BUFFER-X: Towards Zero-Shot Point Cloud Registration in Diverse Scenes

ICCV 2025 🌟Highlight🌟

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*These authors contributed equally to this work.

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(Unit: Success rate [%])

This video includes audio narration

Three Key Factors

Three factors crucial for achieving domain generalization in registration

1. Proper voxel size and search radius

2. Robust keypoint detection for out-of-domain scenes

3. Input Scale normalization

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Issue #1: Most approaches require manual tuning of voxel size and search radius by users.

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Issue #2: Learning-based keypoint extractor modules are empirically brittle to out-of-domain data.

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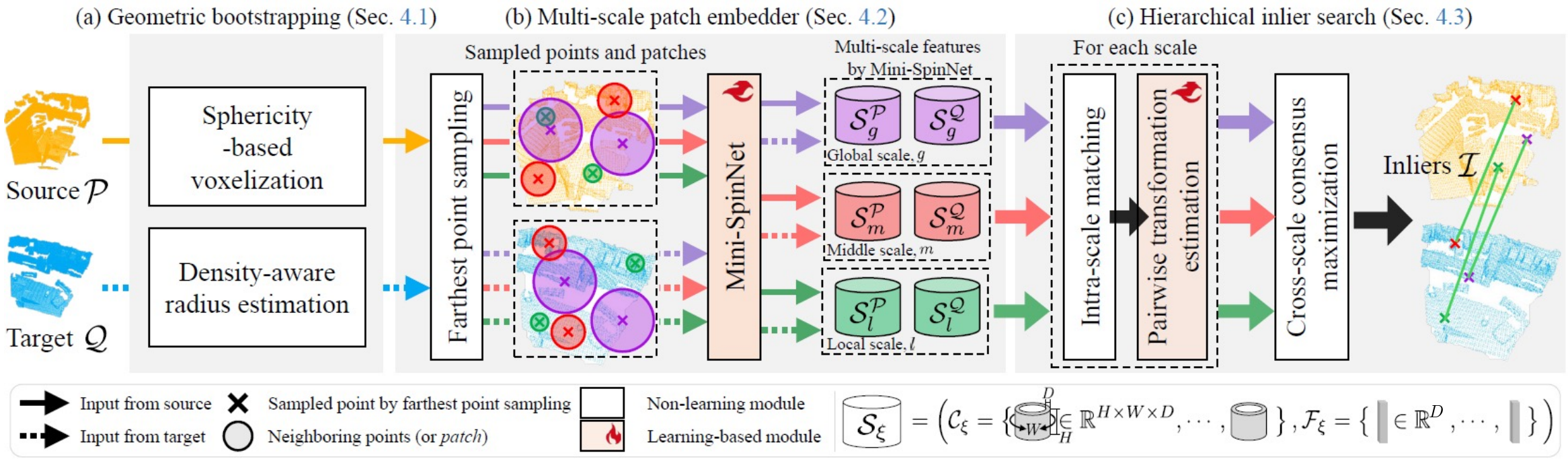
Issue #3: Directly feeding raw x, y, and z values into the network leads to strong in-domain dependency

BUFFER-X: Multi-scale patch-based method for *zero-shot registration*



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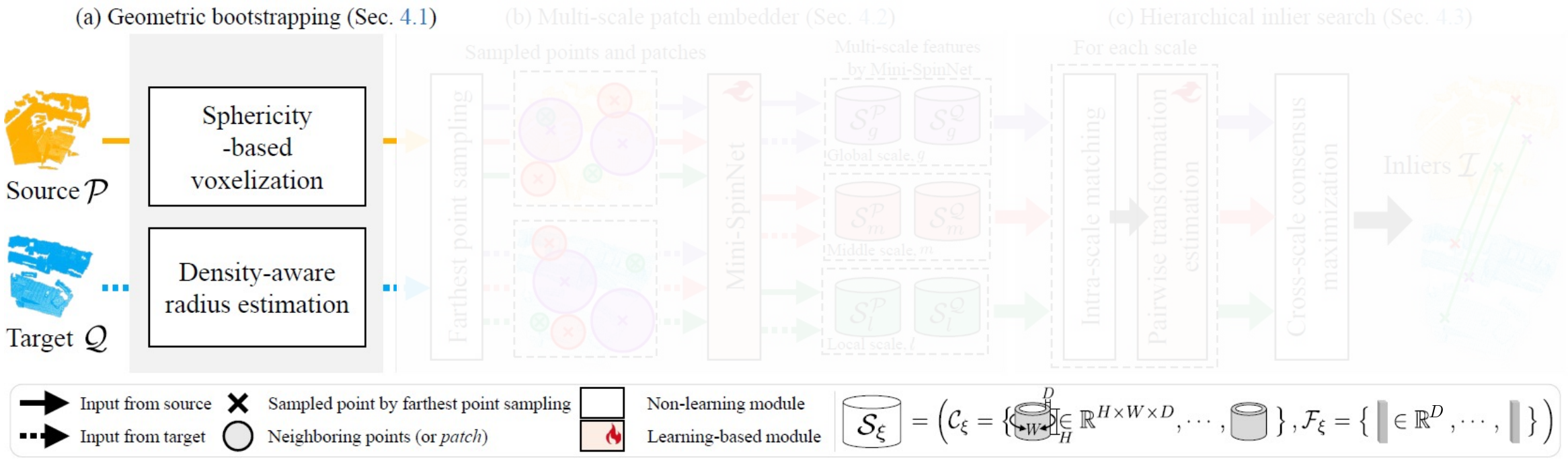
BUFFER-X: Multi-scale patch-based method for *zero-shot registration*

(Cont'd)

※ The highlighted part below addresses the issue above.



