Supplemental Material "Reconstructing Surfaces for Sparse Point Clouds with On-Surface Priors"

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1. Network

We learn both of SDFs and On-surface Decision Functions (ODF) using the same network released by NeuralPull [3]. During testing, we learn SDFs $f_{\boldsymbol{\theta}}$ from a sparse point cloud. In addition, we use the method introduced in NeuralPull [3] to sample queries around each point on the sparse point cloud.

2. Surface Reconstruction

We present more visual comparison in surface reconstruction in Fig. 1. With 100 points/m^2 as input, our method can reconstruct surfaces with more geometry details than the state-of-the-art methods.

We also demonstrate our advantage in surface reconstructions from a large scale real scanning in our video.

3. Effect of Point Density

We highlight our advantages by visually comparing surface reconstructions from point clouds with different point densities. Current state-of-the-art methods, such as COcc [5], IMLS [2], LIG [1], may reconstruct smooth surfaces with high point densities, such as 4000 and 3000 points. However, their performance significantly degenerates when there are much fewer points. With on-surface prior, our method can reconstruct surfaces in high accuracy from sparse point clouds.

4. More Analysis

Comparison with NeuralPull Variations. We report numerical comparisons with NeuralPull (NP) [3] in our paper. Here, we report more numerical comparison with NP variations under the same dataset we used in ablation studies. One strategy to make NP work with sparse point clouds is to pull each query to its K nearest neighbors on the sparse point cloud, and $K > 1$, rather than the nearest one. We can pull a query to the plane formed by 3 nearest neighbors, or the center of the 3 nearest neighbors, or the center of the 5 nearest neighbors. As shown in Tab. 1, our method also significantly outperforms these variations.

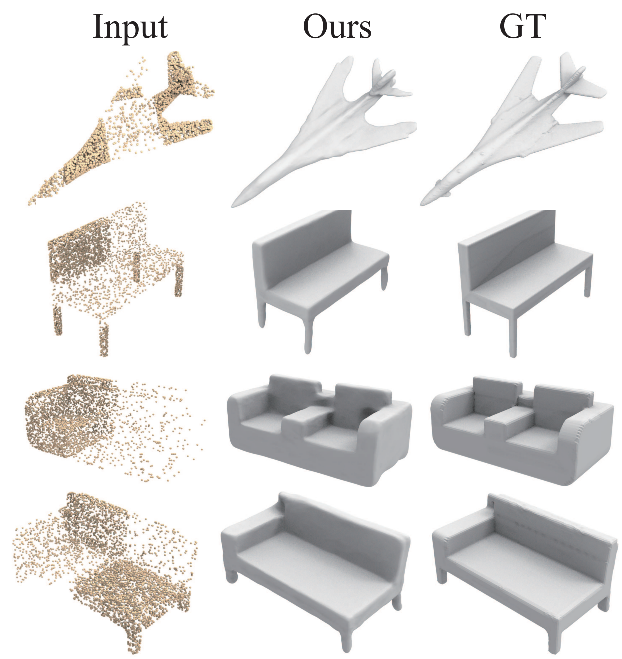

Figure 3. Visualization of reconstruction from extremely irregular point clouds.

Eiknal Loss. We did not observe improvements by the Eiknal Loss [4] which constrains the normal of gradients to be one, as shown by "Eiknal" in Tab. 1.

Irregular Points. All sparse points that we used are irregular and randomly sampled. We also evaluate our performance under extreme irregular cases that were manually generated in Fig. 3. We can see that our method can still handle extremely irregular points well.

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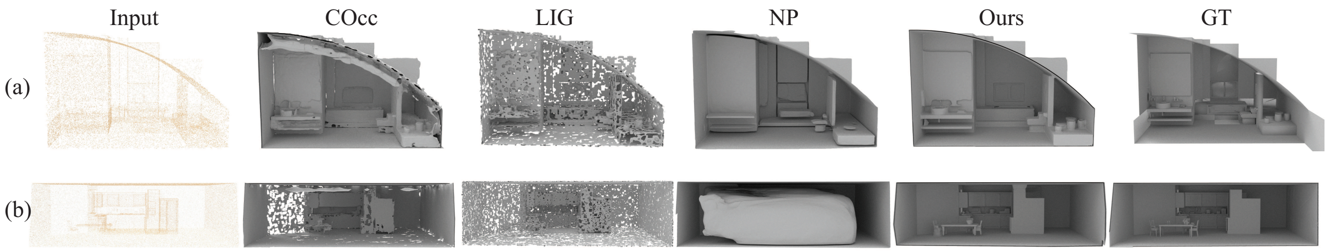

Figure 1. Visual comparison with COcc [5], LIG [1], NP [3] under SceneNet.

