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RSPReg: Reliability-aware Structural Prototype Learning for Point Cloud Registration

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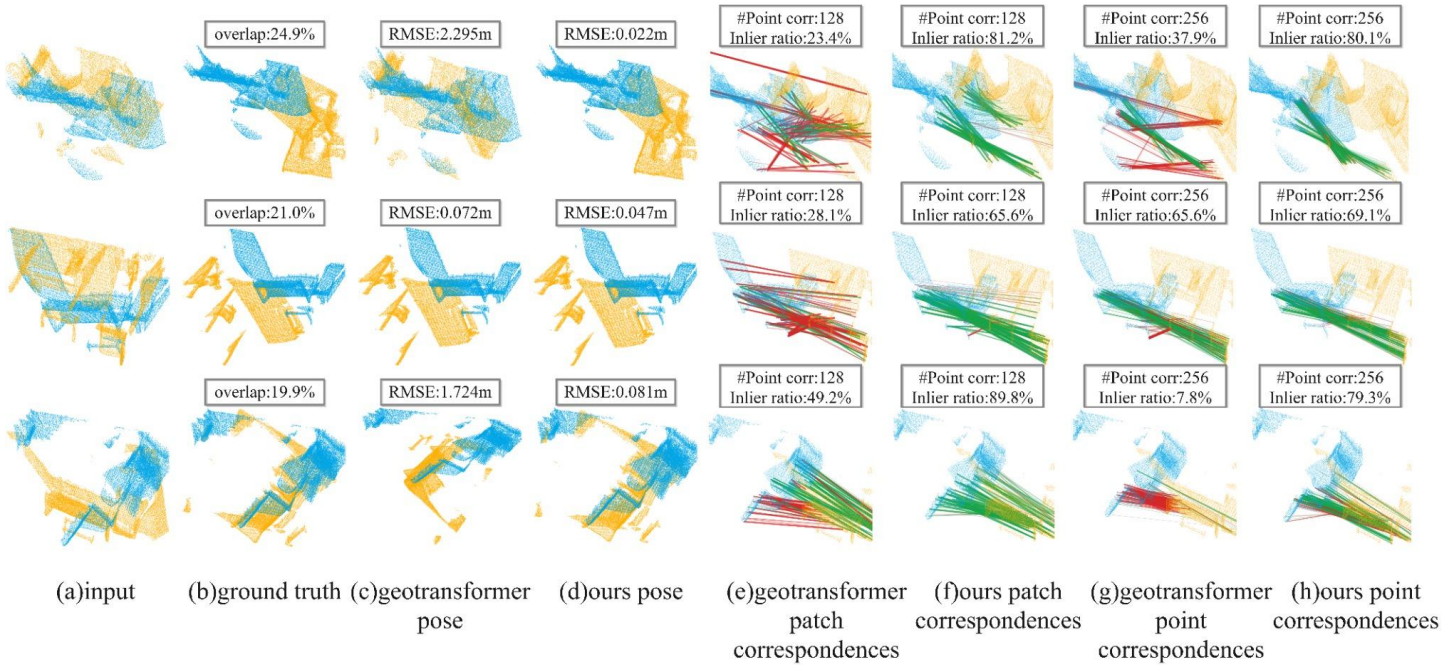
Local geometric similarity does not guarantee reliable matches

Why registration fails

- Low overlap leaves sparse shared geometry.
- Repetitive structures create locally similar regions.
- Ambiguous or non-overlapping regions introduce false correspondences.

We need to assess both structural consistency and its reliability.



Low-overlap examples (19.9%–24.9%): RSPReg produces more accurate poses and more concentrated correspondences.

A structural prior with an explicit reliability estimate

01

Structural prototypes

Learn K prototypes from rotation-invariant coarse superpoint features.

02

Prototype uncertainty

Estimate per-superpoint uncertainty to quantify how trustworthy each structural representation is.

