

# Recognition and 6D Localization of Texture-less Objects

Jiří Matas, Tomáš Hodaň

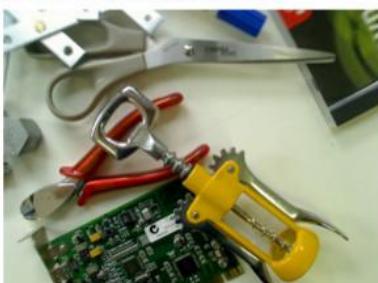
Center for Machine Perception  
Czech Technical University in Prague

17th December 2015, Chile

# Texture-less Object Detection for Robotics

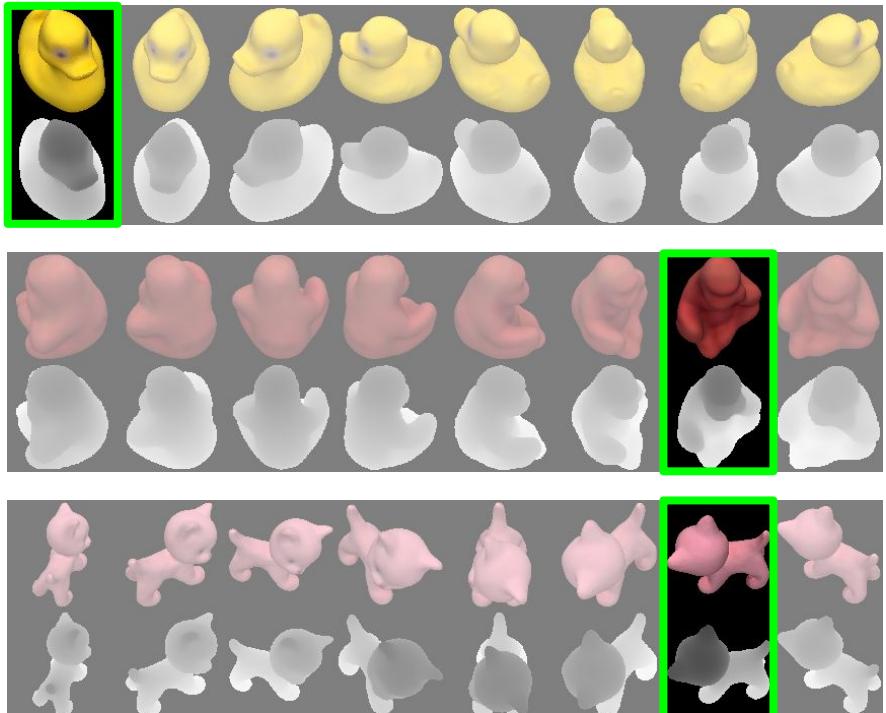


Detection and accurate localization of **texture-less** or **texture-poor** objects is commonly required in personal and industrial robotics

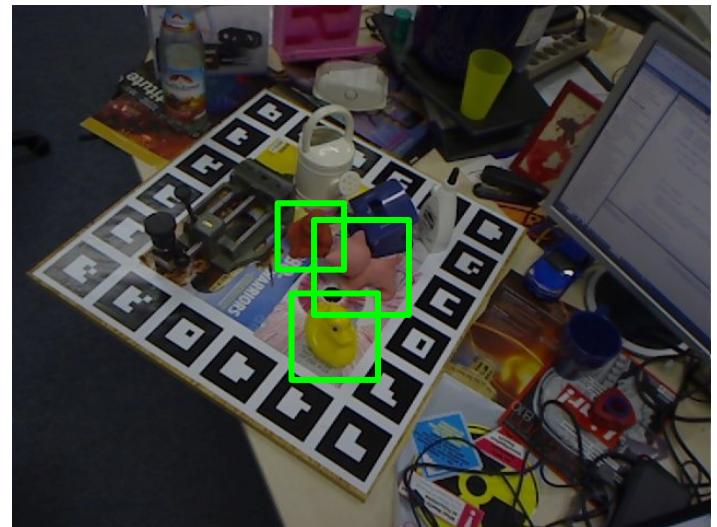


# Problem Formulation

Given a database of training RGB / RGB-D images annotated with 6D poses or 3D model, **detect all instances of known objects** in a test image and **estimate their 6D poses**



Training RGB / RGB-D images  
annotated with 6D poses



Test RGB / RGB-D image

# T-LESS

A new RGB-D dataset and evaluation protocol for  
detection and 6D pose estimation of texture-less objects

<http://cmp.felk.cvut.cz/t-less>



CTU  
Prague



FORTH  
Heraklion



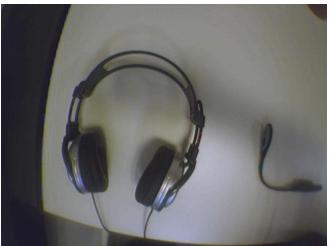
TU  
Wien

# Existing Texture-less Datasets

- RGB datasets



CMP Toys



Bristol Tools



D-Textureless



CMU Kitchen  
Occlusion Dataset



Rios-Cabrera et al.

- RGB-D datasets



**Hinterstoisser et al.**  
(extended GT by Brachmann et al.)  
3D models for 15 objects,  
~1200 test images per object



**UoB Highly Occluded Object Dataset** (Walas et al.)  
25 object categories - 5 objects in each (3D models provided)



**Multi-Object Pose Estimation** (Tejani et al.)  
3D models for 6 objects,  
~1000 test images per object



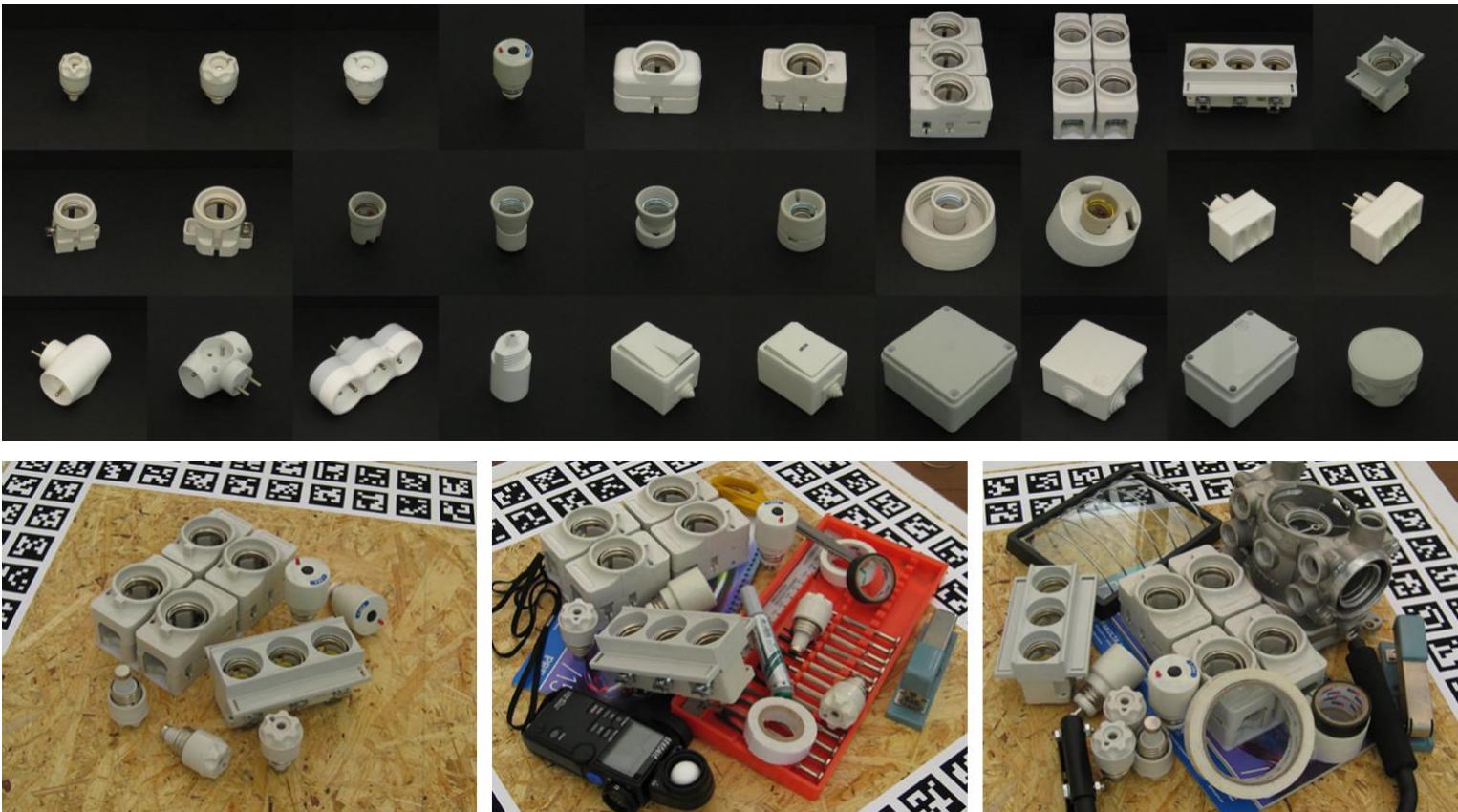
**Articulated Objects** (Michel et al.)  
4 articulated objects

- Common aspect: **objects often dissimilar in size, shape and color**

# T-LESS: Key Features



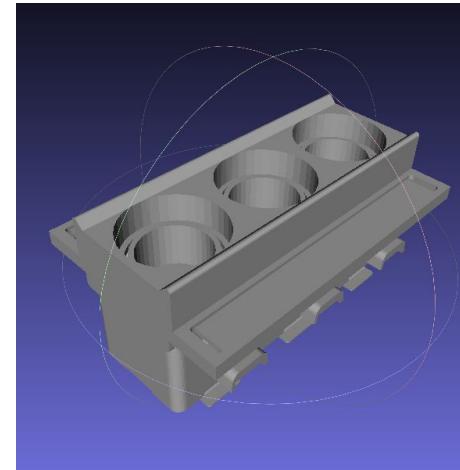
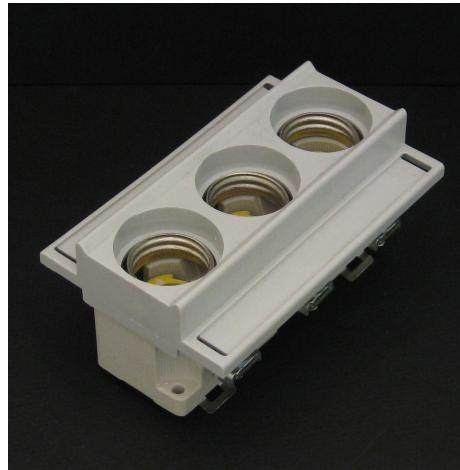
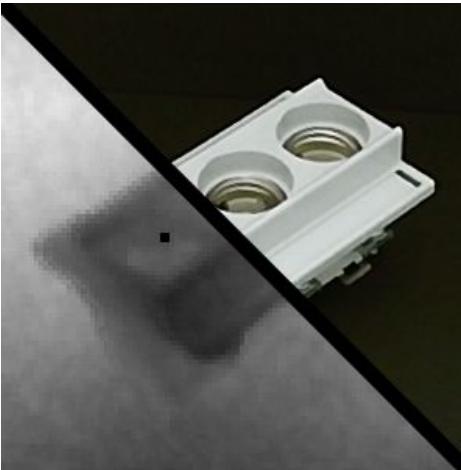
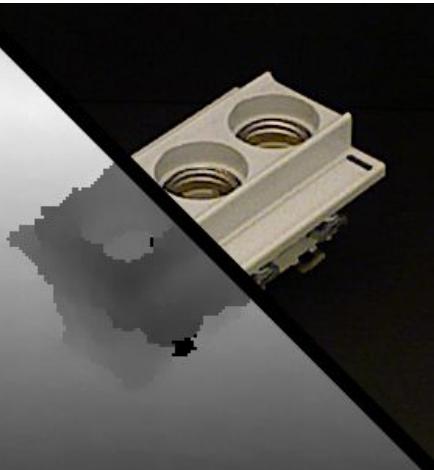
1. Relatively **small objects** often **very similar in shape and color**
2. Test images include significant **clutter and occlusions**
3. Accurate **ground truth 6D pose** for all known objects in each image
4. Data from **three synchronized and mutually calibrated sensors**  
(a structured-light depth sensor, a time-of-flight depth sensor, and a high-resolution camera)



# T-LESS: 30 Texture-less Objects



- **RGB-D & RGB training templates** depicting objects from a uniformly sampled full view sphere ( $10^\circ$  step in elevation and  $5^\circ$  in azimuth)  
→ **1278 templates per object from each sensor**
- Each template is annotated with a **6D pose** of the object
- **Two 3D mesh models** for each object:
  1. Manually created
  2. Automatically reconstructed (TU Wien)



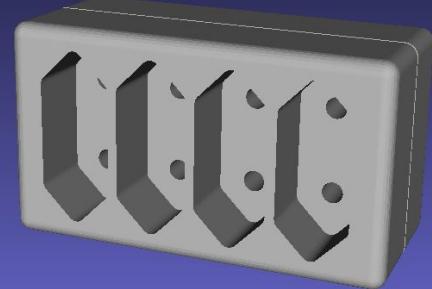
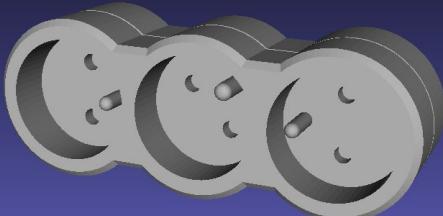
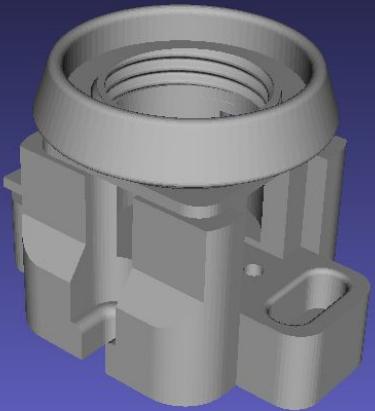
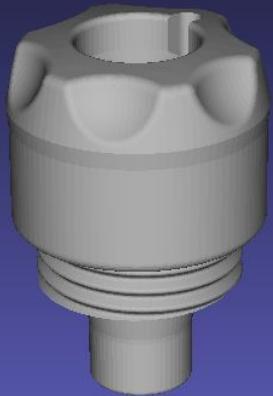
300x300 px RGB-D  
template from  
Primesense  
CARMINE 1.09

300x300 px RGB-D  
template from  
Kinect v2

1280x1280 px RGB  
template from  
Canon IXUS 950 IS

Manually created  
3D model

# T-LESS: 3D Models vs Real Objects



# T-LESS: 21 Test Scenes



- **RGB-D test images** depicting scenes from a uniformly sampled view hemisphere (10° step in elevation and 5° in azimuth)  
→ **568 test images from each scene**
- **Ground truth 6D poses** provided for all known objects
- The test scenes vary from simple ones with only few objects and black table top to very challenging ones **containing many similar objects, significant clutter and occlusion**



# T-LESS: The Objects Can Be Bought



Buy the objects for your own experiments (e.g. grasping)

**K&V ELEKTRO**  
ELEKTROINSTALACNÍ MATERIAŁ

**Prodejka - daňový doklad č.PD1502002187**

**Dodavatel:**  
K & V ELEKTRO a.s.  
Týnská 1053/21  
110 00 Praha 1  
IČ: 28463005  
DIČ: CZ28463005  
Společnost zapsaná v obchodním rejstříku vedeném Městským soudem v Praze, oddíl B, vložka 14678

**Odběratel:**  
České vysoké učení technické v Praze (FAKULTA ELEKTROTECHNICKÁ)  
Technická 2  
16627 Praha 6  
IČ: 68407700  
DIČ: CZ68407700

Datum vystavení: **14.1.2015** Forma úhrady: **V hotovosti**  
 Datum uskutečnění zdanitelného plnění: **14.1.2015**  
 Vystavil: **Tkadlecová Michaela**  
 Zákázka: **ZP15020001986**

Kód	Název zboží	Množství MJ	Slevy	Cena/MJ	Celkem bez DPH	Celkem s DPH
87030002	TASKA IGELITOVÁ KV ELEKTRO	1,000 ks	0/0%	0,83	0,83	21% 1,00
12130070	ADAPTER ROZBOCOVACÍ BILY 3X /2101.01/	4,000 ks	0/0%	17,01	68,04	21% 82,33
12130073	ADAPTER ROZBOCOVACÍ BILY 4X A4 /2103.01/	4,000 ks	0/0%	19,14	76,56	21% 92,64
12130082	ROZBOCKA 5323-23B	4,000 ks	0/0%	44,57	178,28	21% 215,72
12130112	SPOJKA 5543N-C02100 B	4,000 ks	0/0%	44,91	179,64	21% 217,36
12130130	ROZBOCKA KRW-3 BILA 3X KULATA	4,000 ks	0/0%	18,48	73,92	21% 89,44
12130236	ROZBOCKA P94 BILA 3 x 10A	4,000 ks	0/0%	30,00	120,00	21% 145,20
12130190	ROZBOCKA LEGRAND SEDO-BILA 3X2P+T /50639/	4,000 ks	0/0%	79,25	317,00	21% 383,57
50900174	ARMATURA KERAMICKA ROVNA 5716 IP 20	4,000 ks	0/0%	66,82	267,28	21% 323,41
50909570	ARMATURA PLASTOVÁ SIKMA E27 /83125/	4,000 ks	0/0%	26,19	104,76	21% 126,76
30300894	SPINAC 3553-05929 B GO	4,000 ks	0/0%	79,20	316,80	21% 383,33
30303519	SPINAC 3553-25922 B GO	4,000 ks	0/0%	89,14	356,56	21% 431,44
35040102	KRABICE IP55 105X70X50 /LUCASYSTEM00850/	4,000 ks	0/0%	49,91	199,64	21% 241,56
20392953	KRABICE INSTAL. S-BOX 116 IP56 BEZ VÝVODEK /100x100x50/	4,000 ks	0/0%	26,04	104,16	21% 126,03
87030002	TASKA IGELITOVÁ KV ELEKTRO	1,000 ks	0/0%	0,83	0,83	21% 1,00
35040103	KRABICE IP44 80X80X40 /LUCASYSTEM00810/	4,000 ks	0/0%	26,23	104,92	21% 126,95
28002328	QDBOCNA HRANATÁ KRABICE T25 80X51 RAL 7035 /2007029/	4,000 ks	0/0%	20,52	82,08	21% 99,32
46020060	PÓJISTKOVÁ VLOZKA E27 DT II g/l/g	15,000 ks	0/0%	5,28	79,20	21% 95,83
POMALE 20A 026301						
46040011	PÓJ.HLAVICE E27 2310-12 ODLEHCENA	15,000 ks	0/0%	12,07	181,05	21% 219,07
46040012	PÓJ.HLAVICE E33 2320-11 OTRE.VZDORNA	4,000 ks	0/0%	19,85	79,40	21% 96,07
46040013	PÓJ.HLAVICE E33 2320-12 ODLEHCEN/	10,000 ks	0/0%	15,09	150,90	21% 182,59
46020063	PÓJISTKOVÁ VLOZKA E33 DT III g/l/g/	15,000 ks	0/0%	9,15	137,25	21% 166,07
POMALE 50A 0265						
46040135	PÓJ.KROLZEK NA SPODEK E33 /15/ /?	4,000 ks	0/0%	5,81	23,24	21% 28,12
46040020	PÓJ.SPODEK E33 2120-30 KRYT	7,000 ks	0/0%	81,27	568,89	21% 688,36
46040018	PÓJ.SPODEK E33 2122-33 VEST.S. KR./2122-30+15379/	4,000 ks	0/0%	65,64	262,56	21% 317,70
46040014	PÓJ.SPODEK E27 2112-33 VEST.S. K.	4,000 ks	0/0%	45,82	183,28	21% 221,77
87030002	TASKA IGELITOVÁ KV ELEKTRO	2,000 ks	0/0%	0,83	1,66	21% 2,01
50800080	OBJIMKA P-1-C (1323-607) PRISA/	4,000 ks	0/0%	25,04	100,16	21% 121,19

**K&V ELEKTRO**  
ELEKTROINSTALACNÍ MATERIAŁ

**Prodejka - daňový doklad č.PD1502002187**

Kód	Název zboží	Množství MJ	Slevy	Cena/MJ	Celkem bez DPH	DPH	Celkem s DPH
50800205	OBJIMKA E27 SOKL.KERAM.BILA /1333-510/	1,000 ks	0/0%	45,85	183,40	21%	221,91
50800238	OBJIMKA KERAM.VEST.E27 /1335-607/	4,000 ks	0/0%	8,25	33,00	21%	39,93
50800079	OBJIMKA E27 M10X1 /1332-837/	1,000 ks	0/0%	25,41	101,64	21%	122,98
50800082	OBJIMKA (1351-13400) E27/80 BILA HLADKA	4,000 ks	0/0%	16,00	64,00	21%	77,44

**Celkové součty CZK:**

Položky celkem - základ:	4 700,93	Sazba	Základ	DPH
- DPH:	987,17	0 %	0,00	0,00
Zaokrouhlení - základ:	-0,08	15 %	0,00	0,00
- DPH 21%:	-0,02	21 %	4 700,85	987,15
Celkem s DPH:				5 688,00

**Rekapitulace DPH:**

Celkem k úhradě:	<b>5 688,00 CZK</b>
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Při vrácení zboží, které bylo zakoupeno na kterékoli pobočce naší společnosti, bude vystaven doklad a peníze Vám budou zaslány na bankovní účet.

Zboží a doklad převzal:

Vystavil:  
 K&V ELEKTRO  
 prodejka: 14.1.2015  
 Stejný den  
 Michaela Tkadlecová  
 ZP15020001986

# T-LESS: Illumination Conditions



- All training and test data captured in **fixed illumination conditions with dominant ambient light**
- 15 test scenes captured also in **alternative conditions with low ambient light and strong direct light from side**

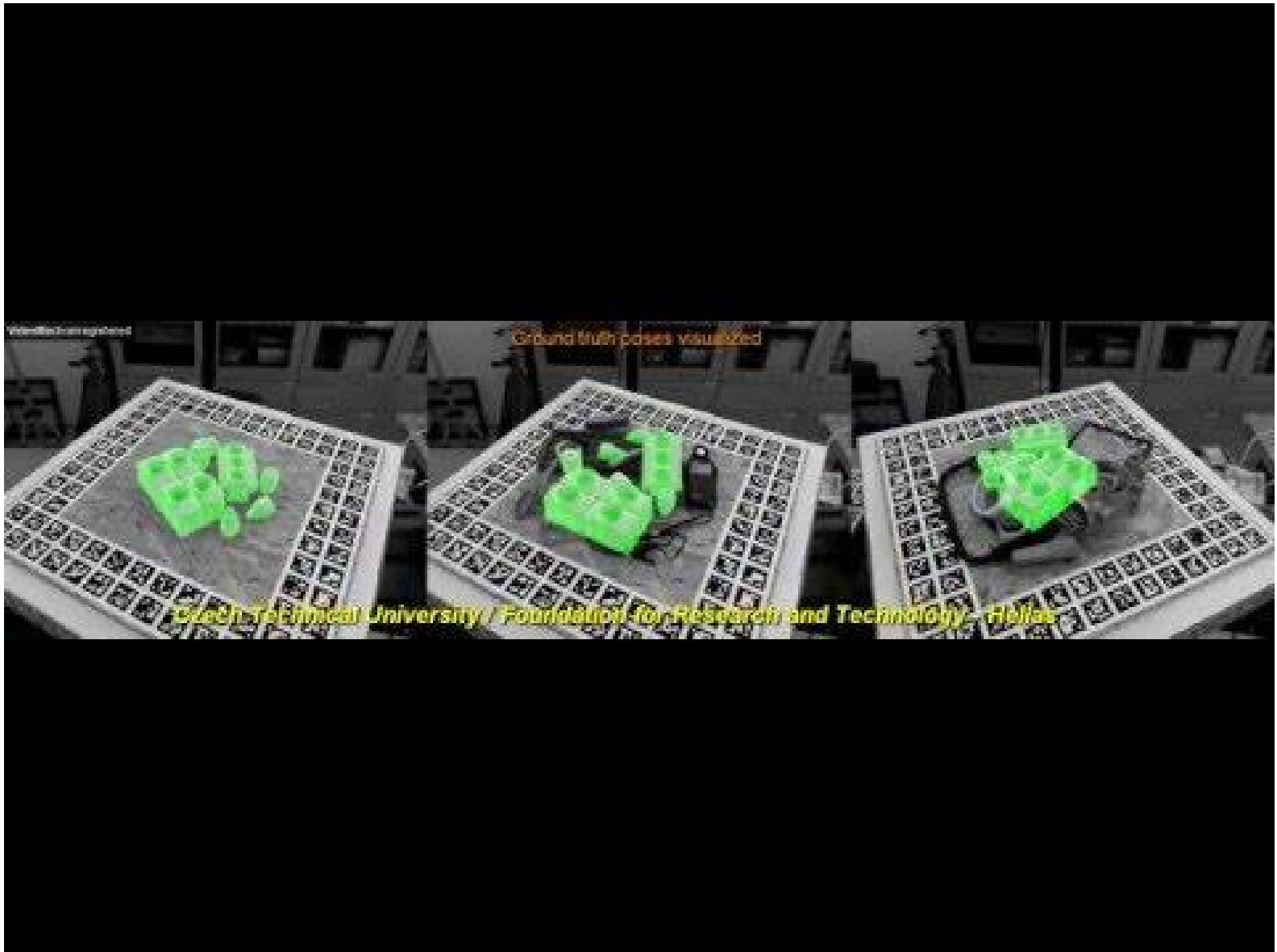
Dominant ambient light



Low ambient light and strong direct light



# T-LESS: Sample Ground Truth 6D Poses



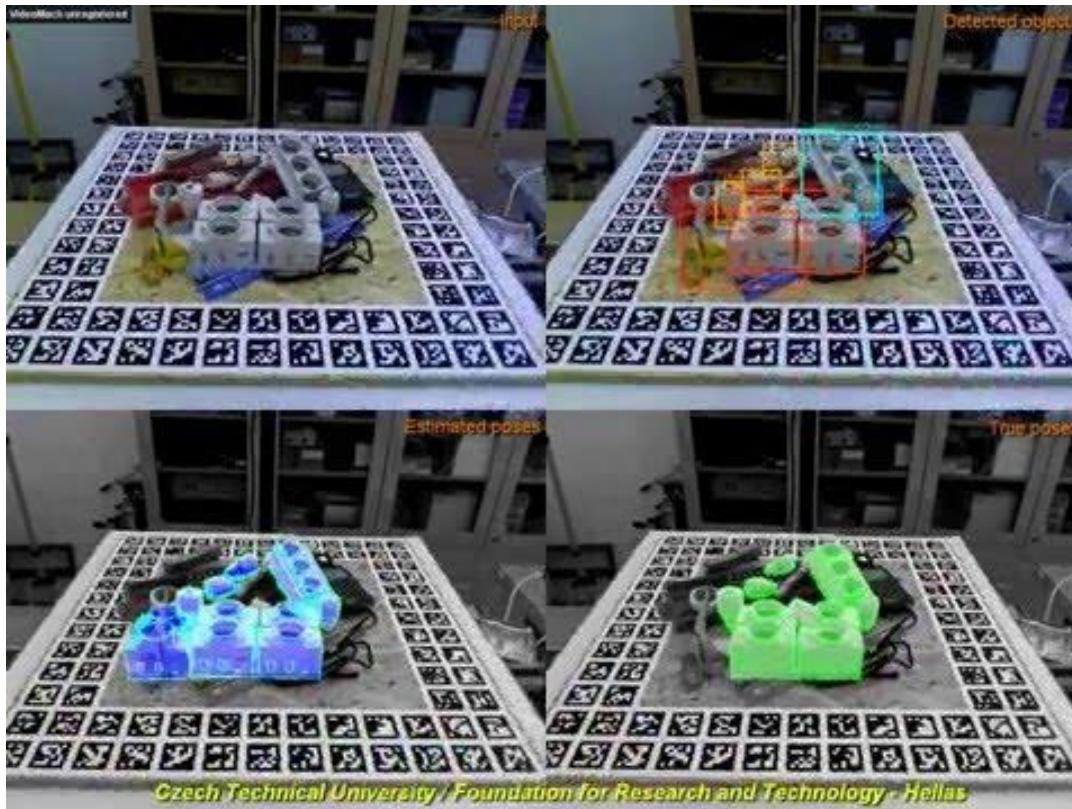
On [YouTube](#)

# T-LESS: Estimation of GT 6D Poses



1. We manually identify a set of images, in which an object's 6D pose can be accurately estimated by the recognition and localization method by Hodan et al. (IROS 2015) = RGB-D template matching + 6D pose refinement by particle swarm optimization
2. Mean of the 6D poses estimated in these images is transformed to all images using camera poses estimated from the fiducial markers

On [YouTube](#)



# T-LESS: Capturing Setup



Sensors (synchronized and mutually calibrated):

- **Primesense Carmine 1.09 (Short Range)**  
registered RGB-D images (RGB:1280x1024 px,  
D:640x480 px)
- **Microsoft Kinect v2**  
registered RGB-D images (1920x1080 px)
- **Canon IXUS 950 IS**  
high resolution RGB images (3264x2448 px)



1. **Sensors** fixed on an arm with adjustable tilt
2. **A turntable with a marker field** for camera pose estimation (the vertical markers enable estimation from low elevations)
3. **A shield to ensure black background** in training templates (it is removed for capturing test data)
4. **A strong reflector** to increase ambient light

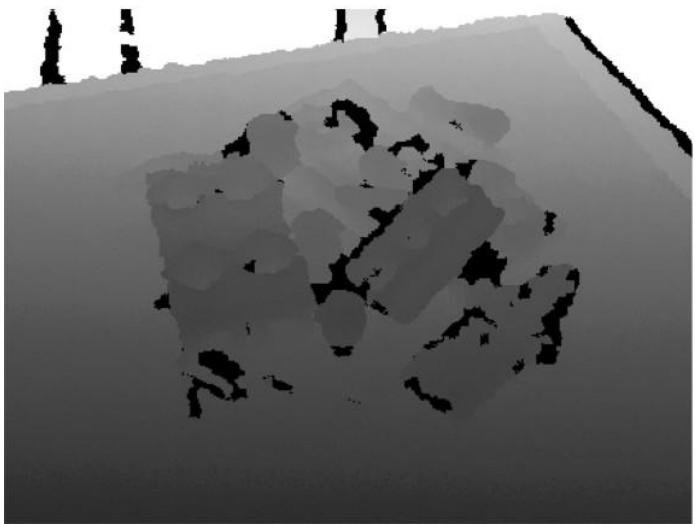
# T-LESS: Primesense vs Kinect v2



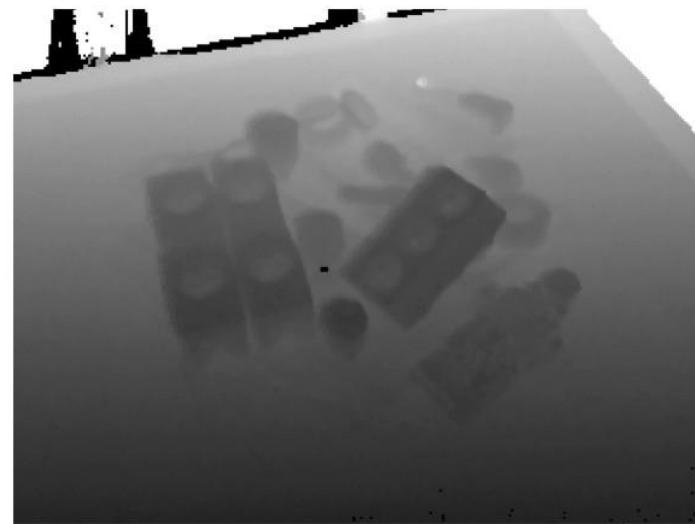
RGB



Depth



Primesense CARMINE 1.09



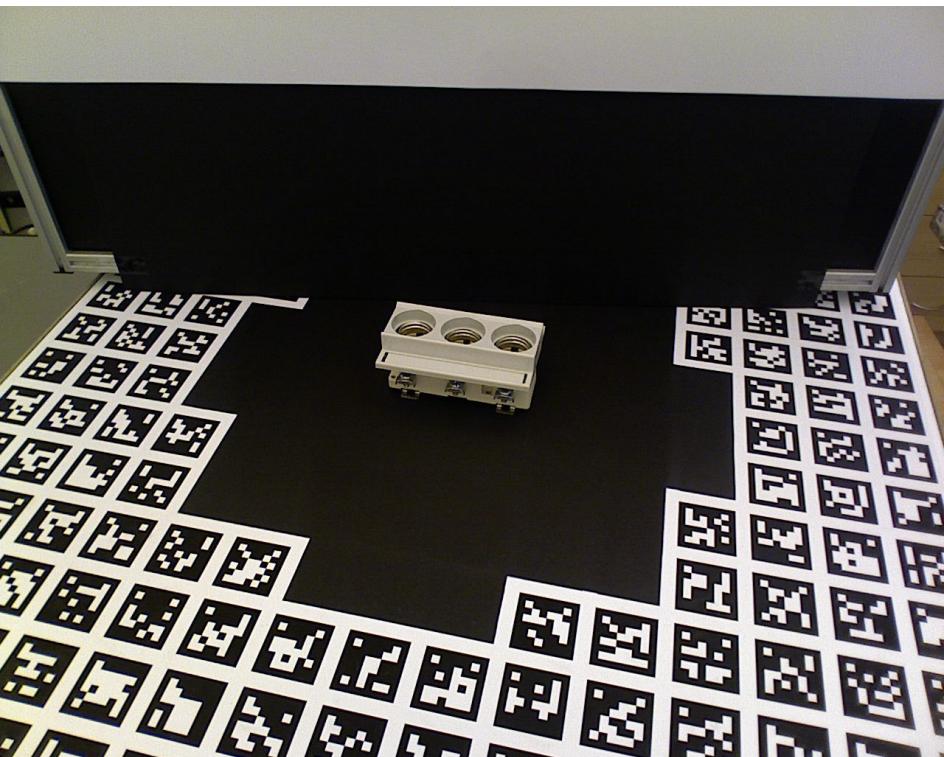
Kinect v2

# T-LESS: Views From Full Sphere

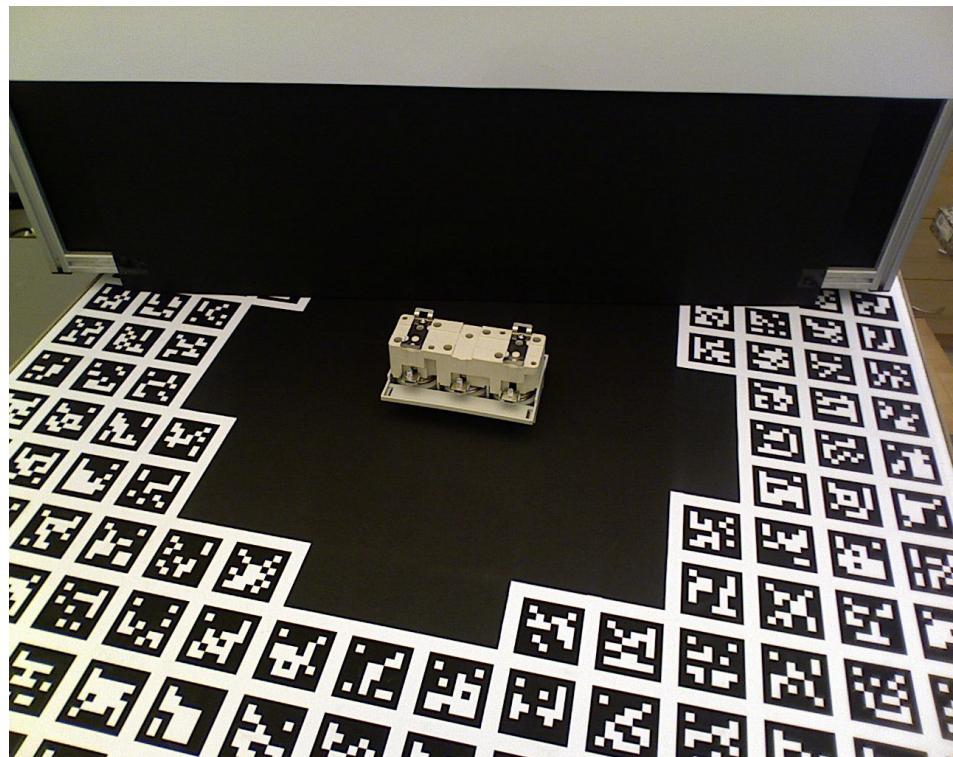


- To obtain views from the full sphere around the object, each object is captured **1) upright** and **2) upside down**, in both cases from elevations  $5^\circ$  to  $85^\circ$  ( $10^\circ$  step in elevation and  $5^\circ$  in azimuth)

Upright



Upside down

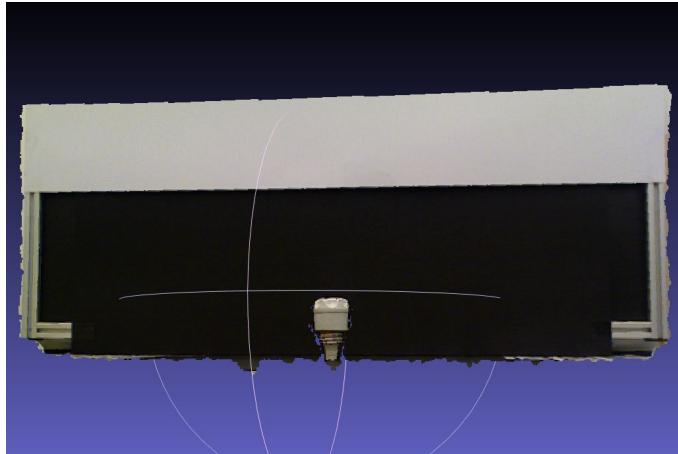


# T-LESS: Primesense vs Kinect v2

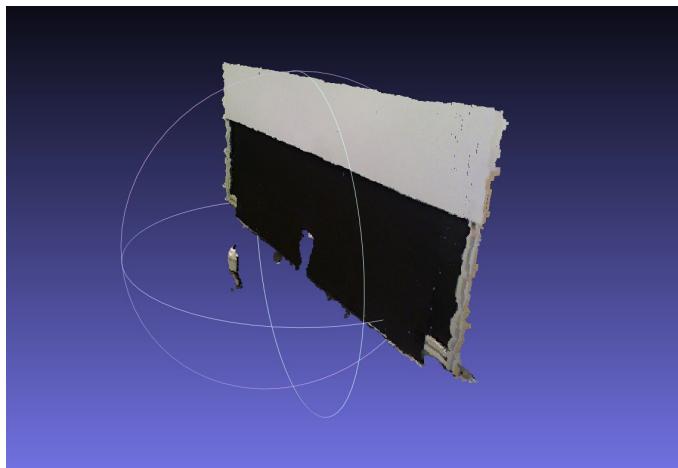


- Primesense: **less noisy, but more missing values** (at slanted surfaces and around occlusion boundaries)

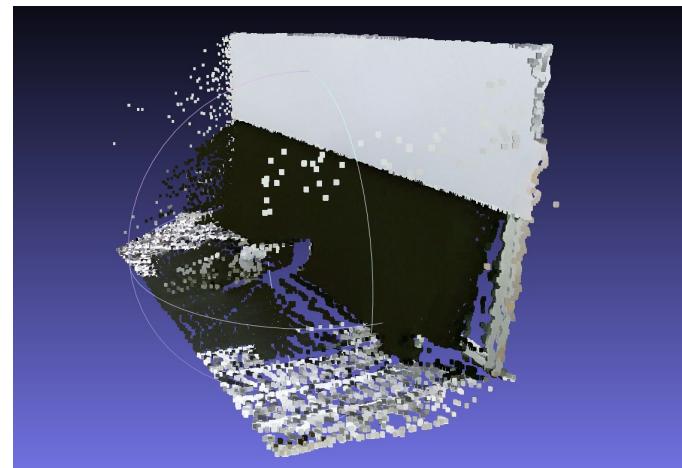
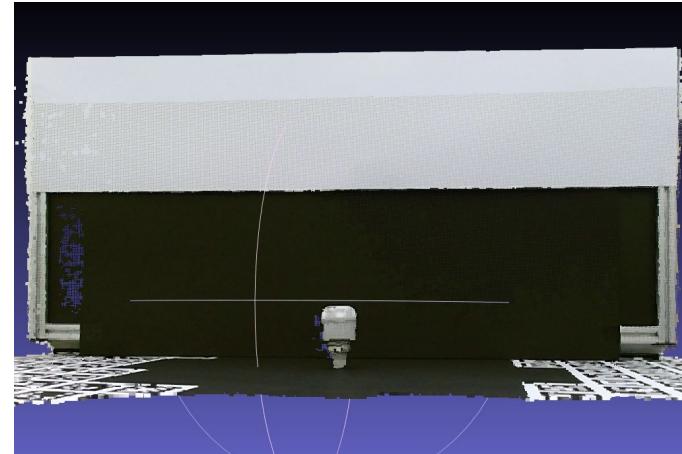
View 1



View 2



Primesense CARMINE 1.09



Kinect v2

# T-LESS: Current State

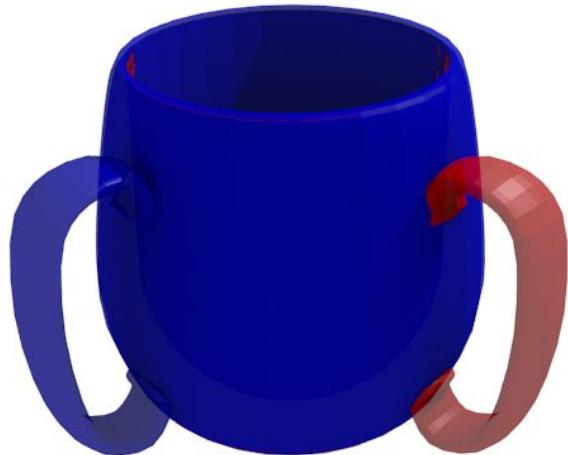


- Ongoing work:
  1. **Automatic reconstruction of 3D models** (the manually created models available)
  2. **Finalization of ground truth 6D poses**
  3. We are considering adding **new test scenes without markers** (the camera pose could be estimated e.g. from the known texture of the top of the turntable)
- **Expected release of the final version: February 2016**

# 6D Pose Evaluation



- Evaluate how well a 3D model in an estimated 6D pose fits the same 3D model in the ground truth 6D pose



A mug in the **ground truth** and an **estimated** pose

**How good is the estimated pose?**

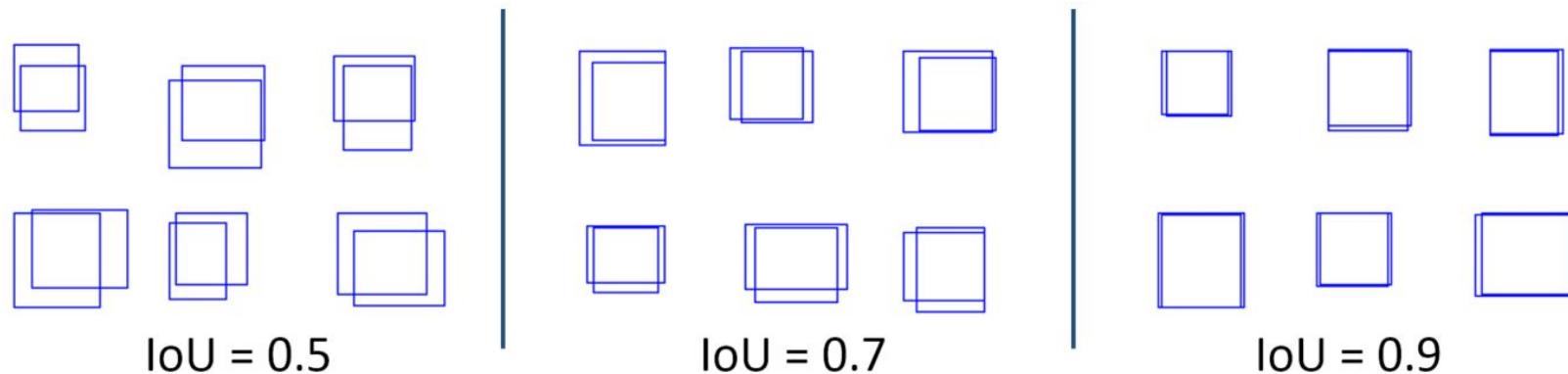
- Commonly used evaluation criteria (used in the most of the challenges at this workshop):
  1. **Average distance (AD) criterion** (Hinterstoisser et al.)
  2. **5cm, 5deg** (Shotton et al.)
  3. **2D intersection over union (IoU) criterion** (Everingham et al.)

# 2D Intersection over Union (IoU) Criterion



M. Everingham, L. Van Gool, C.K.I. Williams, J. Winn, A. Zisserman: The Pascal Visual Object Classes Challenge. IJCV 2010

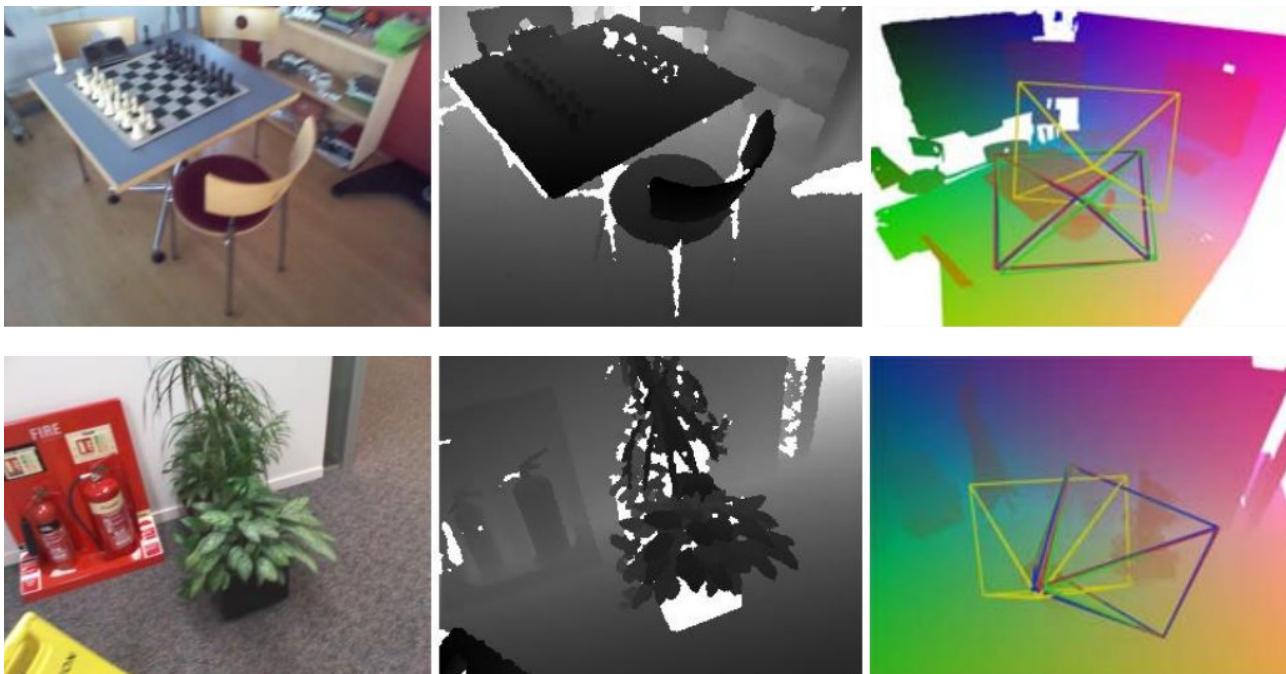
- A pose is considered correct, when **intersection over union of 2D bounding boxes of an object in the estimated and the ground truth pose is above a threshold (e.g. 0.5)**
- Weak, but allows comparison with 2D methods (e.g. Damen et al.)



# 5cm, 5deg Criterion

J. Shotton, B. Glocker, C. Zach, S. Izadi, A. Criminisi, A. Fitzgibbon: Scene Coordinate Regression Forests for Camera Relocalization in RGB-D Images. CVPR 2013

- A pose is considered correct, when **the translational error is below 5cm and the rotational error is below 5deg**
- Not adaptive to the object size
- Originally used for evaluation of camera pose estimation



# Average Distance (AD) Criterion



S. Hinterstoisser, V. Lepetit, S. Ilic, S. Holzer, G. R. Bradski, K. Konolige, N. Navab: Model Based Training, Detection and Pose Estimation of Texture-Less 3D Objects in Heavily Cluttered Scenes. ACCV 2012

- A pose is considered correct, if **the average distance is below 10% of the object diameter**
- Adaptive to the object size
- Average distance for **non-symmetrical objects** ( $\sim 6$ D pose distance):

$$d_h \left( (\mathbf{R}, \mathbf{t}), (\tilde{\mathbf{R}}, \tilde{\mathbf{t}}); \mathcal{M} \right) = \frac{1}{|\mathcal{M}|} \sum_{\mathbf{x} \in \mathcal{M}} \left\| (\mathbf{R}\mathbf{x} + \mathbf{t}) - (\tilde{\mathbf{R}}\mathbf{x} + \tilde{\mathbf{t}}) \right\|_2$$

- Average distance for **symmetrical objects** ( $\sim 3$ D surface distance):

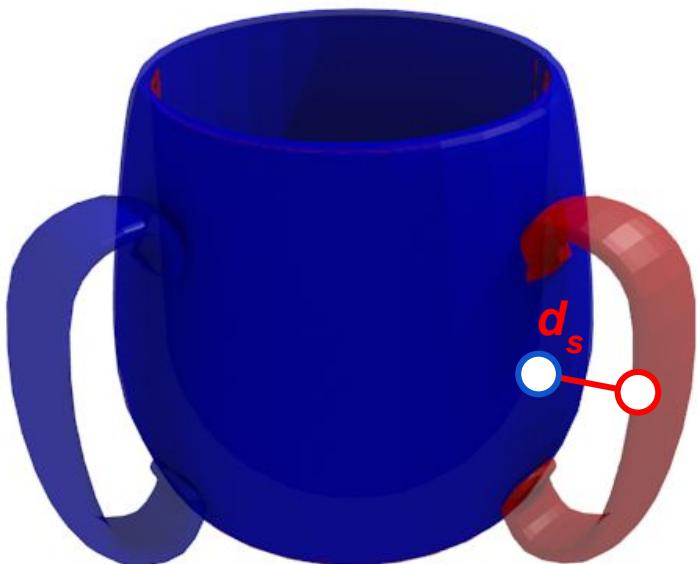
$$d'_h \left( (\mathbf{R}, \mathbf{t}), (\tilde{\mathbf{R}}, \tilde{\mathbf{t}}); \mathcal{M} \right) = \frac{1}{|\mathcal{M}|} \sum_{\mathbf{x}_1 \in \mathcal{M}} \min_{\mathbf{x}_2 \in \mathcal{M}} \left\| (\mathbf{R}\mathbf{x}_1 + \mathbf{t}) - (\tilde{\mathbf{R}}\mathbf{x}_2 + \tilde{\mathbf{t}}) \right\|_2$$

# Surface Distance (proposed)

$$d_s \left( (\mathbf{R}, \mathbf{t}), (\tilde{\mathbf{R}}, \tilde{\mathbf{t}}); \mathcal{M} \right) = \max_{\mathbf{x}_1 \in \mathcal{M}} \min_{\mathbf{x}_2 \in \mathcal{M}} \left\| (\mathbf{R}\mathbf{x}_1 + \mathbf{t}) - (\tilde{\mathbf{R}}\mathbf{x}_2 + \tilde{\mathbf{t}}) \right\|_2$$

- **Maximum instead of average**

- Maximum error is **more relevant** for robotics (grasping, assembly, etc.)
- There is **no noise**, we are matching the same 3D model in two poses



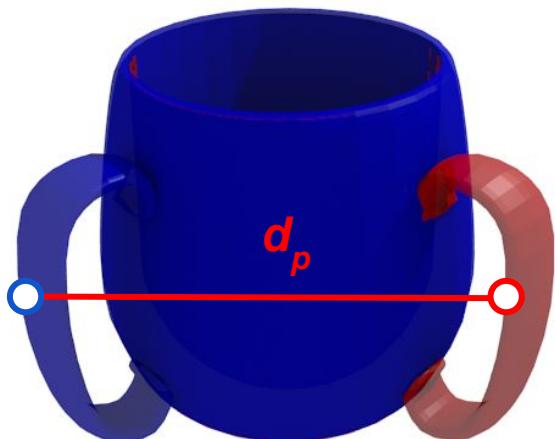
$d_s$  reflects the misalignment better than  $d'_h$  (the average distance for symmetrical objects), which is in this case very low, indicating a good fit

# Corresponding Point Distance (proposed)

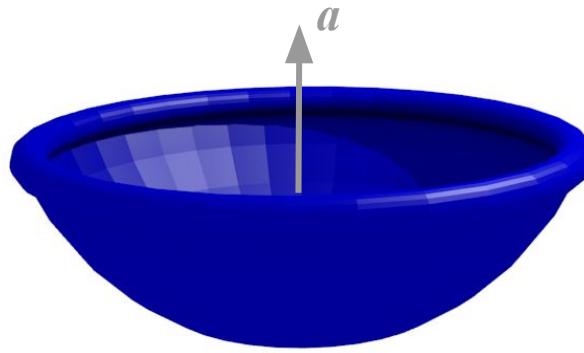


$$d_p \left( (\mathbf{R}, \mathbf{t}), (\tilde{\mathbf{R}}, \tilde{\mathbf{t}}); \mathcal{M} \right) = \min_{(\hat{\mathbf{R}}, \hat{\mathbf{t}}) \in [(\mathbf{R}, \mathbf{t})]} \max_{\mathbf{x} \in \mathcal{M}} \left\| (\hat{\mathbf{R}}\mathbf{x} + \hat{\mathbf{t}}) - (\tilde{\mathbf{R}}\mathbf{x} + \tilde{\mathbf{t}}) \right\|_2$$

- Considers all poses from the equivalence class  $[(\mathbf{R}, \mathbf{t})]$  of the ground truth pose (given by pre-defined **symmetries of the object**)



a non-symmetrical mug



a bowl with rotational symmetry

→ all poses varying in the rotation around  $a$  are considered equivalent

# Definition of Evaluation Tasks

1. **6D localization** (multiple classes, multiple instances)
  - Generalization of the Hinterstoisser's task (one instance per image)
  - **Input:**
    - a test RGB-D image and training data of known objects
    - a list of pairs (*present object class, number of instances*)
  - **Output:**
    - a list  $R$  of tuples (*object class, estimated 6D pose, score*)
2. **Detection and 6D localization** (multiple classes, multiple instances)
  - **Input:**
    - a test RGB-D image and training data of known objects
    - no prior knowledge about the present object instances
  - **Output:**
    - a list  $R$  of tuples (*object class, estimated 6D pose, score*)

# **Detection and Fine 3D Pose Estimation of Texture-less Objects in RGB-D Images**

**Tomáš Hodaň<sup>1</sup>, Xenophon Zabulis<sup>2</sup>, Manolis Lourakis<sup>2</sup>,  
Štěpán Obdržálek<sup>1</sup>, Jiří Matas<sup>1</sup>**



<sup>1</sup> Center for Machine Perception, CTU in Prague, CZ

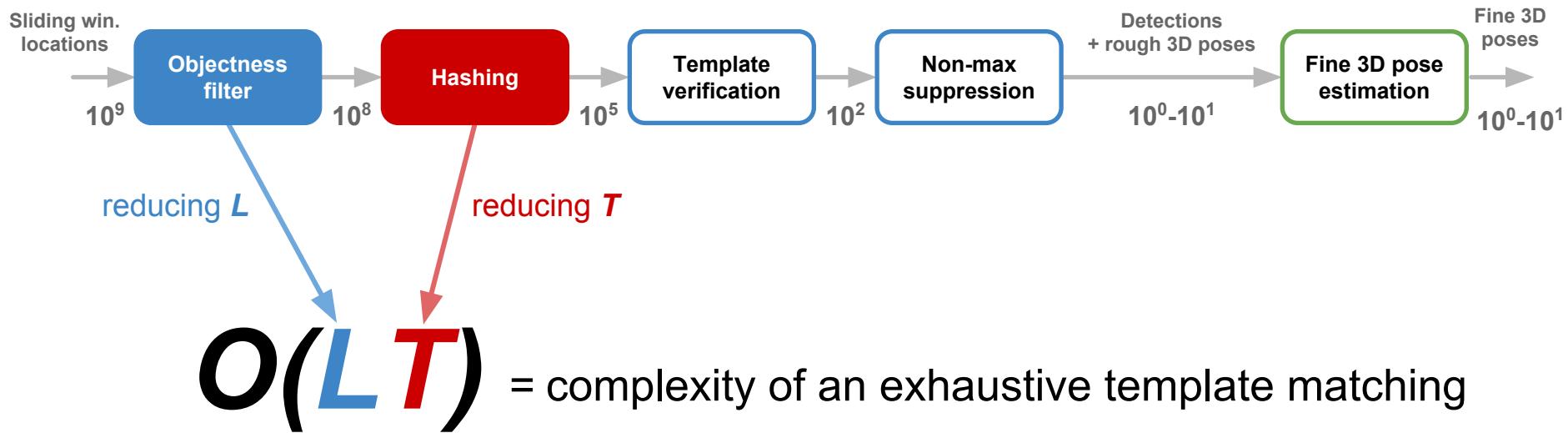


<sup>2</sup> Institute of Computer Science, FORTH, Heraklion, GR

**Published at IROS 2015**

# The Proposed Method

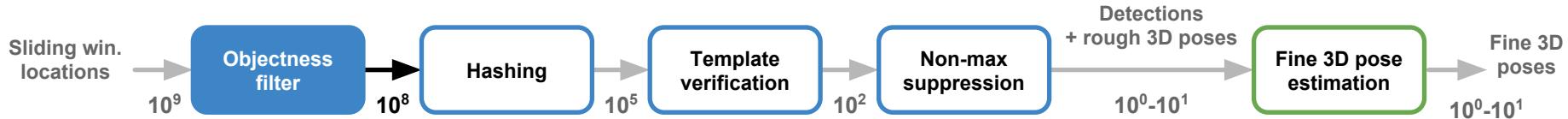
- Multi-scale **sliding window**
- Efficient cascade-style evaluation of each location
- The window has a **fixed size**, the same as the templates
- Stochastic optimization used to **refine the 3D pose**



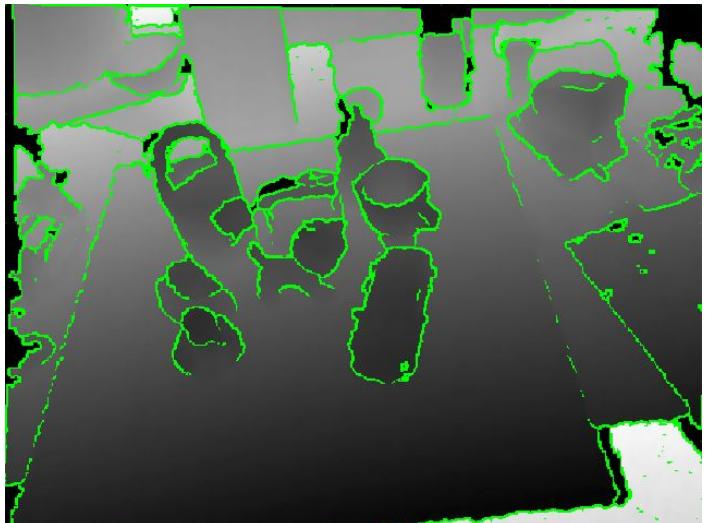
$L$  = the number of **sliding window locations**

$T$  = the number of **training templates**

# Objectness Filter



- Based on the **number of depth edges**
- The number of depth edges in a window is required to be **at least 30% of the minimum from the training templates**
- For false negative rate = 0, **60-90% of locations are pruned**
- Other window proposal methods (e.g. Edge-boxes) are being considered



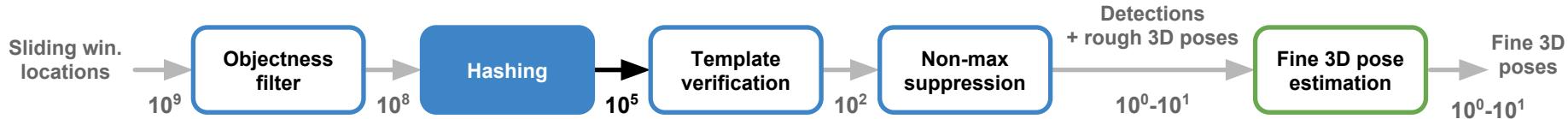
Detected depth edges

Number of detection candidates:  $1.7 \times 10^8$



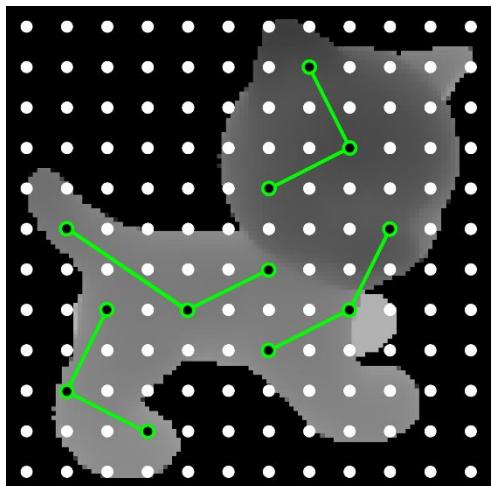
Density of detection candidates  
*detection candidate = (tpl. id, x, y, scale)*

# Hashing

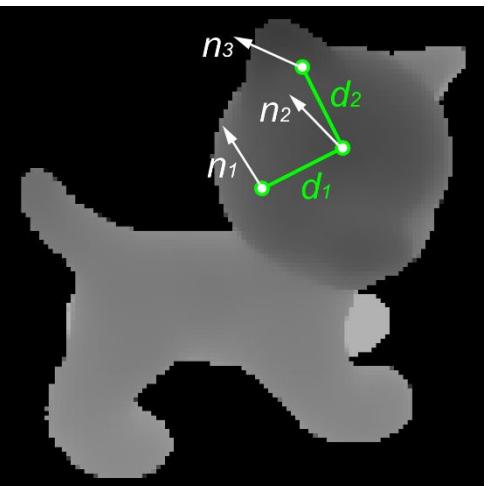


- Voting procedure based on **hashing descriptors of trained triplets of reference points** located on a grid
- Each triplet is described by **surface normals and depth differences**
- **Up to N templates with the most votes** are selected per location

Typically: N = 100, 8 bins for surface normal orientation, 5 bins for depth difference, i.e.  $5^2 8^3 = 12800$  hash table bins



Sample triplets



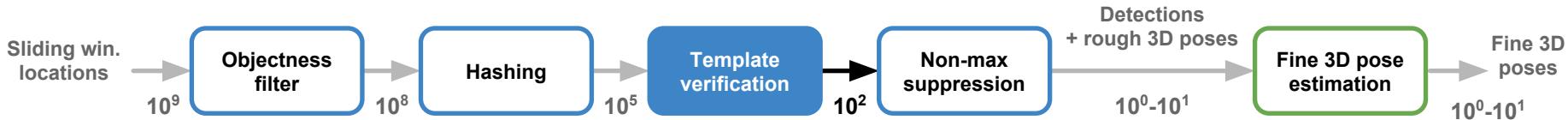
Triplet description

Number of detection candidates:  $5.2 \times 10^5$



Density of detection candidates  
*detection candidate = (tpl. id, x, y, scale)*

# Multimodal Template Verification

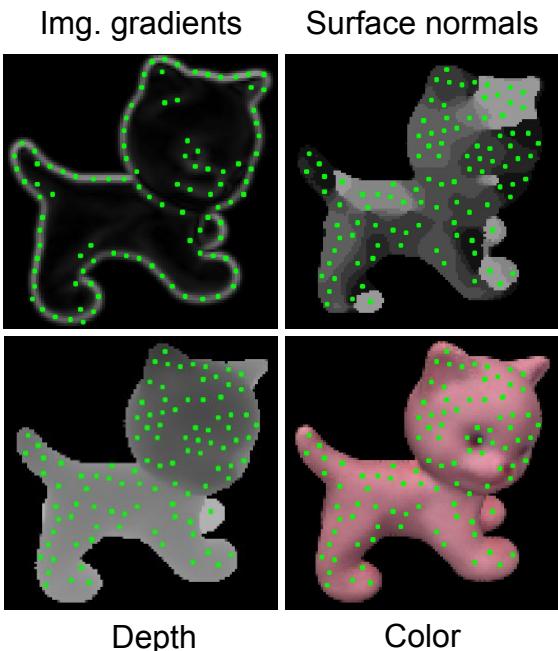


- A sequence of tests evaluating consistency of:

- Object size and the measured depth
- Surface normals
- Image gradients
- Depth
- Color (HSV)

} **Evaluated on learnt feature points**

Based on: Hinterstoisser et al., "Multimodal templates for real-time detection of texture-less objects in heavily cluttered scenes", ICCV, 2011



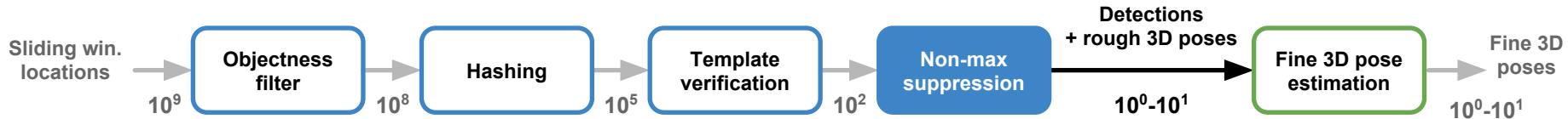
Learnt feature points in different modalities

**Number of detections: 44**



Density of detection candidates  
detection candidate = (tpl. id, x, y, scale)

# Non-maxima Suppression



- Detection candidates with **locally highest score** are retained
- The 3D poses associated with the detected templates are used as **initial poses** in the pose refinement procedure



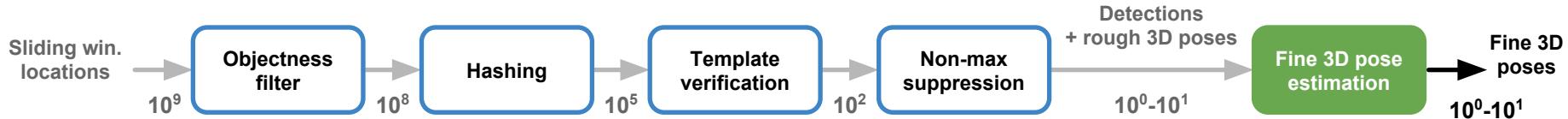
Rendering of the  
3D pose associated  
with the detected  
template

Number of detections: 1



Density of detection candidates  
*detection candidate = (tpl. id, x, y, scale)*

# Fine 3D Pose Estimation



- The rough initial 3D pose is refined using a hypothesize and test scheme based on **Particle Swarm Optimization** (PSO)
- PSO stochastically evolves a population of candidate poses over multiple iterations
- Candidate poses are evaluated by comparing their rendered depth images to the input depth image (using a cost function measuring similarity in **depth, surface normals and depth edges**)
- Pose refinement using PSO is **less sensitive to local minima compared to ICP**

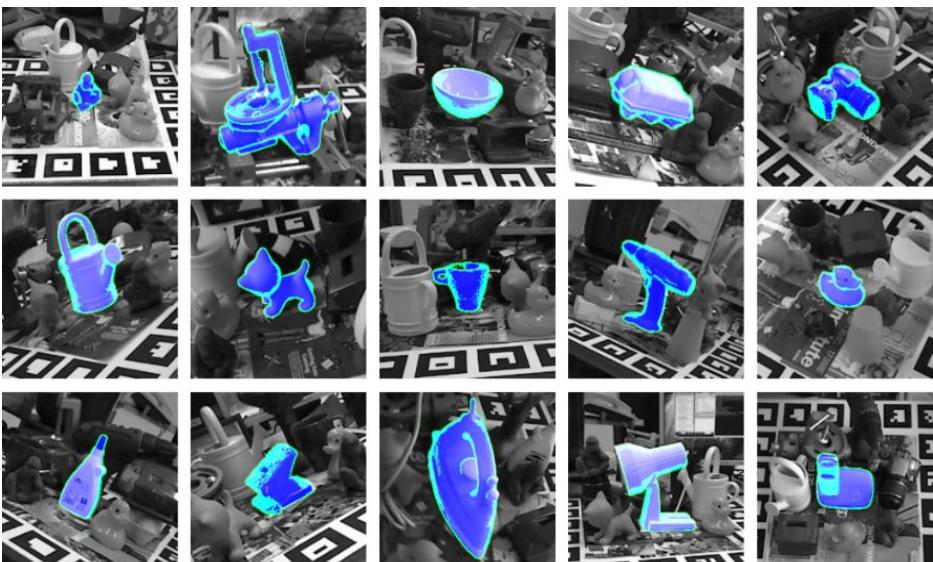
**Details in:** Zabulis, Lourakis and Koutlemanis, "3D Object Pose Refinement in Range Images", Intl Conf. on Computer Vision Systems, ICVS, 2015

# Recognition Rate

- Evaluation on the **dataset of Hinterstoisser** [1]:
  - 15 texture-less objects, 1200 RGB-D test images for each
  - **Object localization:** detect the given object and estimate its pose
- The recognition rate (recall) of our method is **comparable to SOTA**

Sequence	Our method	LINEMOD++	LINEMOD	Drost et al.
1. Ape	93.9	<b>95.8</b>	69.4	86.5
2. Benchvise	<b>99.8</b>	98.7	94.0	70.7
3. Bowl	98.8	<b>99.9</b>	99.5	95.7
4. Box	<b>100.0</b>	99.8	99.1	97.0
5. Cam	95.5	<b>97.5</b>	79.5	78.6
6. Can	<b>95.9</b>	95.4	79.5	80.2
7. Cat	98.2	<b>99.3</b>	88.2	85.4
8. Cup	<b>99.5</b>	97.1	80.7	68.4
9. Driller	<b>94.1</b>	93.6	81.3	87.3
10. Duck	94.3	<b>95.9</b>	75.9	46.0
11. Glue	<b>98.0</b>	91.8	64.3	57.2
12. Hole punch	88.0	<b>95.9</b>	78.4	77.4
13. Iron	97.0	<b>97.5</b>	88.8	84.9
14. Lamp	88.8	<b>97.7</b>	89.8	93.3
15. Phone	89.4	<b>93.3</b>	77.8	80.7
Average	95.4	<b>96.6</b>	83.0	79.3

Recognition rates [%]  
(LINEMOD and LINEMOD++ are methods from [1])



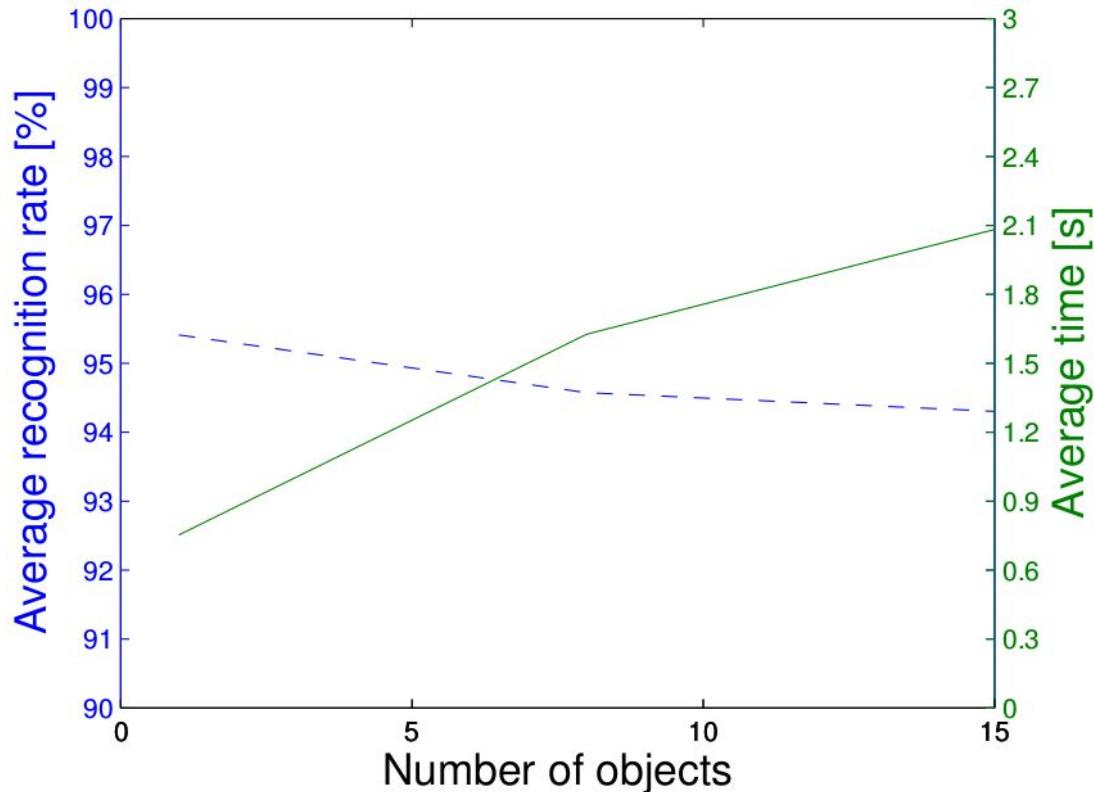
Sample 3D pose estimations

[1] Hinterstoisser et al., "Model based training, detection and pose estimation of texture-less 3D objects in heavily cluttered scenes," ACCV, 2012

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

# Scalability and Speed

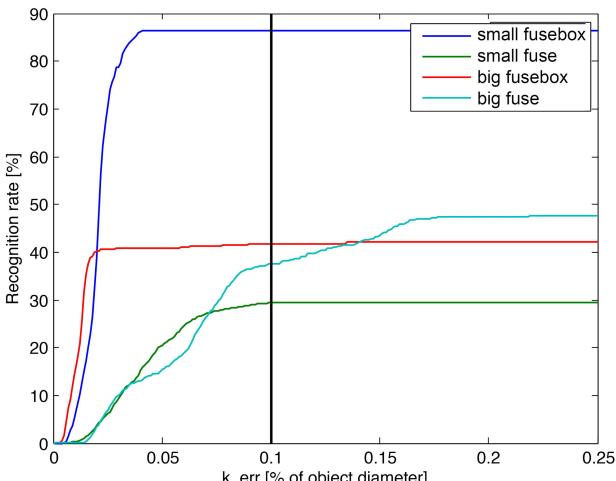
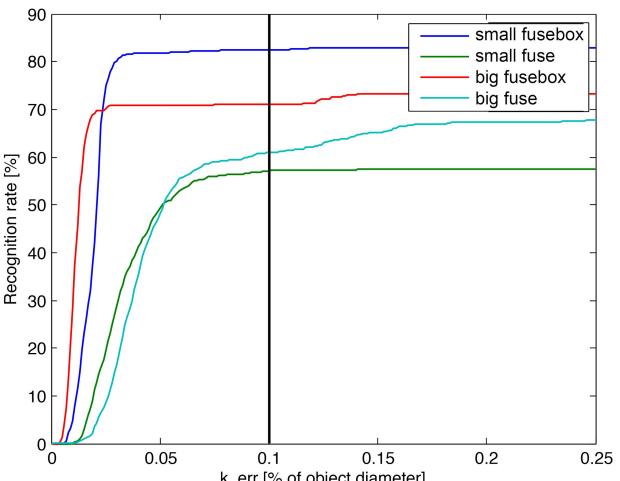
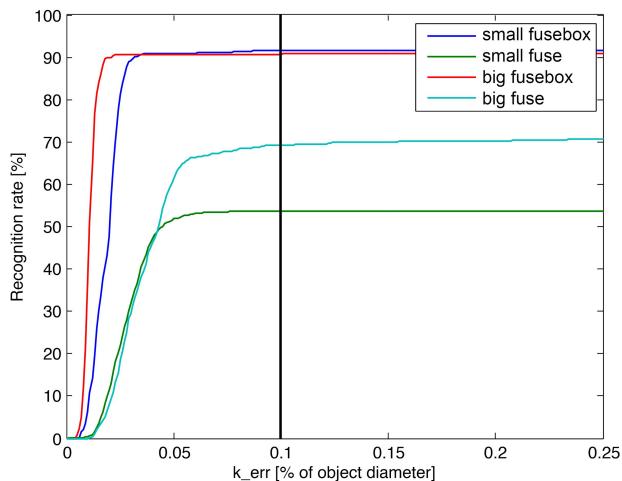
- Time complexity is **sub-linear in the number of templates**
- When the number of loaded templates increased 15 times, the average recognition time increased only less than 3 times:



- **0.75 s** per VGA frame (9 image scales) for a single known object

# T-LESS: Evaluation on the First 3 Scenes

- Evaluation of Hodan et al. (IROS 2015) method
- Hinterstoisser's average distance (AD) criterion



# Conclusions

1. **T-LESS:** A new industry-relevant RGB-D dataset and evaluation protocol for detection and 6D pose estimation of texture-less objects
  - a. Relatively small objects often very similar in shape and color
  - b. Significant clutter and occlusions
  - c. Accurate GT 6D poses for all known objects
  - d. Data from three synchronized and mutually calibrated sensors
2. **Difficulty of the T-LESS dataset** was confirmed in the first evaluation of the method by Hodan et al. (IROS 2015)
3. **Definition of evaluation tasks:**
  - a. 6D localization
  - b. Detection and 6D localization
4. **New 6D pose distances proposed:**
  - a. Surface distance
  - b. Corresponding point distance

# Thank you!

# TP/FP Classification

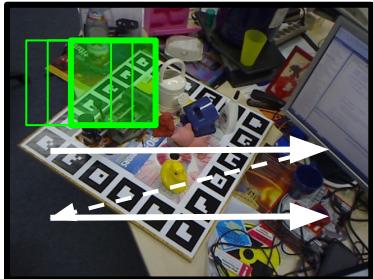


- **Input:**
  - a list  $\mathcal{R}$  of tuples (*object class, estimated 6D pose, score*)  
= an output of the method to be evaluated
  - a list  $\mathcal{G}$  of pairs (*object class, ground truth 6D pose*)
- **Output:** TP/FP labeling of the instances from  $\mathcal{R}$
- **TP/FP classification algorithm:**
  1. (*only for the 6D localization task*) If there are more than the specified number of instances of some class in the output list  $\mathcal{R}$ , keep only the ones with the highest score.
  2. From the list  $\mathcal{R}$  take the instance with the highest score and compare its pose against ground truth poses of the same class (using the distance  $d$  - the 3D surface distance or the 6D pose distance).
  3. If a match was found ( $d < th$ ), classify the estimated pose as a true positive and remove the matched ground truth pose from the list  $\mathcal{G}$ . Otherwise, classify the estimated pose as a false positive.
  4. Go to step 2.

# Performance Evaluation

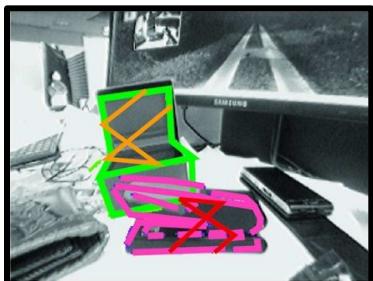
- Calculate “precision vs recall” curve by varying  $th$
- (Calculate the area under the curve)
- ...

# Existing methods



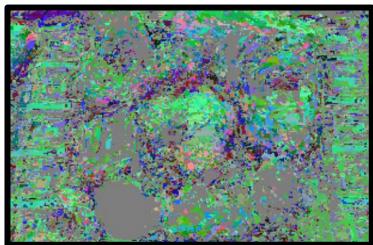
## 1. Template matching methods

Hinterstoisser (ICCV 2011), Rios-Cabrera (ICCV 2013),  
Cai (ICVS 2013), Hodan (IROS 2015)



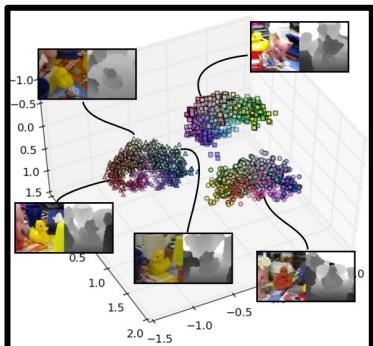
## 2. Shape matching methods

Damen (BMVC 2012), Tombari (ICCV 2013), Drost (CVPR 2010),  
Choi (IROS 2012), Hodan (ISMARW 2015)



## 3. Methods based on dense features

Sun (ECCV 2010), Gall (PAMI 2011), Brachmann (ECCV 2014)



## 4. Deep learning methods

Wohlhart (CVPR 2015), Held (arXiv 2015), Krull (arXiv 2015)