



Endoscopic Vision Challenge

SimCol-to-3D 2022

3D Reconstruction During Colonoscopy



18th September 2022

Intro

Challenge

Results

Intro

Challenge

Results

SimCol Organizers



Anita Rau



Sophia Bano



Yueming Jin



Danail Stoyanov



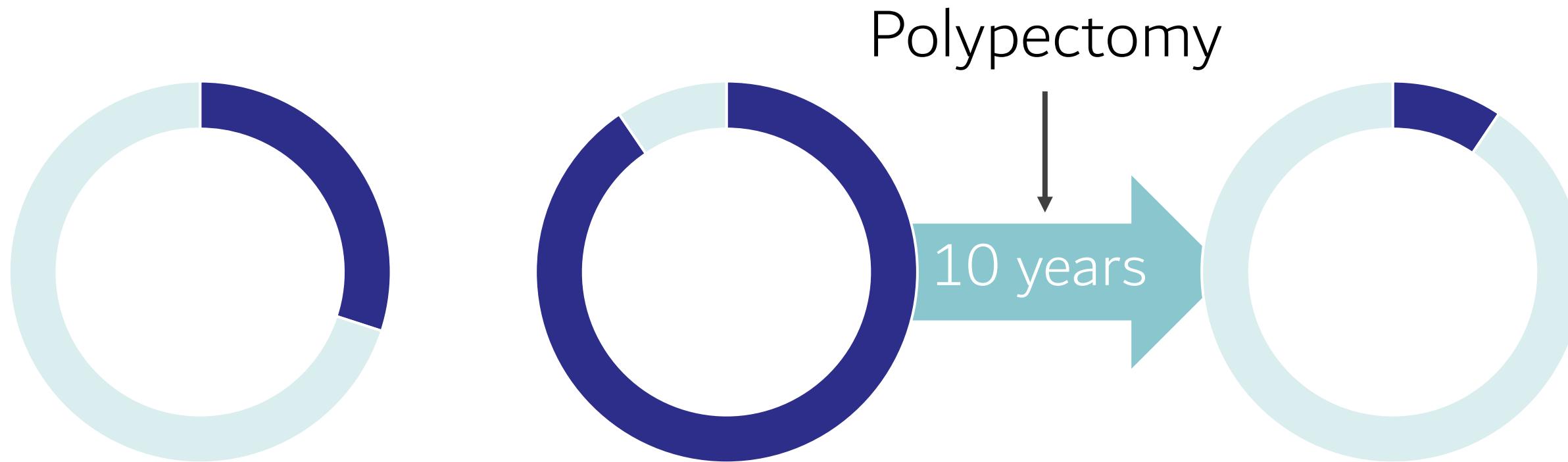
Clinical Partners and affiliated project:



Sponsors:



Clinical Background



Polyp detection
rates highly
depend on skill!

- People > 60 y. with polyps
- Localized stage CRC patients surviving 5 years
- Metastatic CRC patients surviving 5 years

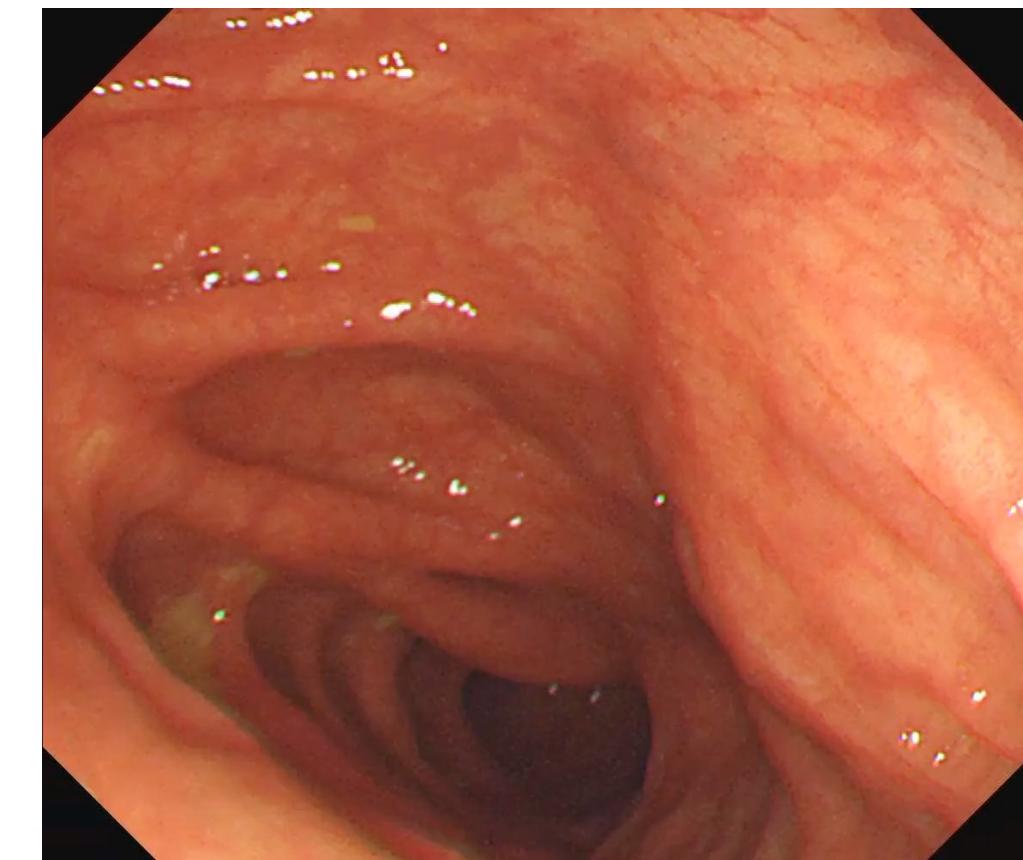
Han, A., 2017. Butyrate, A Major Bacterial-derived Metabolite: Understanding of Butyrate Metabolism in Cancerous Colonocytes.
Hailes, S., 2007, Screening for colorectal cancer in Contemporary Issues in Cancer Imaging.

Clinical Background

Standard Colonoscope



Colonoscopy video



3D model



Olympus Medical Systems <https://www.youtube.com/watch?v=IG6H-VhRiek>

Pablo Azagra et al. Endomapper dataset of complete calibrated endoscopy procedures. arXiv preprint arXiv:2204.14240, 2022

Intro

Challenge

Results

SimCol Challenge Tasks

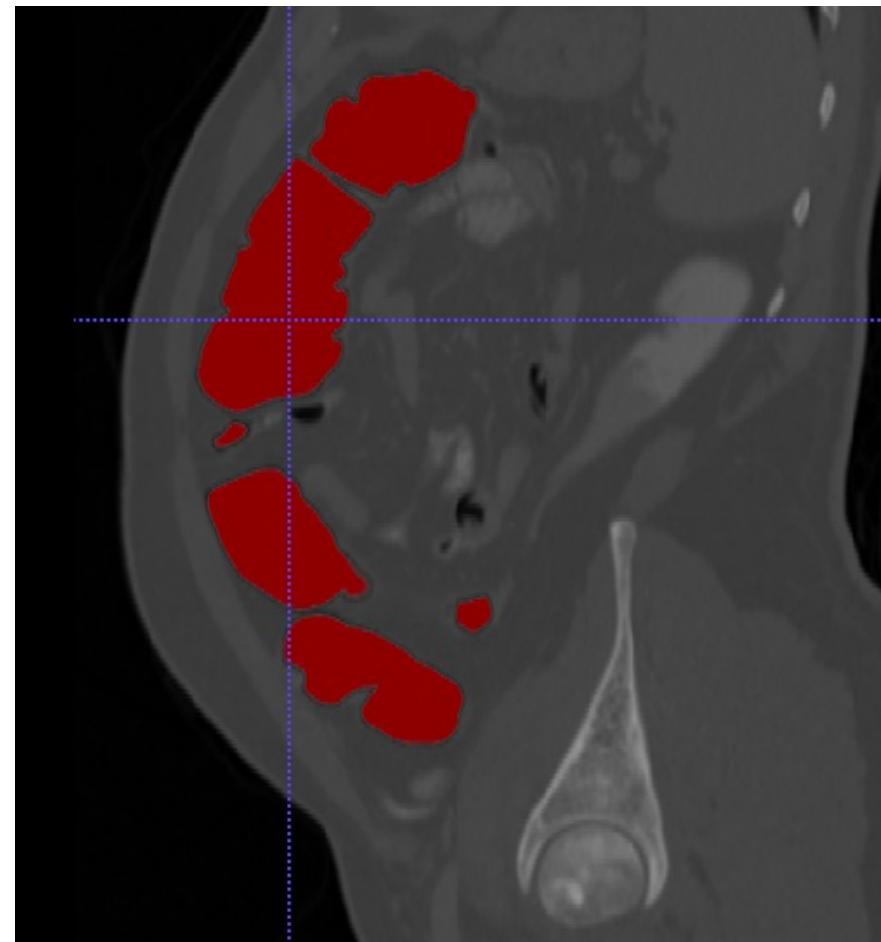
Aims at designing generalized algorithms to solve:

Task 1: Depth prediction in simulated colonoscopy

Task 2: Camera pose estimation in simulated colonoscopy

Task 3: Camera pose estimation in real procedures

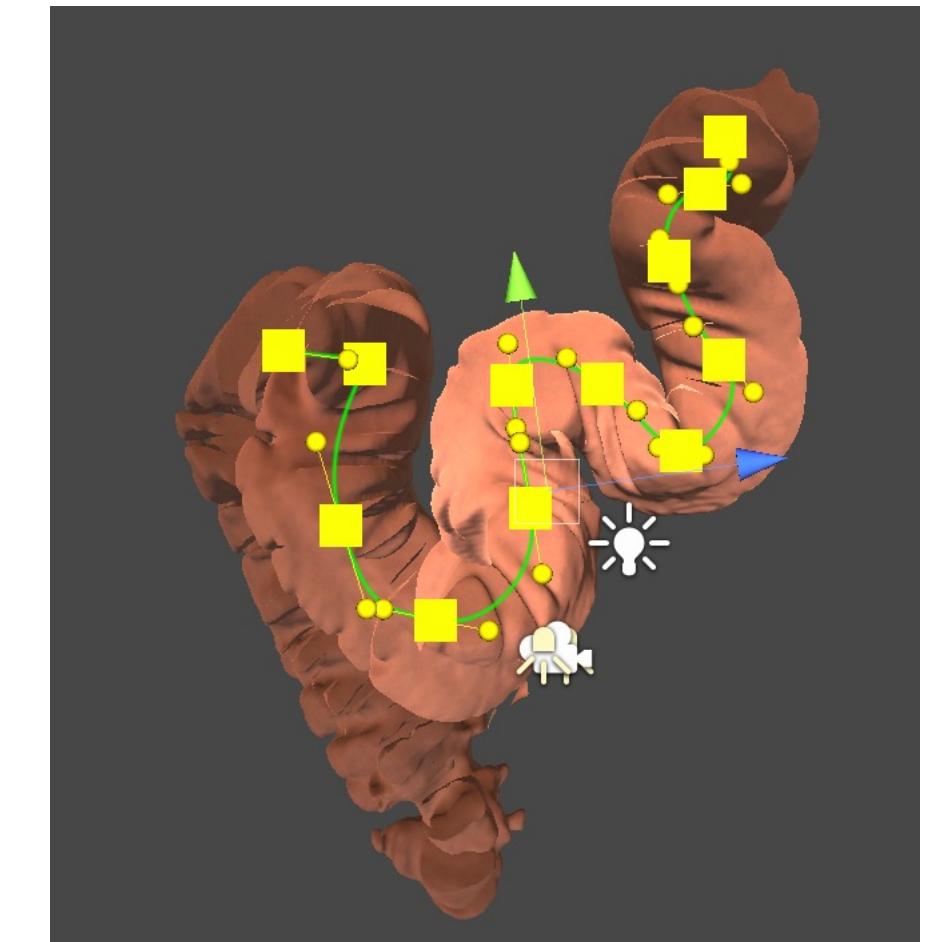
SimCol Data Generation



Segmentation

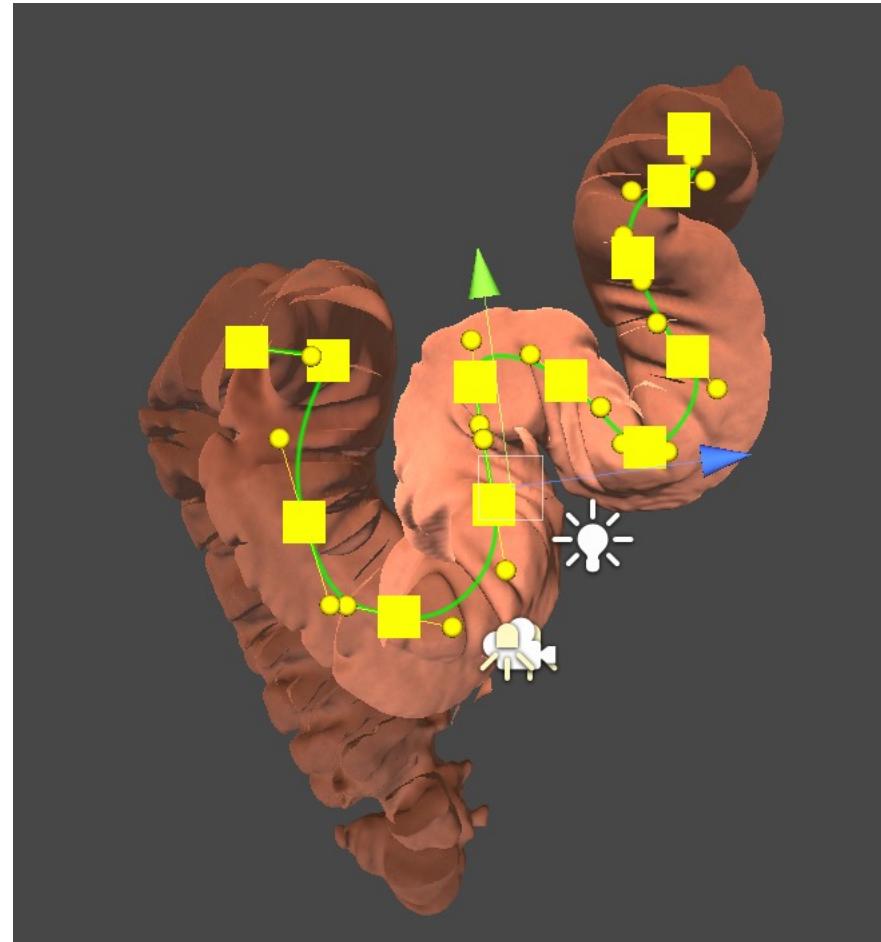


3D mesh

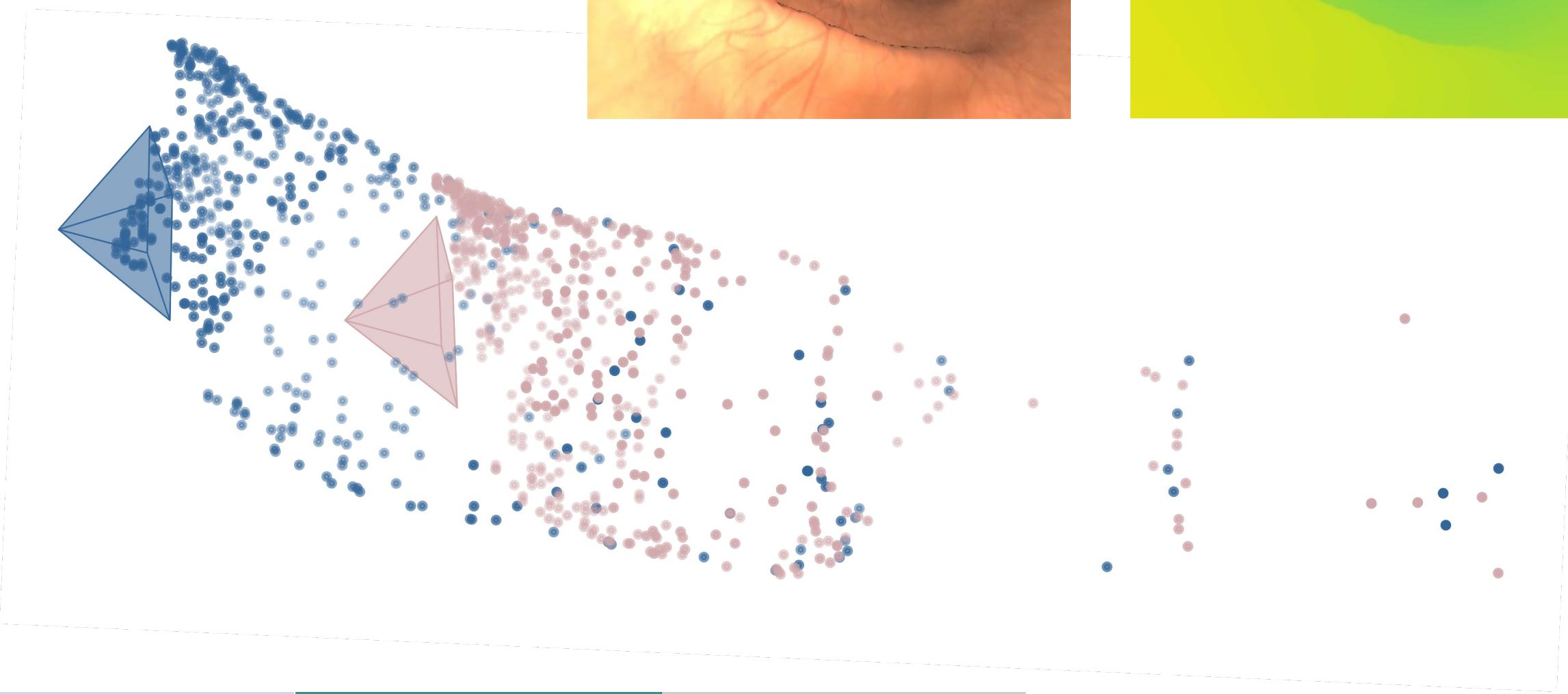


Camera path in
Unity

SimCol Data Generation



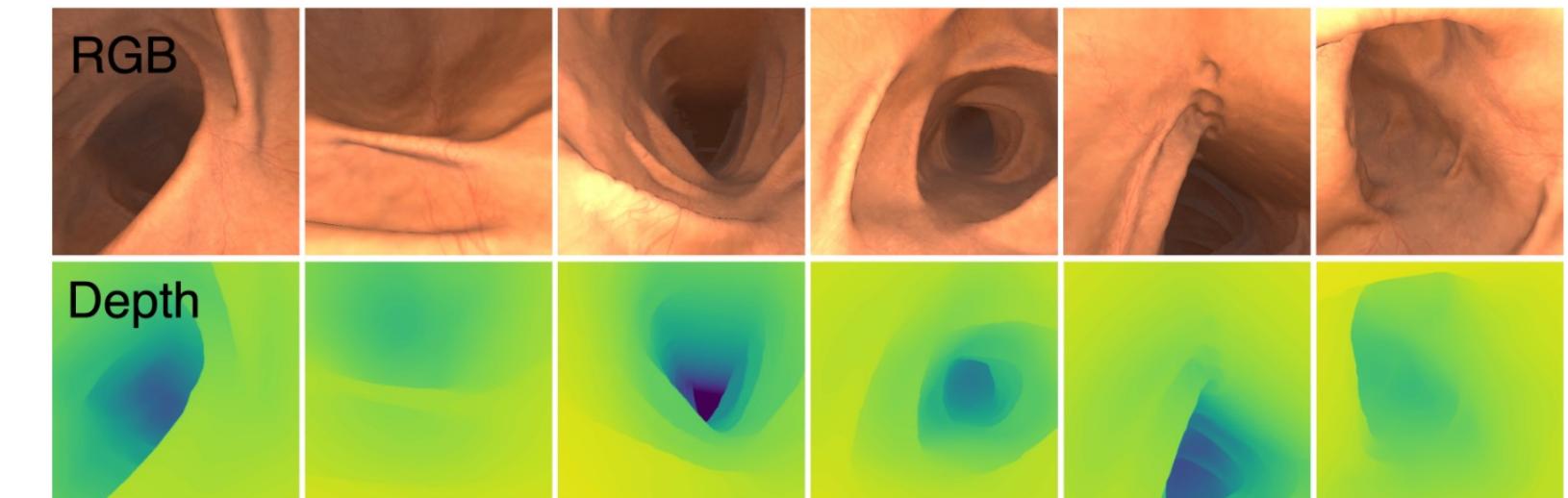
Camera path in
Unity



Training Data

Tasks 1&2: Depth and camera pose estimation in simulated colonoscopy

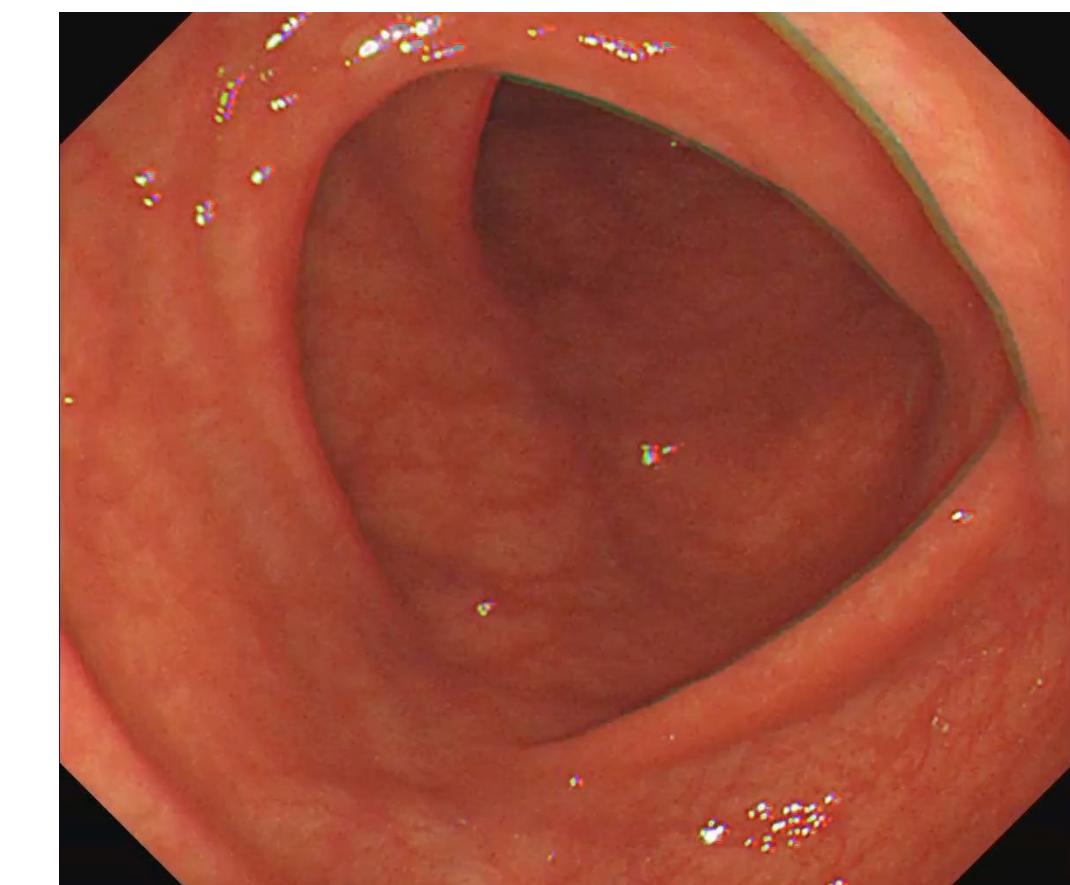
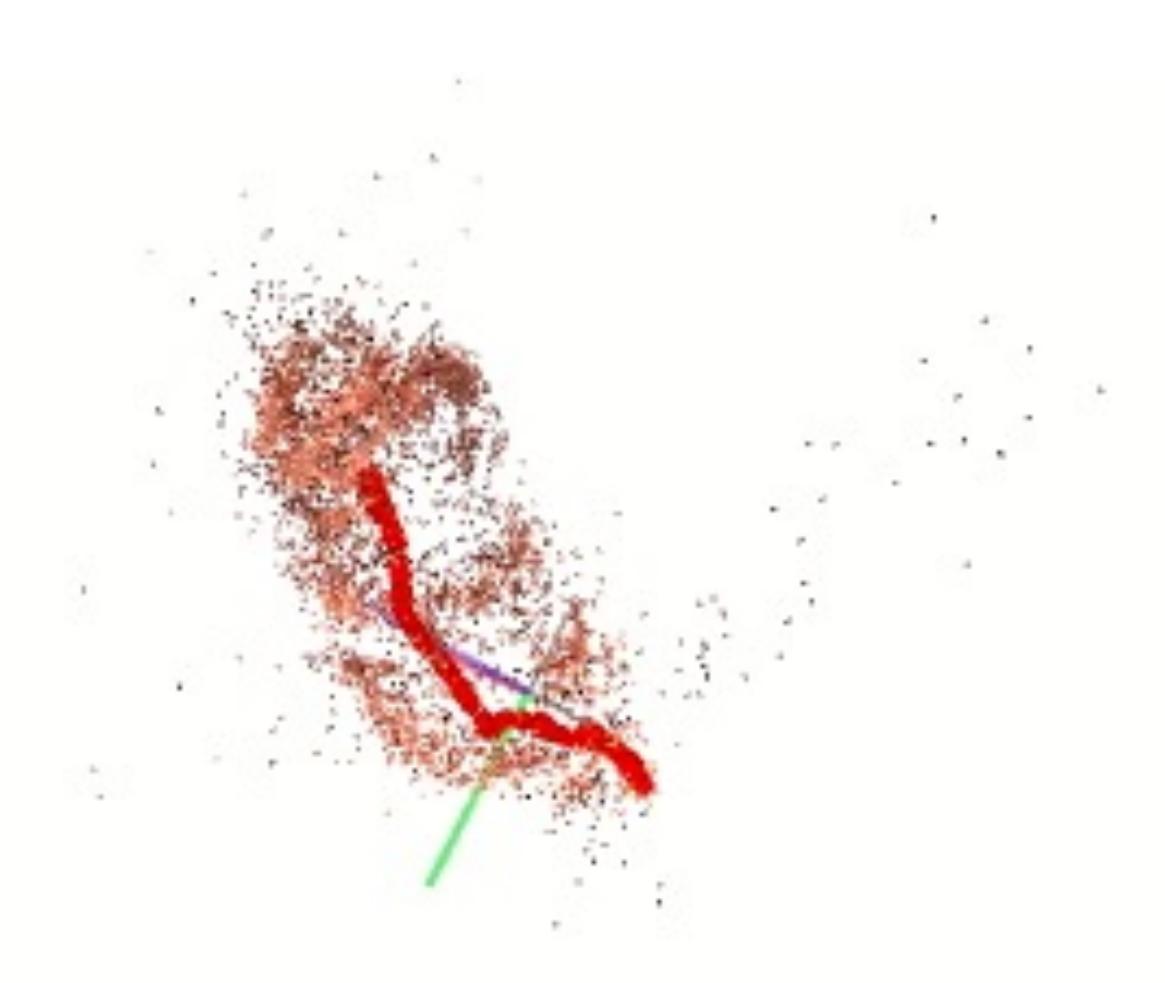
- 2 simulated patient's anatomies → 2 subsets
- In each subset, we generate 12 trajectories with >1,000 images each
- Ground truth for each image:
 - depth map
 - camera pose
 - camera intrinsics



Training Data

Task 3: Camera pose estimation in real procedures

- 96 procedures
- 2 with COLMAP pseudo ground truth (camera poses, intrinsics & sparse depth)



Testing Data

Tasks 1&2: Depth and camera pose estimation in simulated colonoscopy

- 2 anatomies from training & 1 unseen anatomy
- 3 trajectories from each anatomy with 601 or 1,201 images each

Task 3: Camera pose estimation in real procedures

- 3 anatomies
- 1-3 sub-trajectories from each anatomy (7 total)

Task 1: Synthetic depth

$$\begin{aligned}
 L_1 &= \frac{1}{D} \sum_d \|Y(d) - Y'(d)\|_1 \\
 L_{\text{rel}} &= \mu_d \left(\left\| \frac{Y(d) - Y'(d)}{Y(d)} \right\|_1 \right) \\
 L_{\text{RMSE}} &= \sqrt{\frac{1}{D} \sum_d (Y(d) - Y'(d))^2}
 \end{aligned}$$

Y : ground truth depth, Y' : predicted depth, D : number of pixels in Y , μ : median

Evaluation Metrics

Tasks 2 & 3: Synthetic / real pose

$$\begin{aligned}
 RTE &= \mu_\tau(||\text{trans}(\Omega_\tau^{-1}\Omega'_\tau)||) \\
 ATE &= \mu_\tau(||\text{trans}(P_\tau) - \text{trans}(P'_\tau)||) \\
 ROT &= \mu_\tau\left(\frac{\text{trace}(\text{Rot}(\Omega_\tau^{-1}\Omega'_\tau)) - 1}{2} \cdot \frac{180}{\pi}\right)
 \end{aligned}$$

Ω : relative pose, P : absolute pose, ' : prediction, μ : median

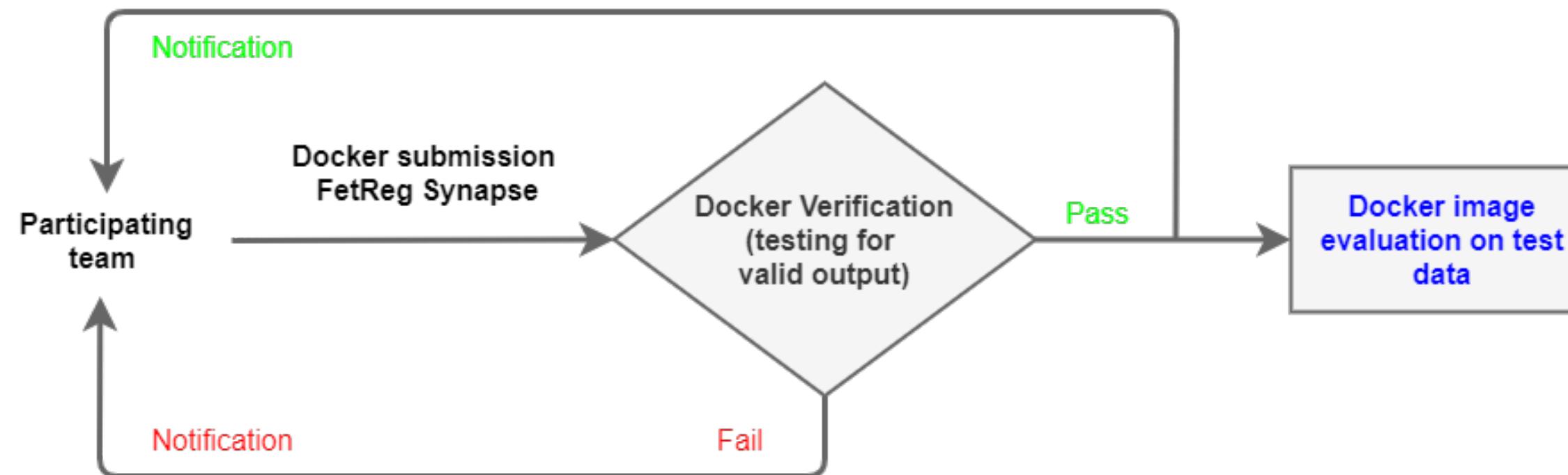
Challenge Setup



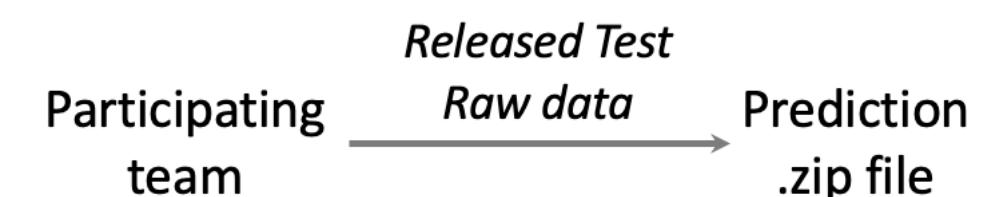
- 51 challenge registration requests
- 13 Team registrations with 31 Team members
- 6 Team submissions
- 6 submissions – Task 1
- 3 submissions – Task 2
- 2 submissions – Task 3

Submission Setup

#1 Docker Submission



#2 Prediction Submission



Test raw dataset

Released

Submission

Synapse platform

Provided

Docker examples (Three tasks)

Submission guidelines

Slack support forum

Participating Teams

CVML

Edward Sanderson and Bogdan J. Matuszewski
Computer Vision and Machine Learning (CVML) Group,
University of Central Lancashire, Preston, UK

KLIV

Sista Raviteja, Varshini Elangovan, Rachana Sathish, Debdoot Sheet
Indian Institute of Technology, Kharagpur

EndoAI

Jiwoon Jeon¹, Jae Young Lee², Dong Jae Lee², Woonghyun Ka²
¹ EndoAI, Korea
² Korea Advanced Institute of Science and Technology, Korea

MIVA

Zhengwen Li, Yichen Zhu, Yihe Chen, Yutong Hu, Xiaoyan Zhang
ZheJiang University, China

IntuitiveIL

Erez Posner, Netanel Frank, Moshe Bouchnik
Intuitive Surgical

MMLAB-NUS-SimCol

Lalithkumar Seenivasan¹, Mobarakol Islam², Hongliang Ren^{1,3}
¹ National University of Singapore, Singapore
² Imperial College London, UK
³ Chinese University of Hong Kong, HK, China

PARTICIPATING TEAMS

PRESENTATIONS

TEAM - CVML

PRESENTATION

Team CVML Group

Edward Sanderson and Bogdan J. Matuszewski

Computer Vision and Machine Learning (CVML) Group, University of
Central Lancashire, Preston, UK

This work was supported by the Science and Technology Facilities Council [grant
number ST/S005404/1]

Method for Task 1

Main components:

1. Two parallel branches:

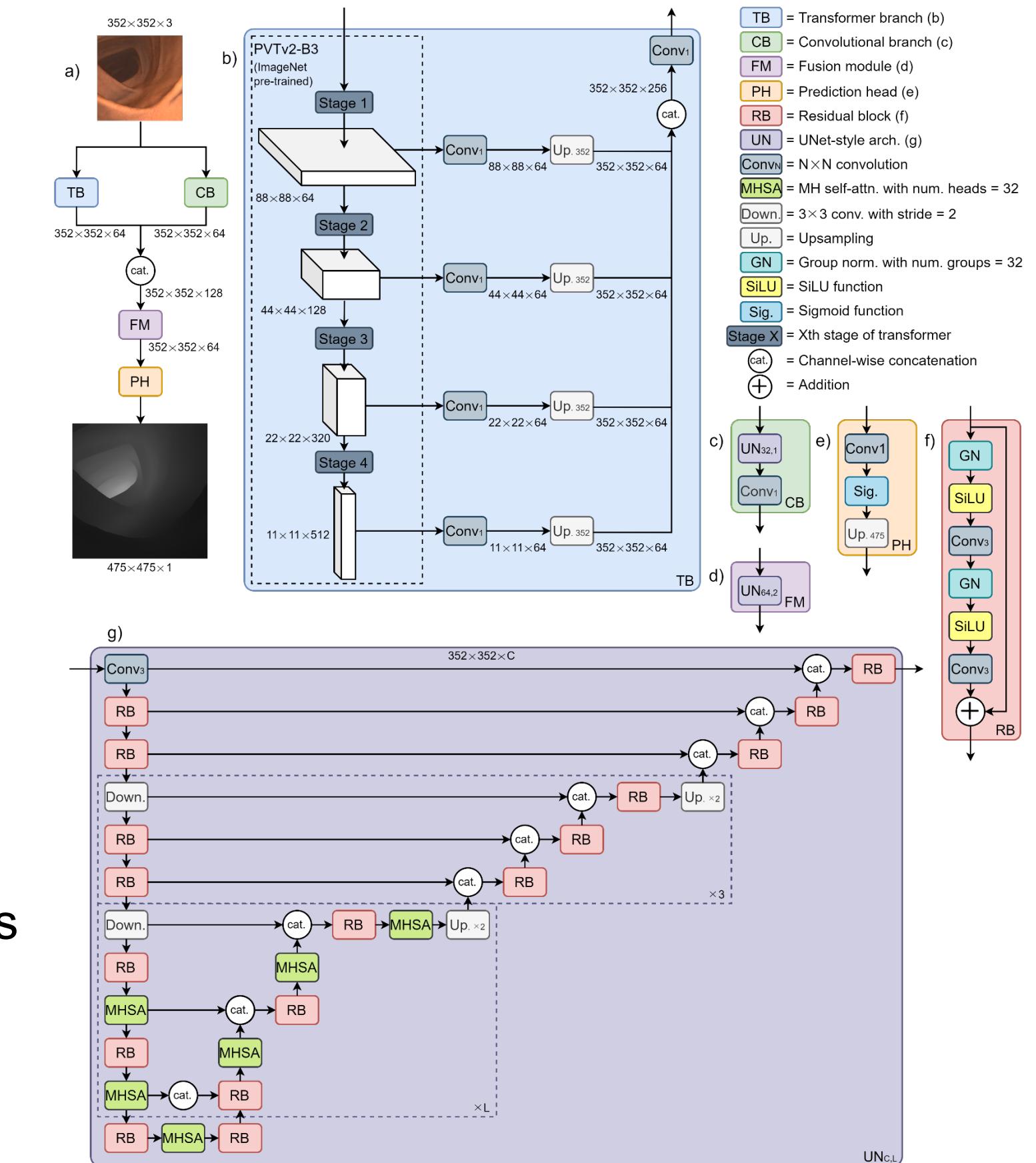
a) Transformer branch (TB) – PVTv2 encoder with lightweight decoder

b) Convolutional branch (CB) – Updated UNet-style architecture

2. Fusion module (FM) – similar to CB but larger

3. Prediction head (PH) – simple architecture for mapping features to depth map of original size

Training performed in supervised manner with MSE loss



Results

Our method reduced the MSE of a standard UNet by 70%

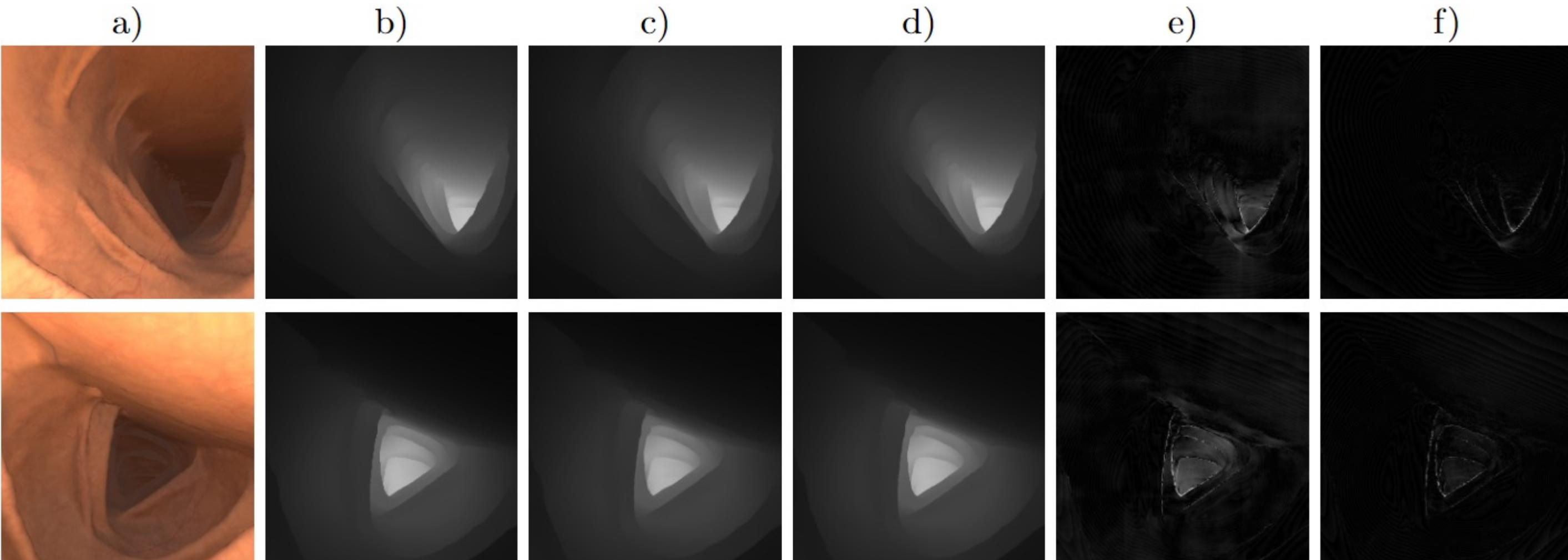


Figure: a) Input RGB, b) ground truth, c) UNet prediction, d) prediction from our method, e) absolute error of UNet (log-scale), f) absolute error of our method (same scale as e))

