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Learning Signed Distance Functions from Noisy 3D Point Clouds via Noise to Noise Mapping

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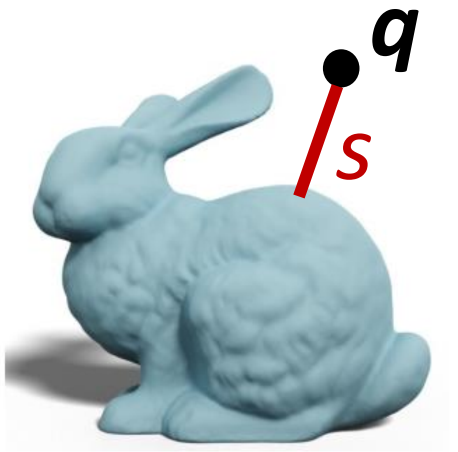
Project page: https://github.com/mabaorui/Noise2NoiseMapping

Code & Data:

Background



- Signed Distance Functions (SDFs) have been successful in representing high resolution shapes with complex topology.
- Signed distance s =***f***(Condition ***c***, Query ***q***)
- Current methods still struggle from learning SDFs from noisy point clouds without ground truth signed distances, point normals or clean point clouds:

- We propose to learn SDFs via a noise to noise mapping which can infer a highly accurate SDF of a single object or scene from its multiple or even single noisy point cloud observations.

Related works

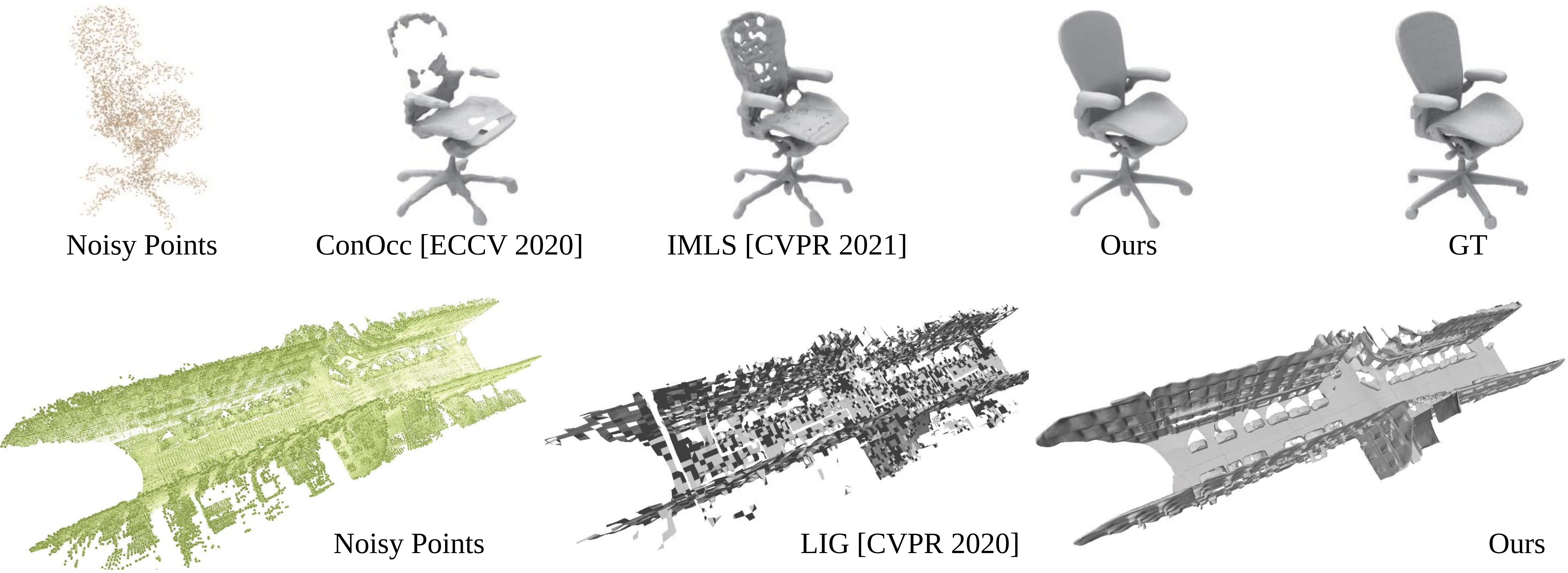
- Current solutions significantly affect the accuracy of SDFs learned for noisy point clouds, either caused by poor generalization or the incapability of denoising.
  - *IMLS, POCO, Cocc*
- These methods need the expensive pairs of the corrupted inputs and clean targets to learn the denoising,

- By introducing a novel loss function containing a geometric consistency regularization, we are enabled to learn a SDF via a task of learning a mapping from one corrupted observation to another corrupted observation or even a mapping from one corrupted observation to the observation itself.

