PointRegGPT:

Boosting 3D **Point** Cloud **Reg**istration using **G**enerative **P**oint-Cloud Pairs for **T**raining

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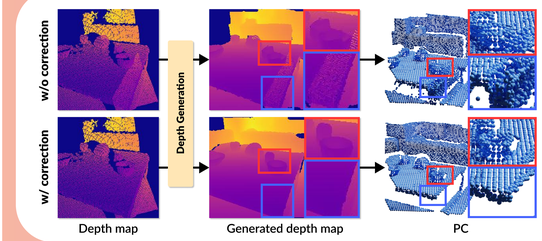
Motivation

Data plays a crucial role in training learning-based methods for 3D point cloud registration. However,

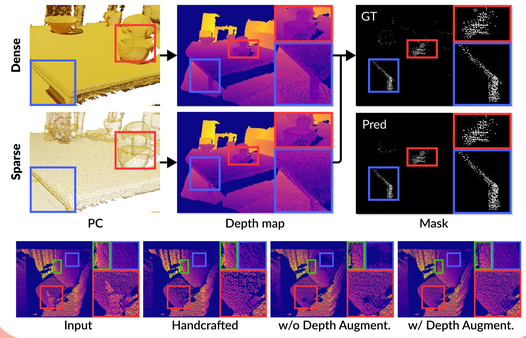
- the real-world dataset is expensive to build; while
- rendering-based synthetic data suffers from domain gaps.

Can generative models offer a solution?

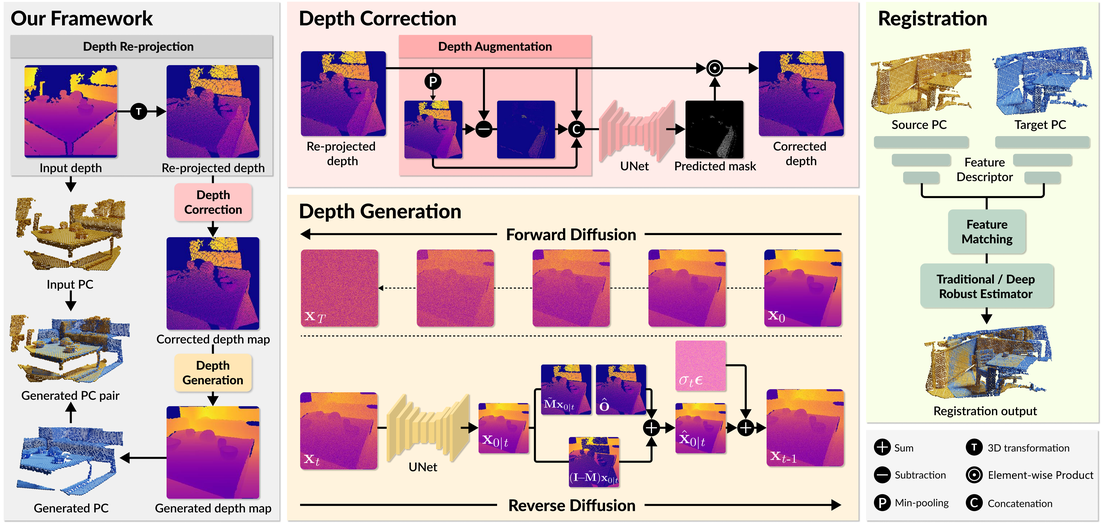
Point Penetration Problem



Depth Corretion



PointRegGPT Architecture Overview



Our PointRegGPT framework:

- the given depth map is processed by re-projection, depth correction, and depth generation to produce a new depth map, which is then converted into a pair of partially-overlapped point clouds;
- depth generation utilizes a pre-trained diffusion model to generate new content while it keeps geometric consistency in the overlap region;
- depth correction is used to correct the unnatural depth values generated by penetrated points during re- projection, where the depth augmentation module enhances detection of the wrong values;
- the generated dataset is used to train registration models.