TEAM - EndoAI

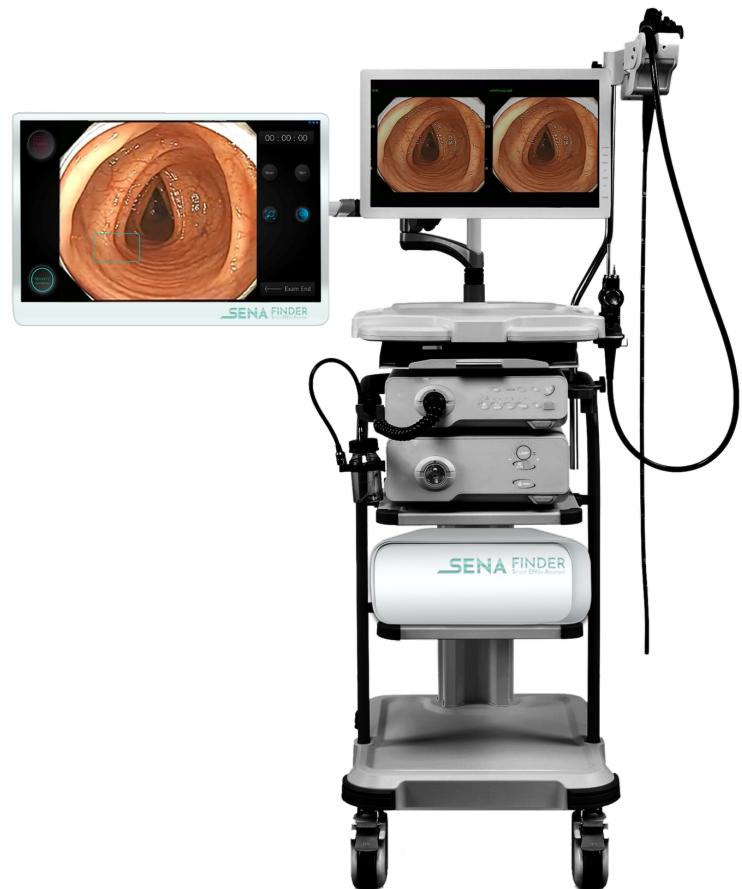
PRESENTATION

Team



Endo AI

AI solution provider for Gastroenterology



- ✓ Real-time Polyp Detection AI Service
- ✓ Diagnosis Software
- ✓ Raw Data Based Report

→ Actual test operation is in progress and is expected to be commercialized soon.

Jiwoon Jeon

Senior researcher at EndoAI

Research interest

Image generation, Image detection

Jae Young Lee

Ph.D Student at KAIST

Research interest

Light field, Depth estimation, Image generation

Dong-Jae Lee

Master Student at KAIST

Research interest

Depth estimation, Transformer

Woonghyun Ka

Master Student at KAIST

Research interest

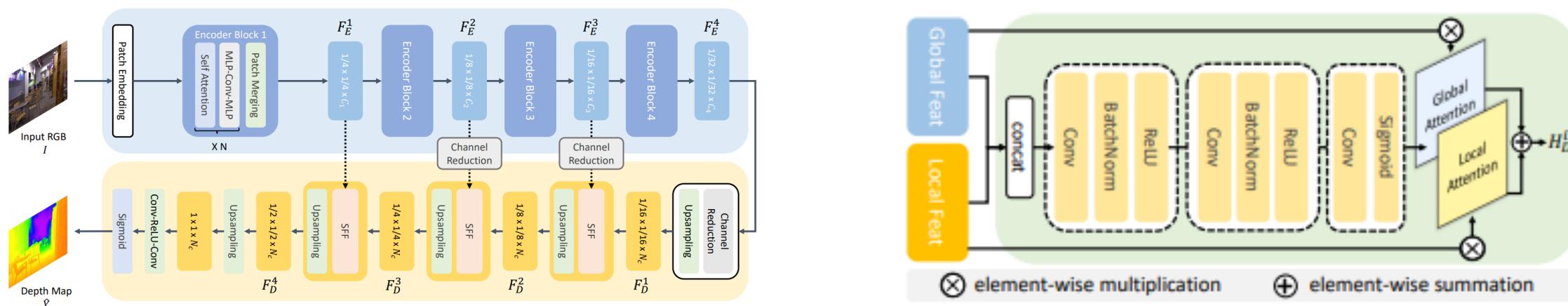
Computer vision related to Autonomous driving

Method (1/2)

■ Task1 : dealing with global and local information simultaneously

▪ GLPDepth [1]: Transformer-based monocular depth estimation

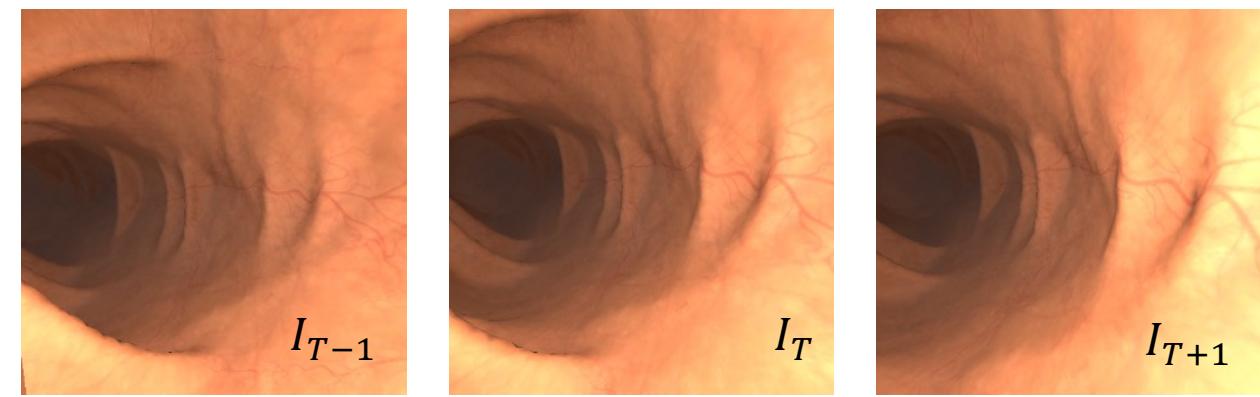
- Backbone: B4 model
- Loss: SiLog loss
- Hyper-parameter tuning



■ Task2 : dealing with depth and pose information simultaneously

▪ MonoDepth2 [2]: Self-supervised monocular depth estimation

- Depth model: replaced to the model used in Task1
- Pose model: resnet encoder + pose decoder
- Warp direction in training time: forward and backward



[1] D. Kim, W. Ka, P. Ahn, D. Joo, S. Chun, and J. Kim, "Global-Local Path Networks for Monocular Depth Estimation with Vertical CutDepth," arXiv, 2021.

[2] C. Godard, O. M. Aodha, M. Firman, G. J. Brostow, "Digging into Self-Supervised Monocular Depth Prediction," ICCV, 2019.

Method (2/2)

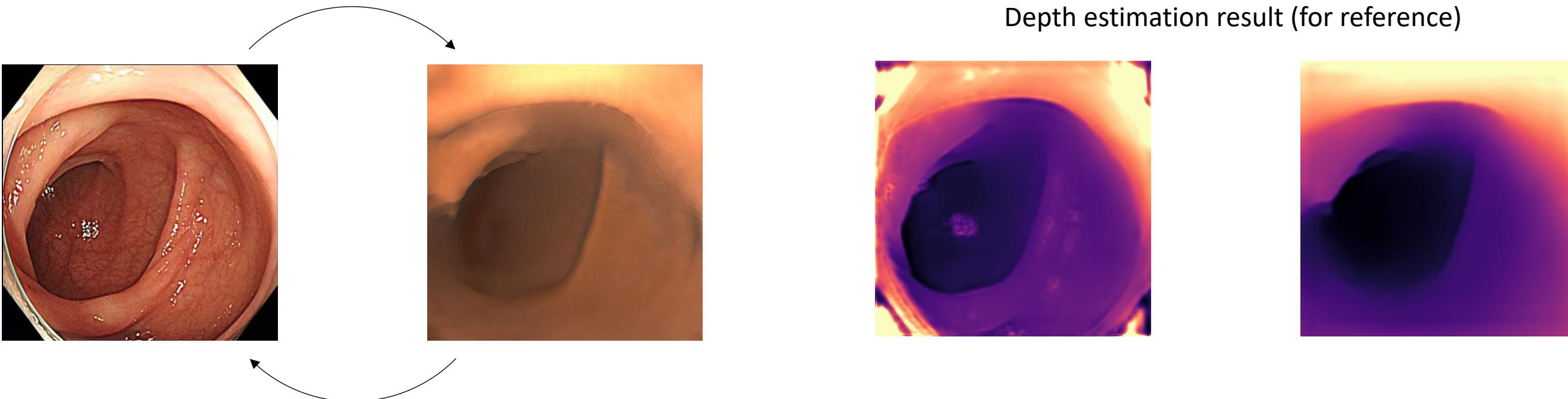
■ Task3 : Change the domain to the same image as the previously trained image domain

- **MonoDepth2**

- Use the same model as Task2

- **Cyclegan [3]: Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks**

- Generator architecture : resnet_9blocks



TEAM - IntuitiveIL

PRESENTATION

Deluminator

Illumination Invariant Augmentation For Colonoscopy



Erez Posner

INTUITIVE



Netanel Frank

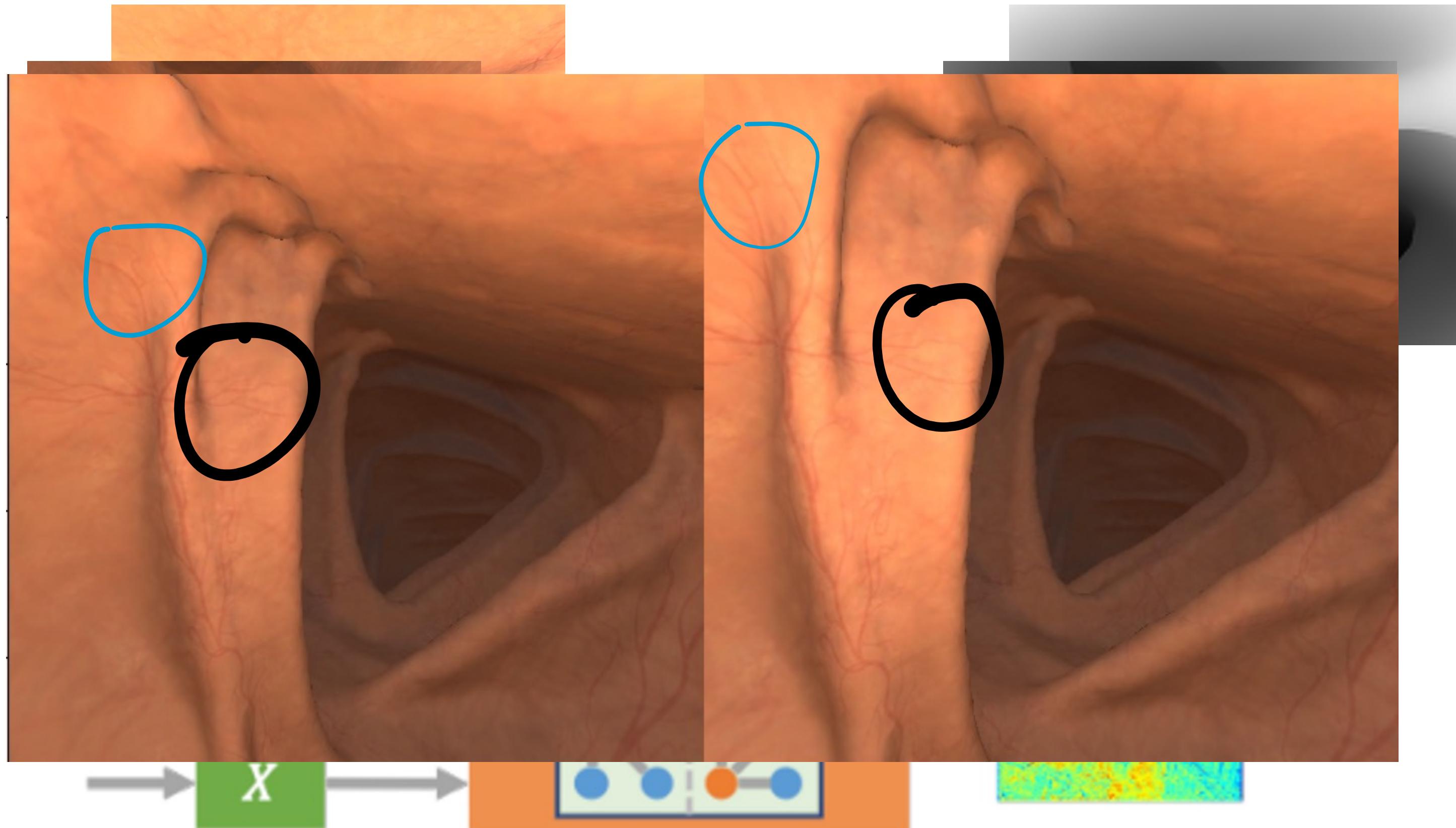
INTUITIVE



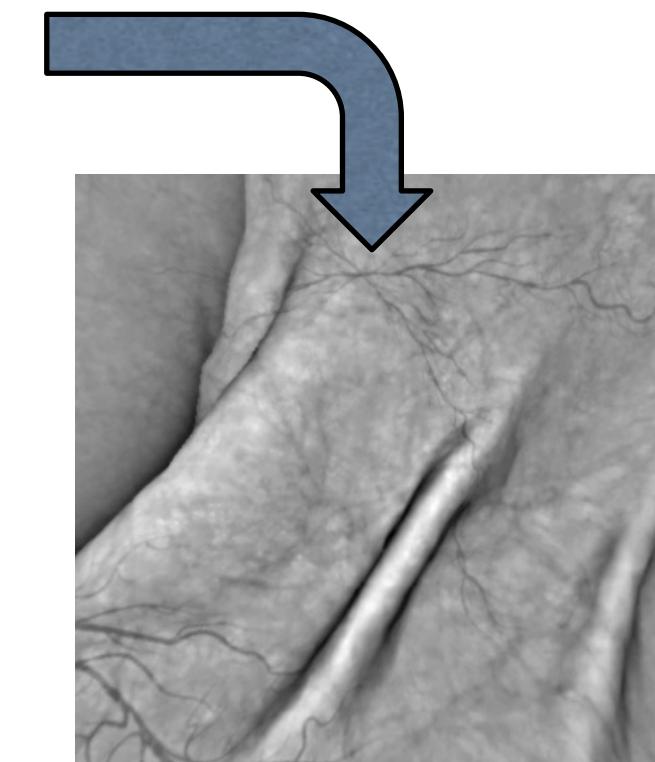
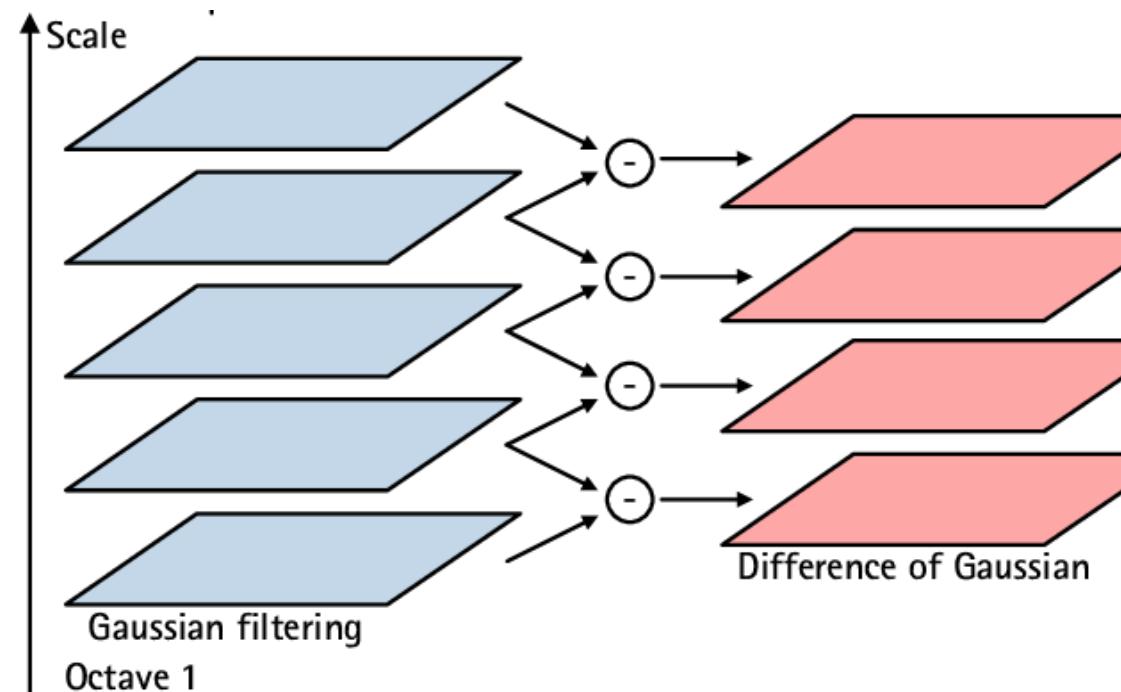
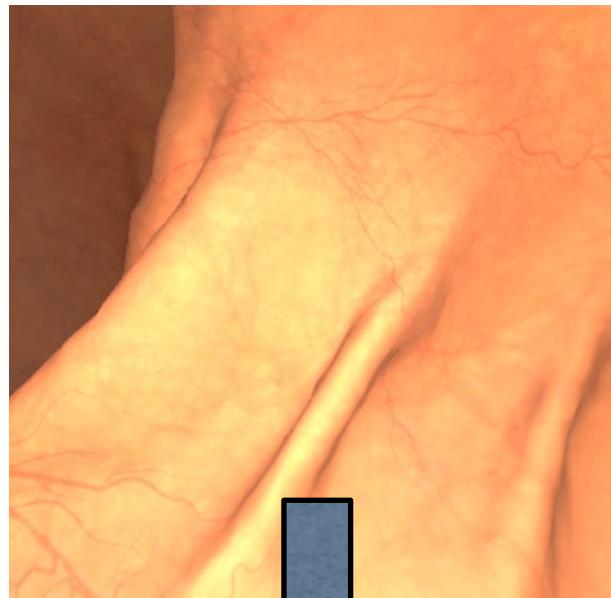
Moshe Bouhnik