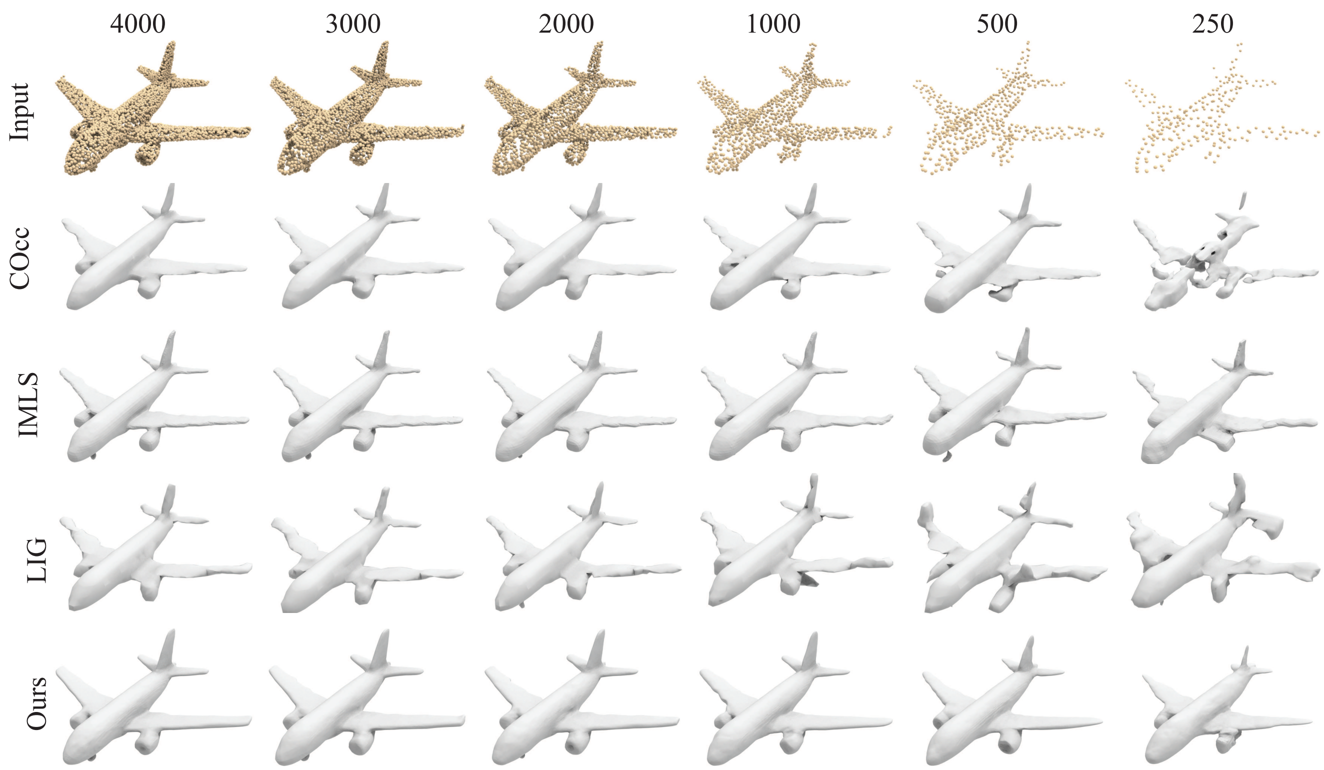

Figure 2. Effect of Point Density on performance of the state-of-the-art methods.

5. Implementation

Code and data are available at https://github.com/mabaorui/OnSurfacePrior.

References

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λ	0	Ours(0.4)	NP	NP 3NN plane	NP 3NN center	NP 5NN center	Eiknal
L1CD	0.050	**0.015**	0.055	0.058	0.052	0.060	0.017
NC	0.569	**0.928**	0.554	0.548	0.588	0.574	0.901

Table 1. More analysis.