[IMLS]: Deep implicit moving least-squares functions for 3D reconstruction, CVPR 2021.
[POCO]: POCO: Point convolution for surface reconstruction, CVPR 2022.
[Cocc]: Convolutional occupancy networks, ECCV, 2020.

It is import to learn *signed distance functions (SDFs)* from *3D point clouds* in various tasks, such as surface reconstruction and point cloud denoising.

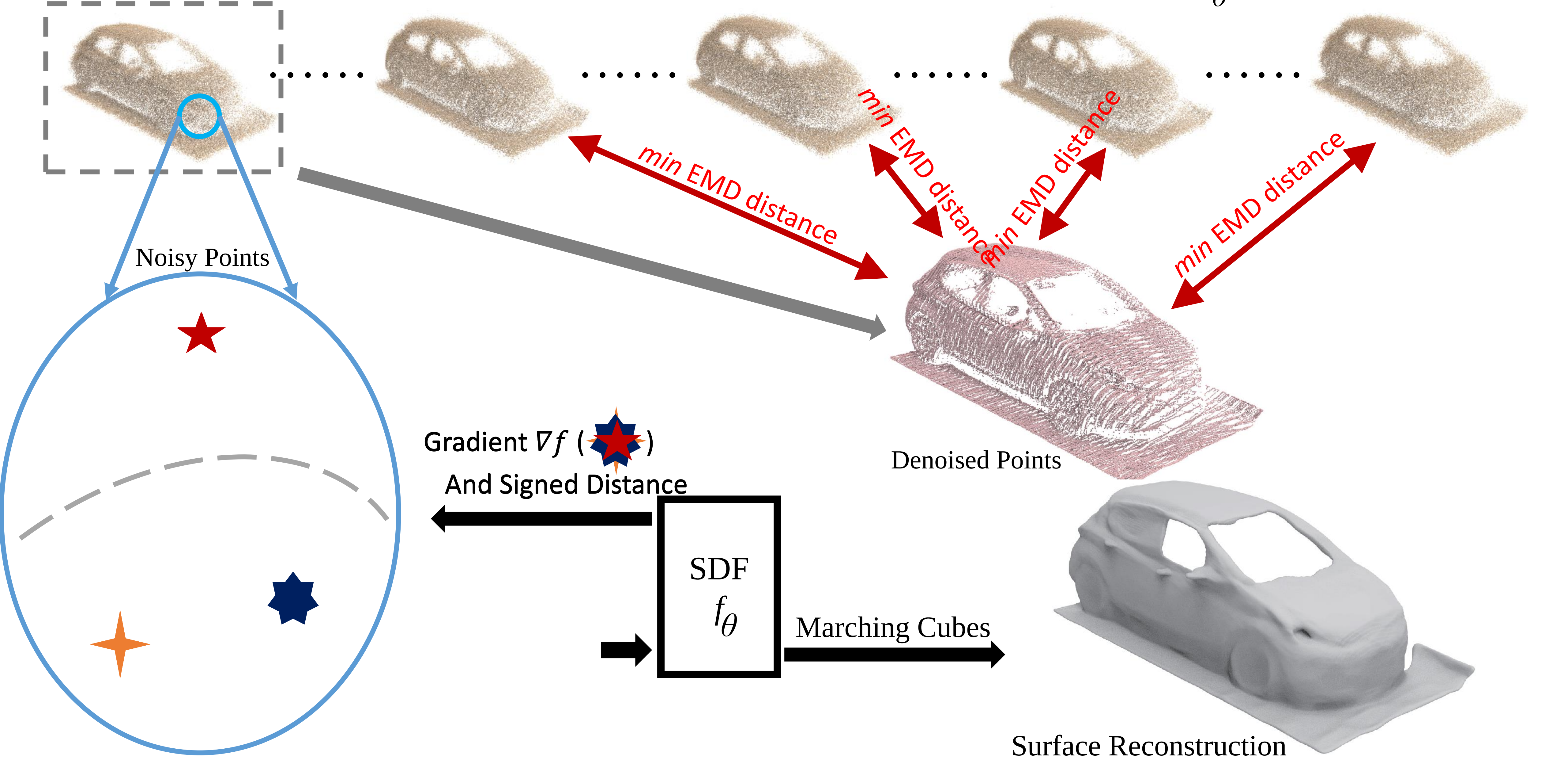
The latest methods struggle to learn *SDFs* from *noisy point clouds*.



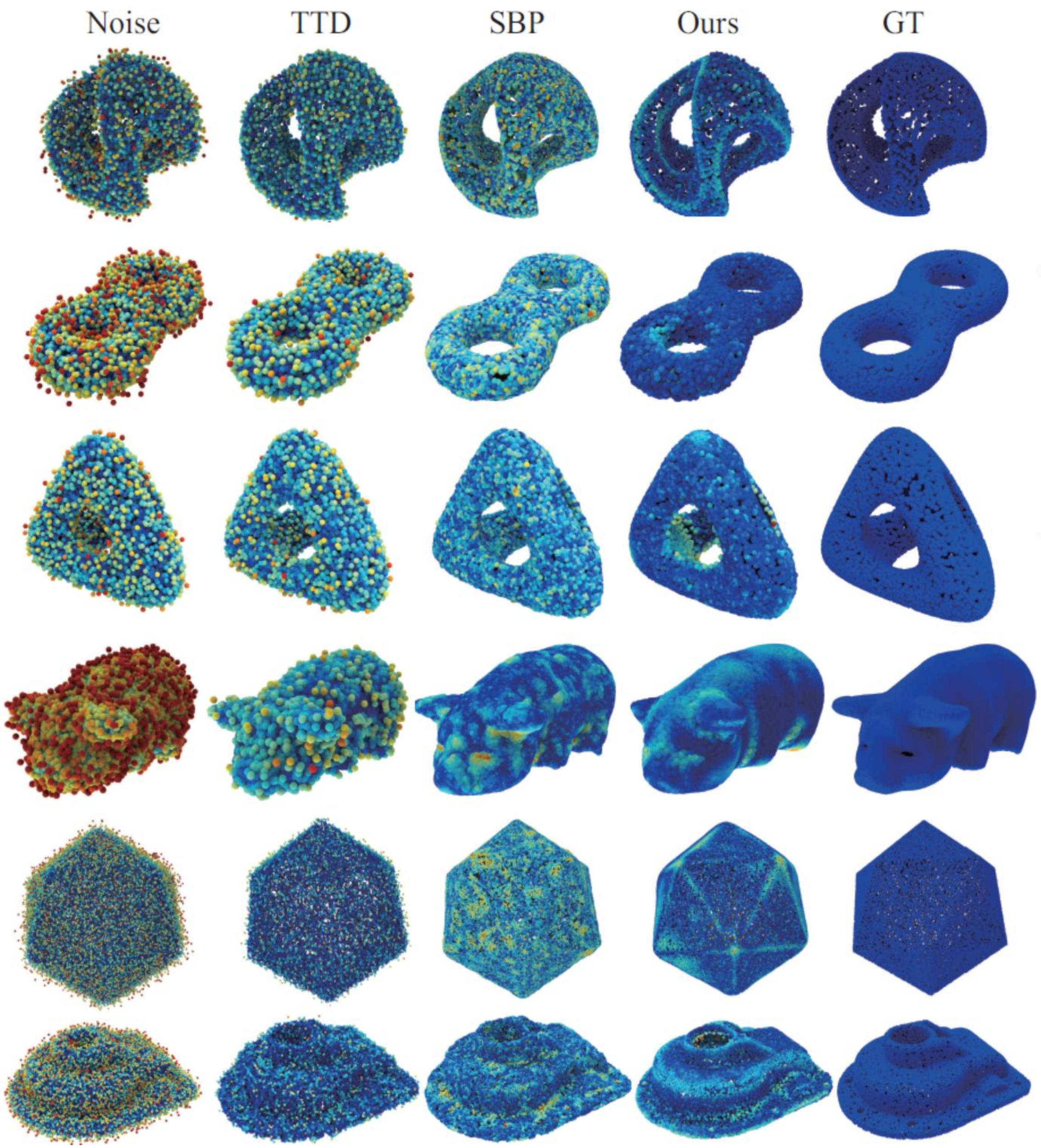
Our method can learn SDFs directly from noisy point clouds without supervision or point normal.

We introduce to learn SDFs via Noise to Noise mapping.

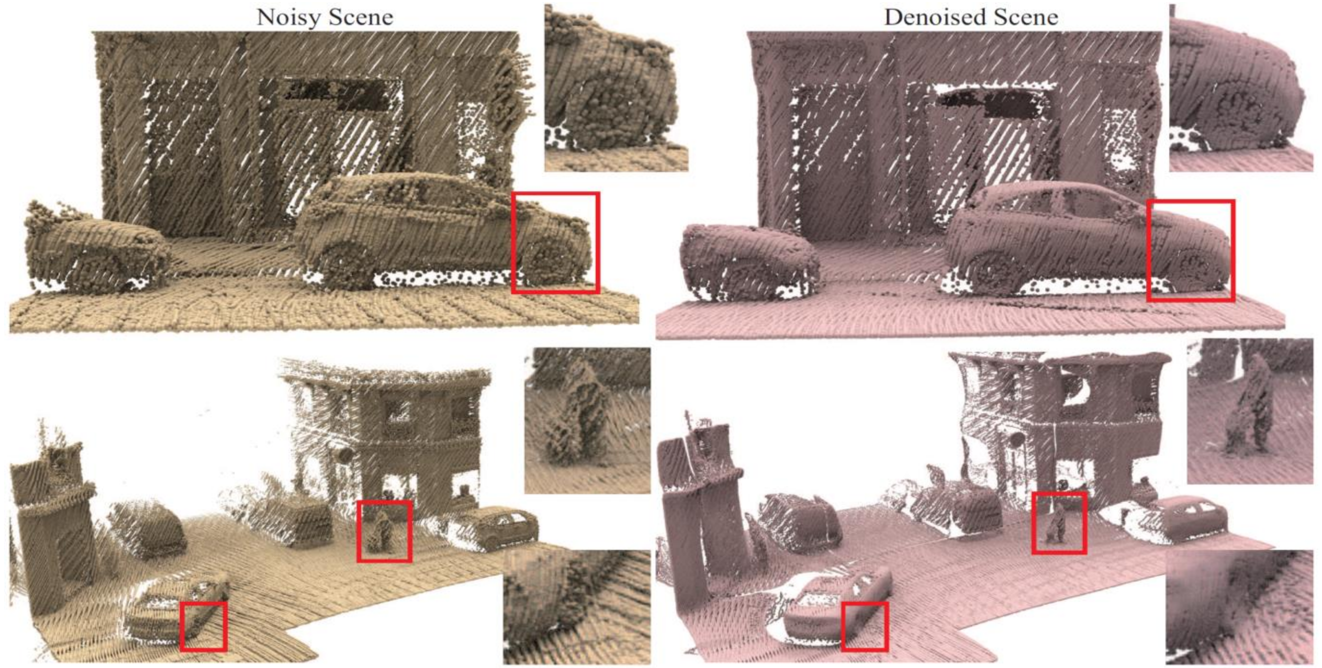
Given $N \geq 1$ corrupted observations from an object or scene, we learn SDFs f_θ