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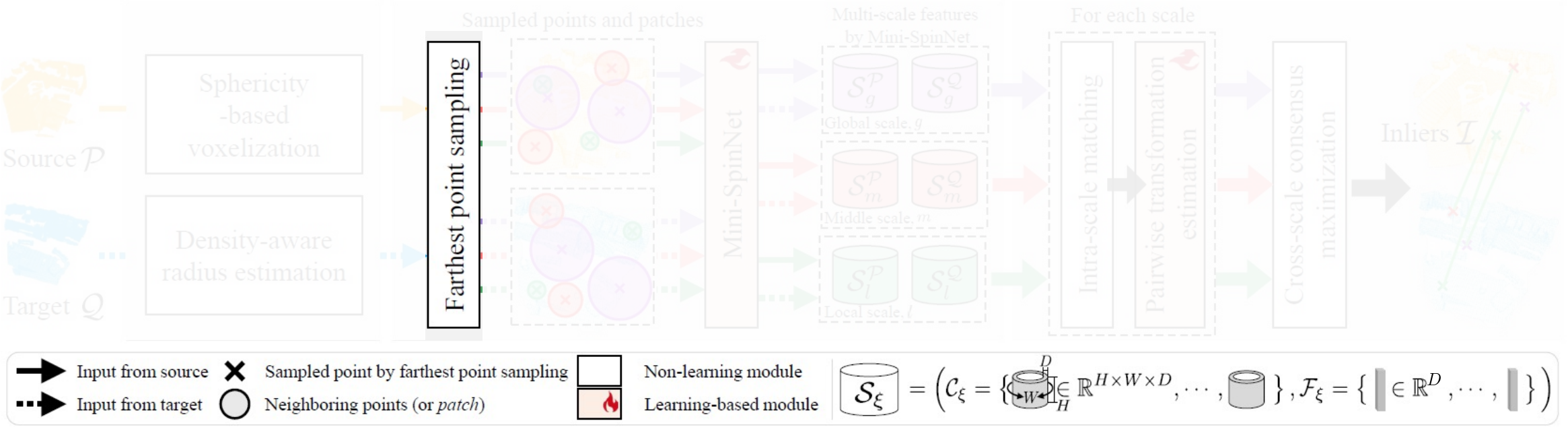

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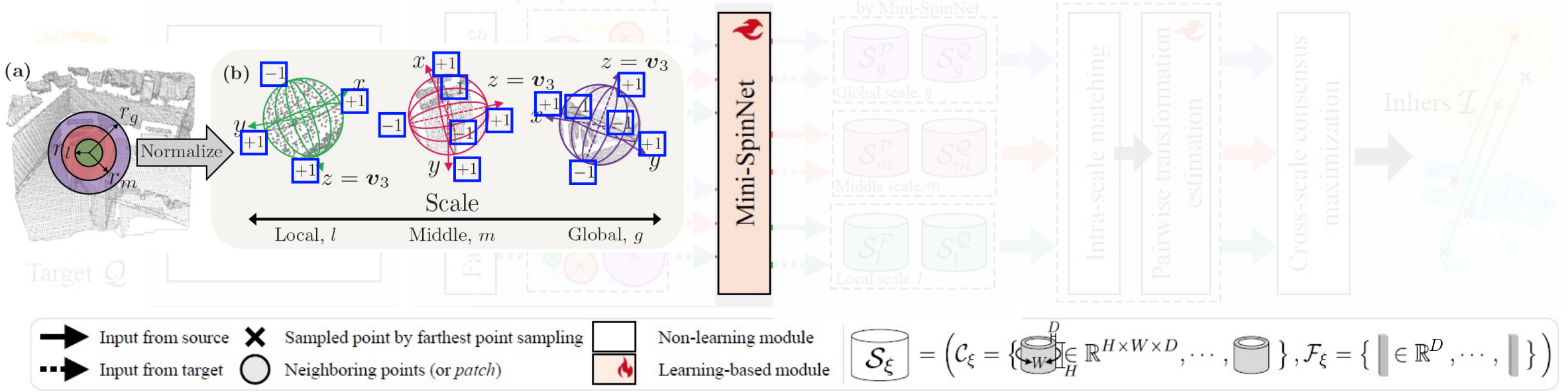

$$\mathcal{S}_\xi = \left(\mathcal{C}_\xi = \{ \in \mathbb{R}^{H\times W\times D}, \cdots, \}, \mathcal{F}_\xi = \{ \in \mathbb{R}^D, \cdots, \}\right)$$

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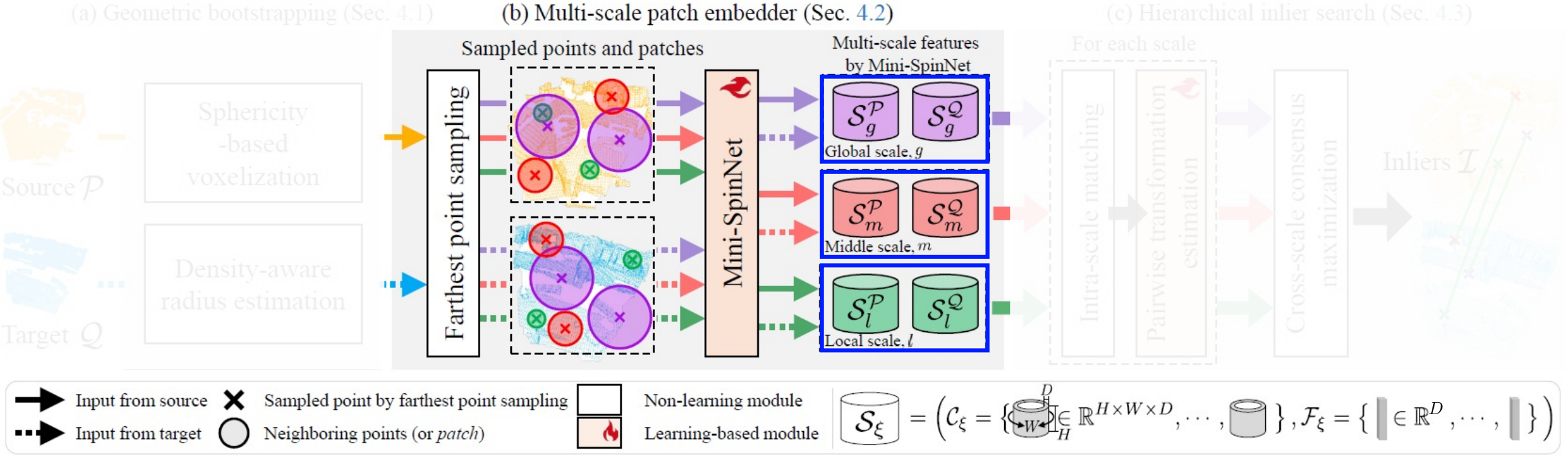
BUFFER-X: Multi-scale patch-based method for *zero-shot registration*