INTUITIVE

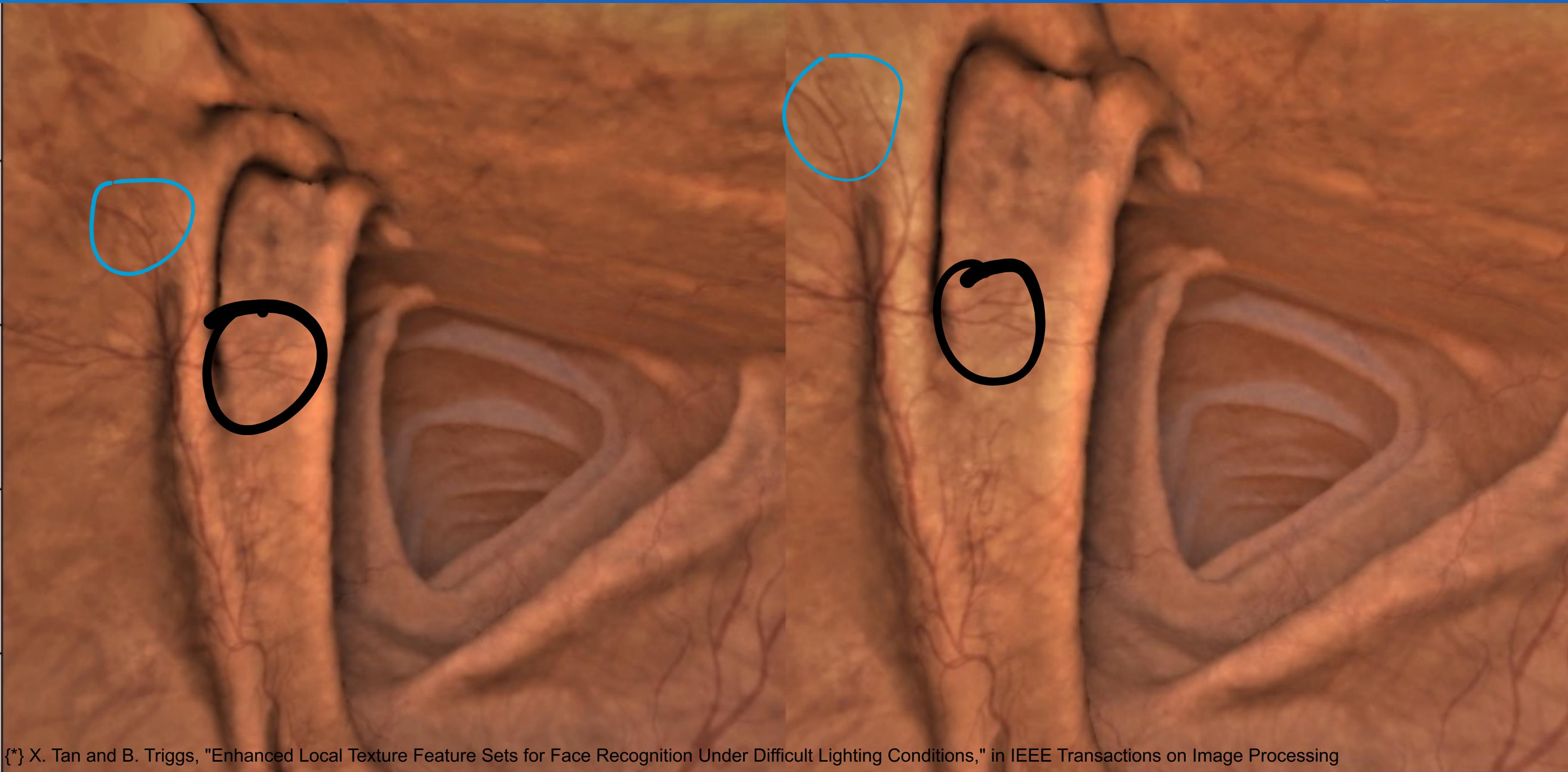
Method



Colon Deluminator Augmentation



Colon Deluminator Augmentation



SimCol2022	AbsRel (%) Train	AbsRel (%) Val
Baseline Training	2.0	2.5
+ DeluminatorAug	1.7	1.8

TEAM - KLIV

PRESENTATION

Team



#iitKLIV

Kharagpur Learning, Imaging and
Visualization Research Group
www.iitkliv.github.io

Depth Estimation in Synthetic Colonoscopy Images using SUMNet



Varshini Elangovan



Sista Raviteja



Rachana Sathish



Dr. Debdoot Sheet

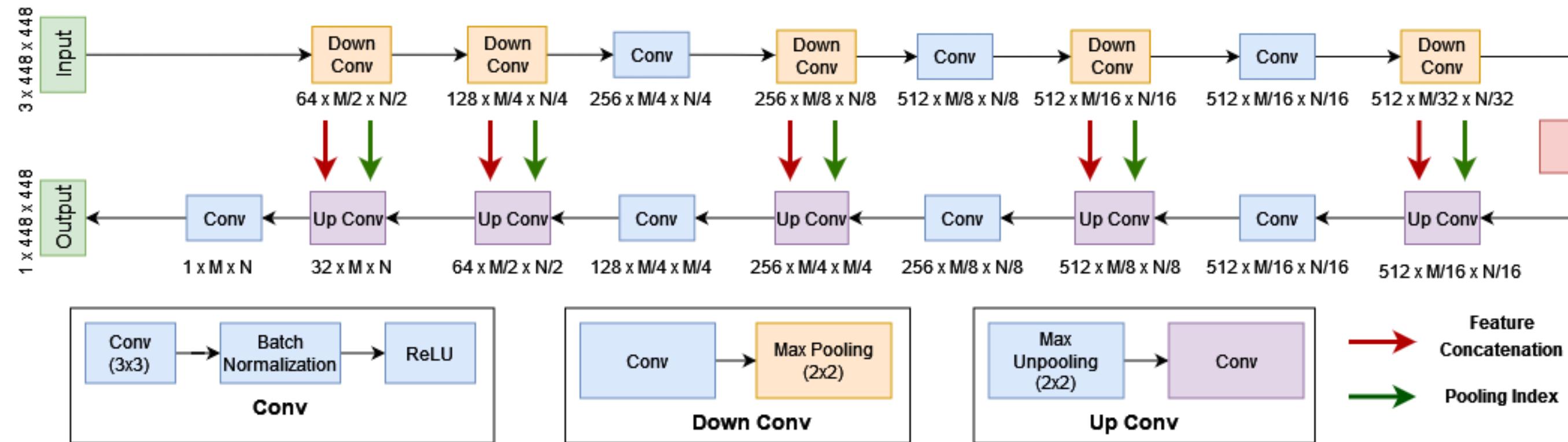


Figure I: SUMNet Architecture

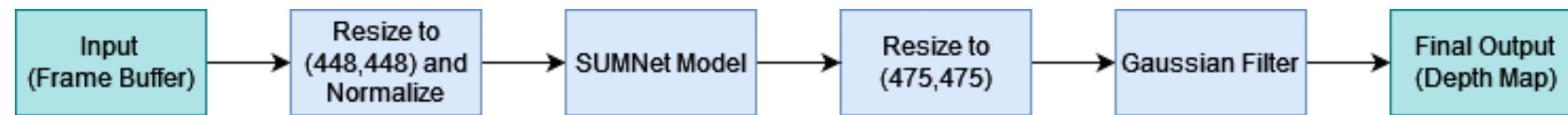


Figure 2: Block Diagram

Results

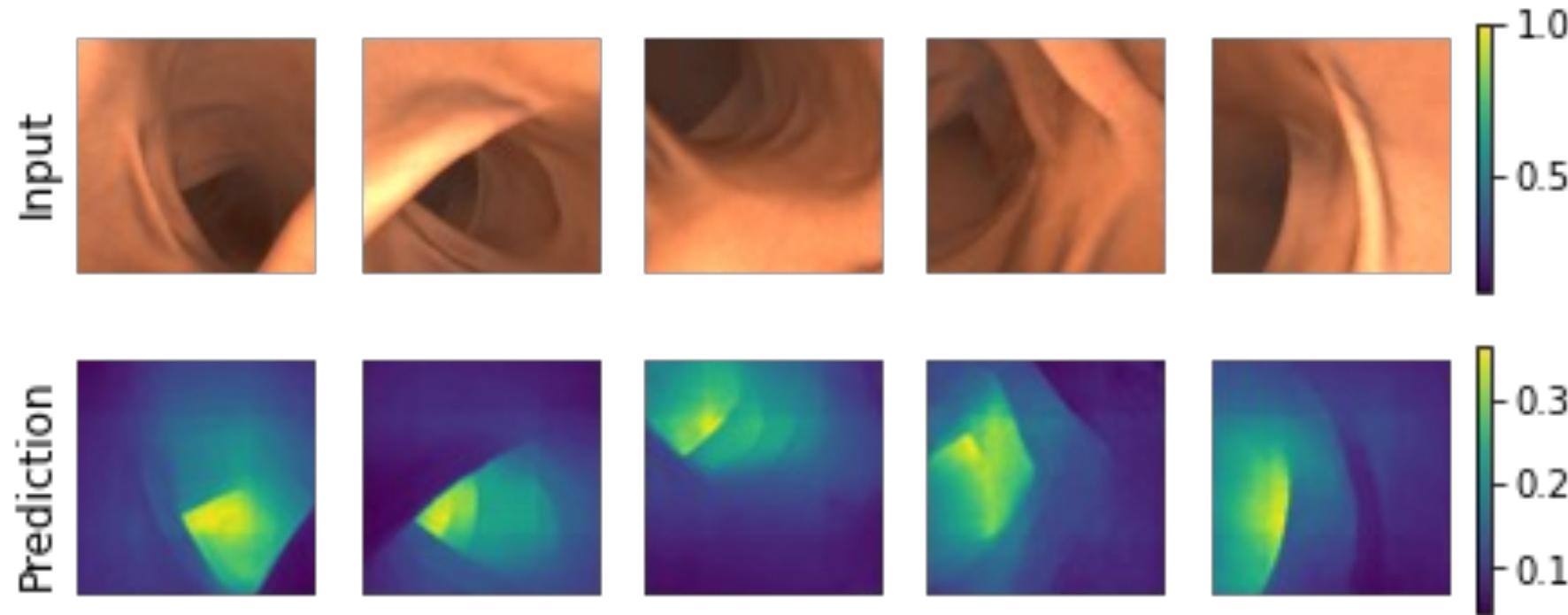


Figure 3: Sample Predictions on Test Data

Table I: RMSE values for the proposed approach

Dataset	Mean RMSE (in cm)
Training	0.227 ± 0.076
Validation	0.23 ± 0.113

TEAM - MIVA

PRESENTATION

Team

Our Team: MIVA (Medical Image Visual Analysis)

Lab of Biomedical Informatics, College of Biomedical Engineering & Instrument Science,
Zhejiang University, Hangzhou, China

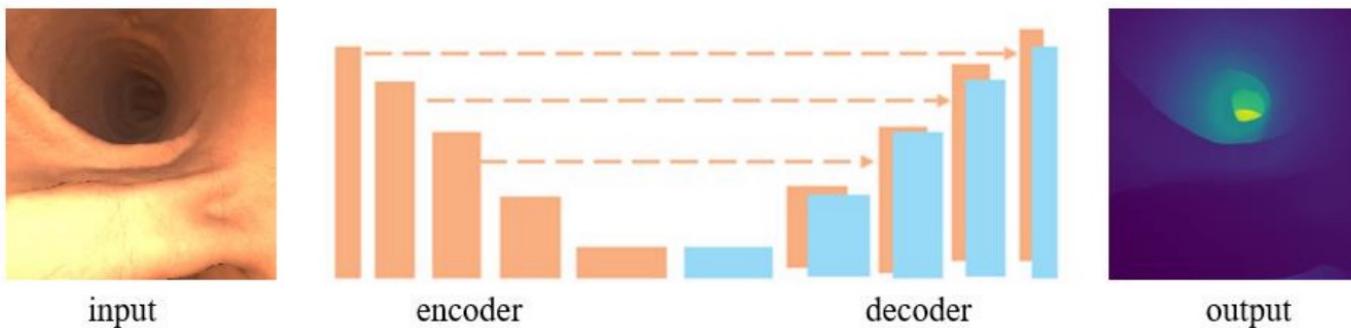
Participants: Zhengwen Li, Yichen Zhu Presenter: Zhengwen Li

Advisor: Jiquan Liu PhD



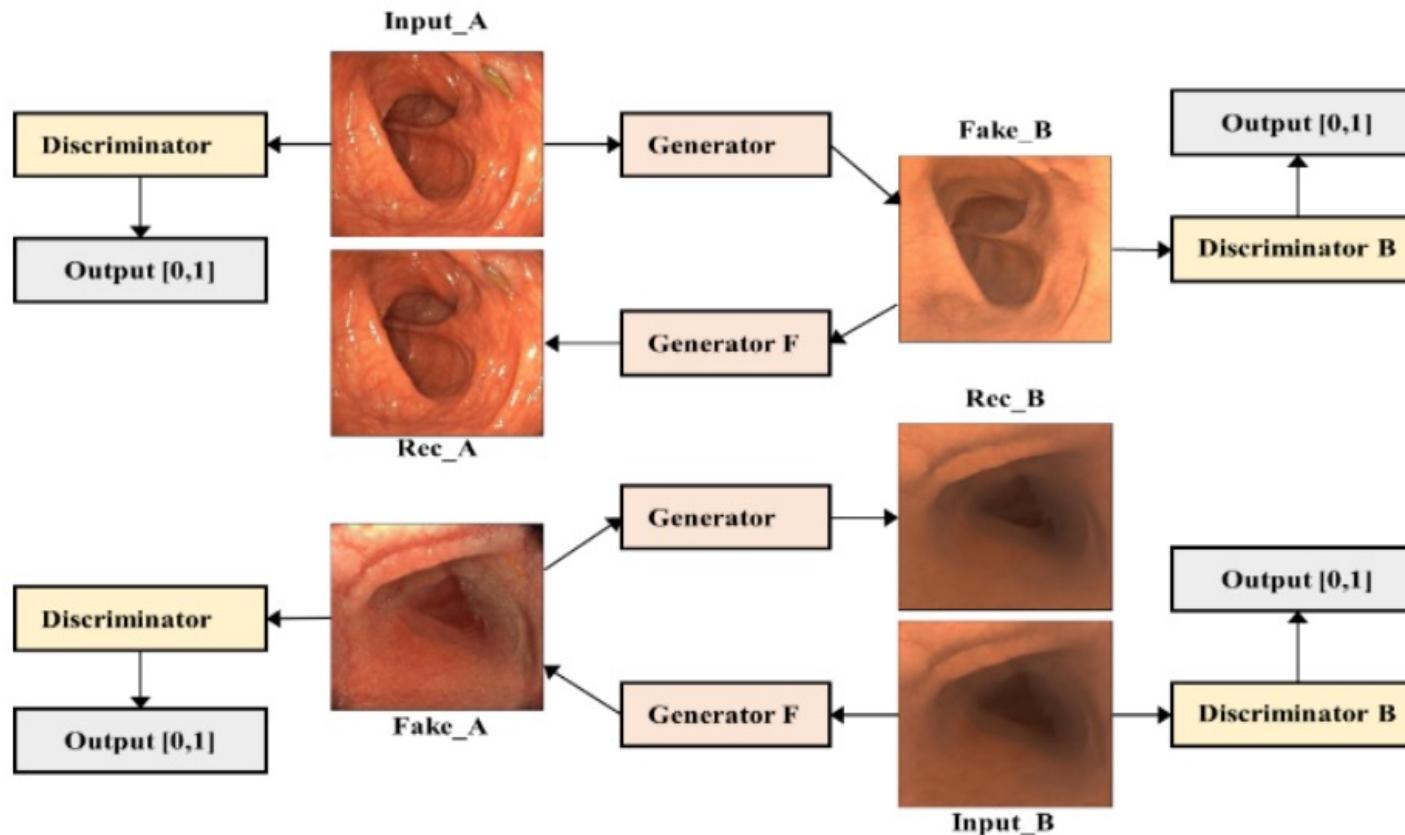
Method

1. subtask 1 DenseDepth

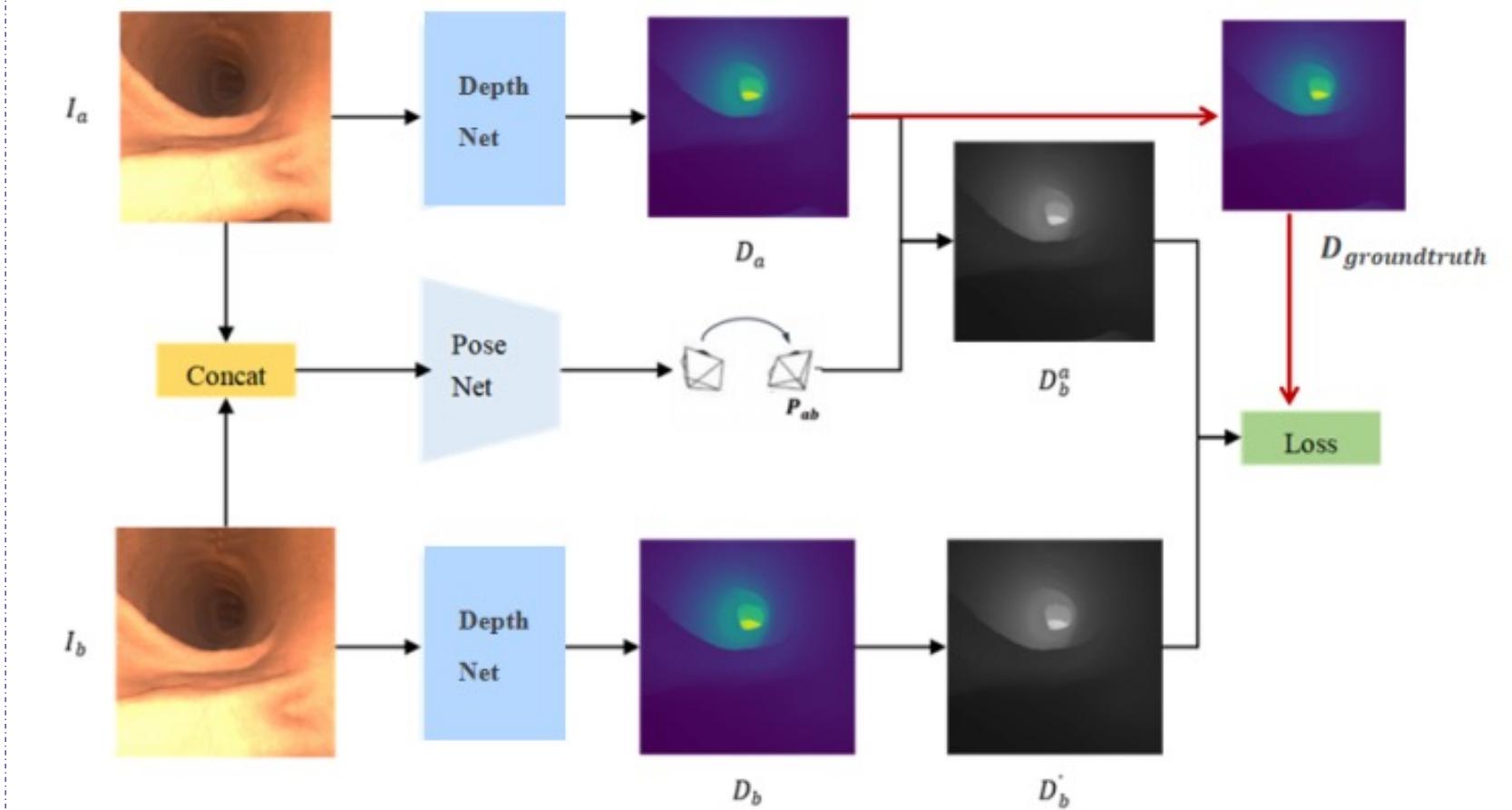


$$L(y, \hat{y}) = 0.1L_{depth}(y, \hat{y}) + L_{SSIM}(y, \hat{y})$$

3. subtask 3 CycleGAN + subtask2



2. subtask 2 SC-SfmLearner + DenseDepth



$$\begin{aligned} L &= L_{SC-Sfmlearner} + \omega L_{DenseDepth} \\ &= L_P^M + 0.1L_S + 0.5L_{GC} + L_{DenseDepth} \end{aligned}$$

