
Technical Appendices

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1 Appendix A Technical Appendices

2 Appendix A.1 Limitation

3 A limitation of NoiseSDF2NoiseSDF emerges when the noise level of input point cloud grows:
4 surface completeness tends to degrade due to the denoising network’s over-smoothing, which erases
5 fine-scale geometry. This shortcoming is compounded by a practical constraint in our pipeline: owing
6 to limited compute, we rely on a pretrained point2SDF encoder that accepts at most 2048 points. The
7 resulting low-resolution SDF representation caps the geometric fidelity that the decoder can ultimately
8 recover, especially in highly corrugated regions. Future work will revisit both the smoothness prior
9 and the encoder capacity to mitigate these effects without incurring prohibitive training cost.

10 Appendix A.2 Broader Impact

11 The proposed NoiseSDF2NoiseSDF framework enables denoising of signed distance fields directly
12 from noisy supervision, making it applicable in settings where clean ground-truth data is difficult or
13 costly to obtain. This can enhance the robustness of 3D reconstruction in domains such as robotics,
14 augmented reality, cultural preservation, and medical imaging, where input data is often imperfect. By
15 removing the dependency on clean supervision, the method also reduces dataset curation overhead and
16 energy consumption. Nevertheless, the model may suppress subtle but meaningful geometric details
17 or reflect biases present in the noisy training data, which warrants caution in critical applications.

18 Looking forward, the core idea underlying our framework—a Noise2Noise-style supervision for
19 implicit representations—may extend beyond SDFs. We believe it opens a promising direction for
20 training NeRFs or other neural fields from noisy observations, offering a generalizable, reusable
21 solution for learning continuous representations from imperfect data.

22 Appendix A.3 Metrics Formula

23 We detail the evaluation metrics adopted in our experiments.

$$\text{CD}(P, Q) = \frac{1}{|P|} \sum_{p \in P} \min_{q \in Q} \|p - q\|_2 + \frac{1}{|Q|} \sum_{q \in Q} \min_{p \in P} \|q - p\|_2,$$

$$\text{F}_1(\tau) = \frac{2 \text{precision}(\tau) \text{recall}(\tau)}{\text{precision}(\tau) + \text{recall}(\tau)}, \quad \tau = 0.02,$$

$$\text{NC} = \frac{1}{N} \sum_{i=1}^N |\langle n_i^{\text{pred}}, n_i^{\text{gt}} \rangle|,$$

$$\text{MNC}(M) = \frac{1}{|E|} \sum_{e=(v_0, v_1) \in E} \left(1 - \frac{\langle (v_1 - v_0) \times (a_e - v_0), (b_e - v_0) \times (v_1 - v_0) \rangle}{\|(v_1 - v_0) \times (a_e - v_0)\| \|(b_e - v_0) \times (v_1 - v_0)\|} \right).$$

Here P and Q are the sets of predicted and ground-truth 3D samples, with $|\cdot|$ denoting cardinality. The Chamfer Distance (CD) measures the average nearest-neighbor distance between the two sets in both directions. It is non-negative (≥ 0), and lower values indicate better geometric alignment.

The threshold τ (set to 0.02) in the $\text{F}_1(\tau)$ score defines precision and recall by counting how many nearest-neighbor distances fall below τ . The F1 score, computed as the harmonic mean of precision and recall, ranges from 0 to 1, with higher values indicating better correspondence between predicted and ground-truth points.

In NC, n_i^{pred} and n_i^{gt} denote the predicted and ground-truth unit normals at sample i (out of N total samples). The Normal Consistency is the mean absolute dot product between matched normals, ranging from 0 to 1. Higher values imply better alignment of surface orientation.

$\text{MNC}(M)$ denotes Mesh Normal Consistency for a mesh M with edge set E . Each edge $e = (v_0, v_1)$ is shared by two faces whose opposite vertices are a_e and b_e . The unnormalized face normals are computed via cross products $(v_1 - v_0) \times (a_e - v_0)$ and $(b_e - v_0) \times (v_1 - v_0)$, and their cosine similarity measures the local smoothness across the edge. The value of MNC is averaged over all edges, and typically falls in the range $[0, 2]$, where lower values correspond to smoother and more consistent surface geometry.

Appendix A.4 More Visualization

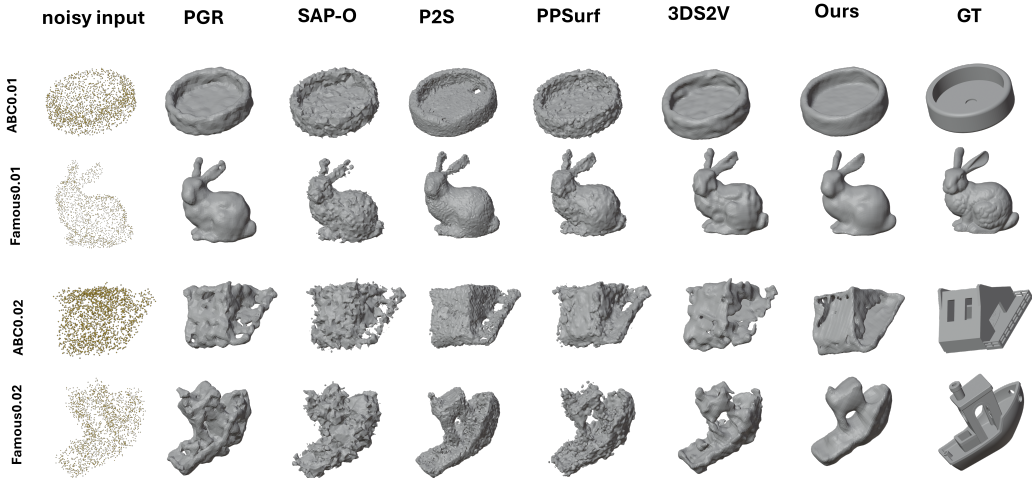


Figure 1: More results on ABC, Famous