BOP Challenge 2019

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Jiří Matas, CTU in Prague
Carsten Rother, Heidelberg Uni

5th International Workshop on Recovering 6D Object Pose
ICCV 2019, October 28, Seoul, Korea

Throwback to BOP'18

Hodaň, Michel et al., BOP: Benchmark for 6D Object Pose Estimation, ECCV 2018

Goal: To capture SOTA in 6D object pose estimation in RGB-D images.

The SiSo task: 6D localization of a **Single instance** of a **Single object**,
at least one instance of the object is guaranteed to be visible in the image.

Evaluation: Visible Surface Discrepancy (VSD).

Results: Methods based on Point Pair Features (PPF) perform best.

#	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-ecsad	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-ecsad	3.70	0.97	3.67	4.00	1.24	2.90	0.17	2.38	39.1

Methods based on point pair features, Template matching methods,
Learning-based methods, Methods based on 3D local features

The ViVo task for BOP'19

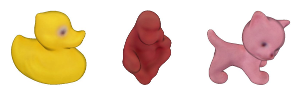
6D localization of a V**arying number of** i**nstances** of a V**arying number of** o**bjects** in a single RGB-D image, the number of instances is known.

The ViVo task for BOP'19

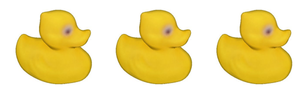
6D localization of a **Varying number of instances** of a **Varying number of objects** in a single RGB-D image, the number of instances is known.

6D localization - A list of instances to localize provided with the image.

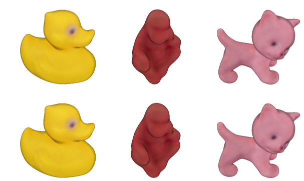
SiSo
a single instance
of a single object



SiMo
a single instance
of multiple objects



MiSo
multiple instances
of a single object



MiMo
multiple instances
of multiple objects

The ViVo task for BOP’19

6D localization of a **Varying number of instances** of a **Varying number of objects** in a single RGB-D image, the number of instances is known.

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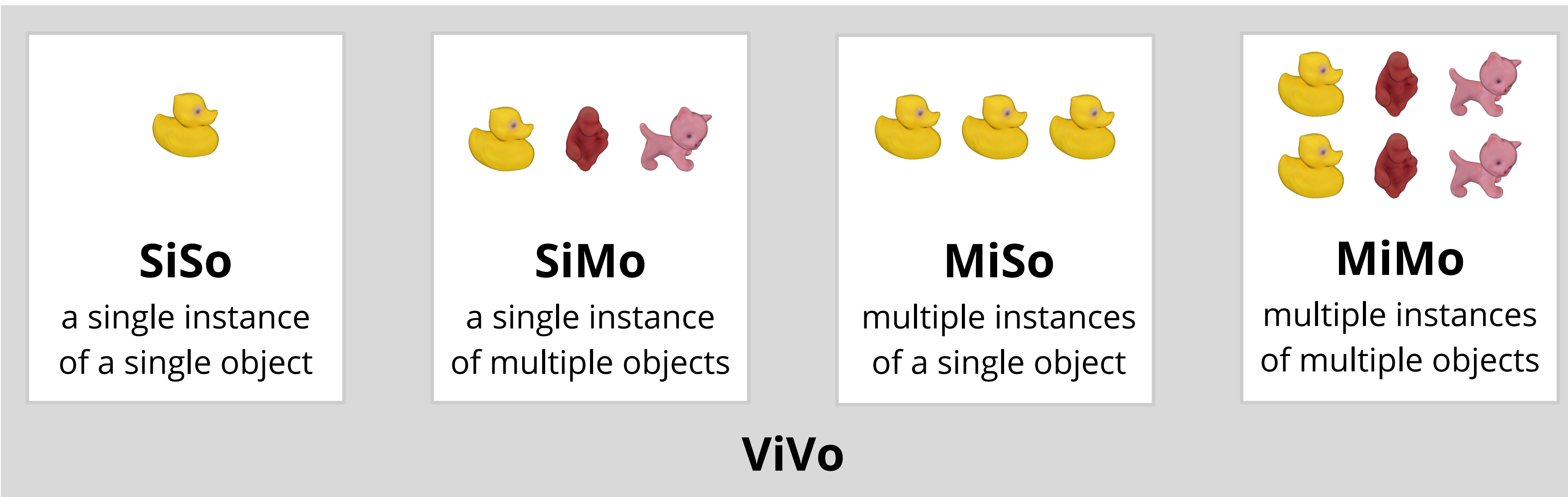

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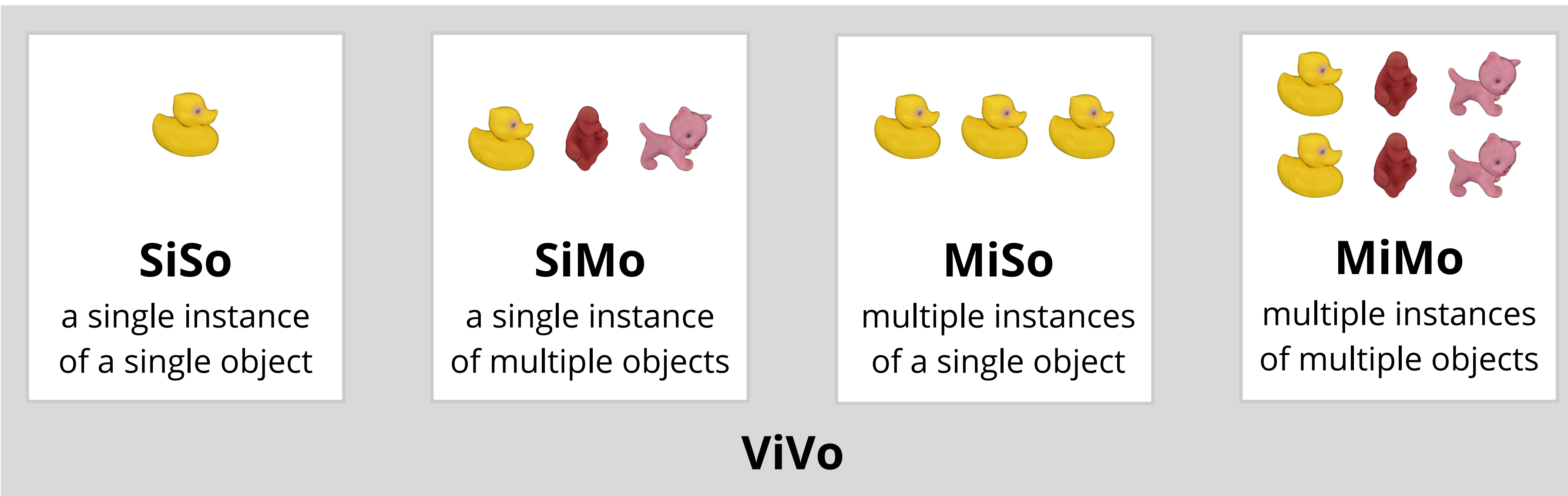
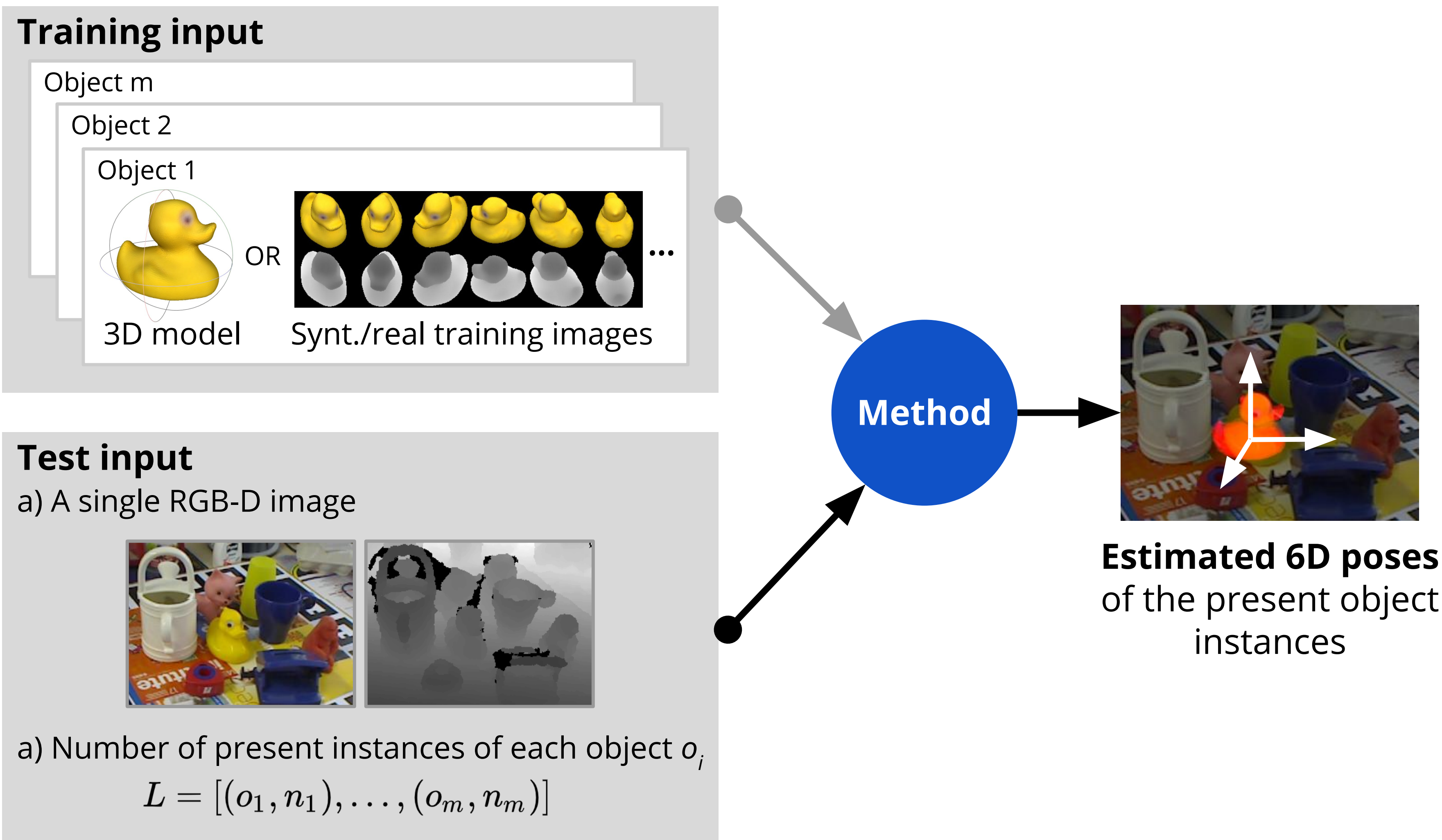


6D detection (not tested in BOP'19) - The number of instances unknown.