03

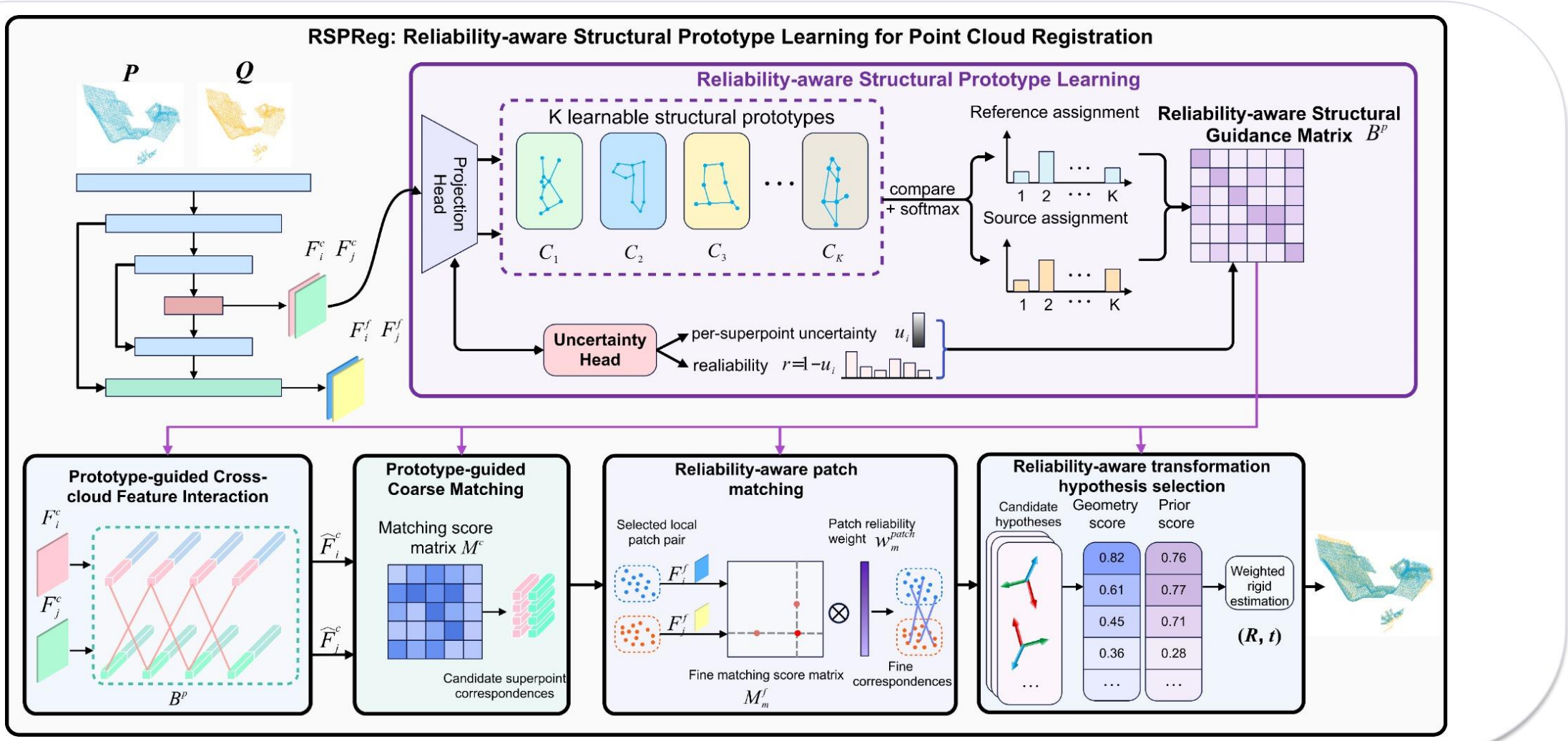
Reliability-aware guidance

Combine prototype consistency and pairwise reliability into a guidance matrix B^p.

Structural consistency × Pairwise reliability → Reliability-aware structural guidance

Prototypes describe whether regions share structural roles; uncertainty determines how much that evidence should be trusted.

One guidance matrix is used throughout coarse-to-fine registration



Full method overview.

Comparison on 3DMatch and 3DLoMatch

Method	Venue	3DMatch			3DLoMatch		
		FMR ↑	IR ↑	RR ↑	FMR ↑	IR ↑	RR ↑
FCGF	ICCV 2019	94.7	31.1	82.8	59.4	9.8	38.0
SpinNet	CVPR 2021	97.6	47.5	88.6	75.3	20.5	59.8
Predator	CVPR 2021	96.6	58.0	89.0	78.2	26.7	64.4
GeoTransformer	CVPR 2022	98.1	70.9	92.4	87.4	43.5	74.3
OIF-Net	NeurIPS 2022	98.1	62.3	92.4	84.6	27.5	76.1
SIRA-PCR	ICCV 2023	98.2	70.8	93.6	88.8	43.3	73.5
RoReg	TPAMI 2023	98.2	81.6	93.0	82.3	39.6	70.1
BUFFER	CVPR 2023	–	–	92.1	–	–	70.3
Diff-Reg	ECCV 2024	95.4	25.7	94.3	68.7	9.3	73.2
DFAT	CVPR 2025	96.1	18.7	94.9	65.2	7.6	76.8
RARE	ICCV 2025	–	–	94.5	–	–	76.7
RSPReg	**Ours**	**99.0**	**74.6**	**95.9**	**88.7**	**44.8**	**78.6**

