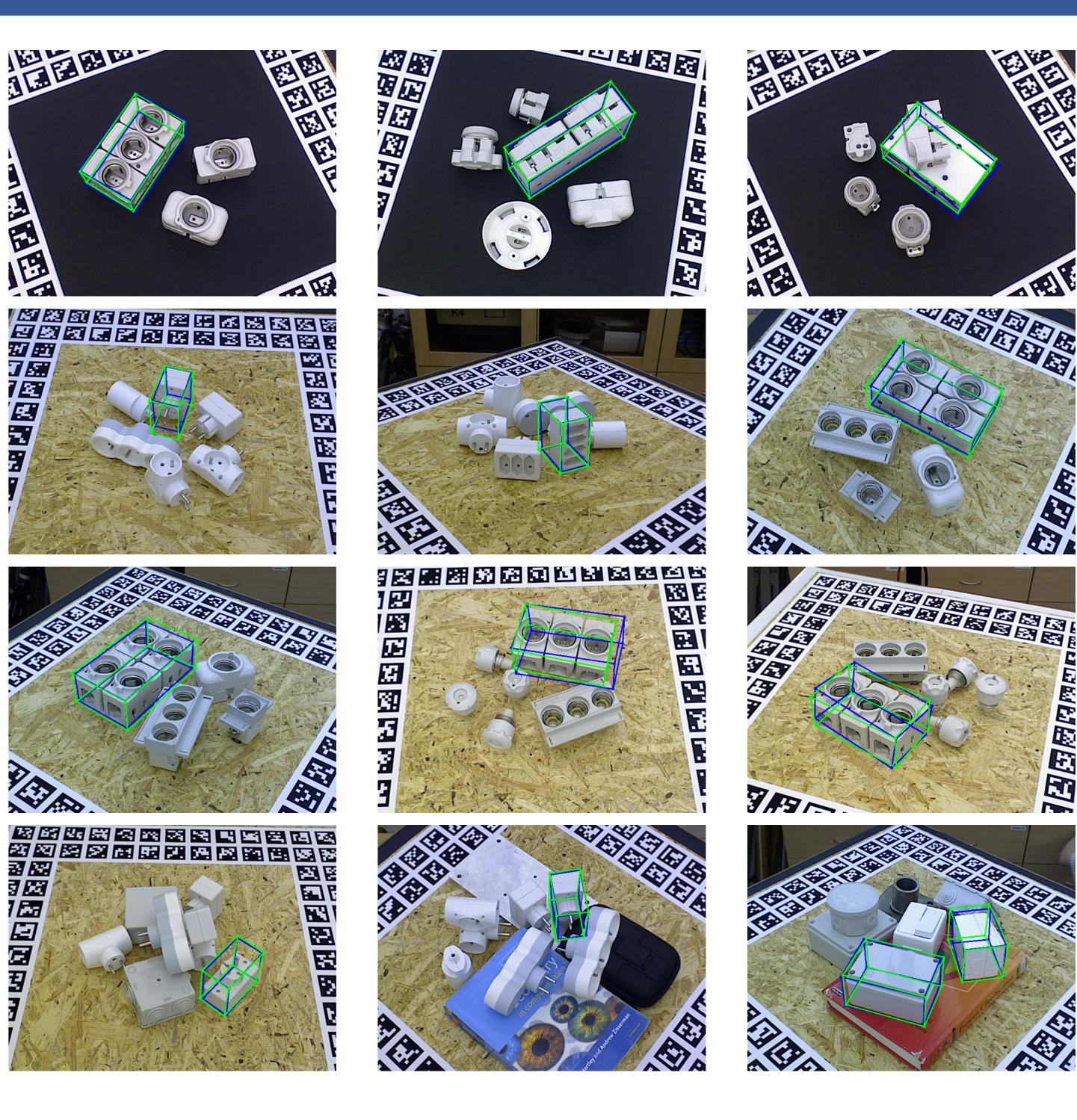
- \blacktriangleright Given one possible 3D pose **p** it is possible to generate the other poses by permuting properly the 2D reprojections of the virtual points.
- ▶ Introduction of two permutations Σ_1 and Σ_2 to permute the 2D reprojections of the 3D virtual points and to generate the other two possible poses from the estimated pose **p**.
 - > Inference: application of Σ_1 and Σ_2 to the estimated pose
 - ▷ **Training**: optimization done on the following cost function

$$|loss = \min_{\Sigma \in \{I_d, \Sigma_1, \Sigma_2\}} ||P^{gt} - \Sigma(f_{\theta}(I))||$$

POSE ESTIMATION ALGORITHM

- ▶ 3D object pose estimation by matching the corners on the CAD model with their detected counterparts in the image by solving a PnP algorithm
- \blacktriangleright Application of the two permutations Σ_1 and Σ_2 to generate the other two possible poses to handle ambiguities
- ► RANSAC-like algorithm based on a **similarity score** to find the best pose among all the possible estimated poses
- **Similarity score**: cross correlation between the gradients of the input image and the image gradients of the CAD model rendered under the 3D pose hypothesys.





	$AD\{D I\}_{10\%}$	$AD\{D I\}_{20\%}$	$AD\{D I\}_{30\%}$	detection $[\%]$
02: 7	68.3	80.1	83.7	67.3
03: 8	57.9	72.5	78.7	76.3
$04:\ 26$	28.1	47.2	56.2	48.3
04: 8	21.2	53.0	68.2	35.7
06: 7	36.8	61.7	78.7	73.7
08: 20	10.0	40.4	56.1	34.1
10: 20	27.8	47.2	58.3	30.0
11: 8	58.8	74.9	85.3	74.3
12: 7	23.1	44.6	47.7	54.6
$13:\ 20$	26.6	57.3	69.0	52.9
15: 29	48.0	59.1	76.7	38.3
$14:\ 20$	10.0	24.6	31.6	44.0
Average	$34.7(\pm 18.5)$	$55.2(\pm 15.2)$	$65.9(\pm 15.6)$	$52.5(\pm 16.2)$

REFERENCES

- [1] A. Crivellaro, M. Rad, Y. Verdie, K. Moo Yi, P. Fua and V. Lepetit: Robust 3D Object Tracking from Monocular Images Using Stable Parts, PAMI, 2017
- [2] M. Rad and V. Lepetit: BB8: A Scalable, Accurate, Robust to Partial Occlusion Method for Predicting the 3D Poses of Challenging Objects Without Using Depth, ICCV, 2017
- [3] T. Hodaň, P. Haluza, S. Obdržaĺek, J. Matas, M. Lourakis and X. Zabulis: *T-LESS*: An RGB-D Dataset for 6D Pose Estimation of Texture-less Objects, IEEE Winter Conference on Applications of Computer Vision (WACV), 2017

ACKNOWLEDGEMENTS

This research work was funded by Siemens AG, Corporate Technology Research & Technology Center, Munich.

RESULTS