Practical limitation - computationally expensive evaluation as many more hypotheses need to be evaluated to calculate the precision/recall curve.

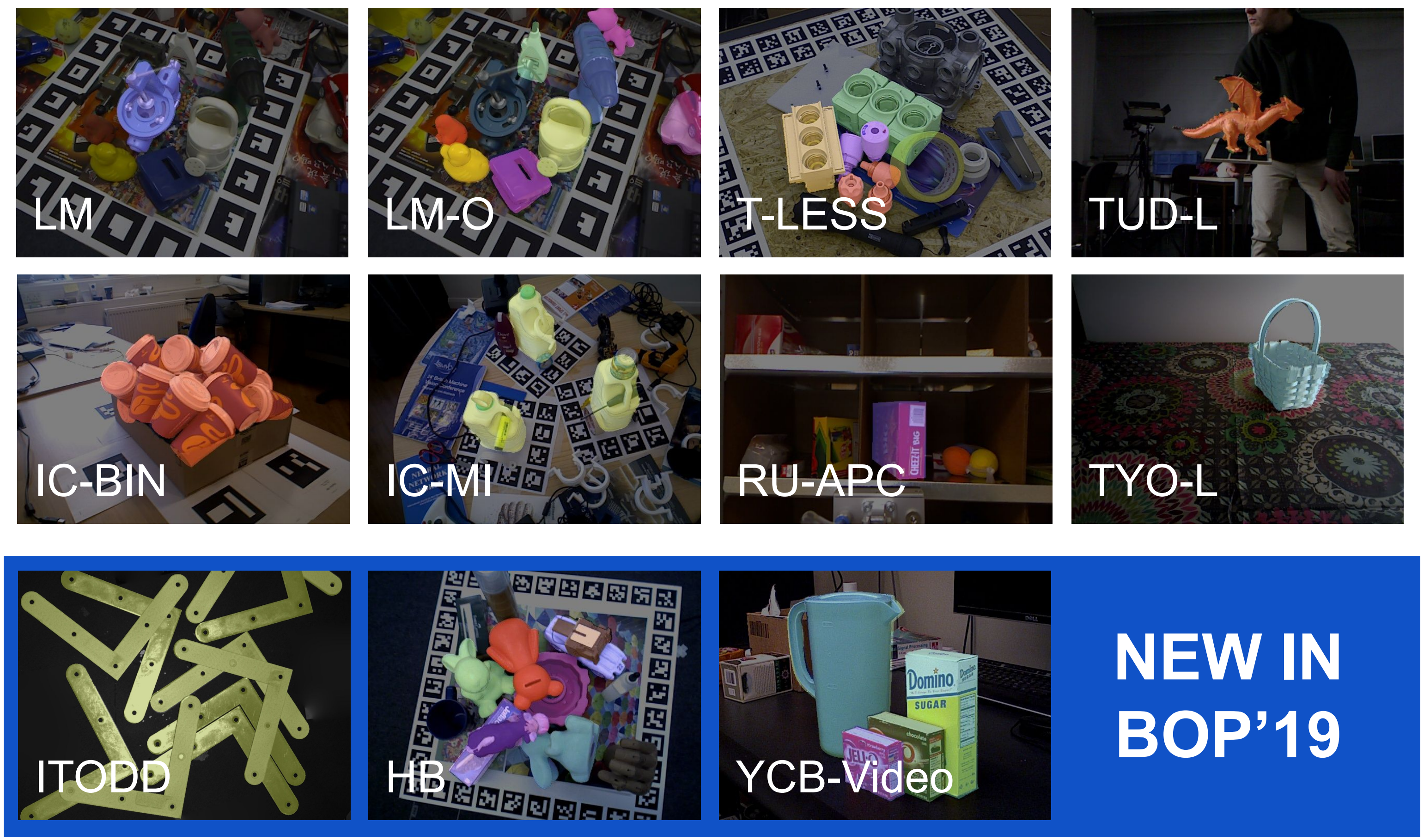
The ViVo task for BOP'19

6D localization of a **Varying number of instances** of a **Varying number of objects** in a single RGB-D image, the number of instances is known.



11 datasets in a unified format

- Texture-mapped 3D models of **171 objects.**
- **>350K training RGB-D images** (mostly synthetic of isolated objects).
- **>100K test RGB-D images** of scenes with graded complexity.
- Images annotated with **ground-truth 6D object poses.**



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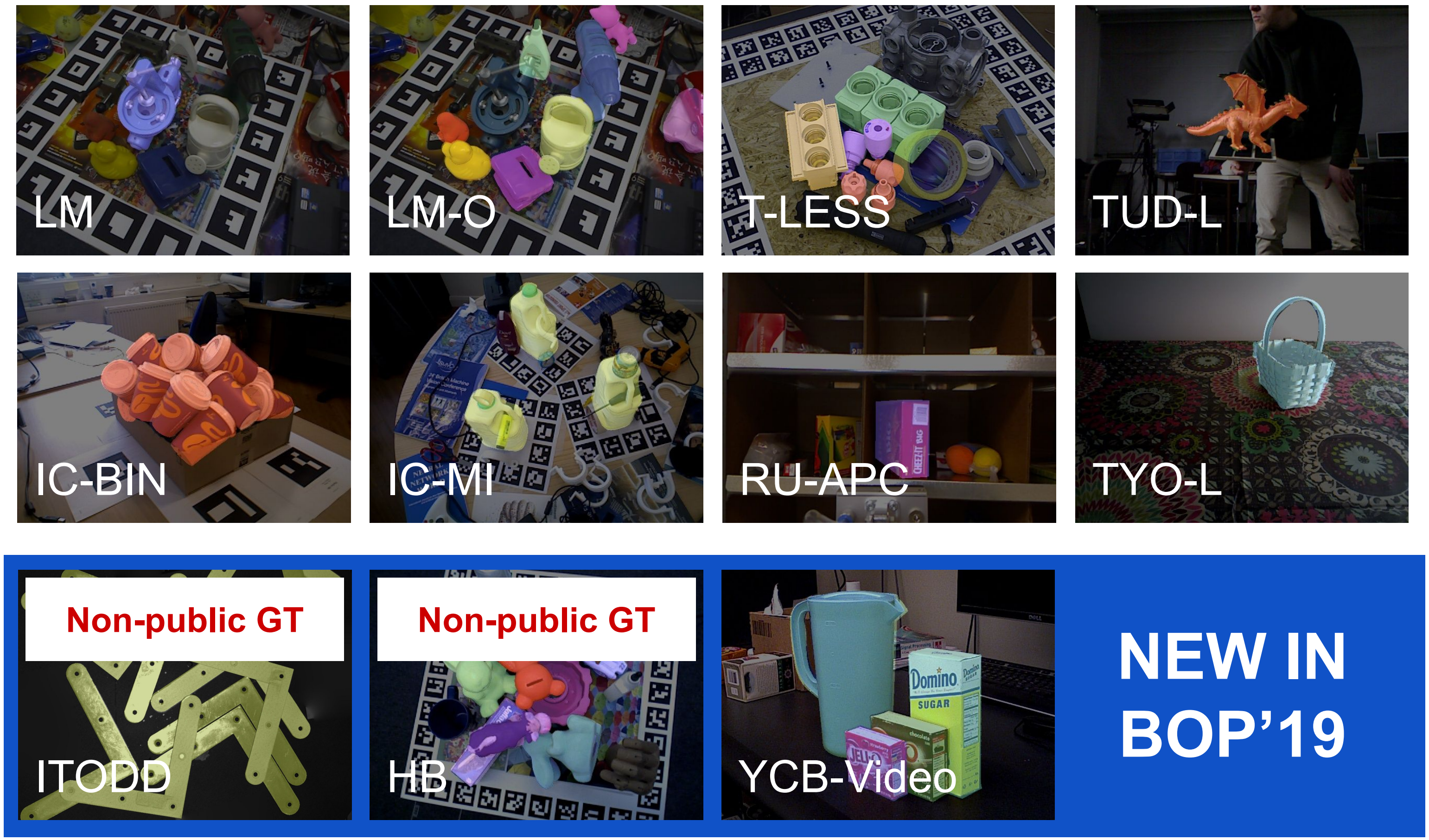
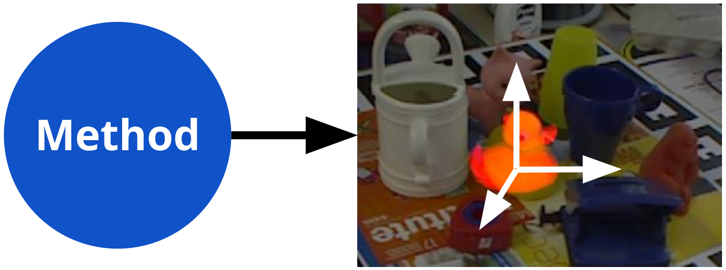
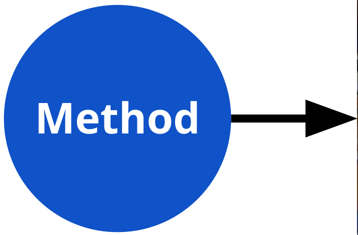


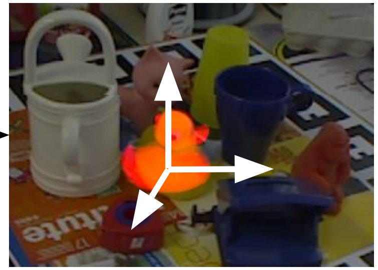
Pose error functions



Estimated pose

Pose error functions





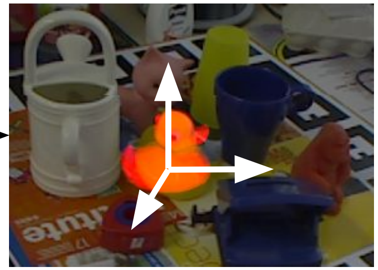
Estimated pose

GT pose

How good is the estimated pose?

Pose error functions

Method



Estimated pose

GT pose

How good is the estimated pose?

The error of an estimated pose w.r.t. the GT pose is measured by **three pose error functions**:

1. **VSD:** Visible Surface Discrepancy
2. **MSSD:** Maximum Symmetry-Aware Surface Distance
3. **MSPD:** Maximum Symmetry-Aware Projection Distance

VSD: Visible Surface Discrepancy

Test image

RGB

Depth

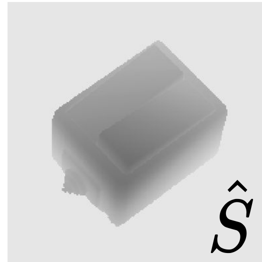
VSD: Visible Surface Discrepancy

Test image

RGB

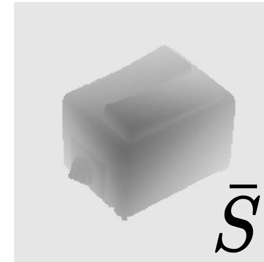
Depth

Estimated pose



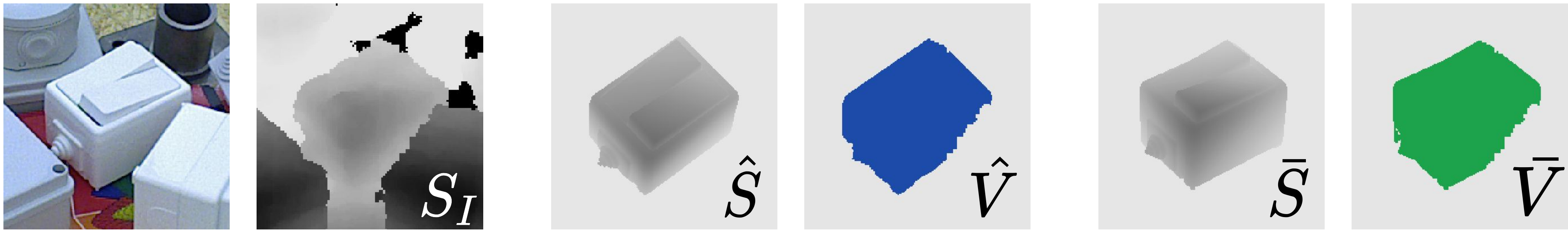
Depth

GT pose



Depth

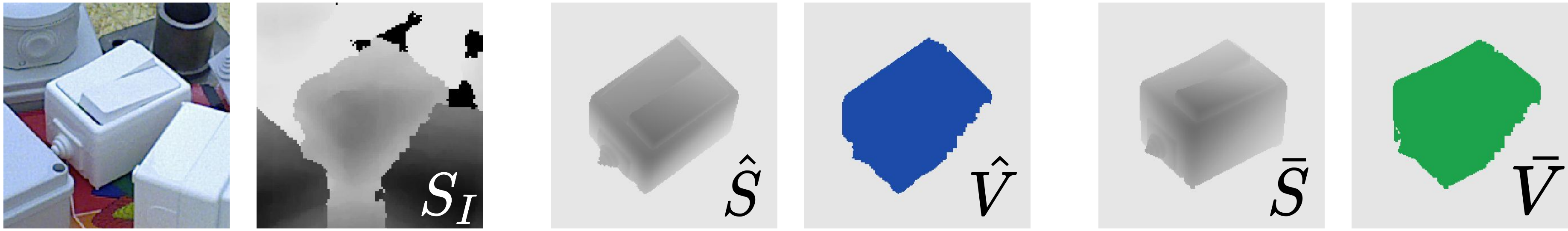
VSD: Visible Surface Discrepancy



Visibility masks are obtained by comparing $\hat{S}$ and $\bar{S}$ with S_I

VSD: Visible Surface Discrepancy

Test image | **Estimated pose** | **GT pose**



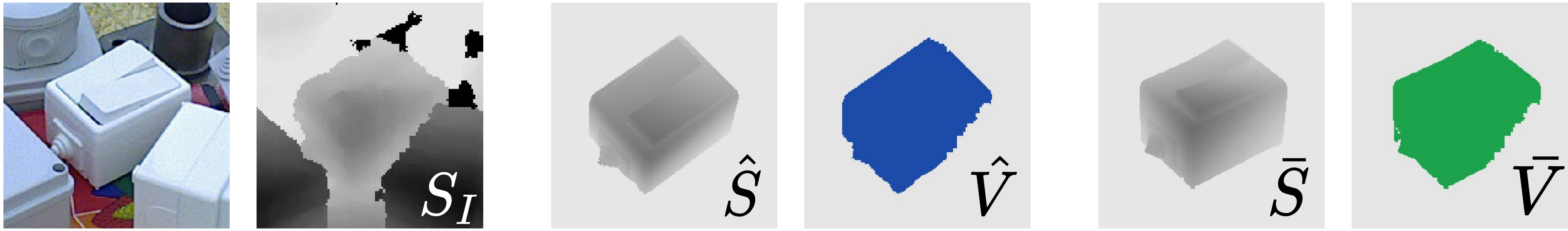
RGB | Depth | Depth | Visibility | Depth | Visibility

Visibility masks are obtained by comparing $\hat{S}$ and $\bar{S}$ with S_I

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

VSD: Visible Surface Discrepancy

Test image | **Estimated pose** | **GT pose**



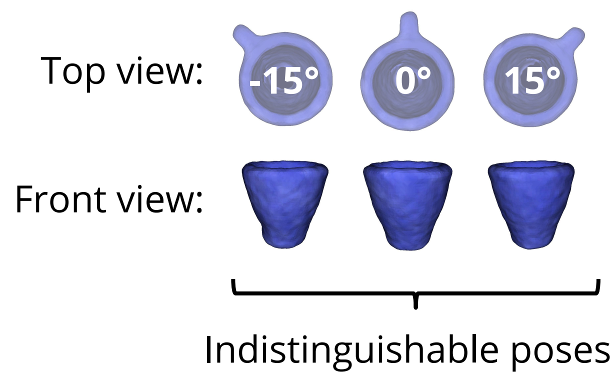
RGB | Depth | Depth | Visibility | Depth | Visibility

Visibility masks are obtained by comparing $\hat{S}$ and $\bar{S}$ with S_I

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

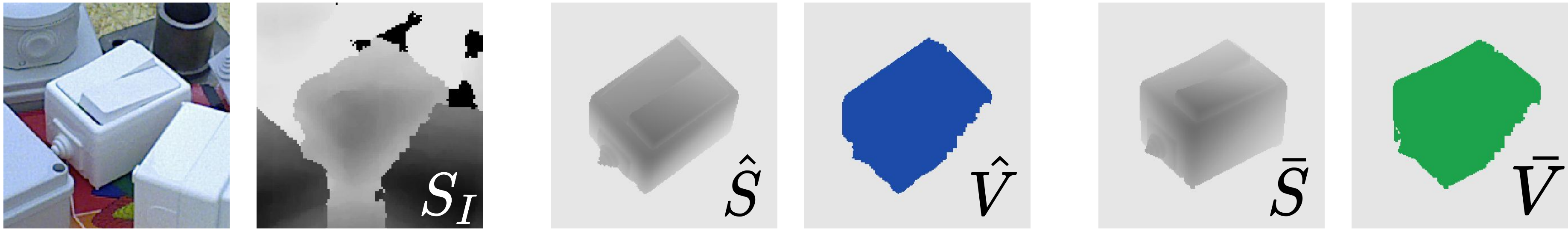
Pose error is calculated over the visible part

⇒ **indistinguishable poses are equivalent.**



VSD: Visible Surface Discrepancy

Test image | **Estimated pose** | **GT pose**



RGB | Depth | Depth | Visibility | Depth | Visibility

Visibility masks are obtained by comparing $\hat{S}$ and $\bar{S}$ with S_I

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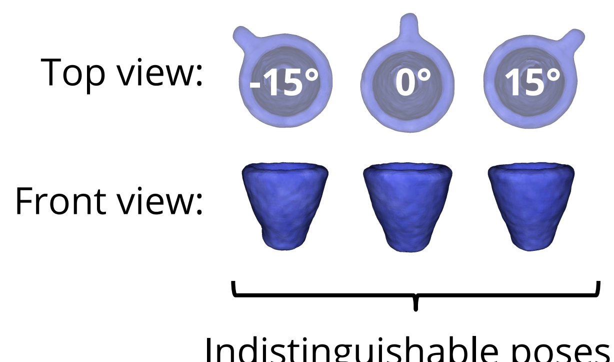
⇒ **indistinguishable poses are equivalent.**



Color not considered.

