Cross-Modal Prior-Guided Training with Visual Foundation Models for Unsupervised LiDAR Point Cloud Registration

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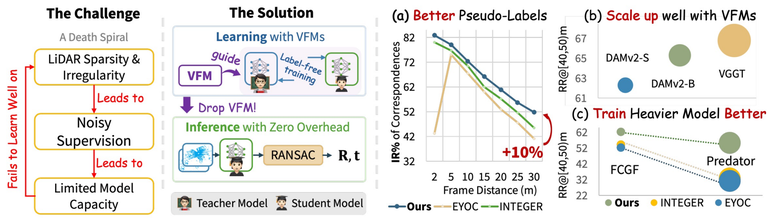
Introduction & Motivation

Breaking the unsupervised "death spiral"

Sparse, irregular LiDAR geometry produces noisy pseudo-labels. The resulting supervision restricts the trainability of larger registration models.



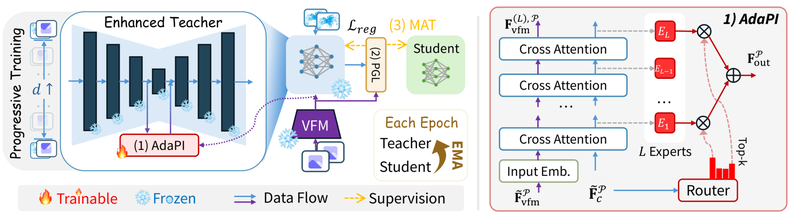
PROMOTER uses visual priors to improve supervision and scale to stronger VFMs and registration models.

Challenges in transferring visual priors

- **Partial coverage.** The 32-beam nuScenes LiDAR covers ≤1% of image pixels, leaving few point–pixel assignments.
- **Ambiguous projection.** Many-to-one mappings, occlusions and calibration errors complicate visual–geometric alignment.
- **Modality and task gaps.** Appearance and irrelevant semantics can distract from the geometry needed for registration.

Method

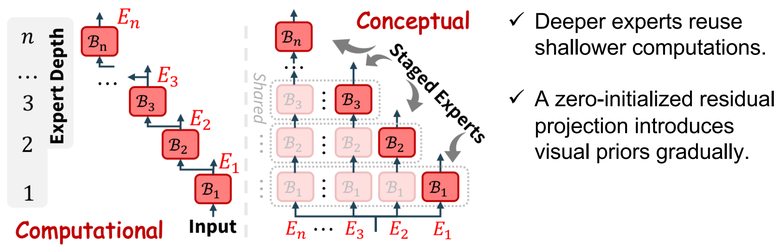
PROMOTER, a novel teacher–student framework



AdaPI enhances the teacher with frozen VFM priors. PGL produces correspondence pseudo-labels. MAT transfers the enhanced teacher's matchability to the student.

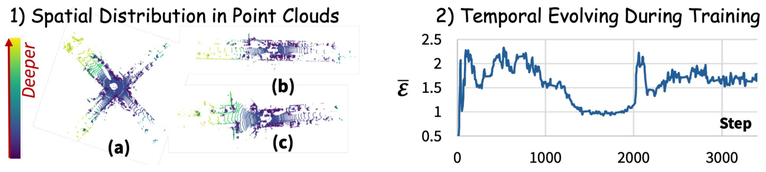
1. Adaptive Prior Integrator (AdaPI)

Geometry-aware embeddings fuse local 3D structure with VFM features. Cross-attention propagates visual priors to the full cloud. A top-k router mixes staged experts per point.



- ✓ Deeper experts reuse shallower computations.
- ✓ A zero-initialized residual projection introduces visual priors gradually.

AdaPI adapts expert routing across points and training stages (Fig. 5).



2. Perceptual-Geometric Labeler (PGL)

Generate pose candidates from spatial compatibility. Rank them using visual consistency × geometric inlier count. Extract correspondences with the final pose.