dataset: SimCol, Endomapper

data augmentation: horizontal flipping, normalization

Results

1. subtask 1 DenseDepth

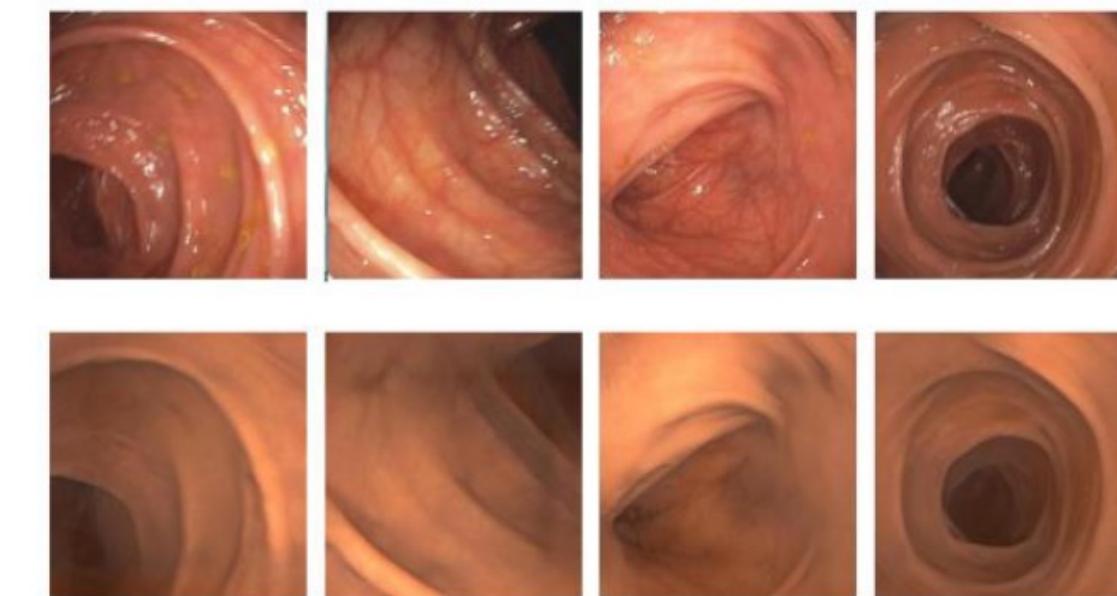
Frames_S4, Frames_S9, Frames_S14, Frames_B4, Frames_B9, Frames_B14

Method	L_1 (cm)	L_{RMSE} (cm)	$L_{rel}\text{(\%)}$
DenthDepth	0.038	0.066	1.22

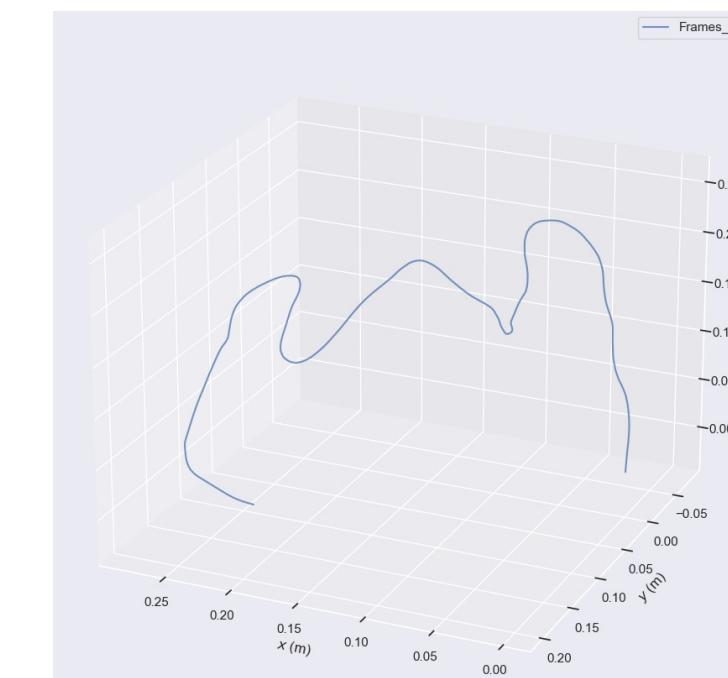
2. subtask 2 SC-SfmLearner + DenseDepth

Trajectory	Scale	ATE(cm)	RTE(mm)	ROT(°)
Frames_S9	1.03	3.34	0.12	0.14
Frames_B9	1.04	2.72	0.14	0.21
Frames_S4	1.01	6.16	0.15	0.15
Frames_B4	1.05	5.10	0.15	0.21
Frames_S14	1.00	7.99	0.15	0.16
Frames_B14	1.05	3.37	0.16	0.21
Average	1.03	4.78	0.145	0.18

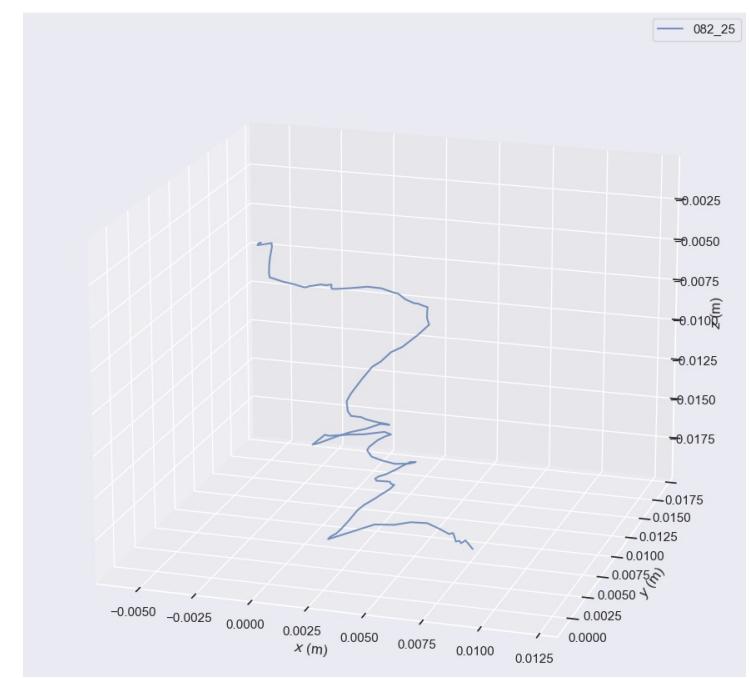
3. subtask 3 CycleGAN + subtask2



Style
transfer



subtask 2: Frames_S5 trajectory

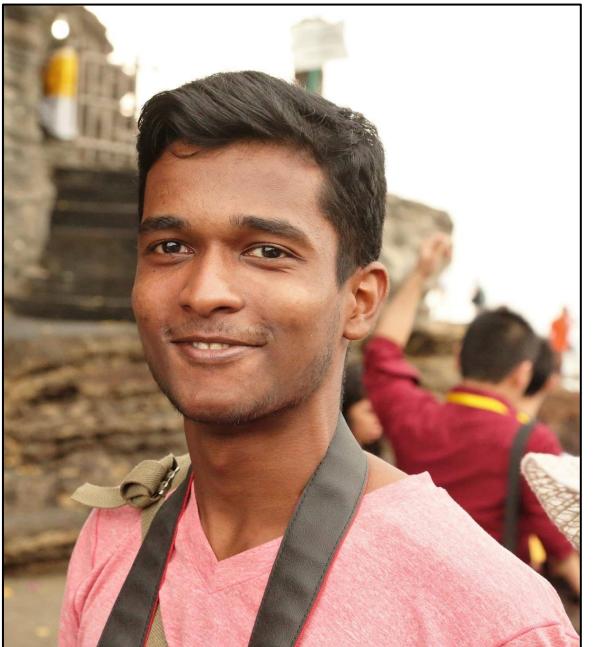


subtask 3: ims_082_25 trajectory

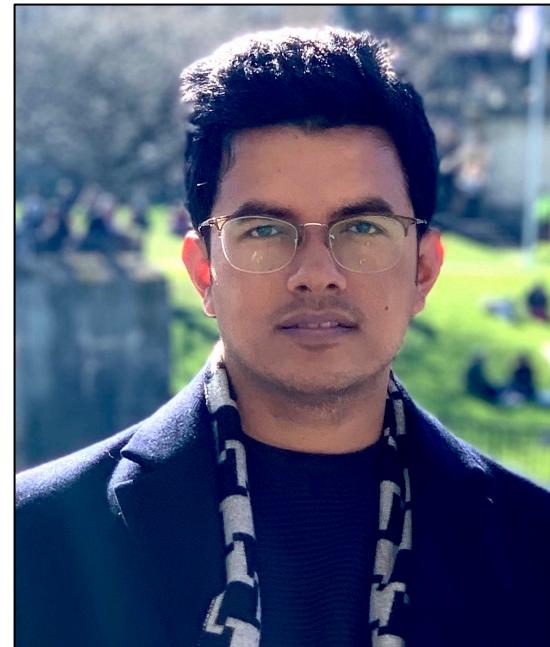
TEAM - MMLAB-NUS-SimCol

PRESENTATION – In person

MMLAB-NUS-SimCol



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Medical Mechatronics Lab (MMLAB),
Department of Biomedical Engineering,
National University of Singapore

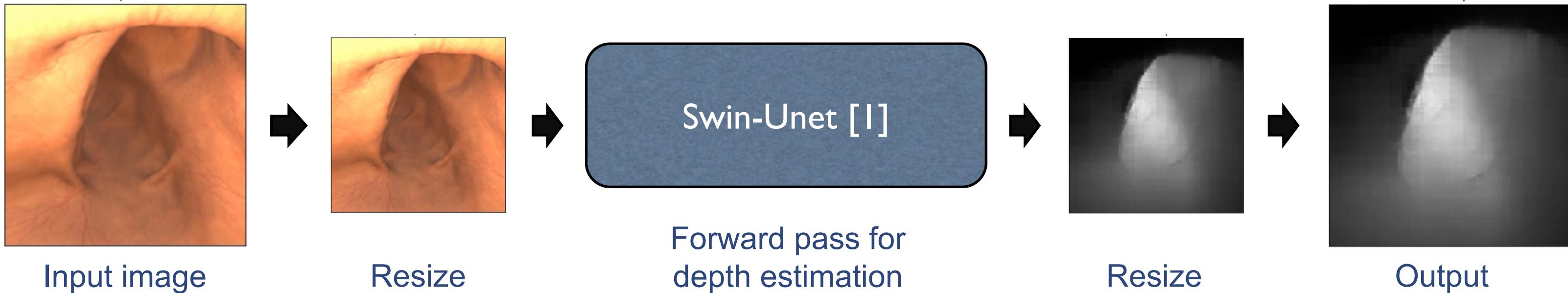


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Dr Hongliang Ren
Medical Mechatronics Lab (MMLAB),
Department of Biomedical Engineering,
National University of Singapore.
& Electronic Engineering Department,
Chinese University of Hongkong

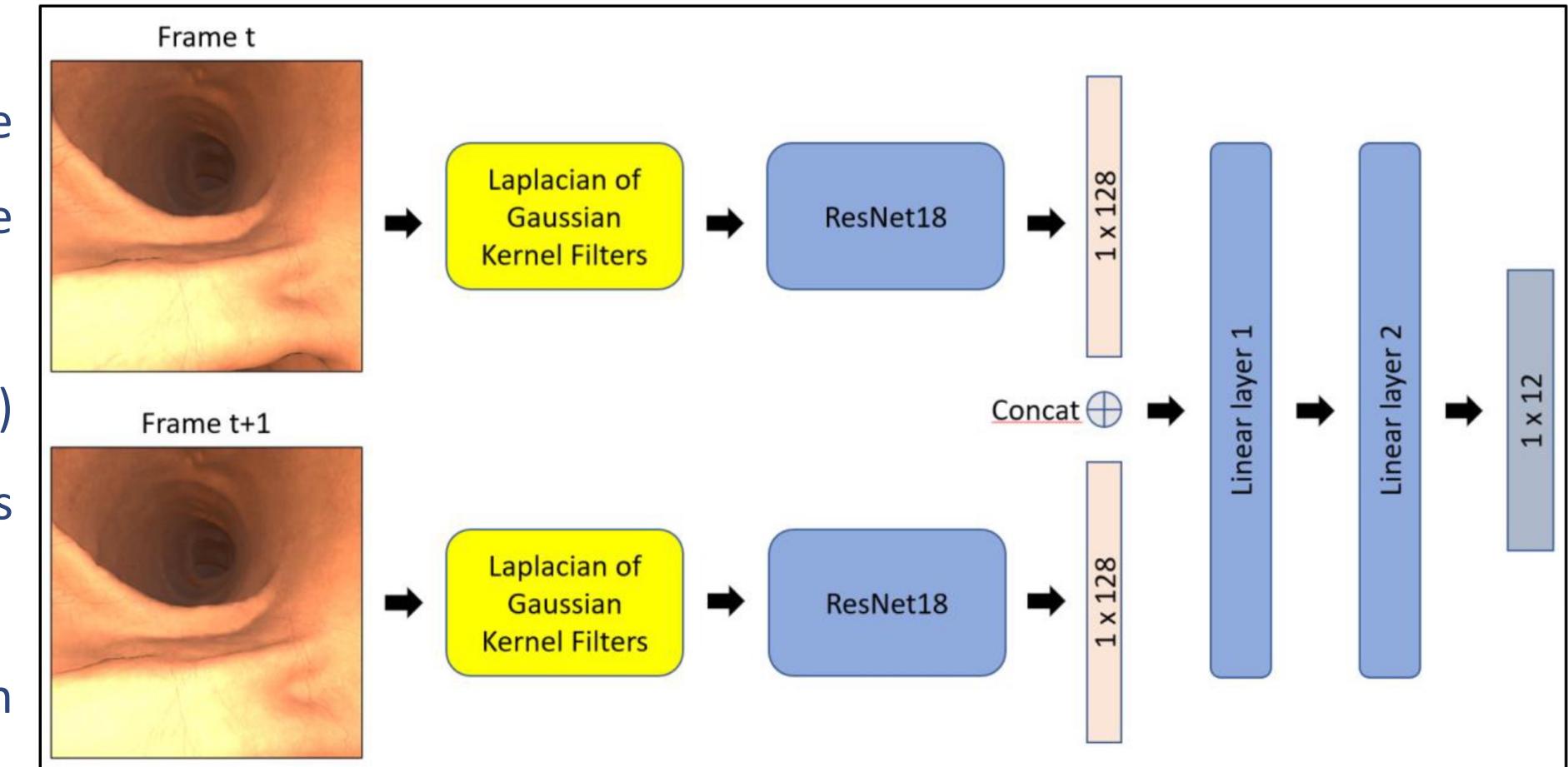
Task 1: Depth Prediction in Simulated Colonoscopy



- Unet-like Swin-Transformer (Swin-Unet) [1] is used for the Depth estimation.
 - Three blocks of encoder and corresponding decoder
- The model trains on L1 loss and SGD optimizer with a learning rate of 0.01, a decay factor of 1e-4, and a momentum of 0.9.
- The input images are resized to 224x224 during training and the predicted depth map is upsampled.
- Different loss functions such as L1, mean square error (MSE), structural similarity index (SSIM), and binary cross entropy (BCE) are used to observe the model performance where L1 outperforms other loss functions with the MSE of 0.000115 and SSIM of 0.984670.

Task 2: Pose Estimation in Simulated Colonoscopy

- We employ ResNet18 [1] and a series of linear layers.
- While the relative ground truth pose has 16 values, the module regresses 12 values as the last four values are constant [0.0, 0.0, 0.0, 1.0].
- Furthermore, we employ Laplacian of Gaussian (LoG) kernel-based filters [2] to enforce attention to contours and perform curriculum (by smoothing) learning [3].
- Initially, the ResNet module is loaded with the PyTorch ImageNet pre-trained weights.
- Then the whole model is trained based on mean-square-error (MSE) loss using adam optimizer with a learning rate of 7.5×10^{-6} .
- During training, the values of the LOG kernel (with a kernel size = 3) are updated with a factor of 0.9 to allow more features to pass through the model as the learning progresses and to enforce attention to contours.