RSPReg achieves the best RR on both benchmarks: 95.9% on 3DMatch and 78.6% on 3DLoMatch.

Outdoor registration and cross-domain generalization

KITTI | Outdoor LiDAR

Relative rotation error

0.23°

Relative translation error

5.2 cm

Registration Recall: 99.8%

ETH | Cross-domain

Train on 3DMatch, then evaluate directly on ETH without fine-tuning.

FMR 97.5% **IR 26.2%**

RR 97.9%

Best registration recall in the reported comparison.

KITTI: RSPReg reports the lowest RTE (5.2 cm) while maintaining 99.8% RR.

Robustness at low overlap and contribution of each component

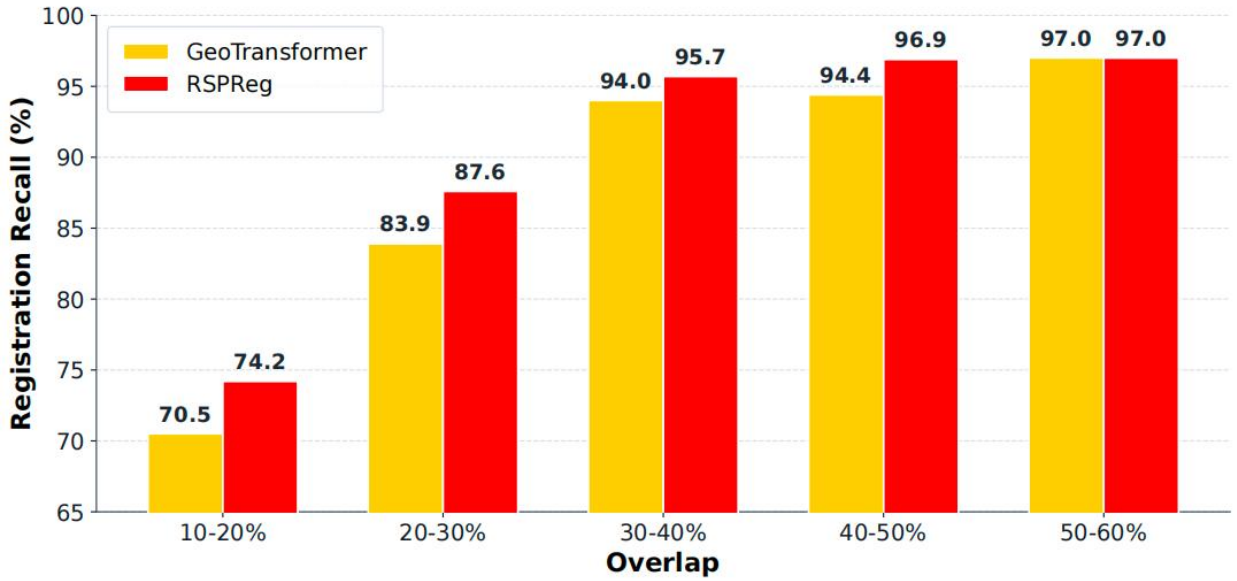


Figure . Registration recall comparison between GeoTransformer and RSPReg under different overlap ratios.

10–20% overlap: 70.5 → 74.2% RR
20–30% overlap: 83.9 → 87.6% RR

Ablation on 3DMatch

RSPL	PG-CFI	PGM	RA-THS	RR
√	×	×	×	95.5
√	√	×	×	93.0
√	√	√	×	94.4
√	√	√	√	**95.9**

The complete pipeline achieves the highest RR (95.9%), combining structural learning with all three guidance stages.

Reliability-aware structural guidance improves robust registration

RSPReg learns structural prototypes and estimates their uncertainty.

The resulting reliability-aware prior guides feature interaction, coarse matching, patch matching, and transformation hypothesis selection.

Low-overlap robustness · Outdoor LiDAR performance · Cross-domain generalization

Thank you.