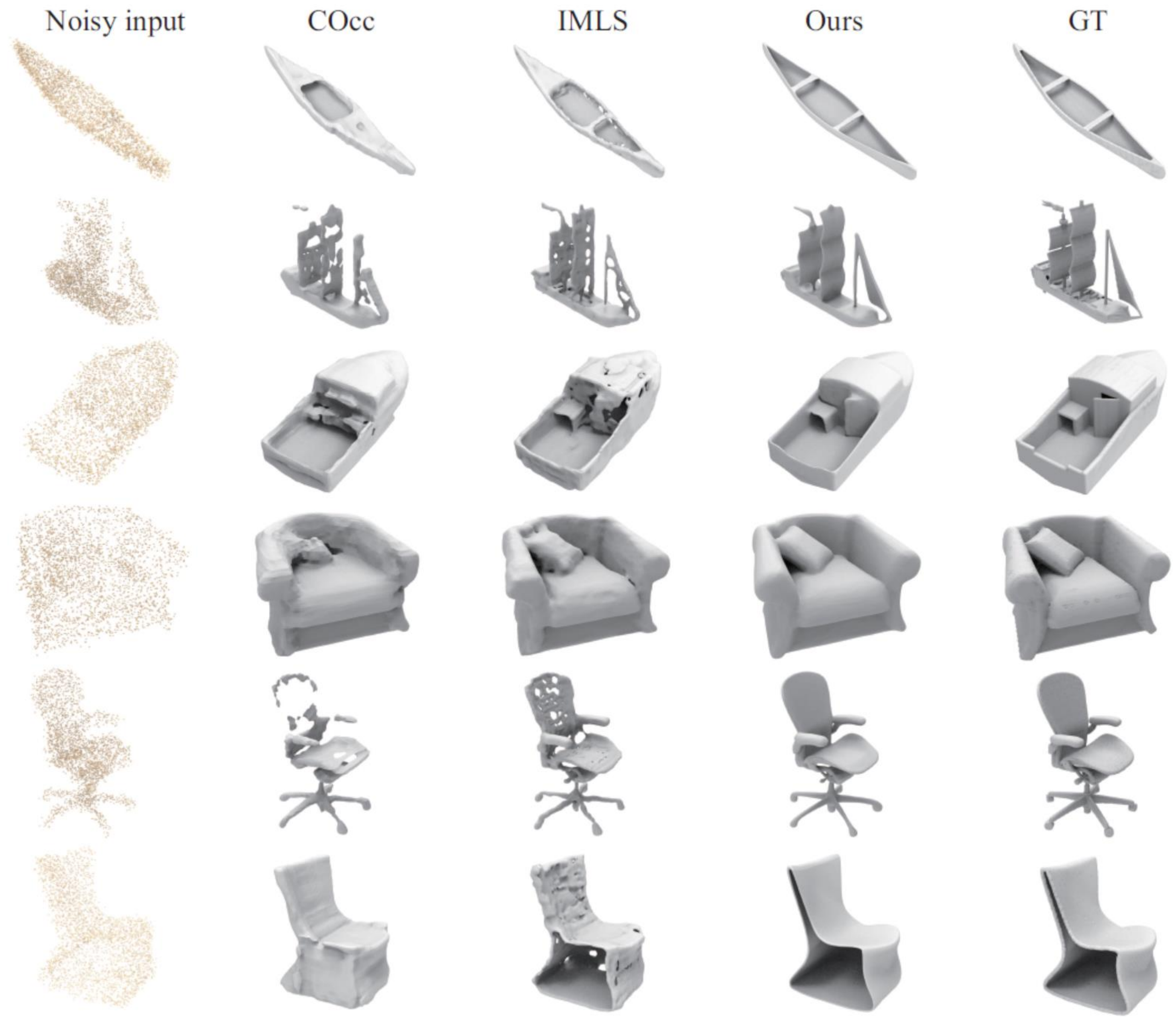
Point Cloud Denoising



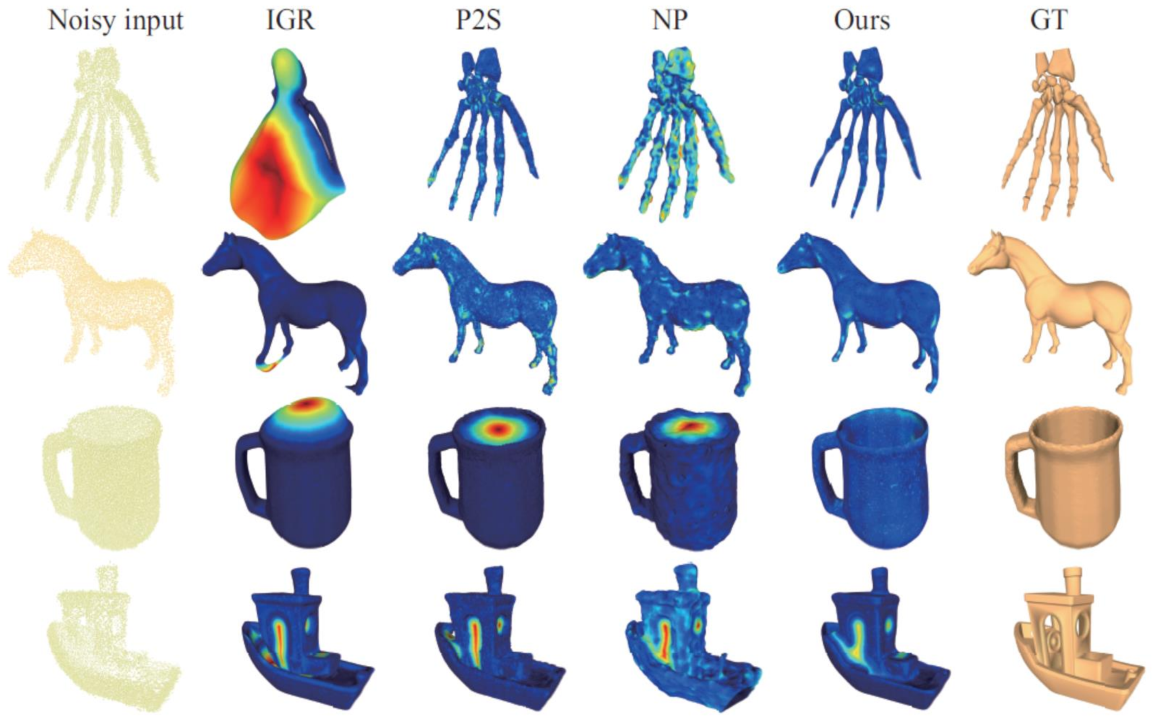
Point Number		10K(Sparse)						50K(Dense)					
Noise		1%		2%		3%		1%		2%		3%	
	Model	CD	P2M	CD	P2M	CD	P2M	CD	P2M	CD	P2M	CD	P2M
PU	Bilateral	3.646	1.342	5.007	2.018	6.998	3.557	0.877	0.234	2.376	1.389	6.304	4.730
	Jet	2.712	0.613	4.155	1.347	6.262	2.921	0.851	0.207	2.432	1.403	5.788	4.267
	MRPCA	2.972	0.922	3.728	1.117	5.009	1.963	0.669	**0.099**	2.008	1.003	5.775	4.081
	GLR	2.959	1.052	3.773	1.306	4.909	2.114	0.696	0.161	1.587	0.830	3.839	2.707
	PCNet	3.515	1.148	7.469	3.965	13.067	8.737	1.049	0.346	1.447	0.608	2.289	1.285
	GPDNet	3.780	1.337	8.007	4.426	13.482	9.114	1.913	1.037	5.021	3.736	9.705	7.998
	DMR	4.482	1.722	4.982	2.115	5.892	2.846	1.162	0.469	1.566	0.800	2.632	1.528
	SBP	2.521	0.463	3.686	1.074	4.708	1.942	0.716	0.150	1.288	0.566	1.928	1.041
	TTD-Un	3.390	0.826	7.251	3.485	13.385	8.740	1.024	0.314	2.722	1.567	7.474	5.729
	SBP-Un	3.107	0.888	4.675	1.829	7.225	3.726	0.918	0.265	2.439	1.411	5.303	3.841
	Ours	**1.060**	**0.241**	**2.925**	**1.010**	**4.221**	**1.847**	**0.377**	0.155	**1.029**	**0.484**	**1.654**	**0.972**
PC	Bilaterall	4.320	1.351	6.171	1.646	8.295	2.392	1.172	0.198	2.478	0.634	6.077	2.189
	Jet	3.032	0.830	5.298	1.372	7.650	2.227	1.091	0.180	2.582	0.700	5.787	2.144
	MRPCA	3.323	0.931	4.874	1.178	6.502	1.676	0.966	0.140	2.153	0.478	5.570	1.976
	GLR	3.399	0.956	5.274	1.146	7.249	1.674	0.964	0.134	2.015	0.417	4.488	1.306
	PCNet	3.849	1.221	8.752	3.043	14.525	5.873	1.293	0.289	1.913	0.505	3.249	1.076
	GPDNet	5.470	1.973	10.006	3.650	15.521	6.353	5.310	1.716	7.709	2.859	11.941	5.130
	DMR	6.602	2.152	7.145	2.237	8.087	2.487	1.566	0.350	2.009	0.485	2.993	0.859
	SBP	3.369	0.830	5.132	1.195	6.776	1.941	1.066	0.177	1.659	0.354	2.494	**0.657**
	Ours	**2.047**	**0.518**	**2.056**	**0.519**	**5.331**	**1.935**	**0.426**	**0.129**	**1.043**	**0.316**	**2.22**	1.096



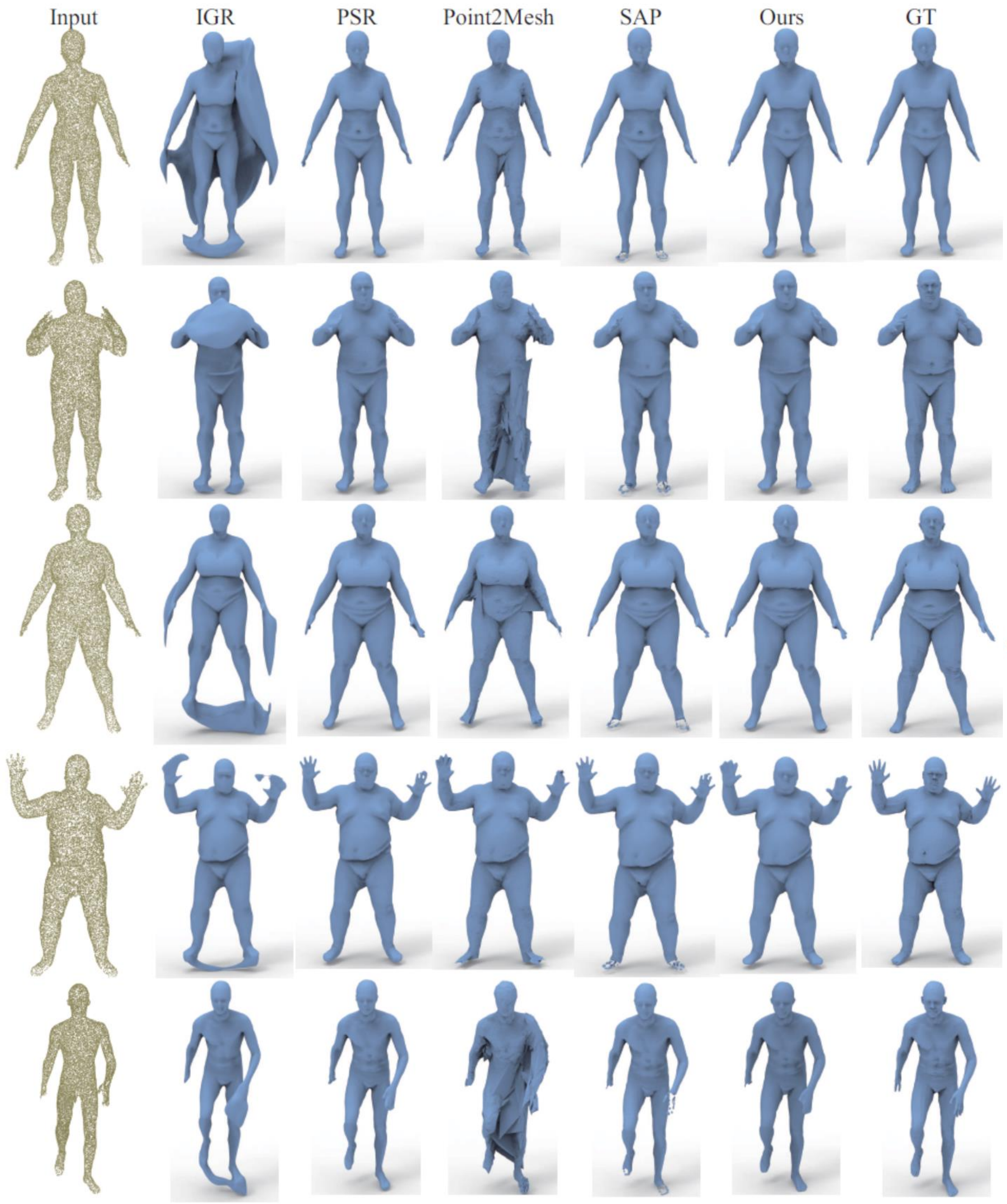
Surface Reconstruction for Shapes

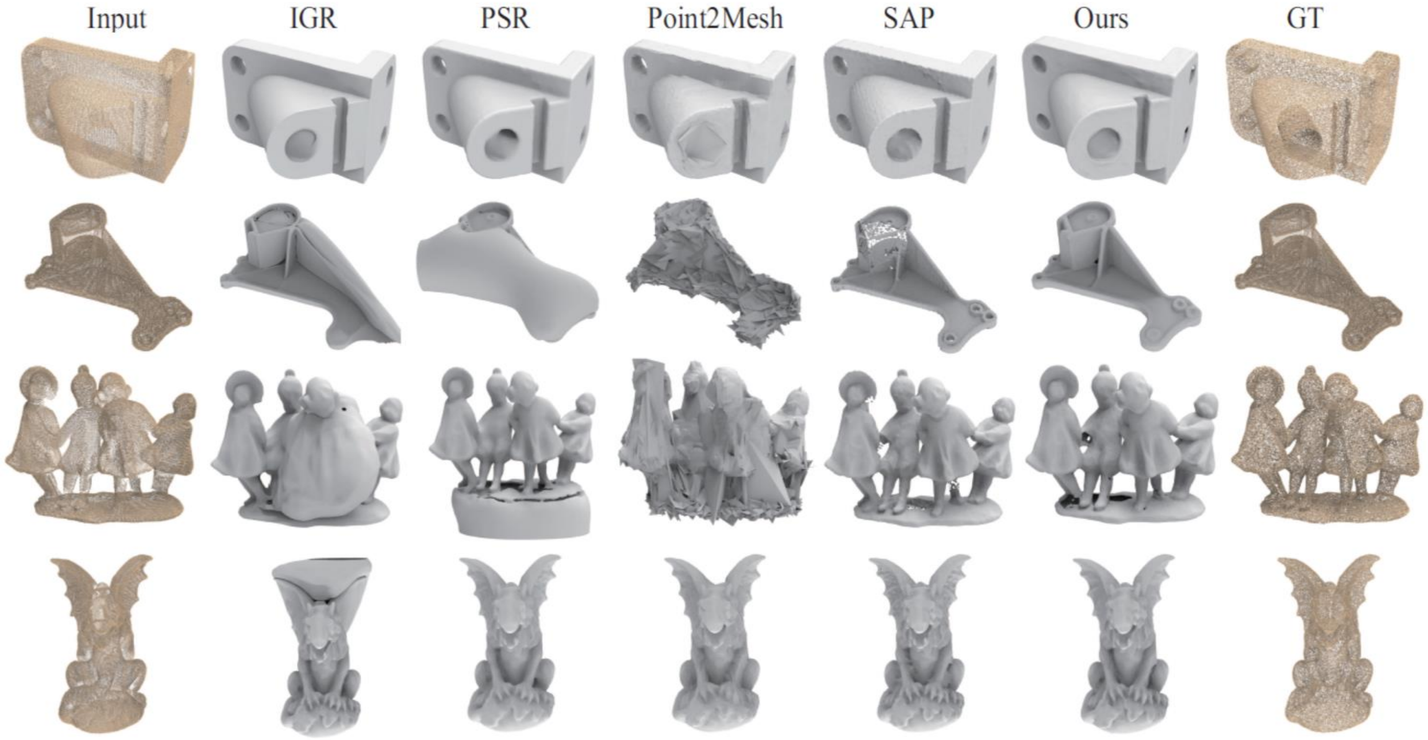


	PSR	PSG	R2N2	Atlas	COcc	SAP	OCNN	IMLS	POCO	**Ours**
airplane	0.437	0.102	0.151	0.064	0.034	0.027	0.063	0.025	0.023	**0.022**
bench	0.544	0.128	0.153	0.073	0.035	0.032	0.065	0.030	0.028	**0.025**
cabinet	0.154	0.164	0.167	0.112	0.047	0.037	0.071	0.035	0.037	**0.034**
car	0.180	0.132	0.197	0.099	0.075	0.045	0.077	0.040	0.041	**0.037**
chair	0.369	0.168	0.181	0.114	0.046	0.036	0.066	0.035	0.033	**0.026**
display	0.280	0.160	0.170	0.089	0.036	0.030	0.066	0.029	0.028	**0.022**
lamp	0.278	0.207	0.243	0.137	0.059	0.047	0.067	0.031	0.033	**0.027**
speaker	0.148	0.205	0.199	0.142	0.063	0.041	0.073	0.040	0.041	**0.033**
rifle	0.409	0.091	0.167	0.051	0.028	0.023	0.062	0.021	0.019	**0.019**
sofa	0.227	0.144	0.160	0.091	0.041	0.032	0.066	0.031	0.030	**0.027**
table	0.393	0.166	0.177	0.102	0.038	0.033	0.066	0.032	0.031	**0.028**
telephone	0.281	0.110	0.130	0.054	0.027	0.023	0.061	0.023	0.022	**0.017**
vessele	0.181	0.130	0.169	0.078	0.043	0.030	0.064	0.027	0.025	**0.024**
mean	0.299	0.147	0.173	0.093	0.044	0.034	0.067	0.031	0.030	**0.026**