3. Matchability-Anchored Training (MAT)

Bidirectional cross-model contrastive learning transfers point relations. A Gram-matrix regularizer aligns global second-order feature structure.

$$\mathcal{L}_{\text{MAT}} = \left(\mathcal{L}_{\text{reg}}(\mathbf{F}_s^{\mathcal{P}}, \text{sg}(\mathbf{F}_t^{\mathcal{Q}}); \hat{\mathcal{C}}) + \mathcal{L}_{\text{reg}}(\text{sg}(\mathbf{F}_t^{\mathcal{P}}), \mathbf{F}_s^{\mathcal{Q}}; \hat{\mathcal{C}})\right) + \lambda_{\mathcal{R}}\mathcal{R}_{struct} \quad (5)$$

$$\mathcal{R}_{struct} = (\left\|\mathbf{G}_s^{\mathcal{P}} - \text{sg}(\mathbf{G}_t^{\mathcal{P}})\right\|_{\text{F}}^2 + \left\|\mathbf{G}_s^{\mathcal{Q}} - \text{sg}(\mathbf{G}_t^{\mathcal{Q}})\right\|_{\text{F}}^2)/2C^2 \quad (6)$$

Full student objective: registration loss + weighted MAT loss

Experiments

U marks unsupervised methods (Table 1).

Dataset	Method	U	mRR	RR@$d \in$ [5, 10)	[10, 20)	[20, 30)	[30, 40)	[40, 50)
KITTI	FCGF	–	77.4	98.4	95.3	86.8	69.7	36.9
	FCGF+C	–	84.6	100.0	97.5	90.1	79.1	56.3
	Predator	–	87.9	100.0	98.6	97.1	80.6	63.1
	SpinNet	–	39.1	99.1	82.5	13.7	0.0	0.0
	D3Feat	–	66.4	99.8	98.2	90.7	38.6	4.5
	CoFiNet	–	82.1	99.9	99.1	94.1	78.6	38.7
	GeoTrans.	–	42.2	100.0	93.9	16.6	0.7	0.0
	EYOC	✓	83.2	**99.5**	96.6	89.1	78.6	52.3
	RIENet	✓	50.7	96.3	72.1	38.2	24.4	22.6
	INTEGER	✓	84.0	**99.5**	97.1	89.6	79.6	54.2
	PROMOTER	✓	**86.5**	**99.5**	**97.5**	**90.6**	**81.6**	**63.3**
nuScenes	FCGF	–	39.5	87.9	63.9	23.6	11.8	10.2
	FCGF+C	–	59.3	96.2	85.1	59.6	35.8	20.0
	Predator	–	51.0	99.7	72.2	52.8	16.2	14.3
	EYOC	✓	61.7	96.7	85.6	61.8	37.5	26.9
	RIENet	✓	47.1	96.5	57.9	36.6	25.8	18.9
	INTEGER	✓	63.2	97.1	86.9	62.9	39.6	29.4
	PROMOTER	✓	**72.0**	**98.9**	**88.4**	**72.5**	**54.6**	**45.5**
KITTI ↓ nuScenes	EYOC	✓	55.3	96.2	75.6	58.7	26.6	19.7
	RIENet	✓	46.2	83.3	73.2	43.5	19.8	11.1
	INTEGER	✓	62.5	97.5	84.6	62.6	37.8	30.2
	PROMOTER	✓	**66.1**	**99.5**	**87.6**	**68.2**	**40.5**	**34.5**

Scaling with stronger priors and models

VFMs (Table 3)

VFM	#Params	mRR	$d \in [40, 50)$ RR	RRE	RTE
► *VFMs for Visual-Geometric Tasks*					
a) DAMv2-S	24.8M	86.5	63.3	1.03	0.56
b) DAMv2-B	97.5M	87.2	65.8	0.98	0.55
c) VGGT	0.94B	**87.5**	**67.3**	**0.91**	**0.52**
► *Other Visual Model Baselines*					
d) DINOv2-B*	86.1M	86.2	62.8	1.17	0.55
e) EfficientNet-B7*	66.0M	*Failed to Converge*			

Registration models (Table 4)

Method	Reg. Model	#Params	mRR	$d \in [40, 50)$ RR	RRE	RTE
PROMOTER	FCGF	8.76M	86.5	63.3	1.03	**0.56**
	D3Feat	14.79M	**87.3**	**66.3**	**0.95**	**0.56**
EYOC	Predator	22.77M	61.1	31.2	1.81	0.65
INTEGER			61.6	32.7	1.38	**0.59**
PROMOTER			**84.3**	**55.8**	**1.36**	0.61

Stronger VFMs improve recall. PROMOTER also improves Predator's mRR from 61.6 to 84.3 vs. INTEGER.

Efficiency on KITTI (Table 2)

Methods	mRR%	RR@$d \in$ [40, 50)	Training (h)	Testing (s/pair)
EYOC	83.2	52.3	**44.9**	
INTEGER⋆	84.0	54.2	76.0	∼0.16
PROMOTER	**86.5**	**63.3**	60.6	
Δ% vs. ⋆	+2.5%	+9.1%	-20%	–