

Imitrob: Imitation Learning Dataset for Training and Evaluating 6D Object Pose Estimators

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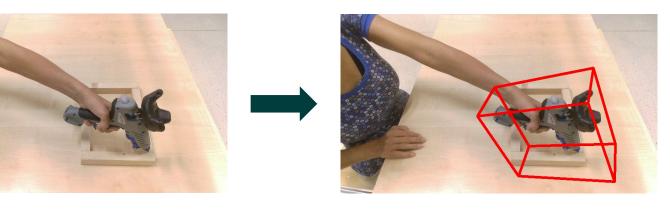
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Motivation



EXAMPLES OF DIFFERENT TASKS WITH ONE TOOL

6D OBJECT POSE ESTIMATION



INPUT IMAGE



Imitation learning in industrial applications

- Robot learns how to perform a task from demonstrations
- Requires 6D pose (position & orientation) of the tool

Challenges for 6D object pose estimation

- Manipulation and occlusion of the tool by the hand
- Lack of benchmarking datasets

Contributions

New 6D object pose benchmarking dataset

- Evaluation of a given 6D object pose estimation method
 - Suitability for imitation learning of a given robotic task
 - Generalization capabilities w.r.t. various setups

Methodology and software for dataset extension

- Acquisition of data for new tools and manipulation tasks
- No need for manual annotation or 3D model of the tool

Dataset and code

• imitrob.ciirc.cvut.cz/imitrobdataset



Imitrob dataset









GUN 2

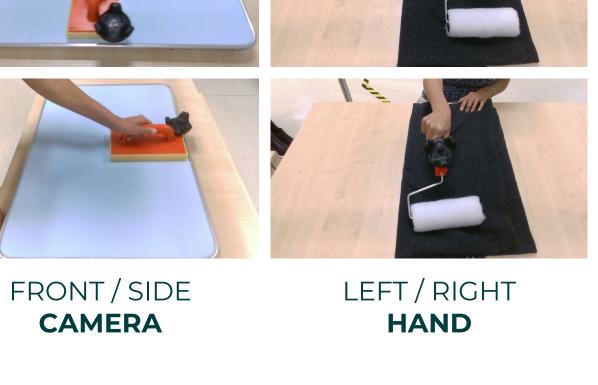
GUN 3

SETUP VARIABILITY

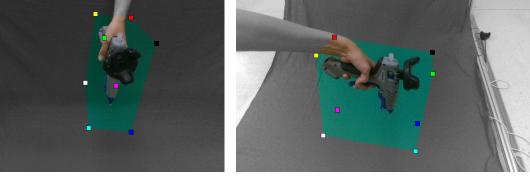




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GROUND TRUTH 6D POSE



TRAINING SET

Test dataset

- 208 videos of 12 manipulation tasks with 9 tools
- Industrial use-cases in manufacturing-like environment
- 2 cameras, left/right hand, 4 demonstrators, (no) clutter

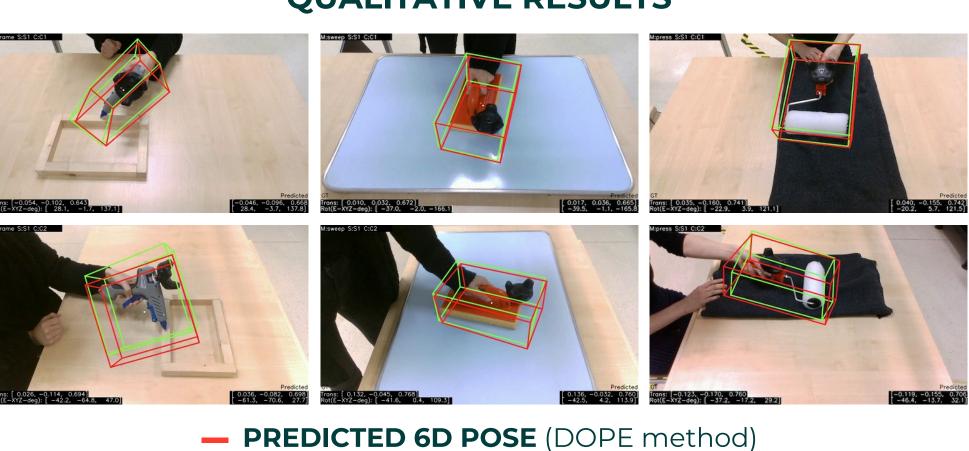
Training dataset

- 144 videos of random manipulation with 9 tools
- 2 cameras, left/right hand, 4 demonstrators

Ground truth 6D object pose

• Measured by HTC Vive tracker attached to the tool

QUALITATIVE RESULTS



— GROUND TRUTH (HTC Vive)

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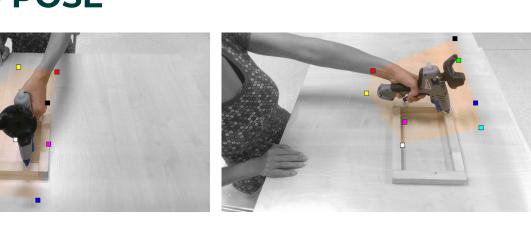


WITHOUT / WITH

CLUTTER



FOUR DEMONSTRATORS



TEST SET

	EX	pe		me	S N	ta	r	25 l	JIts	
Tool	glue gun	grout float	roller	glue gun 2	glue gun 3	glue gun 4	heat gun	power drill	soldering iron	average
$egin{array}{c} \mathrm{ADD}_{5cm}\ E_{\mathrm{rot}}\ E_{\mathrm{tra}} \end{array}$	60.4 7.3 4.0	78.6 4.1 2.5	50.5 8.7 3.7	9.0 38.5 9.9	4.7 40.3 10.2	23.4 20.9 8.4	13.2 14.3 7.0	59.8 8.0 3.8	12.8 35.6 9.0	34.7 <i>%</i> 19.8° 6.5 cm
GENERALIZATION EXPERIMENTS										
	DIFFERENT CAMERA VIEWPOINT									
		OPPOS HANI								
	D	DIFFERE Emonstf								
				TRAIN	IING SET			TEST SET		

Experiments

- Evaluation for each task and tool
- Generalization between training and test data setups

Evaluation metrics

- ADD (average bounding box distance) 5 cm pass rate [%]
- Rotation [deg] and translation [cm] errors

Example usage

- 6D object pose estimation method DOPE [1]
- Depth channel or 3D object model not required

Data augmentation

• Blending of original background with random images (first application in 6D object pose estimation domain)



NoAug (no augmentat

> ADD_{5cm} improveme

[1] Tremblay et al, Deep object pose estimation for semantic robotic grasping of household objects, CoRL 2018.





DATA AUGMENTATION METHODS										
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ation)	В	gNoise	BgRando BgAlterr		BgBlend (best results)					
	NoAug	BgNoise	BgRandom	BgAlternate	BgBlend					
,	29.2%	29.6%	45.6%	56.5%	60.1%					
ent	— 1.0×		1.6×	1.9×	2.1 ×					