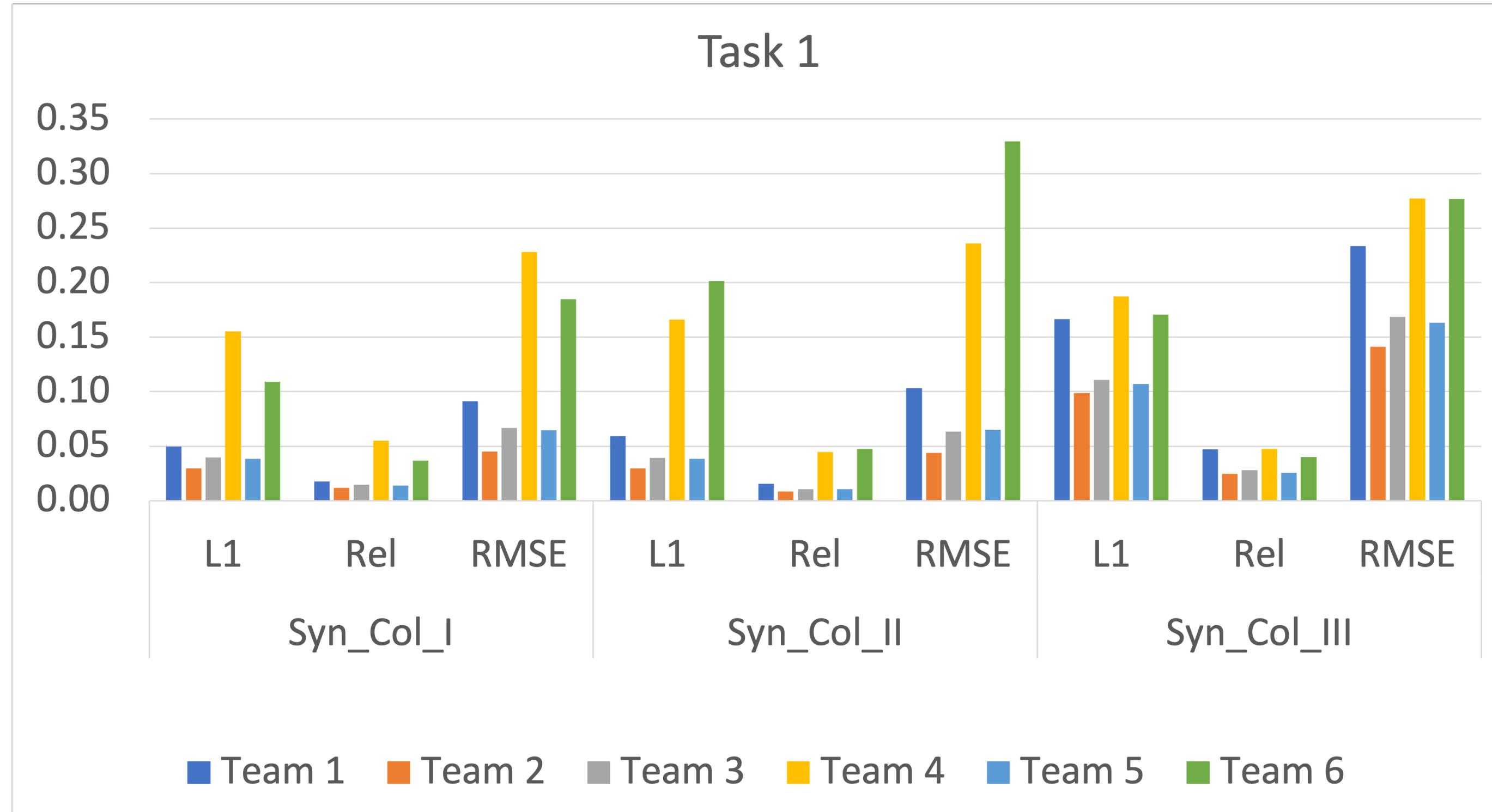
1. He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 770-778).
2. Seenivasan, L., Islam, M., Ng, C. F., Lim, C. M., & Ren, H. (2022). Biomimetic Incremental Domain Generalization with a Graph Network for Surgical Scene Understanding. *Biomimetics*, 7(2), 68.
3. Sinha, S., Garg, A., & Larochelle, H. (2020). Curriculum by smoothing. *Advances in Neural Information Processing Systems*, 33, 21653-21664.

Intro

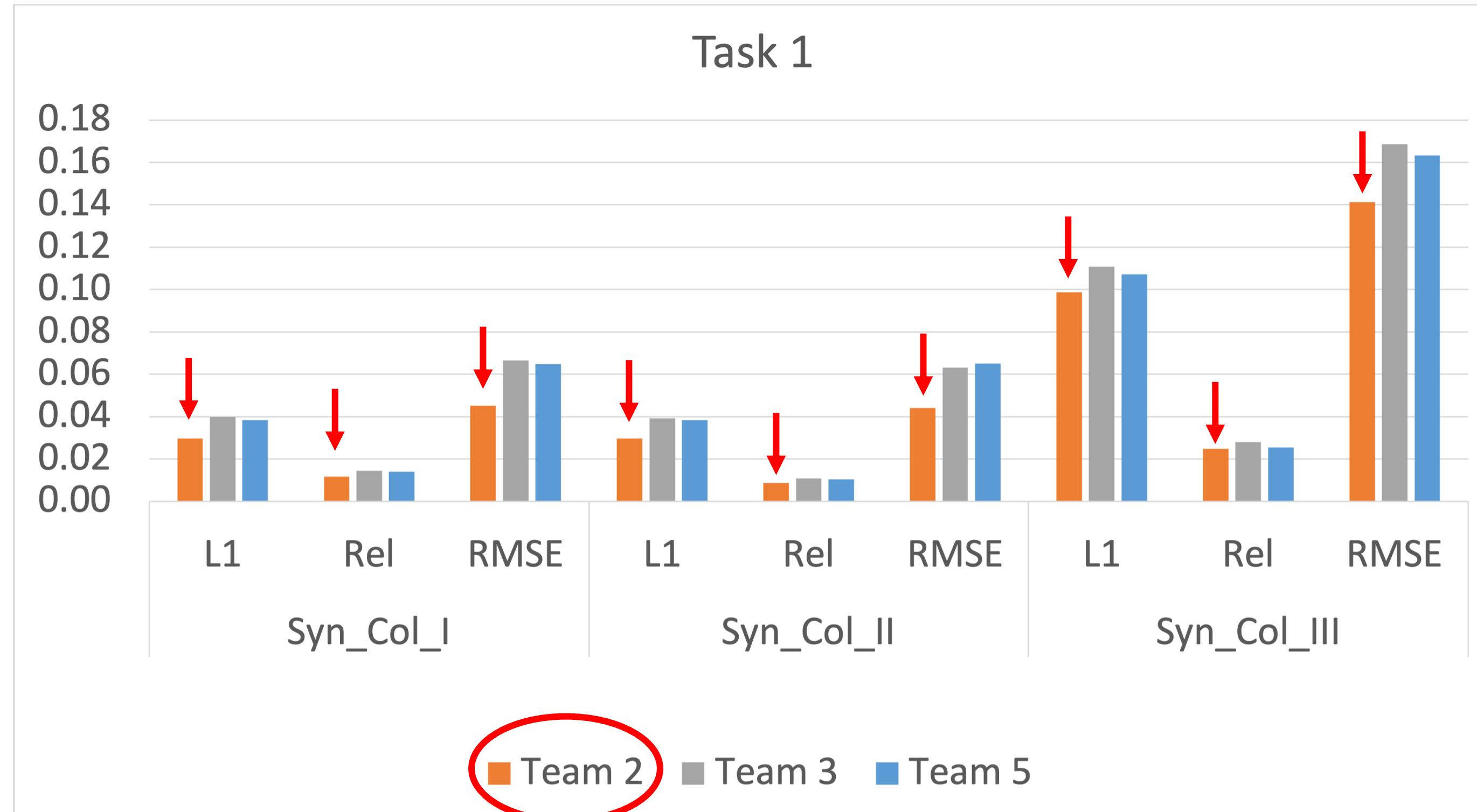
Challenge

Results

Results: Synthetic Depth



Results: Synthetic Depth – TOP 3



Results: Synthetic Depth – Ranks

	Syn_Col_I			Syn_Col_II			Syn_Col_III		
	L1	Rel	RMSE	L1	Rel	RMSE	L1	Rel	RMSE
Winner	Team 2	Team 2	Team 2	Team 2	Team 2	Team 2	Team 2	Team 2	Team 2
Runner-up	Team 5	Team 5	Team 5	Team 5	Team 5	Team 3	Team 5	Team 5	Team 5
Third	Team 3	Team 3	Team 3	Team 3	Team 3	Team 5	Team 3	Team 3	Team 3
Fourth	Team 1	Team 1	Team 1	Team 1	Team 1	Team 1	Team 1	Team 6	Team 1
Fifth	Team 6	Team 6	Team 6	Team 4	Team 4	Team 4	Team 6	Team 1	Team 6
Sixth	Team 4	Team 4	Team 4	Team 6	Team 6	Team 6	Team 4	Team 4	Team 4

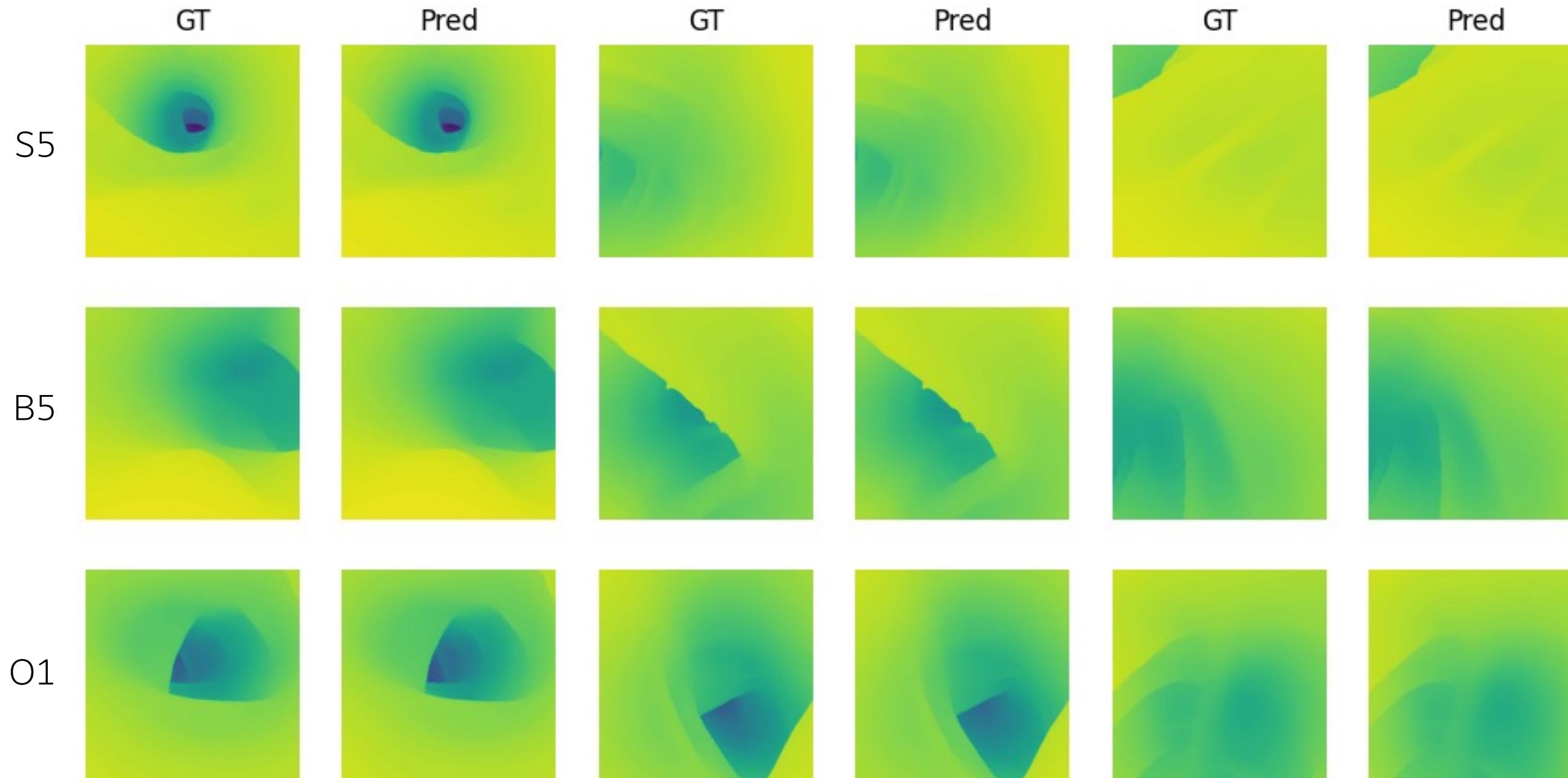
Results: Synthetic Depth – Ranks

	Syn_Col_I			Syn_Col_II			Syn_Col_III		
	L1	Rel	RMSE	L1	Rel	RMSE	L1	Rel	RMSE
Winner	Team 2	Team 2	Team 2	Team 2	Team 2	Team 2	Team 2	Team 2	Team 2
Runner-up	Team 5	Team 5	Team 5	Team 5	Team 5	Team 3	Team 5	Team 5	Team 5
Third	Team 3	Team 3	Team 3	Team 3	Team 3	Team 5	Team 3	Team 3	Team 3
Fourth	Team 1	Team 1	Team 1	Team 1	Team 1	Team 1	Team 1	Team 6	Team 1
Fifth	Team 6	Team 6	Team 6	Team 4	Team 4	Team 4	Team 6	Team 1	Team 6
Sixth	Team 4	Team 4	Team 4	Team 6	Team 6	Team 6	Team 4	Team 4	Team 4

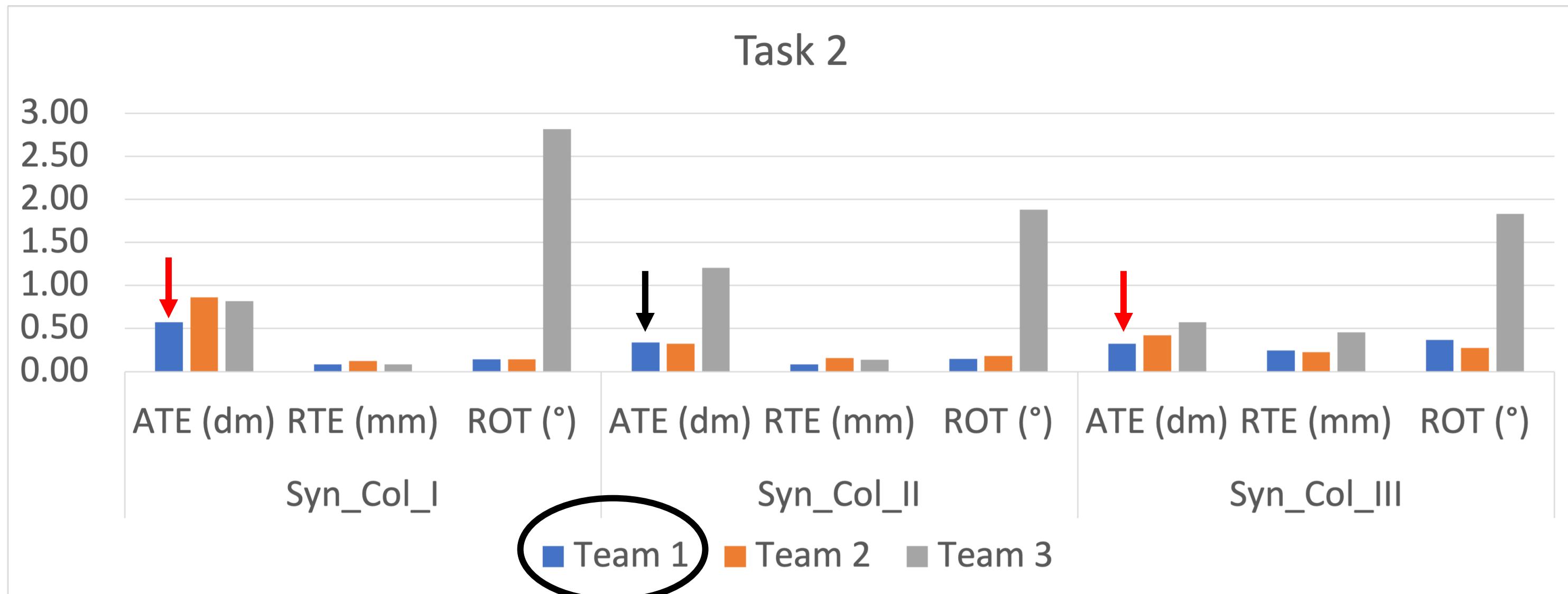
Results: Synthetic Depth – Ranks

	Syn_Col_I			Syn_Col_II			Syn_Col_III		
	L1	Rel	RMSE	L1	Rel	RMSE	L1	Rel	RMSE
Winner	Team 2	Team 2	Team 2	Team 2	Team 2	Team 2	Team 2	Team 2	Team 2
Runner-up	Team 5	Team 5	Team 5	Team 5	Team 5	Team 3	Team 5	Team 5	Team 5
Third	Team 3	Team 3	Team 3	Team 3	Team 3	Team 5	Team 3	Team 3	Team 3
Fourth	Team 1	Team 1	Team 1	Team 1	Team 1	Team 1	Team 1	Team 6	Team 1
Fifth	Team 6	Team 6	Team 6	Team 4	Team 4	Team 4	Team 6	Team 1	Team 6
Sixth	Team 4	Team 4	Team 4	Team 6	Team 6	Team 6	Team 4	Team 4	Team 4