(Cont'd)



BUFFER-X: Multi-scale patch-based method for *zero-shot registration*

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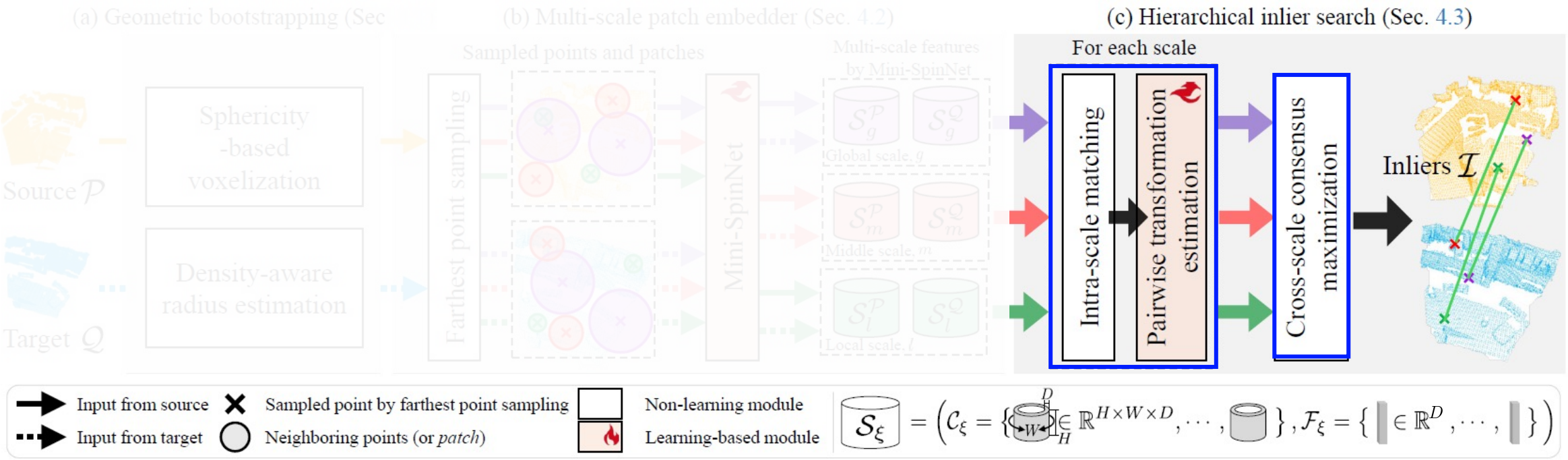

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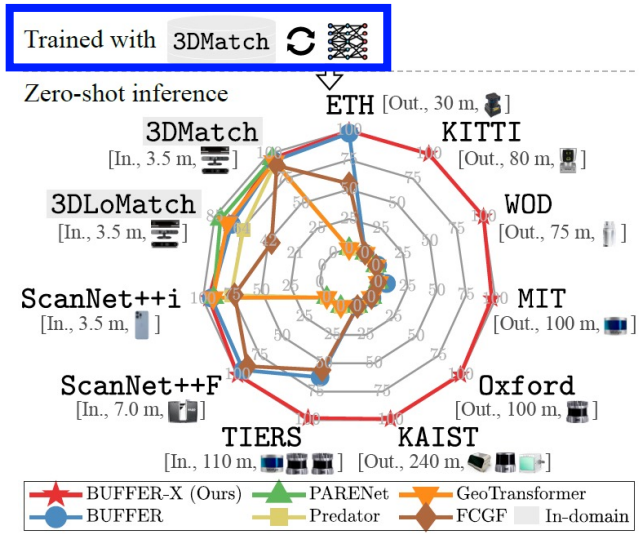
Visual & Geometric Intelligence Lab. SPARKlab

