

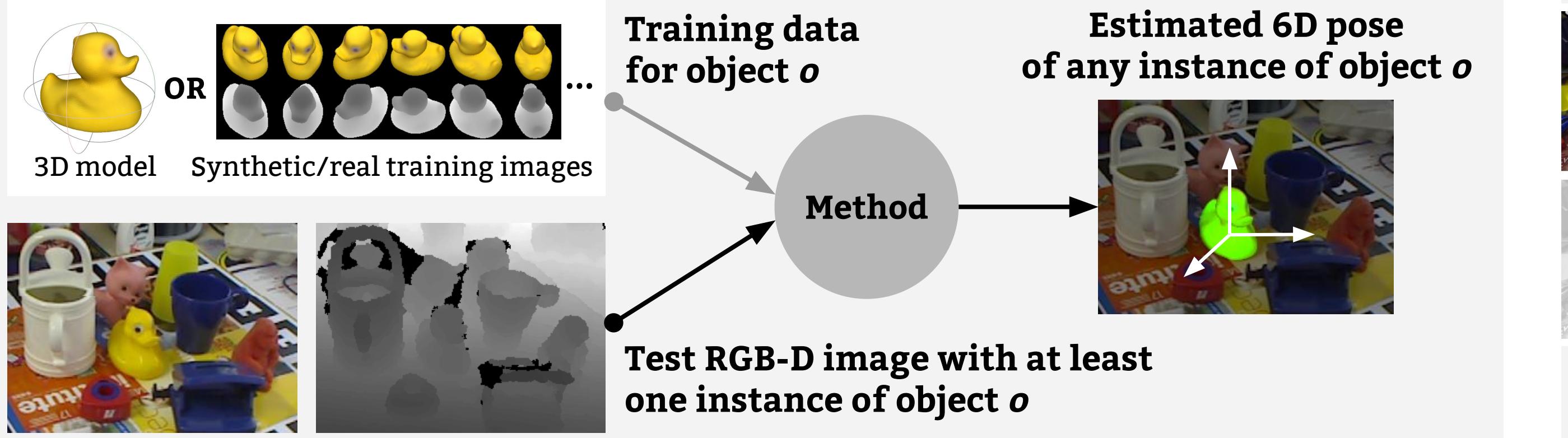
# BOP: Benchmark for 6D Object Pose Estimation

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## Task: 6D pose estimation of a single instance of a single object

Relevant for robotics and augmented reality, addressed by all published methods



## Unclear state of the art

- 1) No standard evaluation method, 2) Datasets have different formats and GT quality,
- 3) Methods compared with only a few competitors on a small number of datasets

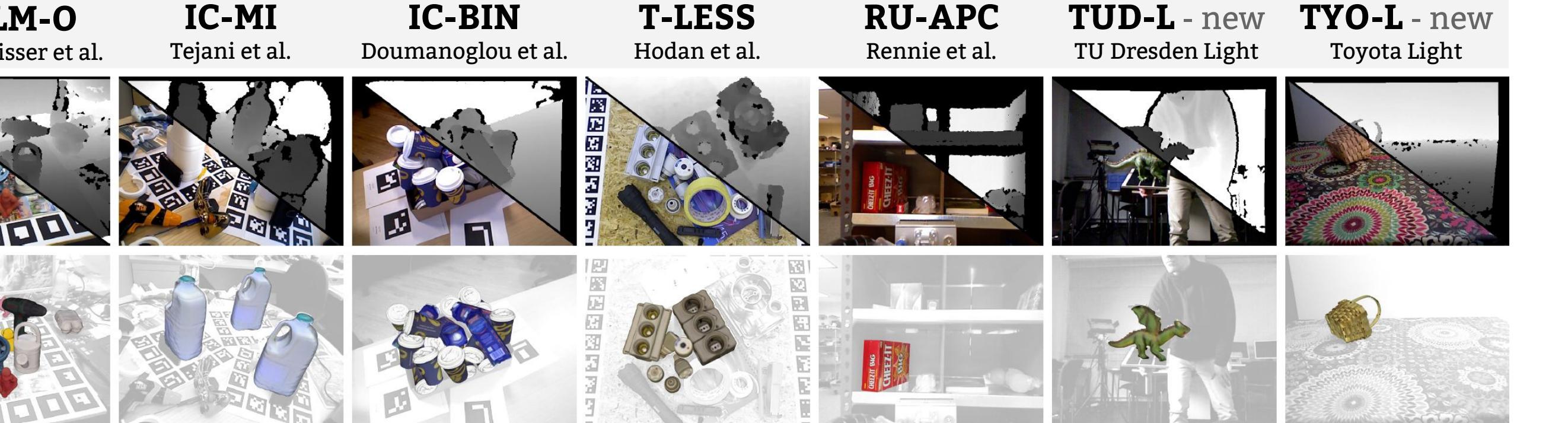
## BOP includes 8 datasets in a unified format with quality GT