Winning Team's results

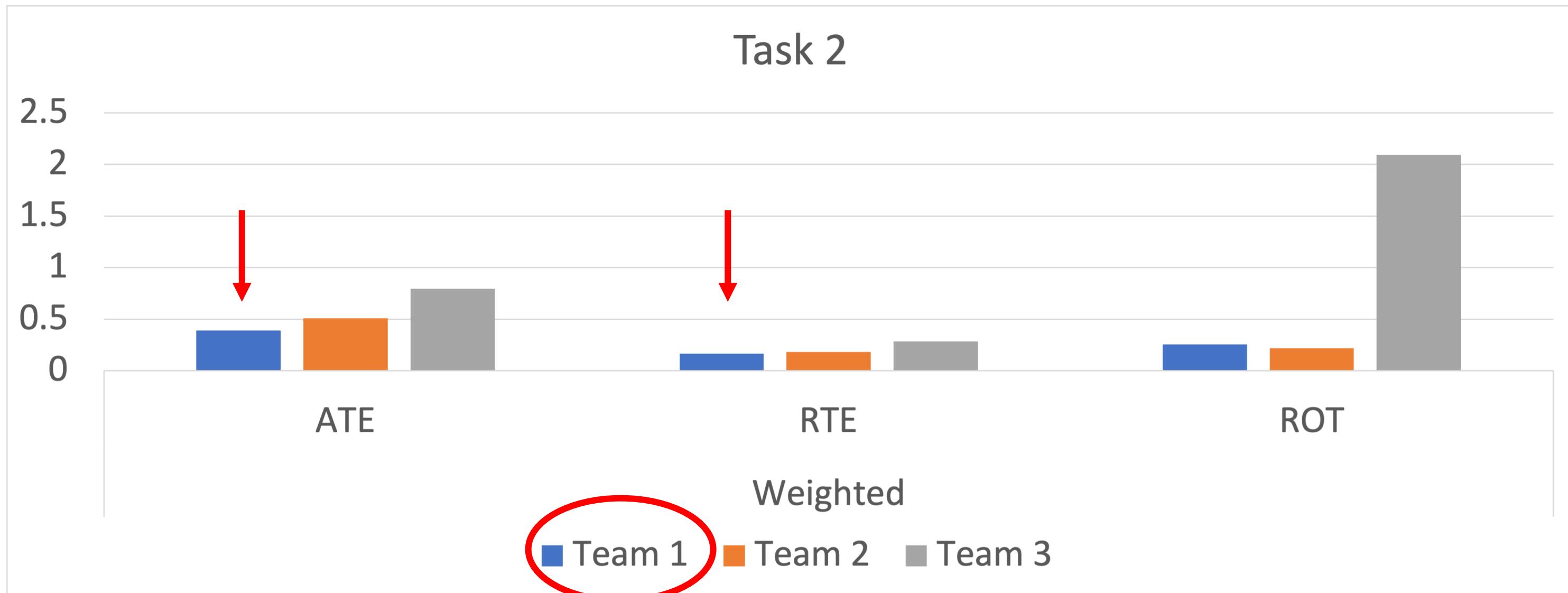


Results: Synthetic Pose



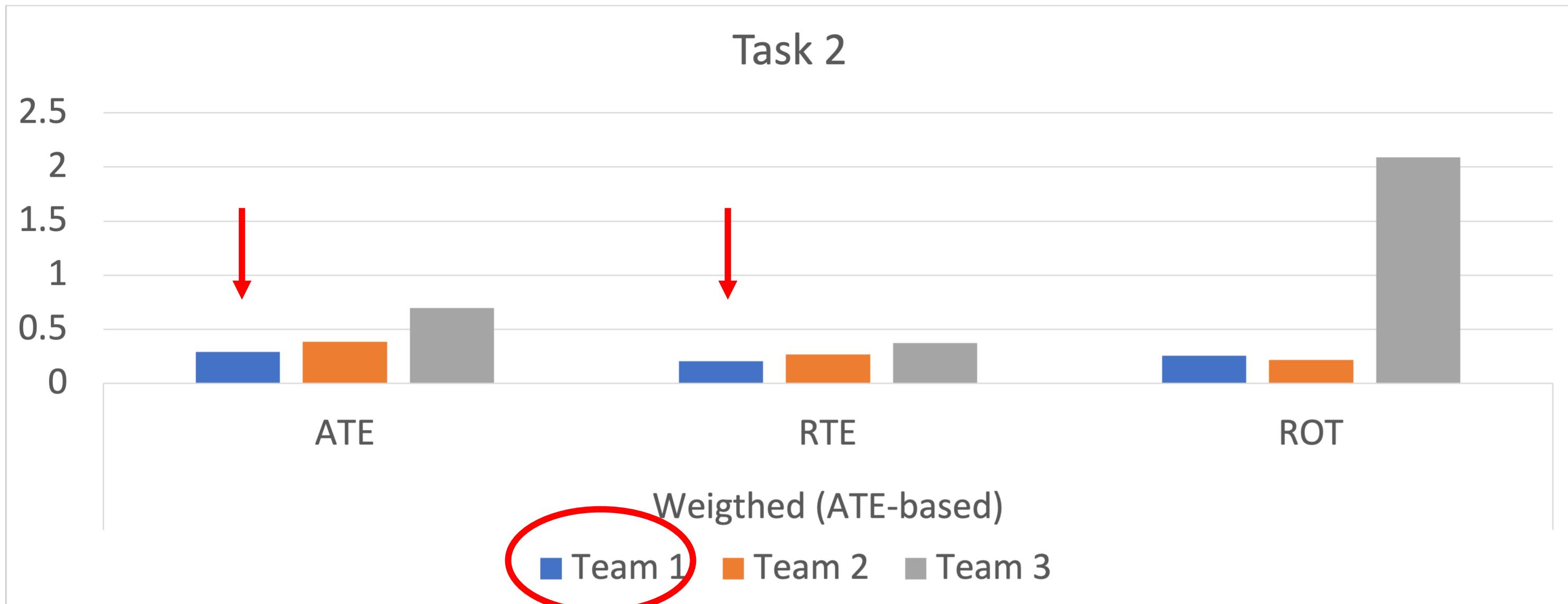
Results: Synthetic Pose

Give double weight to Synthetic_Colon_III



Results: Synthetic Pose

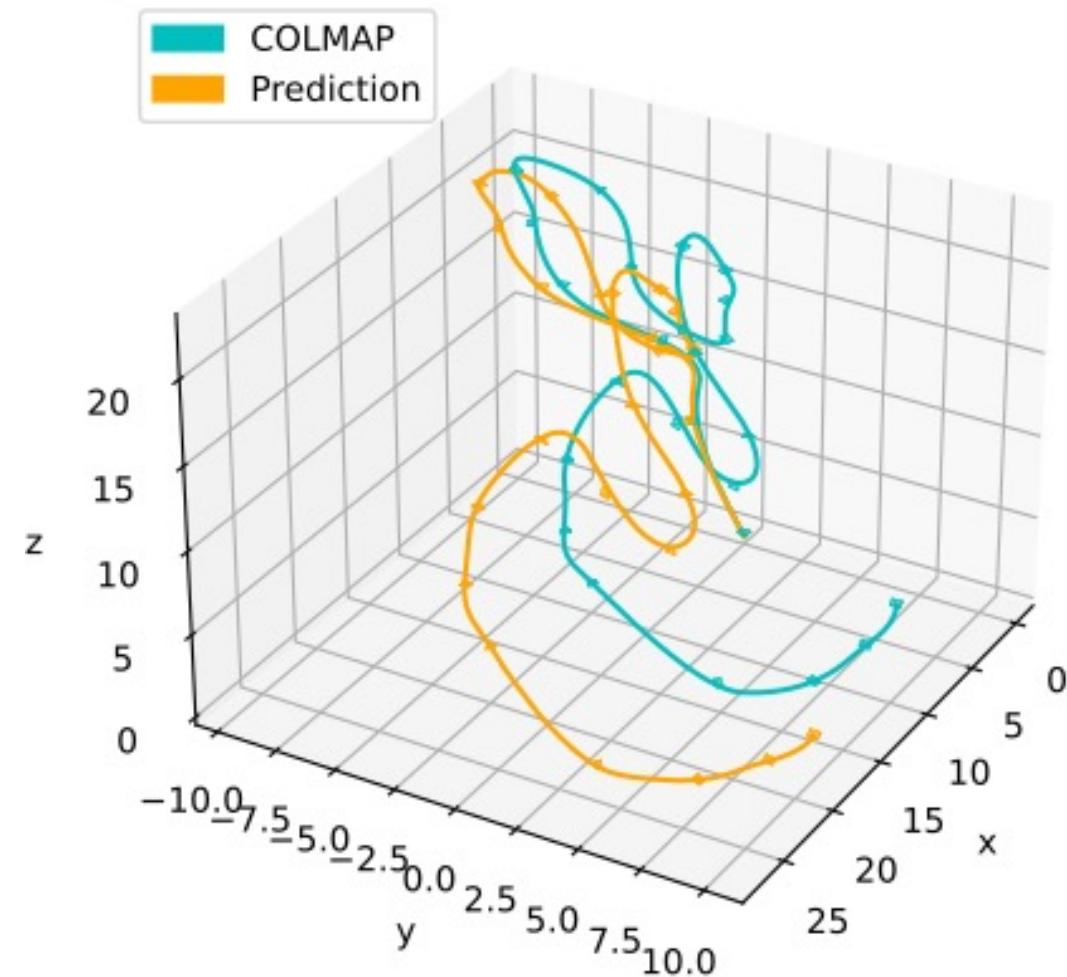
Consistent result using a different scaling:



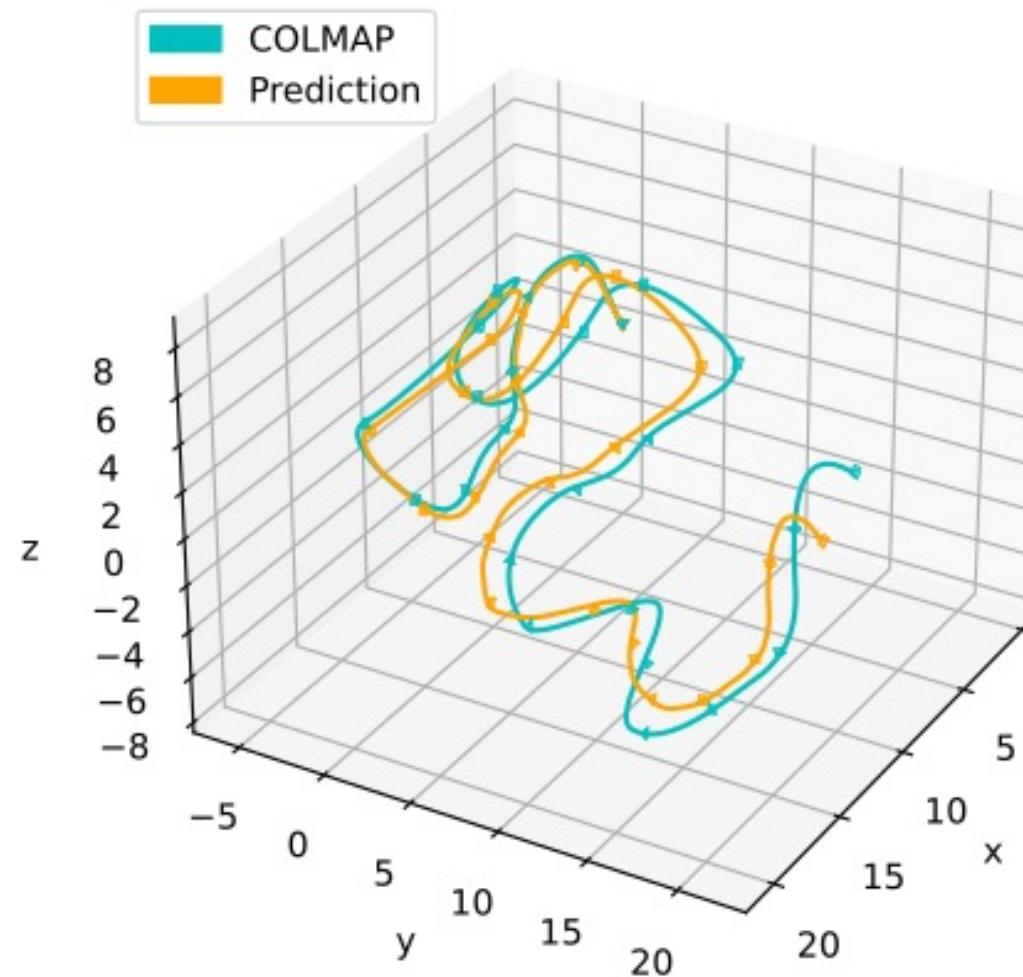
Results: Synthetic Pose – Ranks

	Syn_Col_I			Syn_Col_II			Syn_Col_III		
	ATE (dm)	RTE (mm)	ROT (°)	ATE (dm)	RTE (mm)	ROT (°)	ATE (dm)	RTE (mm)	ROT (°)
Winner	Team 1	Team 1	Team 2	Team 2	Team 1	Team 1	Team 1	Team 2	Team 2
Runner-up	Team 3	Team 3	Team 1	Team 1	Team 3	Team 2	Team 2	Team 1	Team 1
Third	Team 2	Team 2	Team 3	Team 3	Team 2	Team 3	Team 3	Team 3	Team 3