Experimental Results



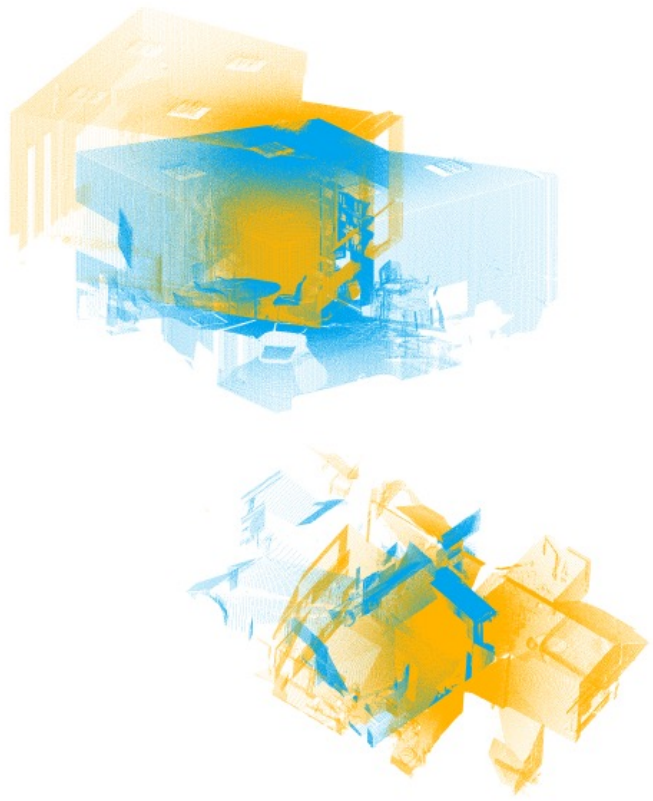
	Env.	Indoor					Outdoor						Average rank
	Dataset	3DMatch	3DLoMatch	ScanNet++i	ScanNet++F	TIERS	KITTI	WOD	KAIST	MIT	ETH	Oxford	
Conventional	FPFH [63] + FGR [94] + 👁	62.53	15.42	77.68	92.31	80.60	98.74	**100.00**	89.80	74.78	91.87	99.00	9.55
	FPFH [63] + Quatro [43] + 👁	8.22	1.74	9.88	97.27	86.57	99.10	**100.00**	91.46	79.57	51.05	91.03	10.73
	FPFH [63] + TEASER++ [77] + 👁	52.00	13.25	66.15	97.22	73.13	98.92	**100.00**	89.20	71.30	93.69	99.34	10.00
Deep learning-based	FCGF [22]	88.18	40.09	72.90	88.69	55.96	0.00	0.00	0.00	0.00	54.98	0.00	15.00
	+ 👁	88.18	40.09	85.87	88.69	78.62	90.27	97.69	92.91	92.61	54.98	93.68	10.18
	+ 👁 +	88.18	40.09	85.87	88.69	80.11	94.41	97.69	93.55	93.04	55.53	95.68	9.55
	Predator [32]	90.60	62.40	75.94	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	15.73
	+ 👁	90.60	62.40	75.94	29.81	56.44	0.00	0.00	0.95	0.00	0.14	0.33	14.55
	+ 👁 +	90.60	62.40	75.94	86.01	75.74	77.29	86.92	87.09	79.56	54.42	93.68	11.82
	GeoTransformer [59]	92.00	75.00	91.18	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	14.00
	+ 👁	92.00	75.00	91.18	7.54	5.06	0.36	0.77	0.25	0.87	0.00	0.33	13.09
	+ 👁 +	92.00	75.00	92.72	97.02	92.99	92.43	89.23	91.86	95.65	71.53	97.01	6.27
	BUFFER [5]	92.90	71.80	92.72	93.75	62.30	0.00	1.54	0.50	6.96	97.62	0.66	10.45
	+ 👁	92.90	71.80	93.01	94.69	88.96	99.46	**100.00**	97.24	95.65	99.30	99.00	3.82
	+ 👁 +	92.90	71.80	93.01	94.69	88.96	99.46	**100.00**	97.24	95.65	99.30	99.00	3.82
	PARENet [80]	95.00	**80.50**	90.84	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	13.27
	+ 👁	95.00	**80.50**	90.84	43.75	6.21	0.18	0.77	0.75	1.30	1.40	1.66	11.55
	+ 👁 +	95.00	**80.50**	90.84	87.95	75.06	84.86	92.31	86.44	84.78	69.42	93.36	8.82
	Ours with only r_m	93.38	71.69	93.10	99.60	90.80	**99.82**	**100.00**	99.05	95.65	99.30	99.34	3.00
	Ours	**95.58**	74.18	**94.99**	**99.90**	**93.45**	**99.82**	**100.00**	**99.15**	**97.30**	**99.72**	**99.67**	**1.55**

(Unit: Success rate [%])

Experimental Results (Cont'd)

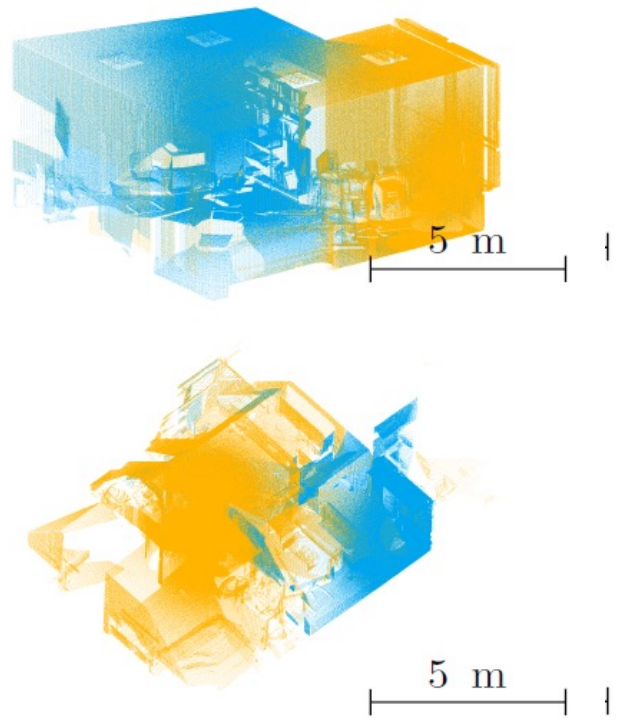
Outdoor scenes acquired by 

*which qualitatively demonstrate applicability across **various sensors and diverse scenes***



Source and target (input)

BUFFER-X (Ours)



Ground truth

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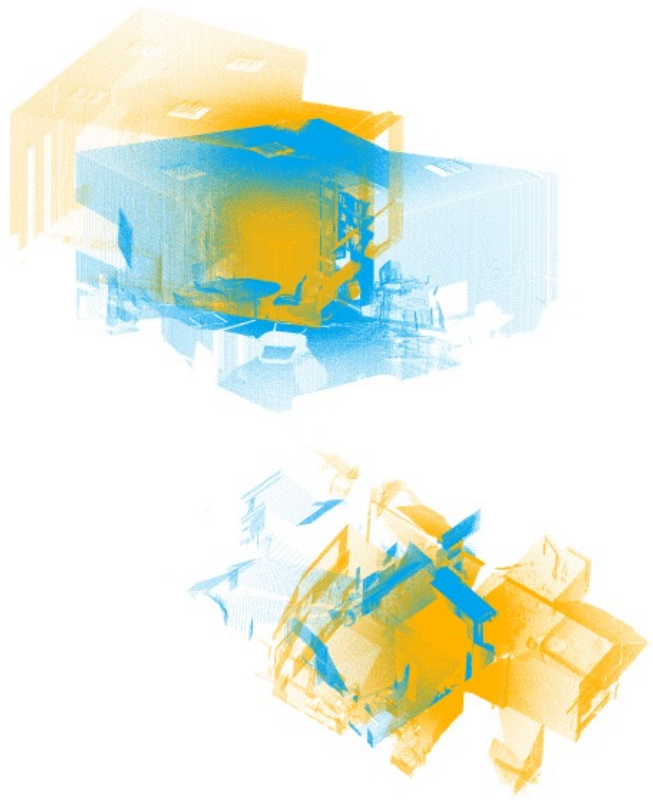

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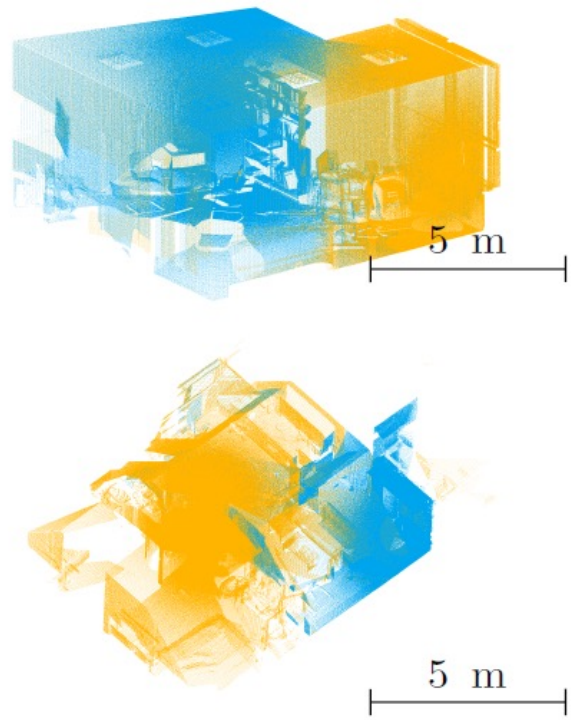

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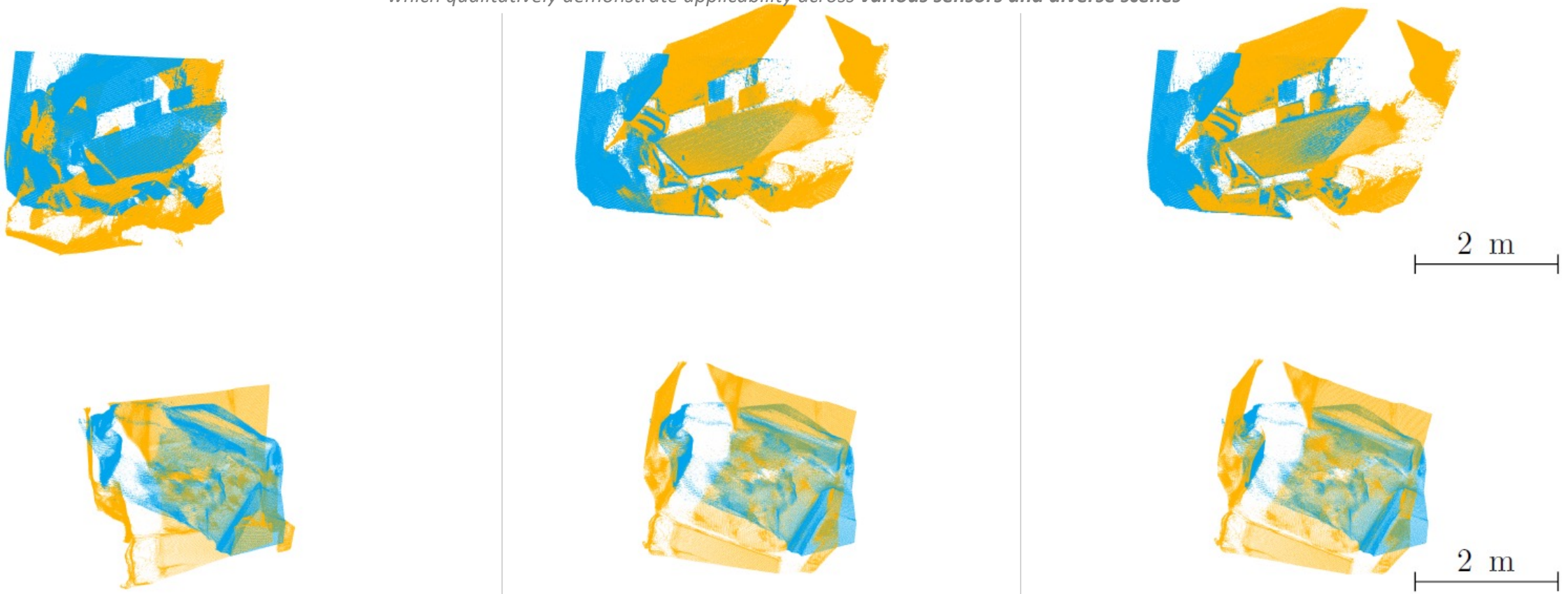

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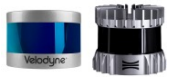
Indoor scenes acquired by 

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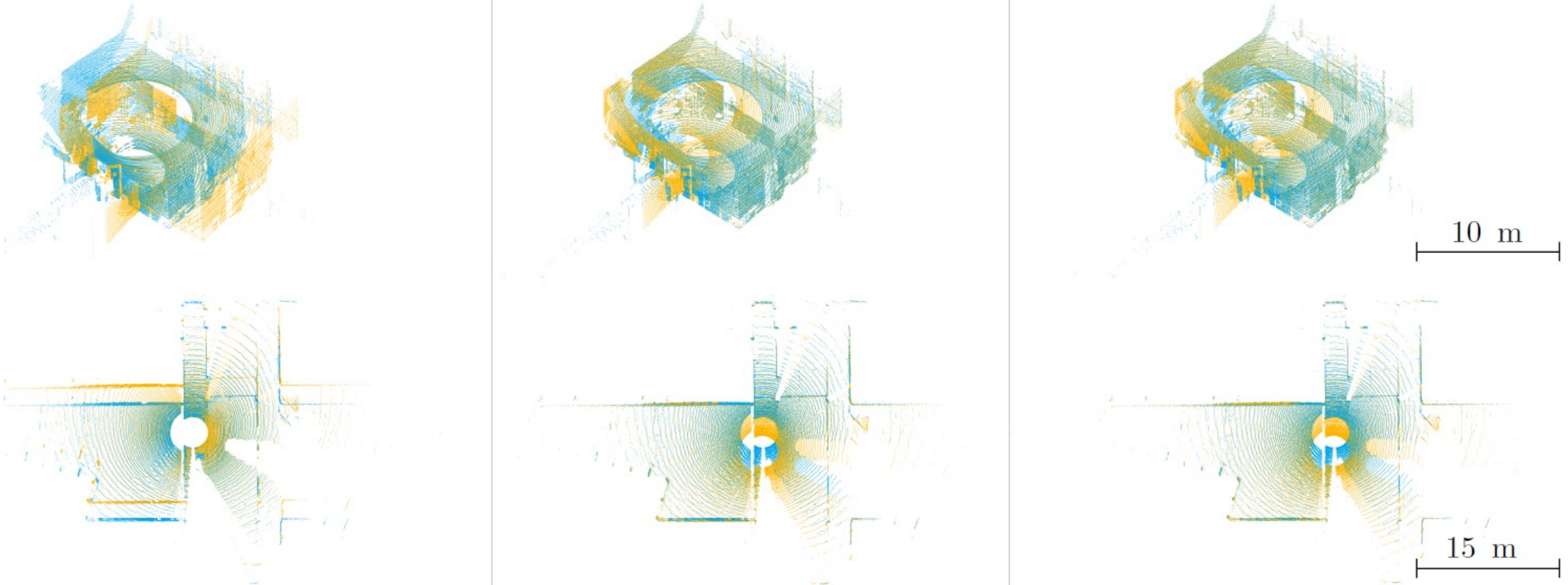

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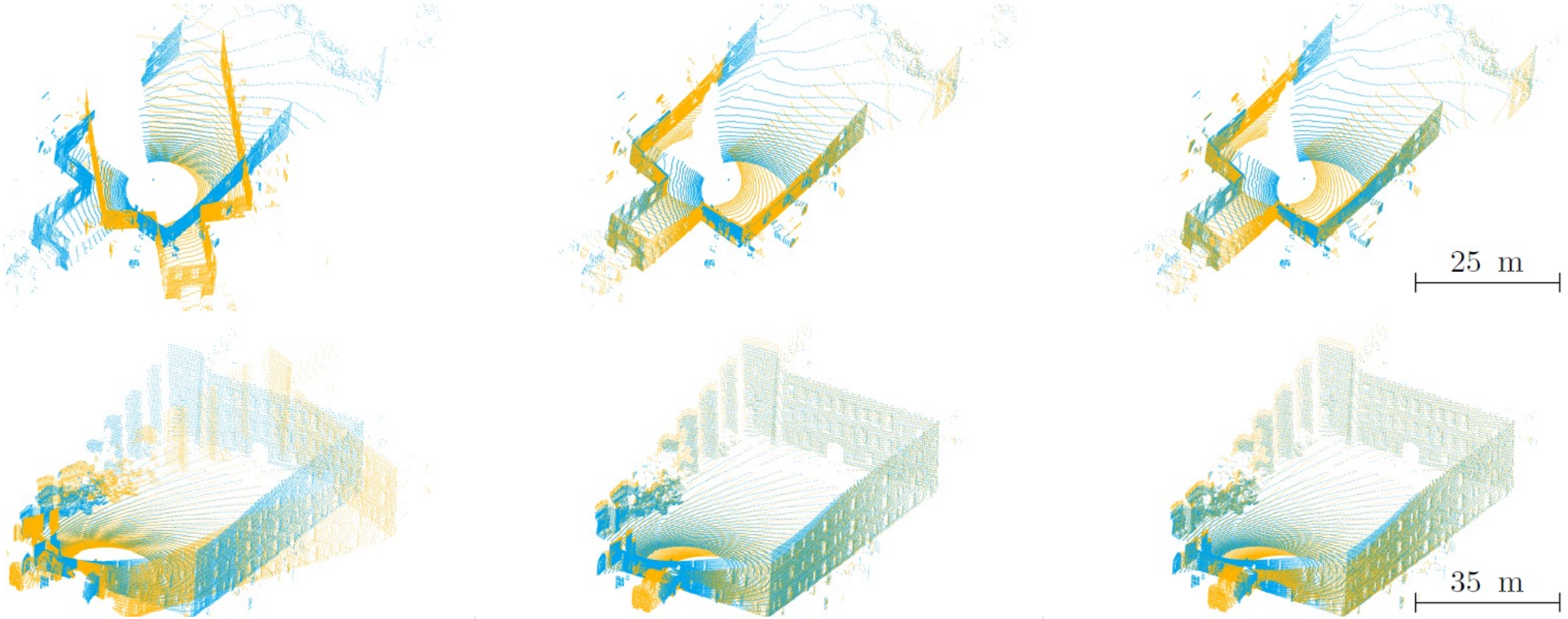

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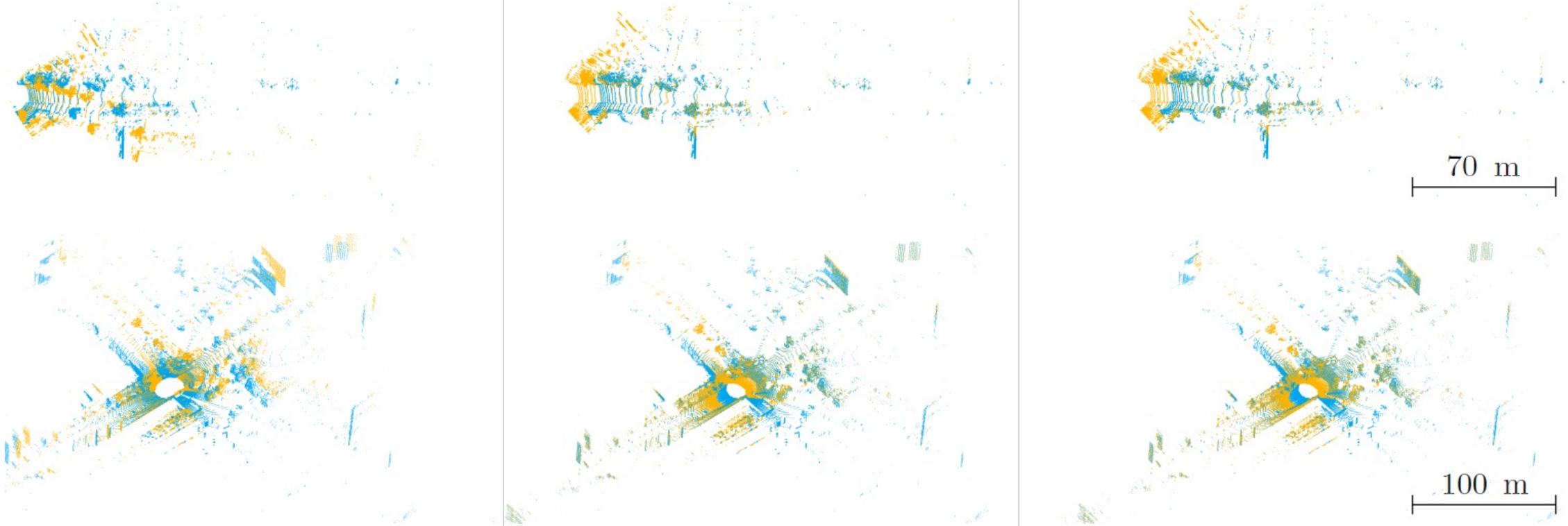

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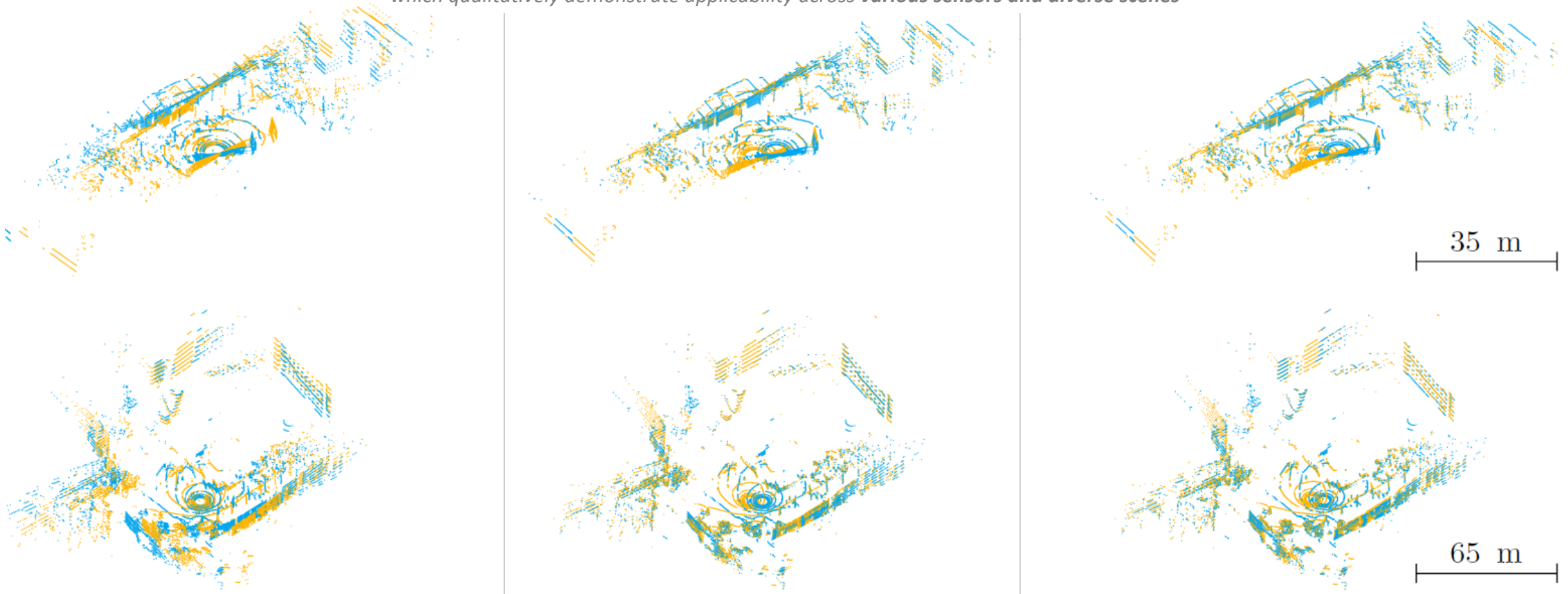