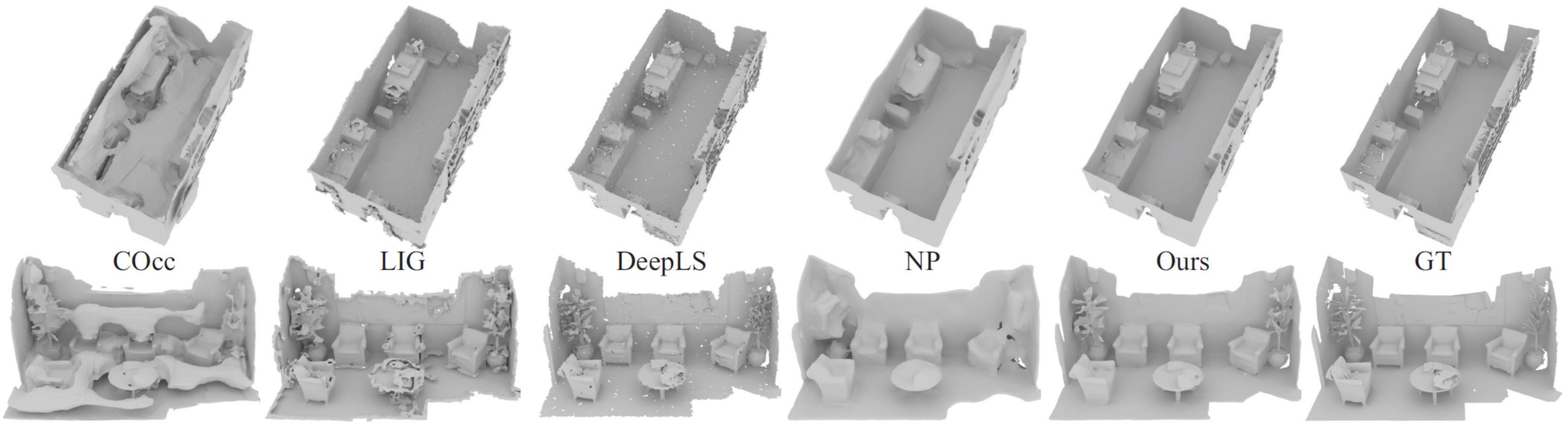


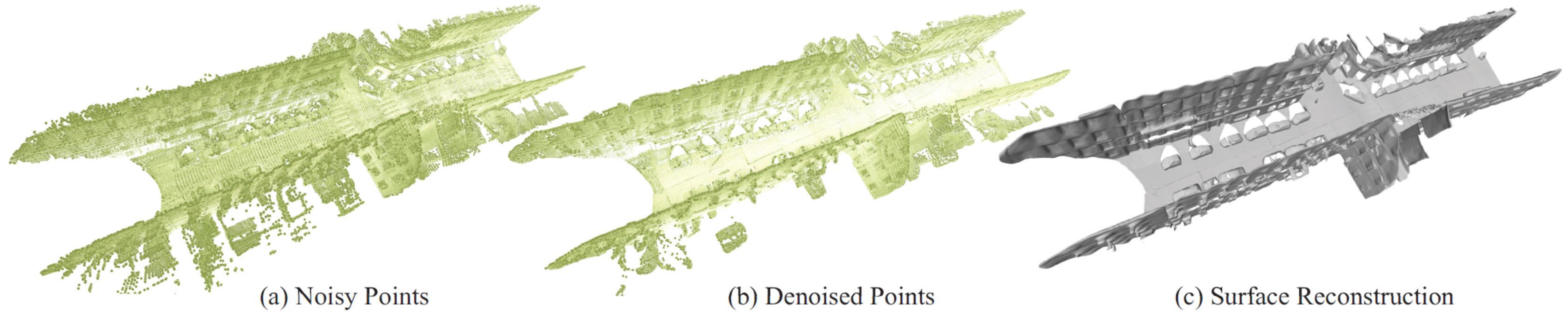
Surface Reconstruction for Shapes





Surface Reconstruction for Scenes





Visualization of Optimization
-Learned Signed Distance Functions-

Thanks for watching!

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