MSSD: Maximum Symmetry-Aware Surface Distance

Vertices of 3D object model

$$e_{\mathrm{MSSD}} = \min_{\mathbf{S} \in S_O} \max_{\mathbf{x} \in O} \|\hat{\mathbf{P}}\mathbf{x} - \bar{\mathbf{P}}\mathbf{S}\mathbf{x}\|_2$$

A set of symmetry transformations

Est. pose

GT pose

Max is **less dependent on sampling** of the model surface (avg. in ADD/ADI [Hinterstoisser'12] is dominated by finer parts).

Max strongly indicates **the chance of a successful grasp.**

Symmetric and **asymmetric** objects treated in the same way.

Only pose ambiguities induced by the global object symmetries are considered, not pose ambiguities induced by **occlusion/self-occlusion**.

MSPD: Maximum Symmetry-Aware Projection Dist.

Vertices of
3D object model

$$e_{\mathrm{MSPD}} = \min_{\mathbf{S} \in S_O} \max_{\mathbf{x} \in O} \left\| \operatorname{proj}\left(\hat{\mathbf{P}}\mathbf{x}\right) - \operatorname{proj}\left(\bar{\mathbf{P}}\mathbf{S}\mathbf{x}\right) \right\|_2$$

A set of symmetry transformations

Est. pose

GT pose

Max is **less dependent on sampling** of the model surface (avg. in “2D Projection” [Brachmann’16] is dominated by finer parts).

Measures **the perceivable discrepancy** (not misalignment along Z)
⇒ Suitable for **AR applications** and evaluation of **RGB-only methods.**

Only pose ambiguities induced by the global object symmetries are considered, not pose ambiguities induced by **occlusion/self-occlusion**.

Identifying object symmetries

The set of **potential** symmetry transformations:

$$S'_O = \{\mathbf{S} : h(O, \mathbf{S}O) < \varepsilon\} \qquad \varepsilon = \max\left(0.1d, 15\,mm\right)$$

Hausdorff distance

Vertices of 3D object model

Object diameter

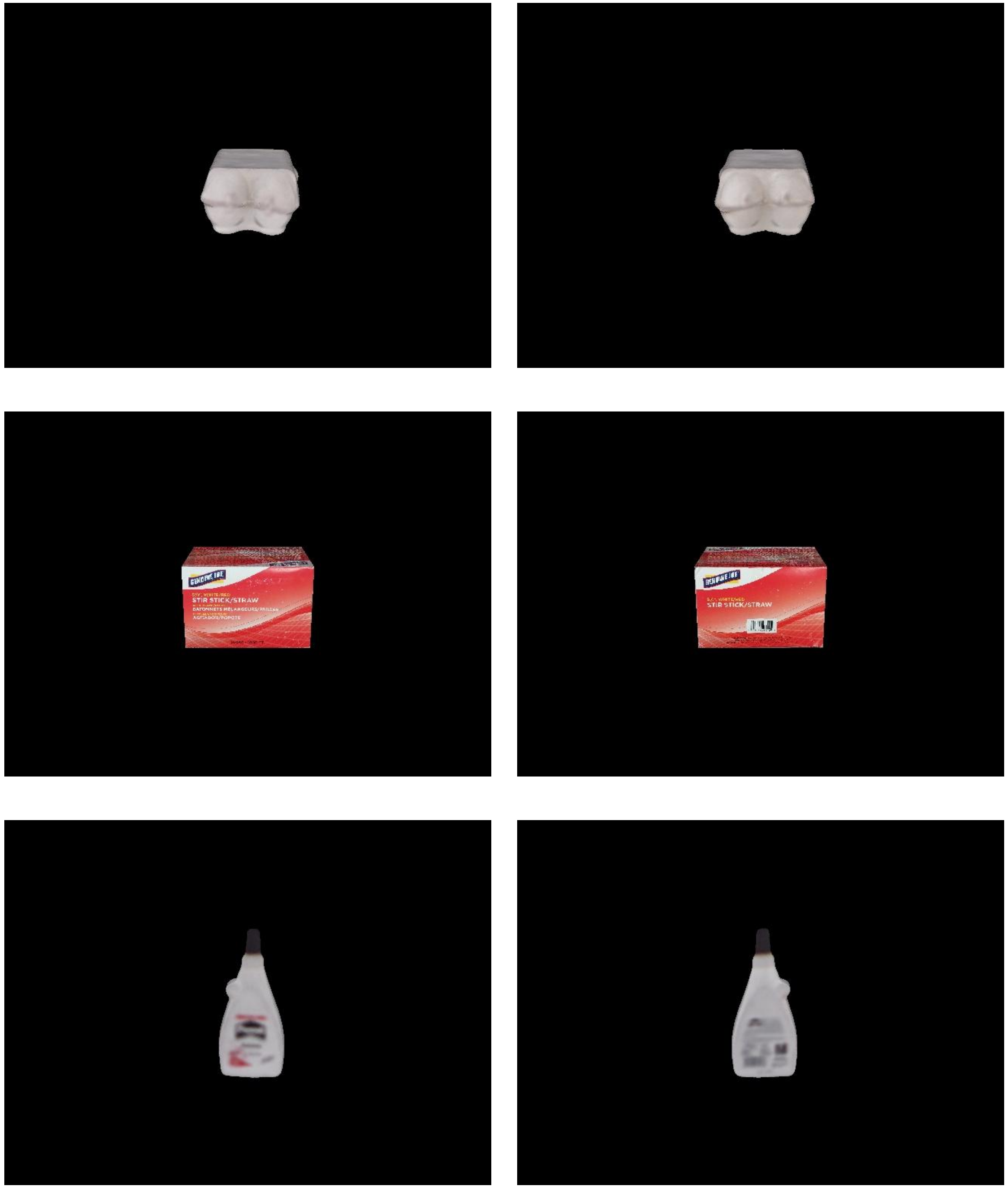
Avoids breaking the symmetries by too small details

Includes **discrete** and **continuous rotational symmetries.**

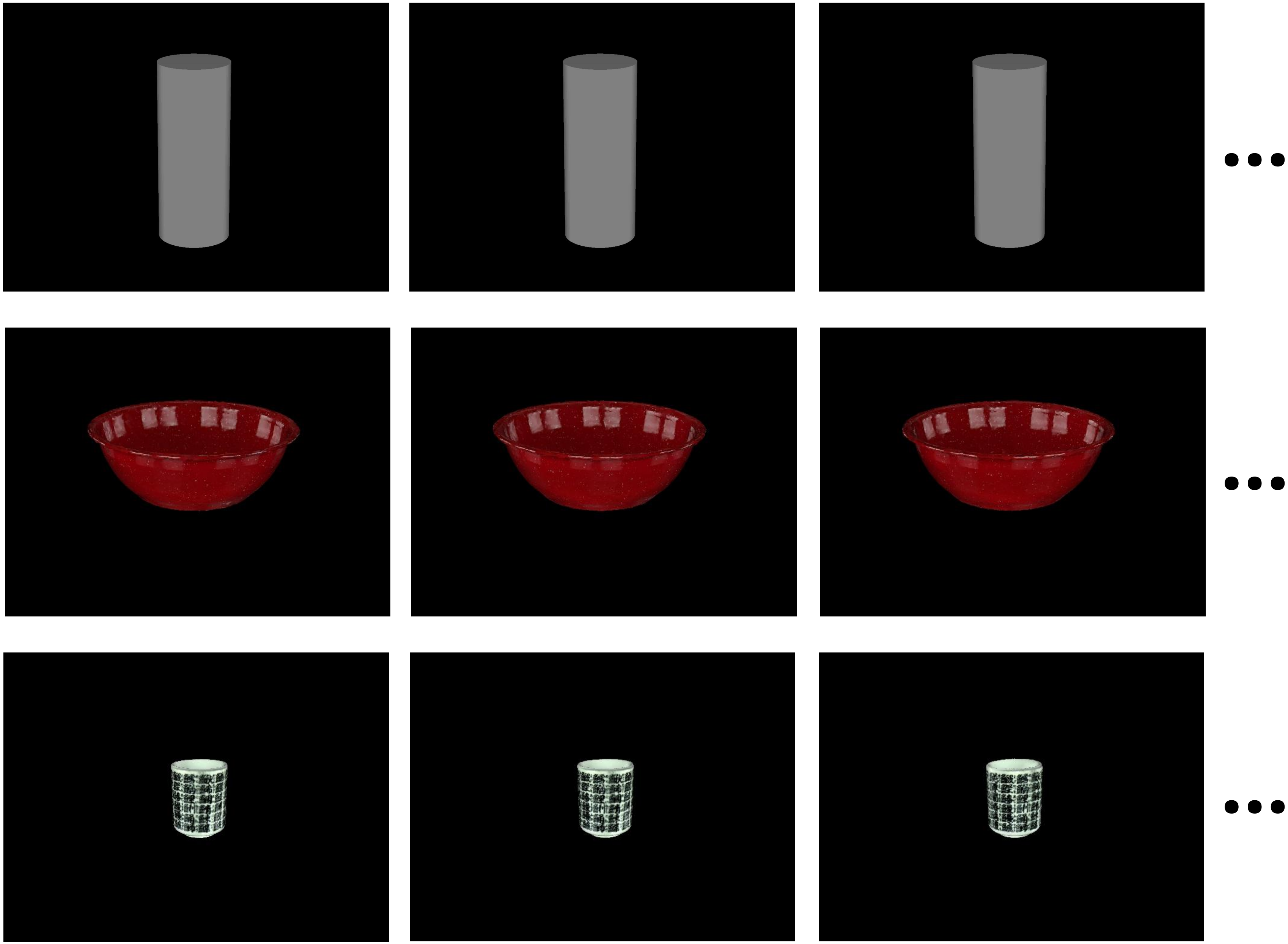
The **continuous rotational symmetries are discretized** such as the vertex which is the furthest from the rotational axis travels not more than 1% of the object diameter.

The final set of symmetry transformations S_O (used in MSSD and MSPD) is a subset of S'_O and consists of those transformations which **cannot be resolved by the model texture** (decided subjectively).

Examples of identified discrete symmetries



Examples of identified continuous symmetries



Performance score

BOP'18:

- Performance measured by **recall**, i.e. the fraction of object instances with correctly estimated pose.
- Pose estimate *P* is **considered correct** if VSD(*P*) < θ = 0.3.

BOP'19:

- The performance w.r.t. each pose error function (VSD, MSSD or MSPD) measured by the **Average Recall (AR)**, i.e. the average of the recall rates calculated for multiple threshold settings.
- **The performance score on a dataset:**

$$\mathrm{AR} = (\mathrm{AR}_{\mathrm{VSD}} + \mathrm{AR}_{\mathrm{MSSD}} + \mathrm{AR}_{\mathrm{MSPD}})/3$$

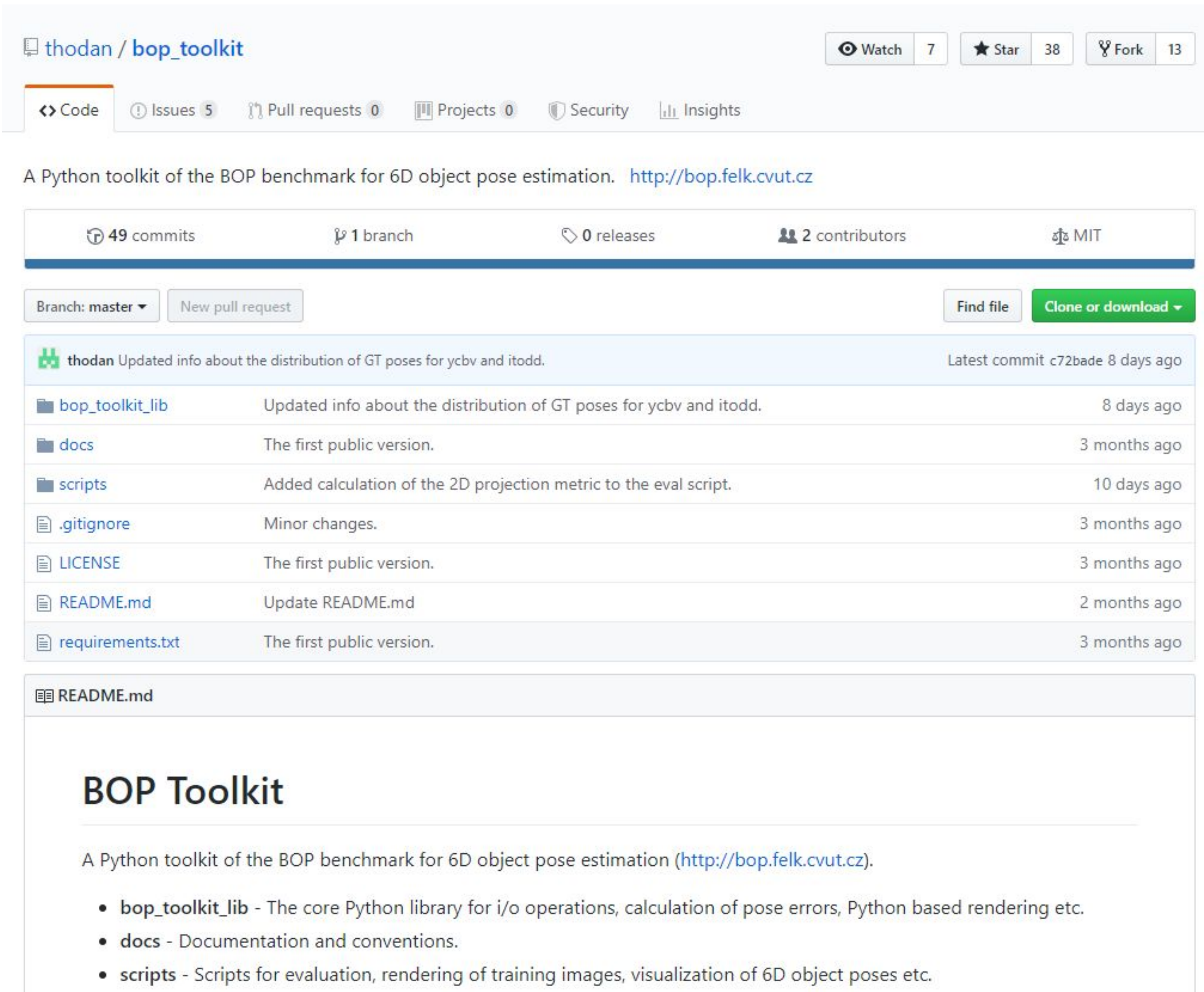
- **The overall score** is calculated as the average of the per-dataset scores ⇒ each dataset is treated as a separate sub-challenge which avoids the overall score being dominated by larger datasets.

Challenge rules

1. **For training**, a method could use the provided 3D object models and training images and could render extra training images.
2. **Not a single pixel of test images** might be used in training, nor the individual ground-truth poses.
3. **The range (not a probability distribution) of all GT poses in the test images**, is the only information about the test set which could be used during training.
4. **A fixed set of hyper-parameters** required for all objects and datasets.
5. **To be considered for the awards**, authors had to provide an implementation of the method (source code or a binary file) which was validated. Methods were not required to be public domain or open source.

BOP Toolkit

Scripts for reading the standard dataset format, rendering, evaluation etc.


thodan / bop_toolkit

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Code | Issues 5 | Pull requests 0 | Projects 0 | Security | Insights

A Python toolkit of the BOP benchmark for 6D object pose estimation. http://bop.felk.cvut.cz

49 commits | 1 branch | 0 releases | 2 contributors | MIT

Branch: master | New pull request | Find file | Clone or download

thodan Updated info about the distribution of GT poses for ycbv and itodd. Latest commit c72bade 8 days ago

bop_toolkit_lib	Updated info about the distribution of GT poses for ycbv and itodd.	8 days ago
docs	The first public version.	3 months ago
scripts	Added calculation of the 2D projection metric to the eval script.	10 days ago
.gitignore	Minor changes.	3 months ago
LICENSE	The first public version.	3 months ago
README.md	Update README.md	2 months ago
requirements.txt	The first public version.	3 months ago

README.md

BOP Toolkit

A Python toolkit of the BOP benchmark for 6D object pose estimation (http://bop.felk.cvut.cz).

- **bop_toolkit_lib** - The core Python library for i/o operations, calculation of pose errors, Python based rendering etc.
- **docs** - Documentation and conventions.
- **scripts** - Scripts for evaluation, rendering of training images, visualization of 6D object poses etc.

Online evaluation system at bop.felk.cvut.cz

BOP: Benchmark for 6D Object Pose Estimation

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BOP Challenge 2019: Core datasets LM LM-O T-LESS ITODD HB YCB-V RU-APC IC-BIN IC-MI TUD-L TYO-L

BOP Challenge 2019 – core datasets

This leaderbord shows overall ranking on the core datasets (LM-O, T-LESS, TUD-L, IC-BIN, ITODD, HB, YCB-V). The date of the latest considered submission is reported. If more submissions of a method are available for a dataset, the submission with the best AR score is considered. The performance scores are defined in the challenge description. The reported time is the average of the per-image average estimation times for the core datasets.

Show 50 entries Search:

	Date (UTC)	Method	Test image	AR_{Core}	$AR_{LM\text{-}O}$	$AR_{T\text{-}LESS}$	$AR_{TUD\text{-}L}$	$AR_{IC\text{-}BIN}$	AR_{ITODD}	AR_{HB}	$AR_{YCB\text{-}V}$	Time (s)
1	2019-10-22 07:57	Vidal-Sensors18	D	0.546	0.582	0.466	0.876	0.379	0.398	0.690	0.435	3.220
2	2019-08-22 06:12	Drost-CVPR10-Edges	RGB-D	0.530	0.515	0.436	0.851	0.354	0.529	0.660	0.368	87.568
3	2019-08-21 06:09	Drost-CVPR10-3D-Edges	D	0.483	0.469	0.354	0.852	0.360	0.428	0.612	0.309	80.055
4	2019-08-20 09:54	Drost-CVPR10-3D-Only	D	0.470	0.527	0.382	0.775	0.374	0.295	0.606	0.332	7.704
5	2019-10-17 07:05	Drost-CVPR10-3D-Only-Faster	D	0.438	0.492	0.347	0.696	0.363	0.254	0.596	0.318	1.383
6	2019-10-22 05:31	Félix&Neves-ICRA2017-IET2019	RGB-D	0.405	0.394	0.192	0.851	0.311	0.065	0.526	0.498	55.780
7	2019-10-22 10:16	Sundermeyer-IJCV19+ICP	RGB-D	0.383	0.237	0.414	0.614	0.271	0.145	0.505	0.498	0.865
8	2019-10-22 04:59	Zhigang-CDPN-ICCV19	RGB	0.346	0.374	0.090	0.757	0.248	0.065	0.470	0.418	0.513
9	2019-10-22 06:48	Sundermeyer-IJCV19	RGB	0.259	0.146	0.251	0.401	0.209	0.090	0.346	0.371	0.186
10	2019-10-14 21:44	Pix2Pose-BOP-ICCV19	RGB	0.197	0.077	0.234	0.349	0.207	0.027	0.199	0.284	0.793
11	2019-10-13 11:22	DPOD (synthetic)	RGB	0.159	0.169	0.070	0.242	0.125	0.000	0.285	0.222	0.231
12	2019-10-14 22:29	Pix2Pose-Original-ICCV19	RGB			0.249						1.522
13	2019-10-16 18:17	gao-cloudpose19	D		0.208						0.569	
14	2019-10-17 09:33	gao-cloudpose19plus	D		0.510							
15	2019-10-18 20:38	Pix2Pose-BOP_w/ICP-ICCV19	RGB-D					0.362			0.668	2.222