Generation

Constraints

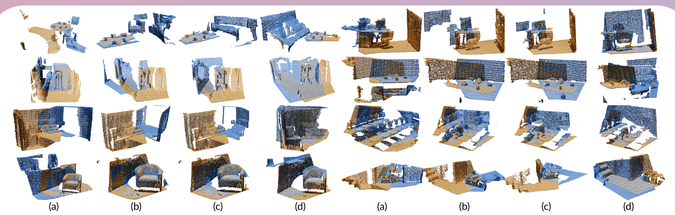
1. Consistency: $\tilde{\mathbf{M}}\mathbf{x}_0 = \hat{\mathbf{o}}$
2. Realism: $\mathbf{x}_0 \sim q(\mathbf{o})$

Range-null space decomposition:

$$\mathbf{x}_0 = \underbrace{\tilde{\mathbf{M}}^\dagger \tilde{\mathbf{M}}\mathbf{x}_0}_{\text{range sapce}} + \underbrace{\left(\mathbf{I} - \tilde{\mathbf{M}}^\dagger \tilde{\mathbf{M}}\right)\mathbf{x}_0}_{\text{null space}}$$

$$\begin{aligned}\tilde{\mathbf{M}}\hat{\mathbf{x}}_0 &= \tilde{\mathbf{M}}\tilde{\mathbf{M}}^\dagger \hat{\mathbf{o}} + \tilde{\mathbf{M}}\left(\mathbf{I} - \tilde{\mathbf{M}}^\dagger \tilde{\mathbf{M}}\right)\mathbf{x}_0 \\ &= \tilde{\mathbf{M}}\tilde{\mathbf{M}}^\dagger \tilde{\mathbf{M}}\mathbf{o} + \tilde{\mathbf{M}}\left(\mathbf{I} - \tilde{\mathbf{M}}^\dagger \tilde{\mathbf{M}}\right)\mathbf{x}_0 \\ &= \tilde{\mathbf{M}}\mathbf{o} + \mathbf{0} \\ &= \hat{\mathbf{o}}\end{aligned}$$

Generated Samples



Note: (a) Nearest Real-World Sample; (b) Generated Sample 1; (c) Generated Sample 2 w/ Same View; (d) Generated Sample 3 w/ Diff. View.

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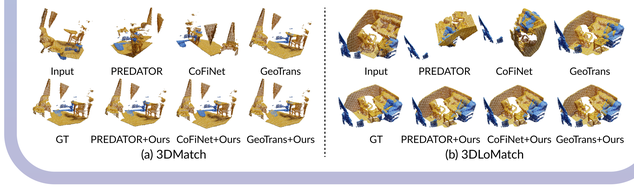
Indoor-Scene Point Cloud Registration

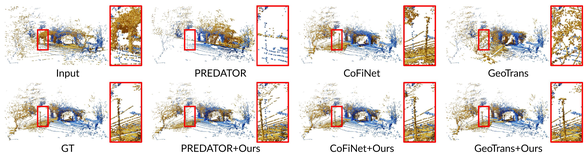
Method		3DMatch			3DLoMatch		
		FMR	IR	RR	FMR	IR	RR
PREDATOR	CVPR'2021	96.5	57.1	90.6	76.3	28.3	62.4
+ Ours	-	98.3	63.7	90.7	82.4	35.1	67.2
CoFiNet	NIPS'2021	98.1	49.8	89.3	83.1	24.4	67.5
+ Ours	-	98.1	49.9	90.6	85.1	25.5	67.5
GeoTrans	CVPR'2022	97.7	70.3	91.5	88.1	43.3	74.0
+ Ours	-	98.7	71.9	93.3	89.4	45.6	77.2



(a) 3DMatch (b) 3DLoMatch

Outdoor-Scene Point Cloud Registration

Method	Venue	Registration Recall				
		5000	2500	1000	500	250
PREDATOR	CVPR'2021	74.7	72.9	67.7	60.3	51.7
+Ours	-	84.1	81.1	75.1	65.6	51.9
CoFiNet	NIPS'2021	83.9	82.7	81.9	77.4	68.8
+Ours	-	88.0	88.6	88.1	85.3	76.7
GeoTrans	CVPR'2022	-		85.5	-	
+Ours	-	-		85.8	-	



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