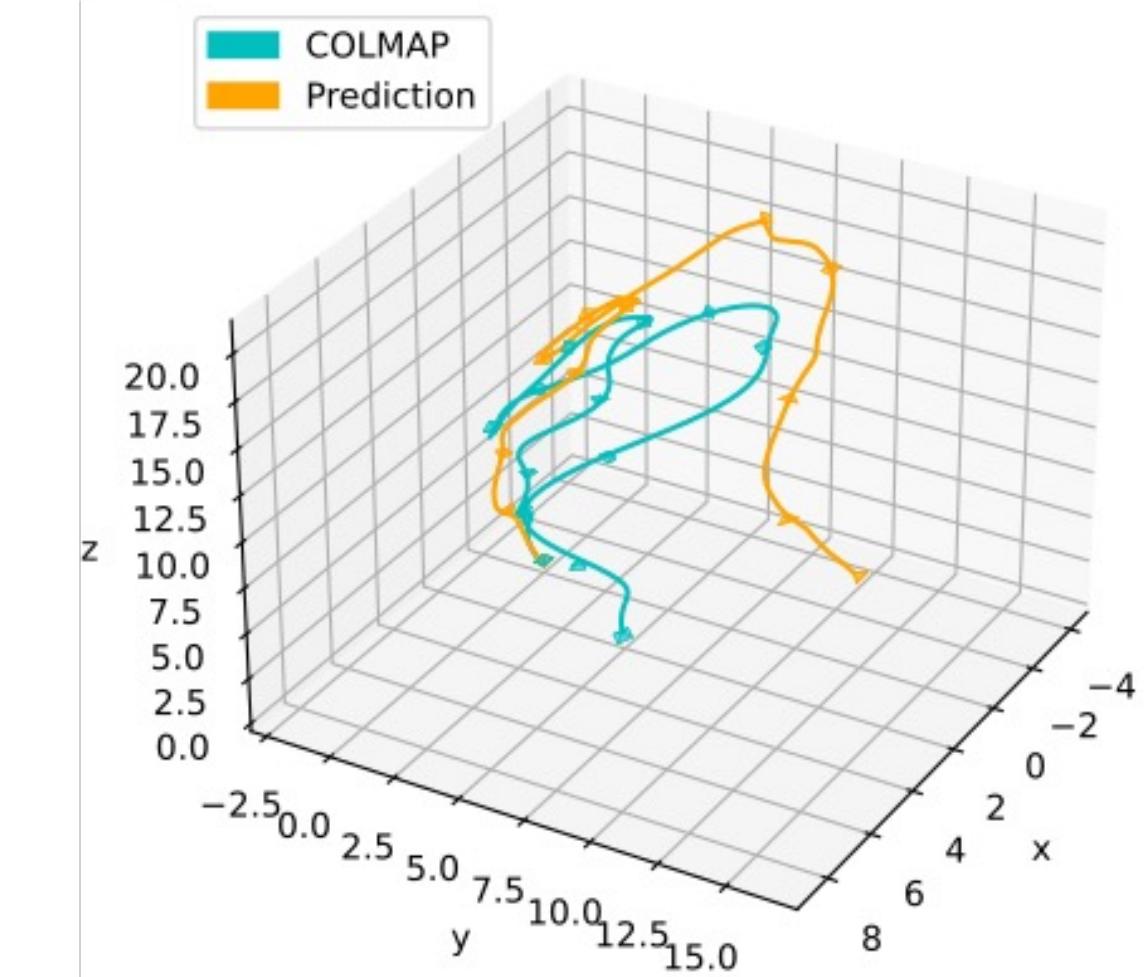
Winning Team's results



S5

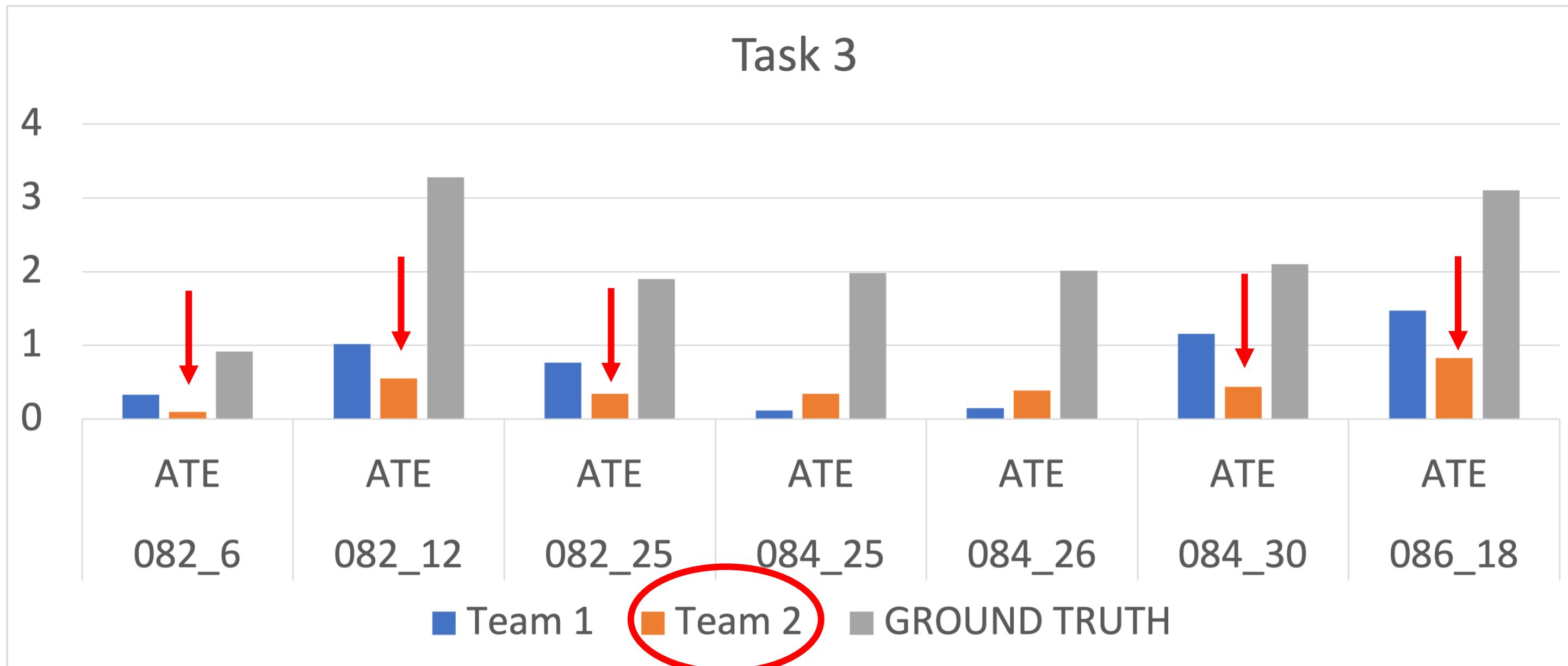


B5

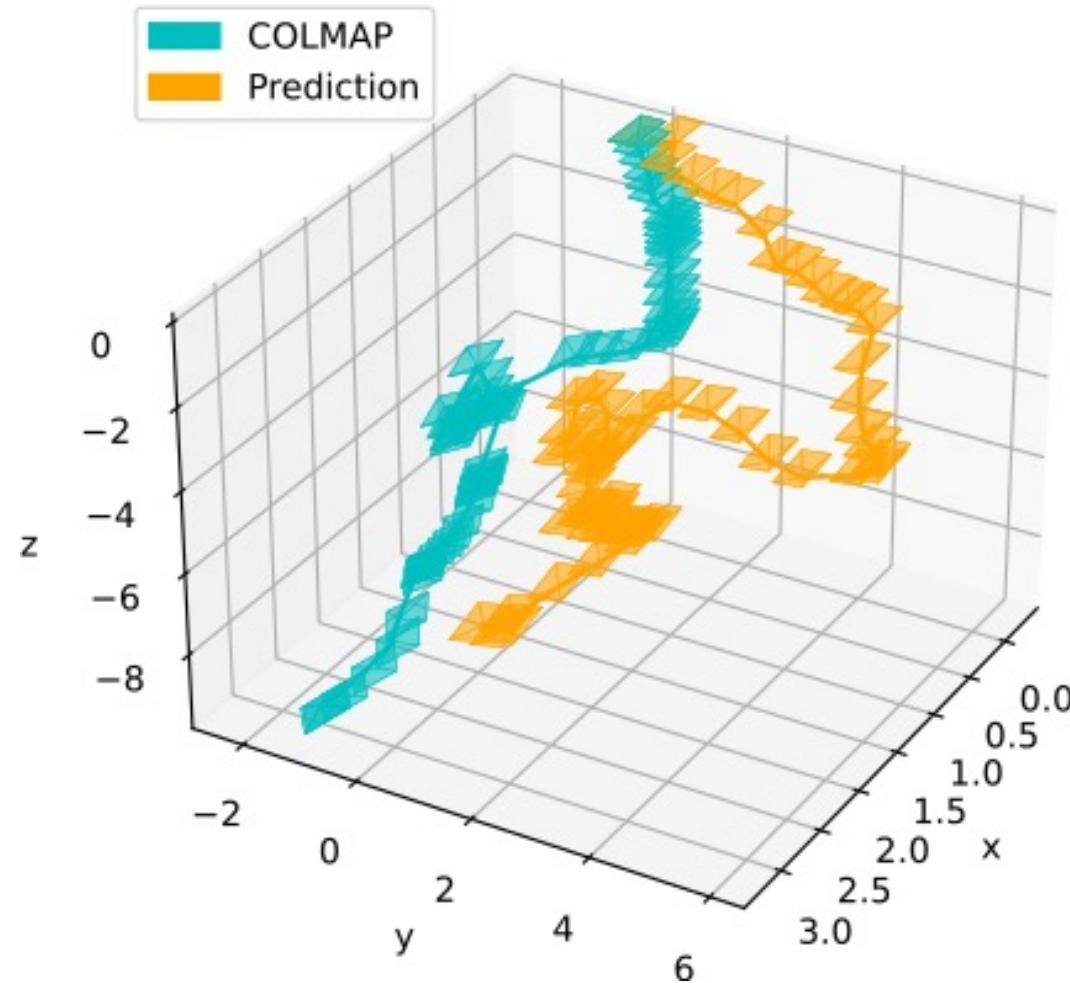


O1

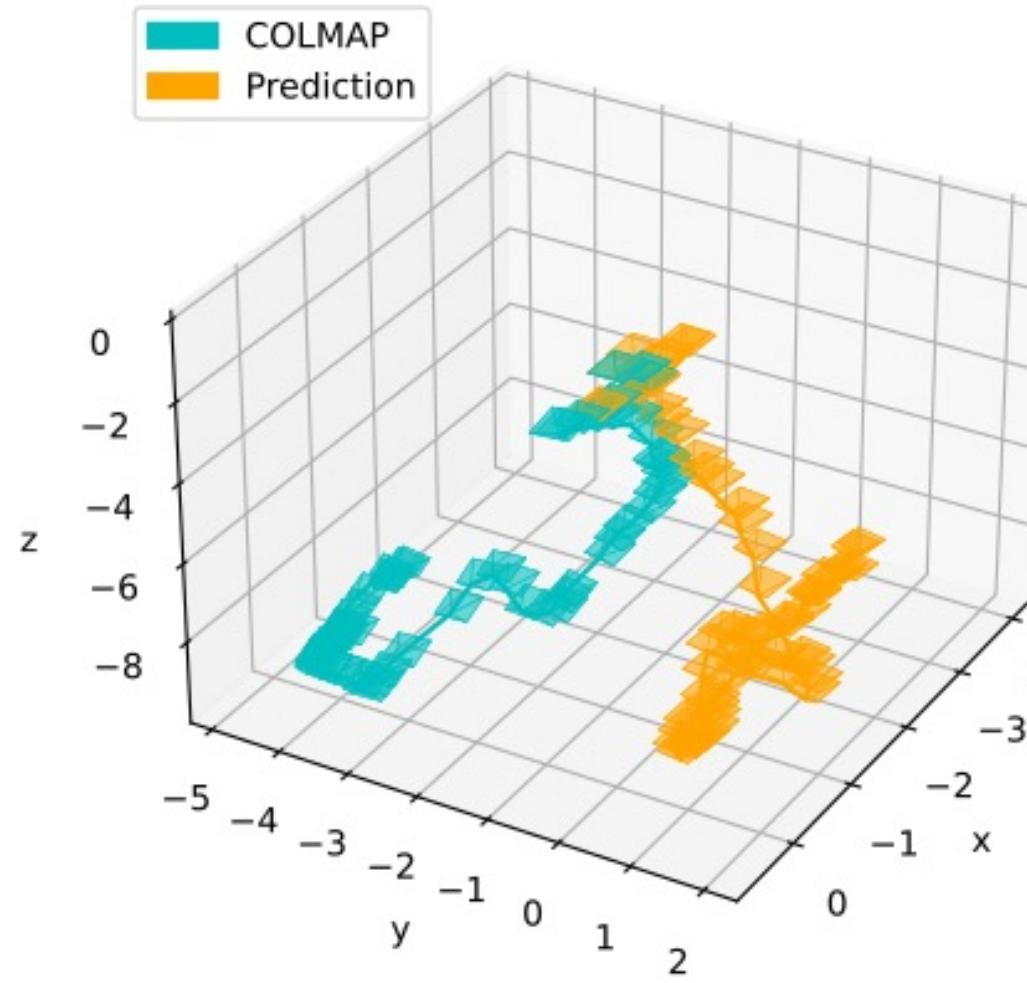
Results: Real Pose



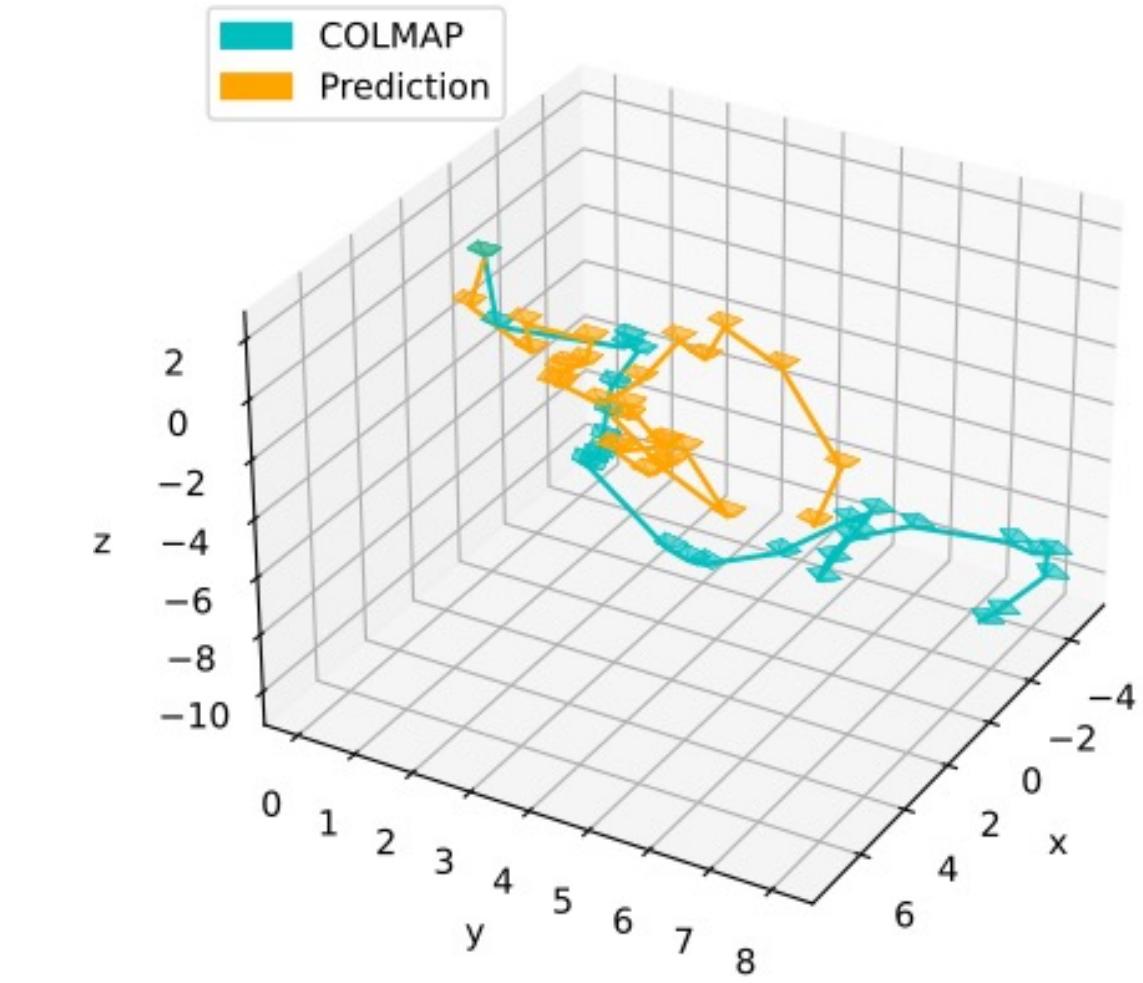
Winning Team's results



082_25

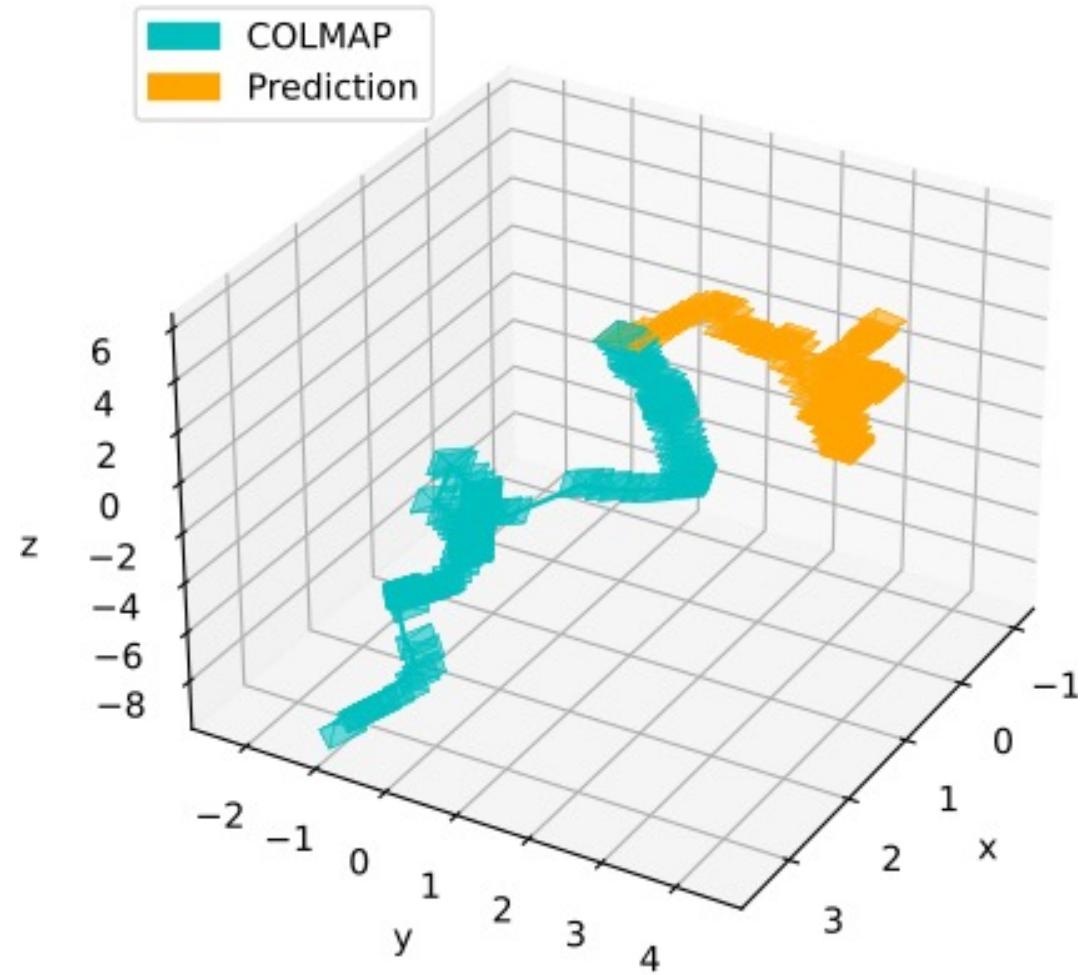


084_26

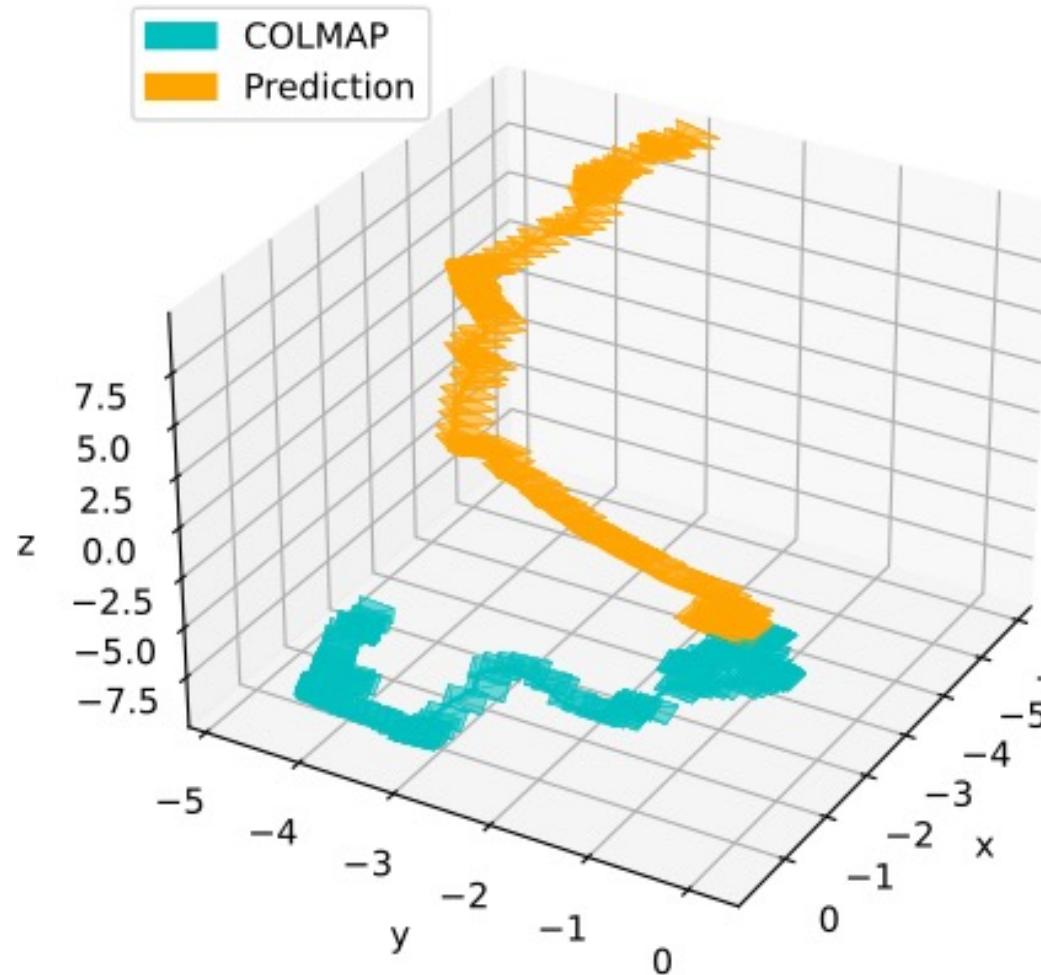


086_18

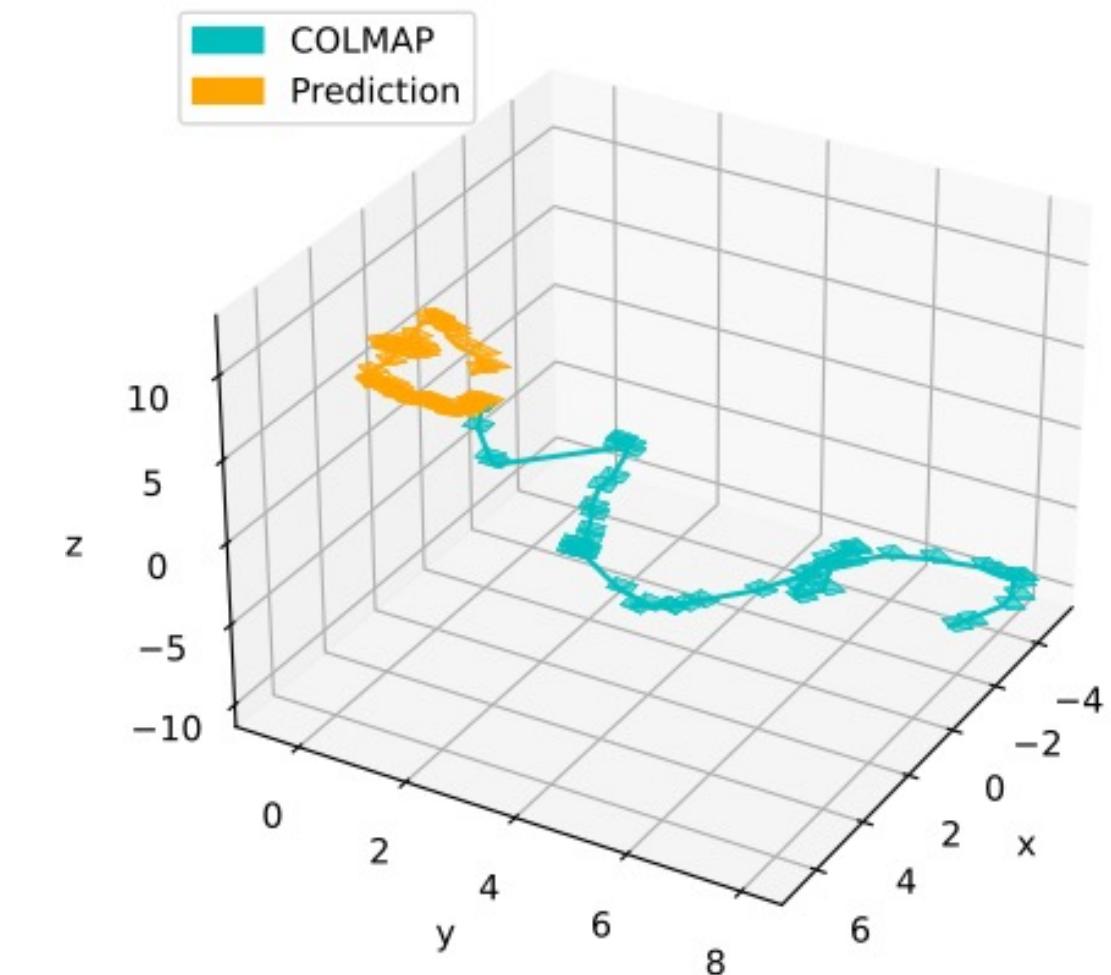
Runner-up Team's results



082_25



084_26



086_18

AWARDS

Sponsors:



Awards

Winner of Task 1: £ 800 (\approx \$910)

Runner-up of Task 1: £ 500 (\approx \$570)

Winner of Task 2: £ 600 (\approx \$680)

Winner of Task 3: £ 600 (\approx \$680)

Sponsors:



Awards

And the winner for task 2 is...

EndoAI

Sponsors:



Medtronic



Detailed Results on Task 2

	Syn_Col_I			Syn_Col_II			Syn_Col_III		
	ATE (dm)	RTE (mm)	ROT (°)	ATE (dm)	RTE (mm)	ROT (°)	ATE (dm)	RTE (mm)	ROT (°)
Winner	EndoAI	EndoAI	MIVA	MIVA	EndoAI	EndoAI	EndoAI	MIVA	MIVA
Runner-up	MMLAB	MMLAB	EndoAI	EndoAI	MMLAB	MIVA	MIVA	EndoAI	EndoAI
Third	MIVA	MIVA	MMLAB	MMLAB	MIVA	MMLAB	MMLAB	MMLAB	MMLAB

Awards

And the winner for task 3 is...

MIVA

Sponsors:



Detailed Results on Task 3

	082_6	082_12	082_25	084_25	084_26	084_30	086_18
	ATE						
Winner	MIVA	MIVA	MIVA	EndoAI	EndoAI	MIVA	MIVA
Runner-up	EndoAI	EndoAI	EndoAI	MIVA	MIVA	EndoAI	EndoAI

Awards

And the runner-up for task 1 is...

MIVA

Sponsors:



Medtronic



Awards

And the winner for task 1 is...

CVML

Sponsors:



Medtronic



Detailed Results on Task 1

	Syn_Col_I			Syn_Col_II			Syn_Col_III		
	L1	Rel	RMSE	L1	Rel	RMSE	L1	Rel	RMSE
Winner	CVML								
Runner-up	MIVA	MIVA	MIVA	MIVA	MIVA	EndoAI	MIVA	MIVA	MIVA
Third	EndoAI	EndoAI	EndoAI	EndoAI	EndoAI	MIVA	EndoAI	EndoAI	EndoAI
Fourth	IntuitiveIL	MMLAB	IntuitiveIL						
Fifth	MMLAB	MMLAB	MMLAB	KLIV	KLIV	KLIV	MMLAB	IntuitiveIL	MMLAB
Sixth	KLIV	KLIV	KLIV	MMLAB	MMLAB	MMLAB	KLIV	KLIV	KLIV

Discussion

Summary

- 6 Teams participated
- At least 2 teams participated in each task
- Most interest in depth prediction
- While depth prediction in virtual environments is very stable, pose estimation remains challenging

Next steps:

- Challenge paper preparation

Thank you! ☺



Anita Rau



Sophia Bano



Yueming Jin



Danail Stoyanov



Clinical Partners and affiliated project:



Sponsors:

