SurfR: Surface Reconstruction with Multi-scale Attention

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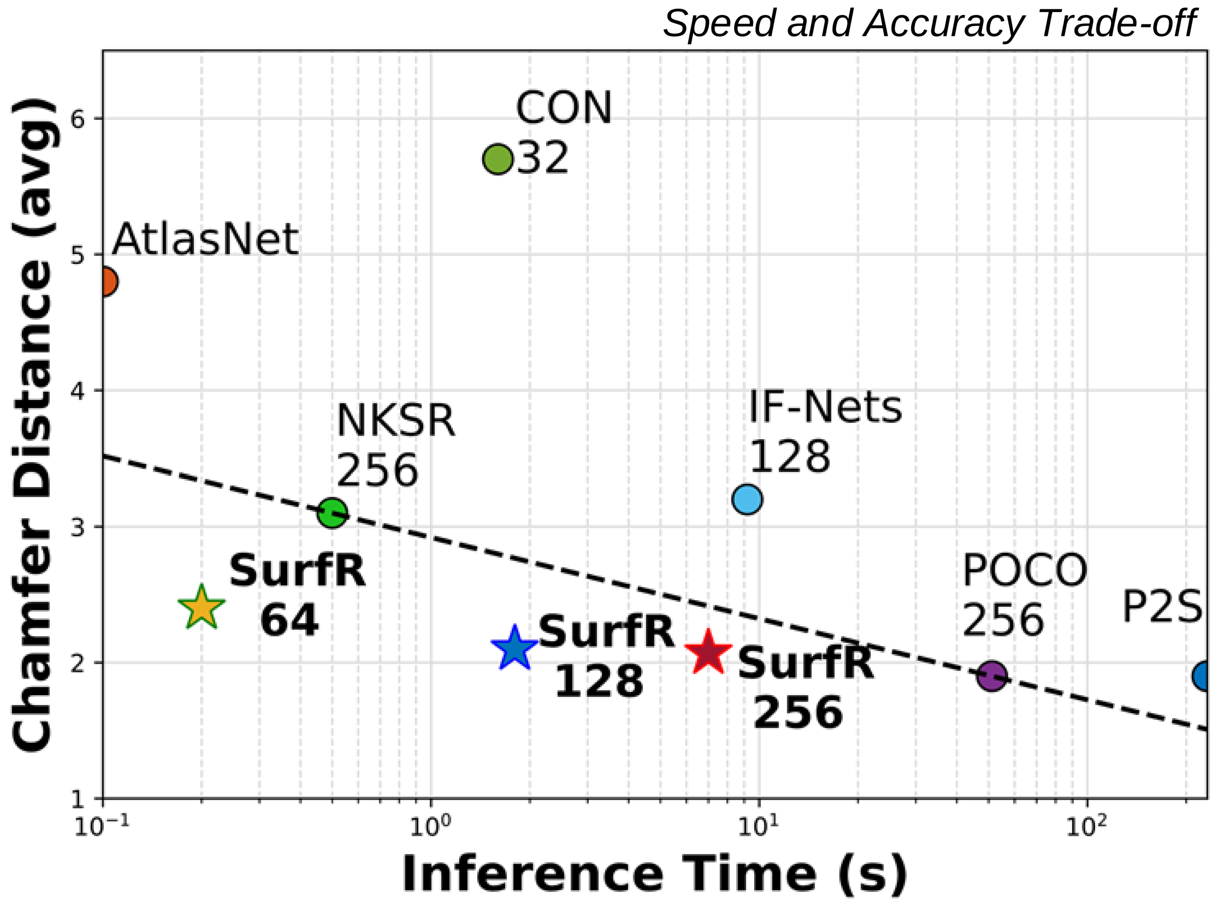
Motivation and Contributions

- Point clouds from real-world scans are usually **sparse, noisy, and incomplete**.
- Current reconstruction methods often **struggle to balance both speed and accuracy**, resulting in either fast but rough reconstructions or slow but detailed ones.
- **SurfR** introduces a fast and accurate implicit surface reconstruction method for unorganized point clouds, achieving an **excellent tradeoff between speed and accuracy**.

Speed and Accuracy Trade-off



Key Contributions:

- **Lazy query processing:** Input points are processed all at once and then their features sampled according to the queries.
- **Multi-scale features:** Interpolate point features at different scale to better handle different noise levels and reconstruction detail.
- **Cross-scale attention:** Fuse features across scales improving details.
- **Best accuracy-speed trade-off.**

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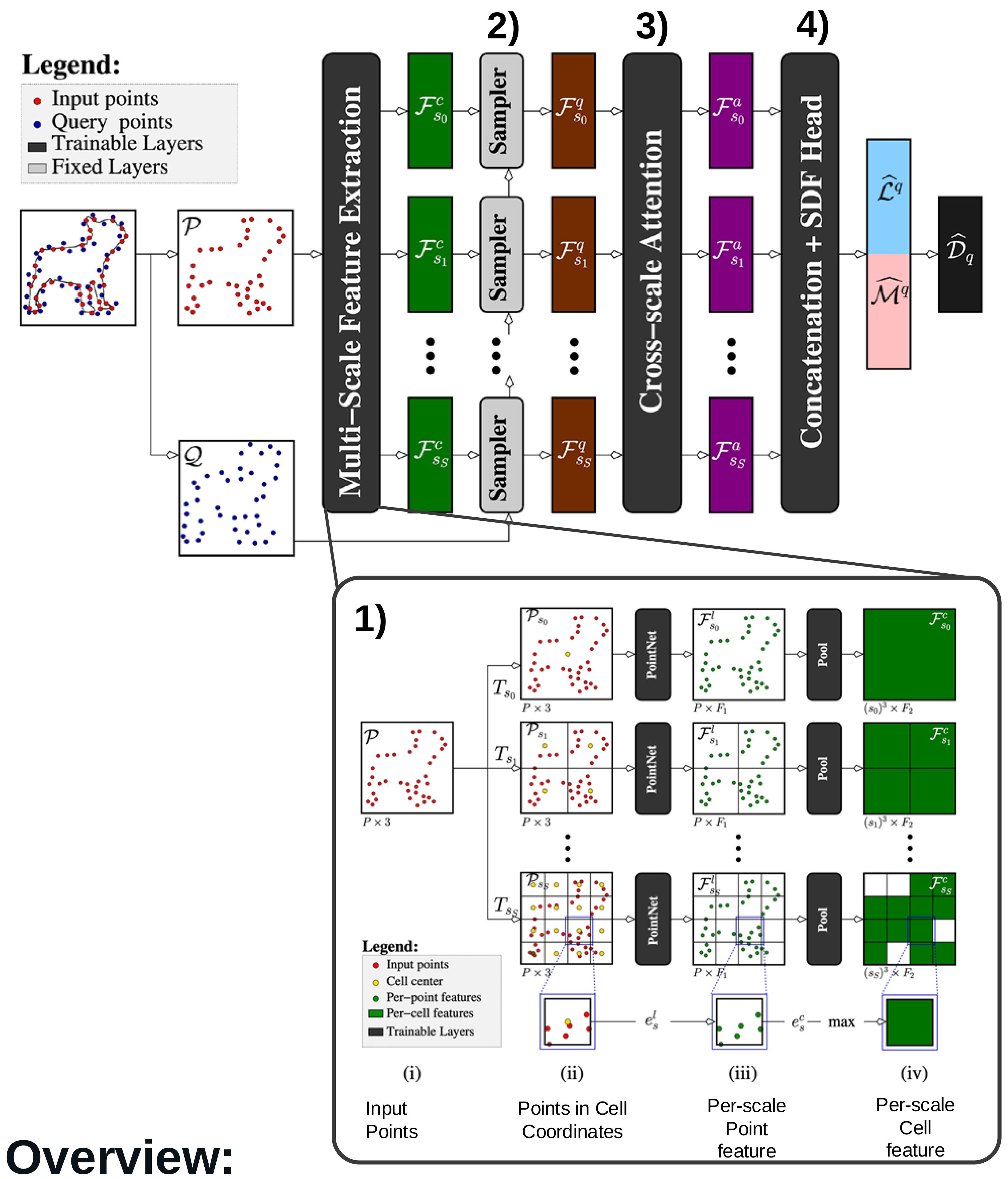
SurfR Algorithm



Overview:

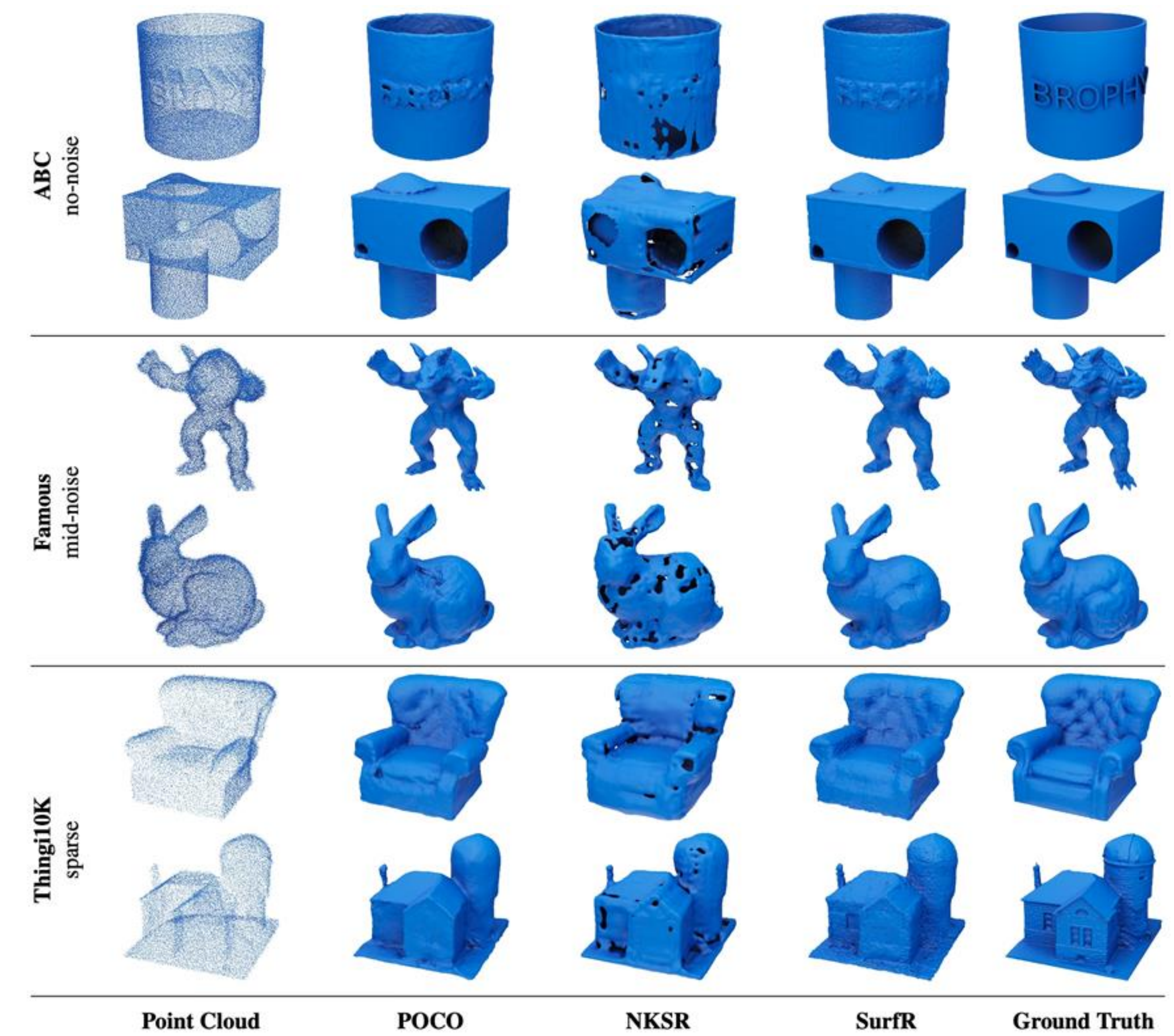
1) Multi-scale feature extraction: Partition the input point cloud into grid cells and extract features from each cell.

2) Query feature sampling: Sample features at query points using a combination of cell, neighbor, and relative position features.

3) Cross-scale feature fusion: Fuse features across scales using a transformer encoder layer to balance local and global information.

4) Signed distance regression: Regress concatenated features to estimate the SDF for surface reconstruction.

Results

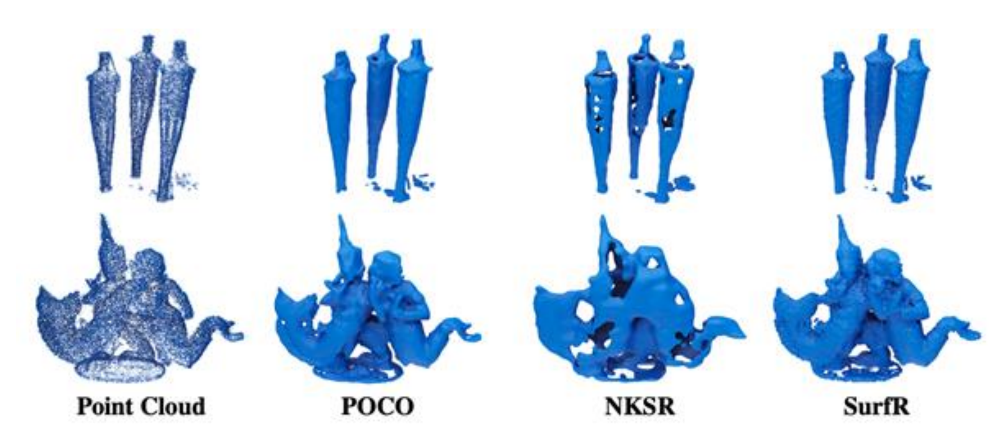


Noise and Densities Qualitative Comparisons

Noise & Sparsity	CD: CON [37]	CD: P2S [17]	CD: SAP [38]	CD: IF [8]	CD: POCO [2]	CD: NKSR [18]	CD: SurfR 64	CD: SurfR 128	CD: SurfR 256	NC: CON [37]	NC: IF [8]	NC: POCO [2]	NC: NKSR [18]	NC: SurfR 64	NC: SurfR 128	NC: SurfR 256
ABC dataset [24] (unseen in training)																
no-noise	2.6	1.8	7.6	2.8	1.7	3.0	2.3	2.1	2.1	0.89	0.62	0.89	0.29	0.87	0.89	0.89
med-noise	7.7	2.1	8.1	3.8	2.1	3.3	2.5	2.4	2.4	0.8	0.61	0.84	0.33	0.81	0.82	0.80
max-noise	14.0	2.8	7.2	5.9	2.7	4.1	3.3	3.2	3.1	0.74	0.57	0.75	0.4	0.78	0.75	0.71
Famous dataset (a collection of 22 popular meshes)																
no-noise	2.4	1.4	9.0	2.2	1.4	2.7	1.8	1.5	1.4	0.84	0.63	0.78	0.18	0.82	0.86	0.86
med-noise	3.3	1.5	8.8	2.3	1.7	2.7	1.9	1.7	1.6	0.83	0.63	0.73	0.17	0.81	0.83	0.81
max-noise	12.8	2.5	7.0	5.2	2.9	3.9	3.3	3.1	3.0	0.7	0.56	0.55	0.26	0.72	0.7	0.68
sparse	3.2	1.9	10.4	2.6	2.0	3.2	2.4	2.1	2.1	0.81	0.63	0.67	0.18	0.77	0.79	0.77
dense	3.7	1.3	7.8	2.4	1.5	2.3	1.8	1.6	1.5	0.84	0.64	0.76	0.19	0.82	0.84	0.83
Thingi10k dataset [54]																
no-noise	1.9	1.4	8.4	2.1	1.4	2.7	1.8	1.5	1.4	0.92	0.65	0.92	0.22	0.89	0.92	0.91
med-noise	3.1	1.5	8.2	2.4	1.5	2.7	1.9	1.6	1.5	0.9	0.65	0.9	0.21	0.88	0.89	0.87
max-noise	12.8	2.6	6.9	5.5	2.7	3.9	3.3	3.1	2.8	0.76	0.58	0.71	0.3	0.79	0.76	0.73
sparse	3.1	2.1	10.1	2.8	2.1	3.3	2.7	2.2	2.4	0.88	0.64	0.81	0.21	0.82	0.84	0.82
dense	3.5	1.4	7.1	2.4	1.4	2.3	1.8	1.5	1.4	0.91	0.65	0.91	0.2	0.89	0.91	0.89
Avg.	5.7	1.9	8.2	3.2	1.9	3.1	2.4	2.1	2.1	0.83	0.84	0.62	0.79	0.24	0.83	0.81

CD = Chamfer Distance L_2 (↓); NC = Normal consistency (↑)

Quantitative Baseline Comparisons



Real-world Objects Comparisons

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