Online evaluation system at bop.felk.cvut.cz

BOP: Benchmark for 6D Object Pose Estimation

HOME | CHALLENGES | DATASETS | LEADERBOARDS | SUBMIT RESULTS | Sign in

BOP Challenge 2019: Core datasets | LM | LM-O | T-LESS | ITODD | HB | YCB-V | RU-APC | IC-BIN | IC-MI | TUD-L | TYO-L

BOP Challenge 2019 – core datasets

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Submission deadline: October 21, 2019

Show 50 entries | Search:

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3	2019-08-21 06:09	Drost-CVPR10-3D-Edges	D	0.483	0.469	0.354	0.852	0.360	0.428	0.612	0.309	80.055
4	2019-08-20 09:54	Drost-CVPR10-3D-Only	D	0.470	0.527	0.382	0.775	0.374	0.295	0.606	0.332	7.704
5	2019-10-17 07:05	Drost-CVPR10-3D-Only-Faster	D	0.438	0.492	0.347	0.696	0.363	0.254	0.596	0.318	1.383
6	2019-10-22 05:31	Félix&Neves-ICRA2017-IET2019	RGB-D	0.405	0.394	0.192	0.851	0.311	0.065	0.526	0.498	55.780
7	2019-10-22 10:16	Sundermeyer-IJCV19+ICP	RGB-D	0.383	0.237	0.414	0.614	0.271	0.145	0.505	0.498	0.865
8	2019-10-22 04:59	Zhigang-CDPN-ICCV19	RGB	0.346	0.374	0.090	0.757	0.248	0.065	0.470	0.418	0.513
9	2019-10-22 06:48	Sundermeyer-IJCV19	RGB	0.259	0.146	0.251	0.401	0.209	0.090	0.346	0.371	0.186
10	2019-10-14 21:44	Pix2Pose-BOP-ICCV19	RGB	0.197	0.077	0.234	0.349	0.207	0.027	0.199	0.284	0.793
11	2019-10-13 11:22	DPOD (synthetic)	RGB	0.159	0.169	0.070	0.242	0.125	0.000	0.285	0.222	0.231
12	2019-10-14 22:29	Pix2Pose-Original-ICCV19	RGB			0.249						1.522
13	2019-10-16 18:17	gao-cloudpose19	D		0.208						0.569	
14	2019-10-17 09:33	gao-cloudpose19plus	D		0.510							
15	2019-10-18 20:38	Pix2Pose-BOP_w/ICP-ICCV19	RGB-D					0.362			0.668	2.222

Online evaluation system at bop.felk.cvut.cz

BOP: Benchmark for 6D Object Pose Estimation

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BOP Challenge 2019: Core datasets LM LM-O T-LESS ITODD HB YCB-V RU-APC IC-BIN IC-MI TUD-L TYO-L

BOP Challenge 2019 – core datasets

This lea[illegible] shows overall ranking on the core datasets (LM-O, T-LESS, TUD-L, IC-BIN, ITODD, HB, YCB-V). The d[illegible] of th[illegible] latest conside[illegible] submission [illegible] submiss[illegible] defin[illegible] in the challenge description. The reported time is the average of the per-image average estimation times for the core datasets.

Submission deadline: October 21, 2019

Show 50 entries Search:

	Date (UTC)	Method	Test image	AR_{Core}	AR_{LM-O}	AR_{T-LESS}	AR_{TUD-L}	AR_{IC-BIN}	AR_{ITODD}	AR_{HB}	AR_{YCB-V}	Time (s)
1	2019-10-22 07:57	Vidal-Sensors18	D	0.546	0.582	0.466	0.876	0.379	0.398	0.690	0.435	3.220
2	2019-08-22 06:12	Drost-CVPR10-Edges	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	0.354	0.529	0.660	0.368	87.568
3	2019-08-21 06:09	Drost-CVPR10-3D-Edges	D	0.483	0.469	0.354	0.852	0.360	0.428	0.612	0.309	80.055
4	[illegible]	[illegible]	D	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
5	2019-10-17 07:05	Drost-CVPR10-3D-Only-Faster	D	0.438	0.492	0.347	0.696	0.363	0.254	0.596	0.318	1.383
6	2019-10-22 05:31	Félix&Neves-ICRA2017-IET2019	RGB-D	0.405	0.394	0.192	0.851	0.311	0.065	0.526	0.498	55.780
7	2019-10-22 10:16	Sundermeyer-IJCV19+ICP	RGB-D	0.383	0.237	0.414	0.614	0.271	0.145	0.505	0.498	0.865
8	2019-10-22 04:59	Zhigang-CDPN-ICCV19	RGB	0.346	0.374	0.090	0.757	0.248	0.065	0.470	0.418	0.513
9	2019-10-22 06:48	Sundermeyer-IJCV19	RGB	0.259	0.146	0.251	0.401	0.209	0.090	0.346	0.371	0.186
10	2019-10-14 21:44	Pix2Pose-BOP-ICCV19	RGB	0.197	0.077	0.234	0.349	0.207	0.027	0.199	0.284	0.793
11	2019-10-13 11:22	DPOD (synthetic)	RGB	0.159	0.169	0.070	0.242	0.125	0.000	0.285	0.222	0.231
12	2019-10-14 22:29	Pix2Pose-Original-ICCV19	RGB			0.249						1.522
13	2019-10-16 18:17	gao-cloudpose19	D		0.208						0.569	
14	2019-10-17 09:33	gao-cloudpose19plus	D		0.510							
15	2019-10-18 20:38	Pix2Pose-BOP_w/ICP-ICCV19	RGB-D					0.362			0.668	2.222

197 submission

(one submission = results of one method on one dataset)

Online evaluation system at bop.felk.cvut.cz

BOP: Benchmark for 6D Object Pose Estimation

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BOP Challenge 2019: Core datasets | LM | LM-O | T-LESS | ITODD | HB | YCB-V | RU-APC | IC-BIN | IC-MI | TUD-L | TYO-L

BOP Challenge 2019 – core datasets

Submission deadline: October 21, 2019

reported time is the average of the per-image average estimation times for the core datasets.

Show 50 entries   Search:

	Date (UTC)	Method	Test image	AR_{Core}	$AR_{LM\text{-}O}$	$AR_{T\text{-}LESS}$	$AR_{TUD\text{-}L}$	$AR_{IC\text{-}BIN}$	AR_{ITODD}	AR_{HB}	$AR_{YCB\text{-}V}$	Time (s)
1	2019-10-22 07:57	Vidal-Sensors18	D	0.546	0.582	0.466	0.876	0.379	0.398	0.690	0.435	3.220
2	2019-08-22 06:12	Drost-CVPR10-Edges	D	[illegible]	[illegible]	[illegible]	[illegible]	0.354	0.529	0.660	0.368	87.568
3	2019-08-21 06:09	Drost-CVPR10-3D-Edges	D	0.483	0.469	0.354	0.852	0.360	0.428	0.612	0.309	80.055
4	[illegible]	Drost-CVPR10-3D-Only	D	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
5	2019-10-17 07:05	Drost-CVPR10-3D-Only-Faster	D	0.438	0.492	0.347	0.696	0.363	0.254	0.596	0.318	1.383
6	2019-10-22 05:31	Félix&Neves-ICRA2017-IET2019	RGB-D	0.405	0.394	0.192	0.851	0.311	0.065	0.526	0.498	55.780
7	2019-10-22 10:16	Sundermeyer-IJCV19+ICP	RGB-D	0.383	0.237	0.414	0.614	0.271	0.145	0.505	0.498	0.865
8	2019-10-22 04:59	Zhigang-CDPN-ICCV19	RGB	[illegible]	[illegible]	0.090	[illegible]	0.248	0.065	[illegible]	0.418	0.513
9	[illegible]	Sundermeyer-IJCV19	RGB	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
10	[illegible]	Pix2Pose-BOP-ICCV19	RGB	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
11	2019-10-13 11:22	DPOD (synthetic)	RGB	0.159	0.169	0.070	0.242	0.125	0.000	0.285	0.222	0.231
12	2019-10-14 22:29	Pix2Pose-Original-ICCV19	RGB			0.249						1.522
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14	2019-10-17 09:33	gao-cloudpose19plus	D		0.510							
15	2019-10-18 20:38	Pix2Pose-BOP_w/ICP-ICCV19	RGB-D					0.362			0.668	2.222

197 submission

(one submission = results of one method on one dataset)

11 methods evaluated on all 7 core datasets

(LM-O, T-LESS, TUD-L, IC-BIN, ITODD, HB, YCB-V)

Evaluation

AR score

#	Method	Image	Average	LM-O	T-LESS	TUD-L	IC-BIN	ITODD	HB	YCB-V	Time (s)
1	**Vidal-Sensors18** [1]	D	**0.569**	0.582	0.538	0.876	0.393	0.435	0.706	0.450	3.220
2	**Drost-CVPR10-Edges** [2]	RGB-D	**0.550**	0.515	0.500	0.851	0.368	0.570	0.671	0.375	87.568
3	**Drost-CVPR10-3D-Edges** [2]	D	**0.500**	0.469	0.404	0.852	0.373	0.462	0.623	0.316	80.055
4	**Drost-CVPR10-3D-Only** [2]	D	**0.487**	0.527	0.444	0.775	0.388	0.316	0.615	0.344	7.704
5	**Drost-CVPR10-3D-Only-Faster** [2]	D	**0.454**	0.492	0.405	0.696	0.377	0.274	0.603	0.330	1.383
6	**Félix&Neves-ICRA17-IET19** [3,4]	RGB-D	**0.412**	0.394	0.212	0.851	0.323	0.069	0.529	0.510	55.780
7	**Sundermeyer-IJCV19+ICP** [5]	RGB-D	**0.398**	0.237	0.487	0.614	0.281	0.158	0.506	0.505	0.865
8	**Zhigang-CDPN-ICCV19** [6]	RGB	**0.353**	0.374	0.124	0.757	0.257	0.070	0.470	0.422	0.513
9	**Sundermeyer-IJCV19** [5]	RGB	**0.270**	0.146	0.304	0.401	0.217	0.101	0.346	0.377	0.186
10	**Pix2Pose-BOP-ICCV19** [7]	RGB	**0.205**	0.077	0.275	0.349	0.215	0.032	0.200	0.290	0.793
11	**DPOD (synthetic)** [8]	RGB	**0.161**	0.169	0.081	0.242	0.130	0.000	0.286	0.222	0.231

***[1] Joel Vidal et al.**, A Method for 6D Pose Estimation of Free-Form Rigid Objects Using Point Pair Features on Range Data, Sensors 2018.*

***[2] Bertram Drost et al.**, Model globally, match locally: Efficient and robust 3D object recognition, CVPR 2010.*

***[3] Pedro Rodrigues et al.**, Deep segmentation leverages geometric pose estimation in computer-aided total knee arthroplasty, Healthcare Technology Letters 2019.*

***[4] Carolina Raposo et al.**, Using 2 point+normal sets for fast registration of point clouds with small overlap, ICRA 2017.*

***[5] Martin Sundermeyer et al.**, Augmented Autoencoders: Implicit 3D Orientation Learning for 6D Object Detection, IJCV 2019.*

***[6] Zhigang Li et al.**, CDPN: Coordinates-Based Disentangled Pose Network for Real-Time RGB-Based 6-DoF Object Pose Estimation, ICCV 2019.*

***[7] Kiru Park et al.**, Pix2Pose: Pixel-Wise Coordinate Regression of Objects for 6D Pose Estimation, ICCV 2019.*

***[8] Sergey Zakharov et al.**, DPOD: Dense 6D Pose Object Detector in RGB images, ICCV 2019.*

The scores were re-calculated on 27th January 2020.

Evaluation

AR score

#	Method	Image	Average	LM-O	T-LESS	TUD-L	IC-BIN	ITODD	HB	YCB-V	Time (s)
1	**Vidal-Sensors18** [1]	D	**0.569**	0.582	0.538	0.876	0.393	0.435	0.706	0.450	3.220
2	**Drost-CVPR10-Edges** [2]	RGB-D	**0.550**	0.515	0.500	0.851	0.368	0.570	0.671	0.375	87.568
3	**Drost-CVPR10-3D-Edges** [2]	D	**0.500**	0.469	0.404	0.852	0.373	0.462	0.623	0.316	80.055
4	**Drost-CVPR10-3D-Only** [2]	D	[illegible]	[illegible]	[illegible]	[illegible]	0.388	0.316	0.615	0.344	7.704
5	**Drost-CVPR10-3D-Only-Faster** [2]	D	**0.454**	0.492	0.405	0.696	0.377	0.274	0.603	0.330	1.383
6	**Félix&Neves-ICRA17-IET19** [3,4]	RGB-D	**0.412**	0.394	0.212	0.851	0.323	0.069	0.529	0.510	55.780
7	**Sundermeyer-IJCV19+ICP** [5]	RGB-D	**0.398**	0.237	0.487	0.614	0.281	0.158	0.506	0.505	0.865
8	**Zhigang-CDPN-ICCV19** [6]	RGB	**0.353**	0.374	0.124	0.757	0.257	0.070	0.470	0.422	0.513
9	**Sundermeyer-IJCV19** [5]	RGB	**0.270**	0.146	0.304	0.401	0.217	0.101	0.346	0.377	0.186
10	**Pix2Pose-BOP-ICCV19** [7]	RGB	**0.205**	0.077	0.275	0.349	0.215	0.032	0.200	0.290	0.793
11	**DPOD (synthetic)** [8]	RGB	**0.161**	0.169	0.081	0.242	0.130	0.000	0.286	0.222	0.231

Methods using depth

***[1] Joel Vidal et al.**, A Method for 6D Pose Estimation of Free-Form Rigid Objects Using Point Pair Features on Range Data, Sensors 2018.*

***[2] Bertram Drost et al.**, Model globally, match locally: Efficient and robust 3D object recognition, CVPR 2010.*

***[3] Pedro Rodrigues et al.**, Deep segmentation leverages geometric pose estimation in computer-aided total knee arthroplasty, Healthcare Technology Letters 2019.*

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***[5] Martin Sundermeyer et al.**, Augmented Autoencoders: Implicit 3D Orientation Learning for 6D Object Detection, IJCV 2019.*

***[6] Zhigang Li et al.**, CDPN: Coordinates-Based Disentangled Pose Network for Real-Time RGB-Based 6-DoF Object Pose Estimation, ICCV 2019.*

***[7] Kiru Park et al.**, Pix2Pose: Pixel-Wise Coordinate Regression of Objects for 6D Pose Estimation, ICCV 2019.*

***[8] Sergey Zakharov et al.**, DPOD: Dense 6D Pose Object Detector in RGB images, ICCV 2019.*

The scores were re-calculated on 27th January 2020.

Evaluation

AR score

#	Method	Image	Average	LM-O	T-LESS	TUD-L	IC-BIN	ITODD	HB	YCB-V	Time (s)
1	**Vidal-Sensors18** [1]	D	**0.569**	0.582	0.538	0.876	0.393	0.435	0.706	0.450	3.220
2	**Drost-CVPR10-Edges** [2]	RGB-D	**0.550**	0.515	0.500	0.851	0.368	0.570	0.671	0.375	87.568
3	**Drost-CVPR10-3D-Edges** [2]	D	**0.500**	0.469	0.404	0.852	0.373	0.462	0.623	0.316	80.055
4	**Drost-CVPR10-3D-Only** [2]	D	**0.487**	0.527	0.444	0.775	0.388	0.316	0.615	0.344	7.704
5	**Drost-CVPR10-3D-Only-Faster** [2]	D	**0.454**	0.492	0.405	0.696	0.377	0.274	0.603	0.330	1.383
6	**Félix&Neves-ICRA17-IET19** [3,4]	RGB-D	**0.412**	0.394	0.212	0.851	0.323	0.069	0.529	0.510	55.780
7	**Sundermeyer-IJCV19+ICP** [5]	RGB-D	**0.398**	0.237	0.487	0.614	0.281	0.158	0.506	0.505	0.865
8	**Zhigang-CDPN-ICCV19** [6]	RGB	**0.353**	0.374	0.124	0.757	0.257	0.070	0.470	0.422	0.513
9	**Sundermeyer-IJCV19** [5]	RGB	**0.270**	0.146	0.304	0.401	0.217	0.101	0.346	0.377	0.186
10	**Pix2Pose-BOP-ICCV19** [7]	RGB	**0.205**	0.077	0.275	0.349	0.215	0.032	0.200	0.290	0.793
11	**DPOD (synthetic)** [8]	RGB	**0.161**	0.169	0.081	0.242	0.130	0.000	0.286	0.222	0.231

Methods based on Point Pair Features [2]

[1] Joel Vidal et al.*, A Method for 6D Pose Estimation of Free-Form Rigid Objects Using Point Pair Features on Range Data, Sensors 2018.*

[2] Bertram Drost et al.*, Model globally, match locally: Efficient and robust 3D object recognition, CVPR 2010.*

[3] Pedro Rodrigues et al.*, Deep segmentation leverages geometric pose estimation in computer-aided total knee arthroplasty, Healthcare Technology Letters 2019.*

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[7] Kiru Park et al.*, Pix2Pose: Pixel-Wise Coordinate Regression of Objects for 6D Pose Estimation, ICCV 2019.*

[8] Sergey Zakharov et al.*, DPOD: Dense 6D Pose Object Detector in RGB images, ICCV 2019.*

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Evaluation

AR score

#	Method	Image	Average	LM-O	T-LESS	TUD-L	IC-BIN	ITODD	HB	YCB-V	Time (s)
1	**Vidal-Sensors18** [1]	D	**0.569**	0.582	0.538	0.876	0.393	0.435	0.706	0.450	3.220
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8	**Zhigang-CDPN-ICCV19** [6]	RGB	**0.353**	0.374	0.124	0.757	0.257	0.070	0.470	0.422	0.513
9	**Sundermeyer-IJCV19** [5]	RGB	**0.270**	0.146	0.304	0.401	0.217	0.101	0.346	0.377	0.186
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CNN-based methods

[1] Joel Vidal et al., *A Method for 6D Pose Estimation of Free-Form Rigid Objects Using Point Pair Features on Range Data, Sensors 2018.*

[2] Bertram Drost et al., *Model globally, match locally: Efficient and robust 3D object recognition, CVPR 2010.*

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Evaluation

AR score

#	Method	Image	Average	LM-O	T-LESS	TUD-L	IC-BIN	ITODD	HB	YCB-V	Time (s)
1	**Vidal-Sensors18** [1]	D	**0.569**	0.582	0.538	0.876	0.393	0.435	0.706	0.450	3.220
2	**Drost-CVPR10-Edges** [2]	RGB-D	**0.550**	0.515	0.500	0.851	0.368	0.570	0.671	0.375	87.568
3	**Drost-CVPR10-3D-Edges** [2]	D	**0.500**	0.469	0.404	0.852	0.373	0.462	0.623	0.316	80.055
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5	**Drost-CVPR10-3D-Only-Faster** [2]	D	**0.454**	0.492	0.405	0.696	0.377	0.274	0.603	0.330	1.383
6	**Félix&Neves-ICRA17-IET19** [3,4]	RGB-D	**0.412**	0.394	0.212	0.851	0.323	0.069	0.529	0.510	55.780
7	**Sundermeyer-IJCV19+ICP** [5]	RGB-D	**0.398**	0.237	0.487	0.614	0.281	0.158	0.506	0.505	0.865
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[8] Sergey Zakharov et al.*, DPOD: Dense 6D Pose Object Detector in RGB images, ICCV 2019.*

The scores were re-calculated on 27th January 2020.

Evaluation

AR_{MSPD} score (friendly to RGB-only methods)

#	Method	Image	Average	LM-O	T-LESS	TUD-L	IC-BIN	ITODD	HB	YCB-V	Time (s)
1	**Vidal-Sensors18** [1]	D	**0.563**	0.647	0.574	0.907	0.322	0.434	0.708	0.347	3.220
2	**Drost-CVPR10-Edges** [2]	RGB-D	**0.543**	0.569	0.518	0.881	0.293	0.596	0.670	0.275	87.568
3	**Drost-CVPR10-3D-Edges** [2]	D	**0.491**	0.511	0.420	0.872	0.294	0.478	0.626	0.233	80.055
4	**Drost-CVPR10-3D-Only** [2]	D	**0.483**	0.581	0.480	0.791	0.320	0.320	0.627	0.263	7.704
5	**Zhigang-CDPN-ICCV19** [6]	RGB	**0.448**	0.558	0.170	0.895	0.319	0.115	0.569	0.512	0.513
6	**Drost-CVPR10-3D-Only-Faster** [2]	D	**0.446**	0.542	0.436	0.709	0.305	0.275	0.611	0.244	1.383
7	**Sundermeyer-IJCV19+ICP** [5]	RGB-D	**0.431**	0.285	0.514	0.710	0.286	0.215	0.533	0.475	0.865
8	**Félix&Neves-ICRA17-IET19** [3,4]	RGB-D	**0.395**	0.430	0.213	0.889	0.251	0.073	0.523	0.384	55.780
9	**Sundermeyer-IJCV19** [5]	RGB	**0.391**	0.254	0.504	0.613	0.285	0.208	0.461	0.410	0.186
10	**Pix2Pose-BOP-ICCV19** [7]	RGB	**0.316**	0.165	0.403	0.535	0.316	0.073	0.311	0.407	0.793
11	**DPOD (synthetic)** [8]	RGB	**0.225**	0.278	0.139	0.341	0.185	0.000	0.379	0.256	0.231

[1] Joel Vidal et al., *A Method for 6D Pose Estimation of Free-Form Rigid Objects Using Point Pair Features on Range Data, Sensors 2018.*

[2] Bertram Drost et al., *Model globally, match locally: Efficient and robust 3D object recognition, CVPR 2010.*

[3] Pedro Rodrigues et al., *Deep segmentation leverages geometric pose estimation in computer-aided total knee arthroplasty, Healthcare Technology Letters 2019.*

[4] Carolina Raposo et al., *Using 2 point+normal sets for fast registration of point clouds with small overlap, ICRA 2017.*

[5] Martin Sundermeyer et al., *Augmented Autoencoders: Implicit 3D Orientation Learning for 6D Object Detection, IJCV 2019.*

[6] Zhigang Li et al., *CDPN: Coordinates-Based Disentangled Pose Network for Real-Time RGB-Based 6-DoF Object Pose Estimation, ICCV 2019.*

[7] Kiru Park et al., *Pix2Pose: Pixel-Wise Coordinate Regression of Objects for 6D Pose Estimation, ICCV 2019.*

[8] Sergey Zakharov et al., *DPOD: Dense 6D Pose Object Detector in RGB images, ICCV 2019.*

The scores were re-calculated on 27th January 2020.

Evaluation

AR_{MSPD} score (friendly to RGB-only methods)

#	Method	Image	Average	LM-O	T-LESS	TUD-L	IC-BIN	ITODD	HB	YCB-V	Time (s)
1	**Vidal-Sensors18** [1]	D	**0.563**	0.647	0.574	0.907	0.322	0.434	0.708	0.347	3.220
2	**Drost-CVPR10-Edges** [2]	RGB-D	**0.543**	0.569	0.518	0.881	0.293	0.596	0.670	0.275	87.568
3	**Drost-CVPR10-3D-Edges** [2]	D	**0.491**	0.511	0.420	0.872	0.294	0.478	0.626	0.233	80.055
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5	**Zhigang-CDPN-ICCV19** [6]	RGB	**0.448**	0.558	0.170	0.895	0.319	0.115	0.569	0.512	0.513
6	**Drost-CVPR10-3D-Only-Faster** [2]	D	**0.446**	0.543	0.436	0.796	0.305	0.275	0.611	0.244	1.383
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8	**Félix&Neves-ICRA17-IET19** [3,4]	RGB-D	**0.395**	0.430	0.213	0.889	0.251	0.073	0.523	0.384	55.780
9	**Sundermeyer-IJCV19** [5]	RGB	**0.391**	0.254	0.504	0.613	0.285	0.208	0.461	0.410	0.186
10	**Pix2Pose-BOP-ICCV19** [7]	RGB	**0.316**	0.165	0.403	0.535	0.316	0.073	0.311	0.407	0.793
11	**DPOD (synthetic)** [8]	RGB	**0.225**	0.278	0.139	0.341	0.185	0.000	0.379	0.256	0.231

Only a small change in the ranking suggests that
D is important not only for estimation of the object distance
(the distance is not directly evaluated by MSPD).

[1] Joel Vidal et al.*, A Method for 6D Pose Estimation of Free-Form Rigid Objects Using Point Pair Features on Range Data, Sensors 2018.*
[2] Bertram Drost et al.*, Model globally, match locally: Efficient and robust 3D object recognition, CVPR 2010.*
[3] Pedro Rodrigues et al.*, Deep segmentation leverages geometric pose estimation in computer-aided total knee arthroplasty, Healthcare Technology Letters 2019.*
[4] Carolina Raposo et al.*, Using 2 point+normal sets for fast registration of point clouds with small overlap, ICRA 2017.*
[5] Martin Sundermeyer et al.*, Augmented Autoencoders: Implicit 3D Orientation Learning for 6D Object Detection, IJCV 2019.*
[6] Zhigang Li et al.*, CDPN: Coordinates-Based Disentangled Pose Network for Real-Time RGB-Based 6-DoF Object Pose Estimation, ICCV 2019.*
[7] Kiru Park et al.*, Pix2Pose: Pixel-Wise Coordinate Regression of Objects for 6D Pose Estimation, ICCV 2019.*
[8] Sergey Zakharov et al.*, DPOD: Dense 6D Pose Object Detector in RGB images, ICCV 2019.*

The scores were re-calculated on 27th January 2020.

BOP 2019

BOP Challenge 2019 Awards

The Best Method on Individual Datasets

LM-O, T-LESS, HB, IC-BIN, TUD-L:

Vidal-Sensors18: ***Joel Vidal, Chyi-Yeu Lin, Xavier Lladó, Robert Martí***, *A Method for 6D Pose Estimation of Free-Form Rigid Objects Using Point Pair Features on Range Data, Sensors 2018.*

LM, IC-MI, ITODD, TYO-L:

Drost-CVPR10-3D-Only / Drost-CVPR10-Edges: ***Bertram Drost, Markus Ulrich, Nassir Navab, Slobodan Ilic***, *Model globally, match locally: Efficient and robust 3D object recognition, CVPR 2010.*

YCB-V, RU-APC:

Pix2Pose-BOP_w/ICP-ICCV19: ***Kiru Park, Timothy Patten, Markus Vincze***, *Pix2Pose: Pixel-Wise Coordinate Regression of Objects for 6D Pose Estimation, ICCV 2019.*

BOP
2019

BOP Challenge 2019 Awards

The Best Open Source Method

The best method on the 7 core datasets (LM-O, T-LESS, TUD-L, IC-BIN, ITODD, HB, YCB-V) whose source code is publicly available.

Sundermeyer-IJCV19+ICP: ***Martin Sundermeyer, Zoltan-Csaba Marton, Maximilian Durner, Manuel Brucker, Rudolph Triebel****, Augmented Autoencoders: Implicit 3D Orientation Learning for 6D Object Detection, IJCV 2019.*

https://github.com/DLR-RM/AugmentedAutoencoder

BOP Challenge 2019 Awards

The Best Fast Method

The best method on the 7 core datasets (LM-O, T-LESS, TUD-L, IC-BIN, ITODD, HB, YCB-V) with the average running time per image below 1s.

Sundermeyer-IJCV19+ICP: ***Martin Sundermeyer, Zoltan-Csaba Marton, Maximilian Durner, Manuel Brucker, Rudolph Triebel***, *Augmented Autoencoders: Implicit 3D Orientation Learning for 6D Object Detection, IJCV 2019.*

Average time per image: 0.865 s

BOP Challenge 2019 Awards

The Best RGB-Only Method

The best method on the 7 core datasets (LM-O, T-LESS, TUD-L, IC-BIN, ITODD, HB, YCB-V) which uses only RGB channels of the test images.

Zhigang-CDPN-ICCV19: ***Zhigang Li, Gu Wang, Xiangyang Ji****, CDPN: Coordinates-Based Disentangled Pose Network for Real-Time RGB-Based 6-DoF Object Pose Estimation, ICCV 2019.*

BOP Challenge 2019 Awards

The Overall Best Method

The best method on the 7 core datasets (LM-O, T-LESS, TUD-L, IC-BIN, ITODD, HB, YCB-V).

Vidal-Sensors18: ***Joel Vidal, Chyi-Yeu Lin, Xavier Lladó, Robert Martí****, A Method for 6D Pose Estimation of Free-Form Rigid Objects Using Point Pair Features on Range Data, Sensors 2018.*

Conclusions

- **New evaluation protocol:**
  - ViVo task.
  - Pose error functions VSD, MSSD, MSPD.
  - Performance score measured by the average recall.

- **New datasets in the BOP format** (ITODD, HomebrewedDB, YCB-V).

- PPF-based methods **still perform best.**

- The submission form for the BOP Challenge 2019 **stays open!**