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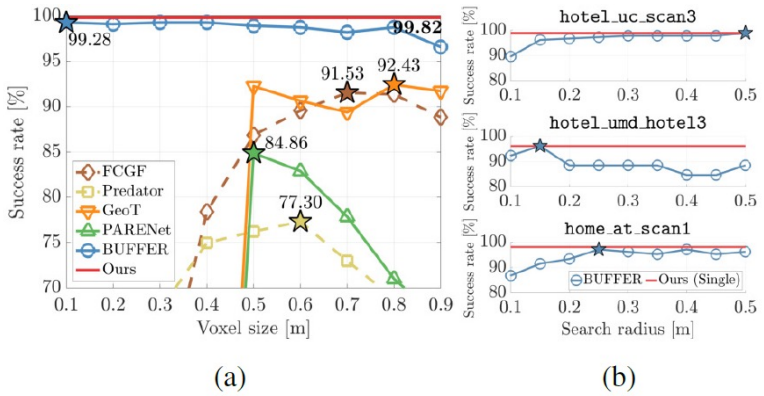
Experimental Results (Cont'd)

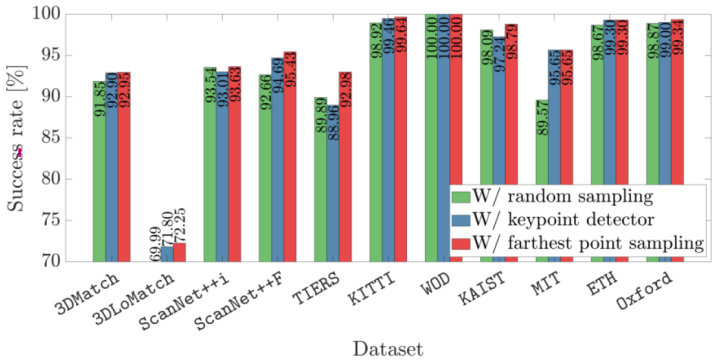
+ Ablation studies are also provided

Impact of geometric bootstrapping



Success rate changes depending on voxel size and search radius

Learning-based keypoint detector vs. Farthest point sampling

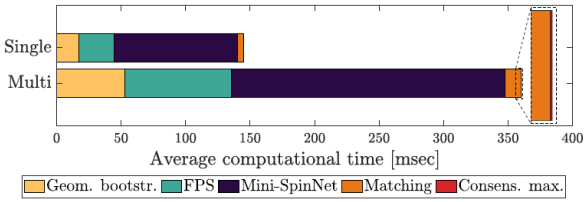


Success rate comparison across keypoint selection strategies

Impact of multi-scale

Local	Middle	Global	RTE [cm] ↓	RRE [°] ↓	Succ. rate [%] ↑	Hz ↑
✓			6.57	2.15	84.06	**5.61**
	✓		5.87	1.85	93.38	5.47
		✓	6.06	1.91	93.57	5.49
✓	✓		**5.73**	1.81	94.31	2.35
✓		✓	5.77	1.81	94.02	2.36
	✓	✓	5.78	1.81	94.62	2.33
✓	✓	✓	5.78	**1.79**	**95.58**	1.81

Ablation study of multi-scale design



Runtime analysis

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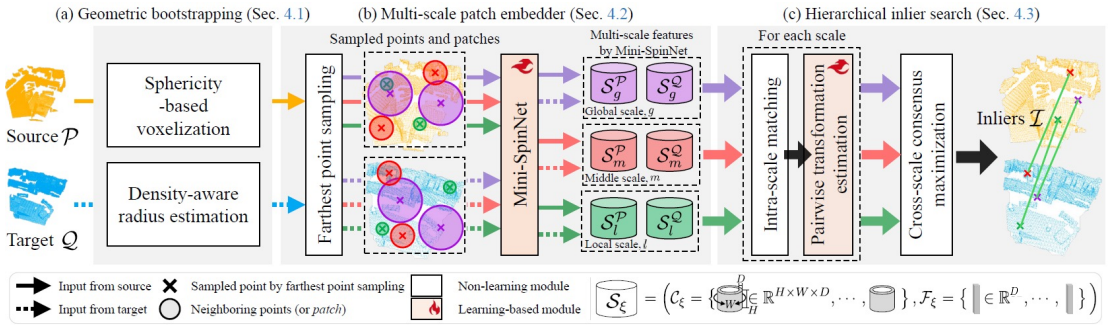
Conclusion

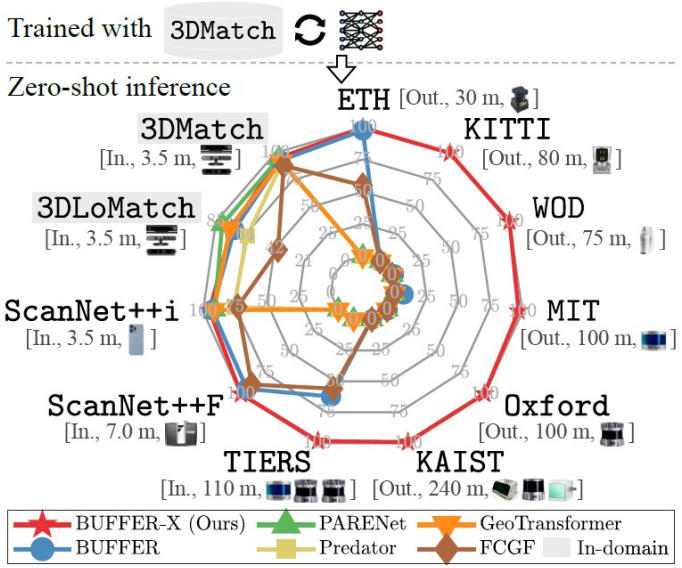
Key contribution #1:

Zero-shot registration pipeline called *BUFFER-X*



Key contribution #2:

Comprehensive benchmark to evaluate generalization capability



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Visual & Geometric Intelligence Lab.

SPARKlab

Thank you!
More results in the paper
& code is available

arXiv version paper

GitHub code