Agimus Winter School 11/12/2023 - 15/12/2023 Banyuls (France)



INNOVATIVE ROBOTICS FOR AGILE PRODUCTION

Perception

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Founded by the European Union under GA no 101070165



Motivation

- ▶ You know how to control robot to reach the target pose (SE3)
- ▶ Where to get the pose for the given task?





Motivation

- ▶ You know how to control robot to reach the target pose (SE3)
- ▶ Where to get the pose for the given task? Vision

Static objects reaching

Scene cam:



Robot cam:







6D pose estimation



$$T_{CO}, M = f_{\text{estimate}}(I, K, D)$$

- ► / image
- K camera matrix
- $\blacktriangleright \ \mathcal{D}$ database of meshes
- ▶ $M \in \mathcal{D}$ mesh of the object







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6D pose tracking



$$T_{CO}^{i+1} = f_{track}(I, K, M, T_{CO}^i)$$

I image

- K camera matrix
- M mesh







Why is 6D pose estimation difficult?

 $^{1} https://docs.opencv.org/4.x/d9/d0c/group__calib3d.html$







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6D pose estimation pipeline



Object detection in image

Coarse pose estimation

Pose refinement









Object detection

Object detection

► Goal: detect object in image

mask

- bounding box
- object instance id
- confidence of prediction





Object detection

- ► Goal: detect object in image
 - mask
 - bounding box
 - object instance id
 - confidence of prediction
- ▶ Neural network Mask R-CNN
 - needs good training data
 - annotated images
 - synthetic images









































Object detection without retraining

- Segment Anything Model (SAM)
 - segment any object, in any image, with a single click
 - dataset of 10M images, 1B masks



Universal segmentation model





SAM results







SAM results









CosyPose

Consistent multi-view multi-object 6D pose estimation

Coarse pose estimation

- Input: image crop and mesh model²
- ▶ Goal: estimate 6D pose
- Approach:
 - render and compare strategy
 - neural network
 - initial position is estimated from camera matrix
 - initial orientation is identity
- Training
 - synthetic and real data
 - 10 hours on 32 GPUs

²Image based on: https://arxiv.org/pdf/2204.05145.pdf







Coarse pose estimation results







Refiner

- The same render-and-compare strategy
- Network learns to predict small corrections
- Evaluated iteratively
- ▶ Another 10 hours on 32 GPUs







Refiner results







Refiner results







BOP challenge

- ▶ BOP: Benchmark for 6D Object Pose Estimation
- Main benchmark/competition for 6D pose estimation





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- Tasks on seen objects
 - ▶ Model-based 2D detection/segmentation of seen objects [new in 2022]
 - Model-based 6D localization of seen objects







BOP challenge

- ▶ BOP: Benchmark for 6D Object Pose Estimation
- Main benchmark/competition for 6D pose estimation
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 - Model-based 2D detection/segmentation of seen objects [new in 2022]
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- ▶ Tasks on unseen objects [new in 2023]
 - Model-based 2D detection/segmentation of unseen objects
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CosyPose at BOP challenge