- Texture-mapped 3D models of 89 diverse objects
- 277K training RGB-D images showing isolated objects (mostly synthetic)
- 62K test RGB-D images of scenes with graded complexity
- High-quality ground-truth 6D object poses for all images
- Six publicly available datasets, some reduced and re-annotated
- Two new datasets focusing on varying lighting conditions

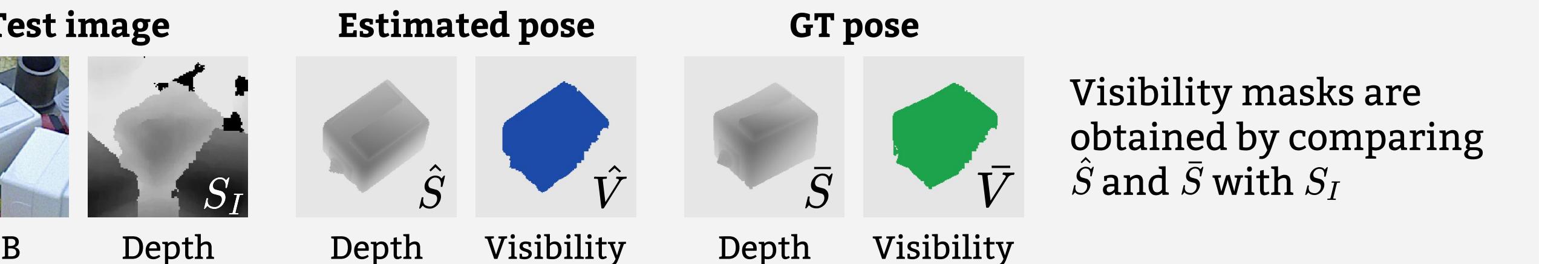


TUD-L

## Test images cover different application scenarios

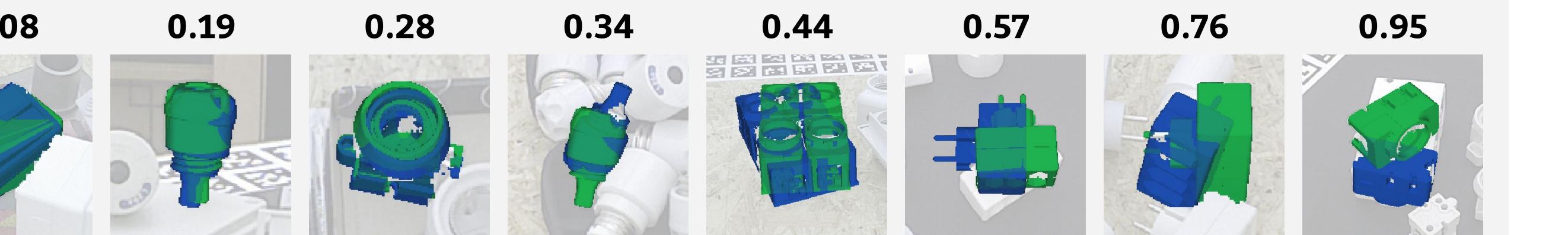


## Pose error measured by Visible Surface Discrepancy (VSD)



$$e_{\text{VSD}}(\hat{S}, \bar{S}, S_I, \hat{V}, \bar{V}, \tau) = \operatorname{avg}_{p \in \hat{V} \cup \bar{V}} \begin{cases} 0 & \text{if } p \in \hat{V} \cap \bar{V} \wedge |\hat{S}(p) - \bar{S}(p)| < \tau \\ 1 & \text{otherwise} \end{cases}$$

- Estimated pose considered correct if  $e_{\text{VSD}} < \theta$
- Pose error is calculated only over the visible part of the surface  
⇒ Indistinguishable poses are treated as equivalent



Values of  $e_{\text{VSD}}$  for example pose estimates, in blue, the GT in green

## Experimental setup

- The methods were evaluated by their authors
- Parameters of each method were fixed for all objects and datasets
- Test defined by a pair  $(I, o)$ , image  $I$  shows at least one instance of object  $o$
- The performance was measured by recall, i.e. the fraction of tests for which a correct object pose was estimated, with misalignment tolerance  $\tau = 20$  mm and correctness threshold  $\theta = 0.3$