#	Method	Year	PPF	CNN	models	Train. im.	type	Test im.	Refine.	Avg.	LM-O		TUD-L	IC-BIN		HB		Time
1	CosyPose-ECCV20-Synt+Real-1View-ICP	2020	No	Yes	3/dataset	RGB	Synt+real	RGB-D	RGB+ICP	0.698	0.714	0.701	0.939	0.647	0.313	0.712	0.861	13.743
2	Koenig-Hybrid-DL-PointPairs		Yes	Yes	1/dataset	RGB	Synt+real	RGB-D	ICP					0.430	0.483			0.633
3	CosyPose-EP 20-Syn Paal-1View		No	Yes	3/dataset	RGB	Synt+real	RGB	RGB	0.637					0.216			0.449
4	Pix2Post 20_w/ICP-IC		No	Yes	1/object	RGB	Synt+real	RGB-D	ICP	0.591				0.390				4.844
5	Cosyly EC DO DVie	2022	10	Yes	Hataset	RGB	PBColv	RGP	191	2.570	0 633				0.216		0.574	0.475
6	Vida Sors DUP	201		e,	U VE	rai	ье	SL	Me	LUIC	0.582				0.435	0.706		3.220
7	CDP BOTOTO &		No	Yes	1/object	RGB	Synt+real	RGB-D	ICP	0.568		0.464		0.450	0.186			1.462
8	Drost RZUZU	20 🕑	os	vΡ	ose-	ECC\	/20-S	vnt	+Rea	I-1V	'iew	-ICP	0.851	0.368				
9	CDPNv2 20 (PBR-only mp)	2020	No	Yes	1/object	RGB	PBR only	RGB-D	ICP	0.534	0.630	0.435		0.450	0.186			1.491
10	CDPNv2_B	2030	No	Yey.	abbá	RGBuct	Synt+mal	RGB	Ntior	Mat	hiau	All	n ^{0,772}	0.473	cilvi	0.722		0.935
11	Drost-CVPR10-3D-Edges	2019	ųŋ	NoL	ubbe	, jusi	in cu	ipei	iuer,	muu	meu	Aut	'' y, j	Uşej	5101	0.623	0.316	
12	Drost-CVPR10-3D-Only	20 🕑	os	vPo	ose: I	Cons	isten	t m	ulti-v	iew	mul	ti-oł	biect	: 6D	pos	e ^{0.615}	0.344	7.704
13	CDPN_BOP19 (RGB-only)	2020	No.	í Yes	1/object	FCC	V/20	RGB	No	0.479		0.490	0.769		0.067		0.457	0.480
14	CDPNv2_BOP20 (PBR-only&RGB-only)	205	รม	Пa	uiộn,	ECC	v _B ZQ,	RGB	No	0.472	0.624	0.407		0.473			0.390	0.978
15	leaping from 2D to 6D		No	Yes	1/object	RGB	Synt+real	RGB	No	0.471		0.403		0.342			0.543	0.425
16	EPOS-BOP20-PBR		No	Yes	1/dataset	RGB	PBR only	RGB	No	0.457		0.467		0.363	0.186		0.499	1.874
17	Drost-CVPR10-3D-Only-Faster	2019	Yes	No					ICP	0.454	0.492	0.405	0.696		0.274			1.383
18	Félix&Neves-ICRA2017-IET2019	2019	Yes	Yes	1/dataset	RGB-D	Synt+real	RGB-D	ICP	0.412	0.394				0.069			
19	Sundermeyer-IJCV19+ICP	2019	No	Yes	1/object	RGB	Synt+real	RGB-D	ICP	0.398		0.487		0.281	0.158	0.506		0.865
20	Zhigang-CDPN-ICCV19	2019	No	Yes	1/object	RGB	Synt+real	RGB	No	0.353	0.374	0.124				0.470	0.422	0.513
21	PointVoteNet2		No	Yes	1/object	RGB-D	PBR only	RGB-D	ICP	0.351		0.004		0.264	0.001	0.556	0.308	
22	Pix2Pose-BOP20-ICCV19		No	Yes	1/object	RGB	Synt+real	RGB	No	0.342	0.363	0.344	0.420	0.226	0.134	0.446	0.457	1.215
23	Sundermeyer-IJCV19	2019	No	Yes	1/object	RGB	Synt+real	RGB	No	0.270	0.146	0.304	0.401			0.346		0.186
24	SingleMultiPathEncoder-CVPR20		No	Yes	1/all	RGB	Synt+real	RGB	No	0.241	0.217		0.334		0.067			0.186
25	Pix2Pose-BOP19-ICCV19	2019	No	Yes	1/object	RGB	Synt+real	RGB	No	0.205			0.349				0.290	0.793
26	DPOD (synthetic)	2019	No	Yes	1/scene	RGB	Synt	RGB	No	0.161	0.169	0.081	0.242	0.130	0.000	0.286		0.231





CosyPose variants: FocalPose, FocalPose++







CosyPose variants: RoboPose







CosyPose variants: RoboPose







CosyPose limitations

► Training time

For each dataset

- ▶ 10 hours on 32 GPUs for coarse estimator
- ▶ 10 hours on 32 GPUs for refiner

Coarse pose estimation often not accurate enough for refinement









MegaPose

6D Pose Estimation of Novel Objects via Render & Compare

MegaPose - coarse estimation

- Re-casted estimation into classification
- Poses sampled randomly [original]
- Poses uniformly distributed [new]
- Allows multi-hypothesis evaluation







MegaPose - refiner

- Multi-view rendering
- ► Render and compare
- Iterative refinement







MegaPose - training data

- Generalization to unseen object achieved by big training dataset
 - only synthetic dataset
 - thousands of objects
 - 2 millions of images
- ► Training
 - ▶ 100 hours on 32 GPUs
 - trained only once, models are available









MegaPose - results









HappyPose

Open-source toolbox for 6D pose estimation

HappyPose

- Developed in AGIMUS project (https://github.com/agimus-project/happypose)
- Re-implements CosyPose and MegaPose
- Packaging, testing, documentation
- Used for the practicals









HappyPose at BOP









Applications

PCB manipulation based on the estimated pose







euROBIN taskboard pose estimation



euROBIN

- robotics network of excellence
- technology exchange programme
- brain magnet programme
- workshops/schools
- WP1 taskboard
 - measures the performance of robotics skills
 - used in Robothon challenge





Practicals

- Mask R-CNN detection
- CosyPose pose estimation
- MegaPose pose estimation
- CosyPose/MegaPose for tracker initialization







Questions and Answers



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