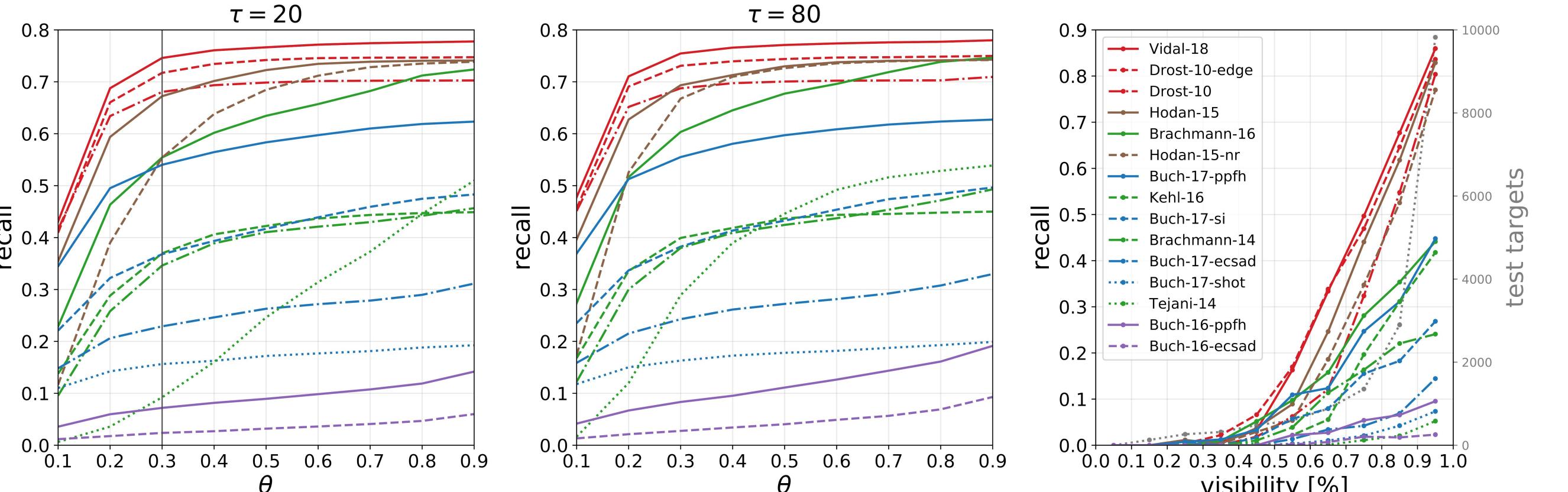
## Online evaluation system: [bop.felk.cvut.cz](http://bop.felk.cvut.cz)

Up-to-date leaderboards + a form for submission of new results

### Evaluation of 15 recent methods

- 1) Methods based on point pair features, 2) Template matching methods,
- 3) Learning-based methods, 4) Methods based on 3D local features

# Method	LM	LM-O	IC-MI	IC-BIN	T-LESS	RU-APC	TUD-L	Average	Time (s)
1. Vidal-18	87.83	59.31	95.33	96.50	66.51	36.52	80.17	74.60	4.7
2. Drost-10-edge	79.13	54.95	94.00	92.00	67.50	27.17	87.33	71.73	21.5
3. Drost-10	82.00	55.36	94.33	87.00	56.81	22.25	78.67	68.06	2.3
4. Hodan-15	87.10	51.42	95.33	90.50	63.18	37.61	45.50	67.23	13.5
5. Brachmann-16	75.33	52.04	73.33	56.50	17.84	24.35	88.67	55.44	4.4
6. Hodan-15-nopso	69.83	34.39	84.67	76.00	62.70	32.39	27.83	55.40	12.3
7. Buch-17-ppfh	56.60	36.96	95.00	75.00	25.10	20.80	68.67	54.02	14.2
8. Kehl-16	58.20	33.91	65.00	44.00	24.60	25.58	7.50	36.97	1.8
9. Buch-17-si	33.33	20.35	67.33	59.00	13.34	23.12	41.17	36.81	15.9
10. Brachmann-14	67.60	41.52	78.67	24.00	0.25	30.22	0.00	34.61	1.4
11. Buch-17-ecsd	13.27	9.62	40.67	59.00	7.16	6.59	24.00	22.90	5.9
12. Buch-17-shot	5.97	1.45	43.00	38.50	3.83	0.07	16.67	15.64	6.7
13. Tejani-14	12.10	4.50	36.33	10.00	0.13	1.52	0.00	9.23	1.4
14. Buch-16-ppfh	8.13	2.28	20.00	2.50	7.81	8.99	0.67	7.20	47.1
15. Buch-16-ecsd	3.70	0.97	3.67	4.00	1.24	2.90	0.17	2.38	39.1



- Poses estimated by most methods are either of a high quality or totally off – the scores increase only slightly if  $\tau$  is increased from 20 to 80 mm, or if  $\theta > 0.3$
- Occlusion is a big challenge for current methods – all methods perform on LM by at least 30% better than on LM-O, which includes the same but occluded objects
- Object symmetries and similarities of the T-LESS objects cause problems to methods based on 3D local features and learning-based methods
- Varying lighting conditions present a challenge for methods that rely on synthetic training RGB images rendered with fixed lighting
- Noisy depth images in RU-APC present problems to all methods
- Methods were optimized primarily for recall, not for speed