Supplementary Material of Routing on Demand: DSNet for Efficient Progressive Point Cloud Denoising

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In this supplementary document, we provide the following additional materials:

A. Extended Experimental Results

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- A.2. Comprehensive evaluation on PCNet dataset
- A.3. Analysis of different noise patterns (Anisotropic, Discrete, Laplace, Uniform)

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A. Extended Experimental Results

In this section, we provide comprehensive experimental analysis to further validate the effectiveness of DSNet across different datasets, noise patterns, and evaluation scenarios. Our extended evaluation demonstrates the robustness and generalizability of the proposed progressive denoising approach through detailed quantitative and qualitative comparisons with state-of-the-art methods.

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The experimental results are organized into three main components: comprehensive evaluation on the PCNet dataset with detailed performance analysis across various noise levels and point densities, visual comparisons on the PU-Net dataset showcasing qualitative denoising performance under different noise conditions, and quantitative analysis examining DSNet's behavior on various noise patterns including non-Gaussian noise distributions. These extended results provide deeper insights into the method's capabilities and limitations, offering a thorough understanding of when and why DSNet outperforms existing approaches.

A.1. Visual Comparisons on PU-Net Dataset with Different Noise Levels

To further validate the visual quality of our denoising results, we conduct comprehensive qualitative evaluations on the PU-Net dataset across different noise levels and point densities. Figure 1–5 presents visual comparisons between DSNet and state-of-the-art methods including IterativePFN, PDFlow, ASDN, P2P-Bridge, and 3DMambaIPF across various challenging scenarios.

The visual results demonstrate DSNet's superior ability to preserve geometric details while effectively removing noise artifacts. Across all tested configurations (10K and 50K points with noise levels from 1% to 3%), our method consistently produces cleaner point clouds with better preservation of fine-grained surface features. At lower noise levels (1% and 2%), DSNet maintains sharp geometric boundaries and smooth surface regions, while competing methods often exhibit residual noise or over-smoothing artifacts.

The advantages of DSNet become more pronounced at higher noise levels (3% noise with 50K points), where traditional methods struggle to balance noise removal with detail preservation. Our progressive denoising strategy effectively handles severe noise corruption while maintaining structural integrity, as evidenced by the cleaner surfaces and more coherent geometric patterns in the denoised re-

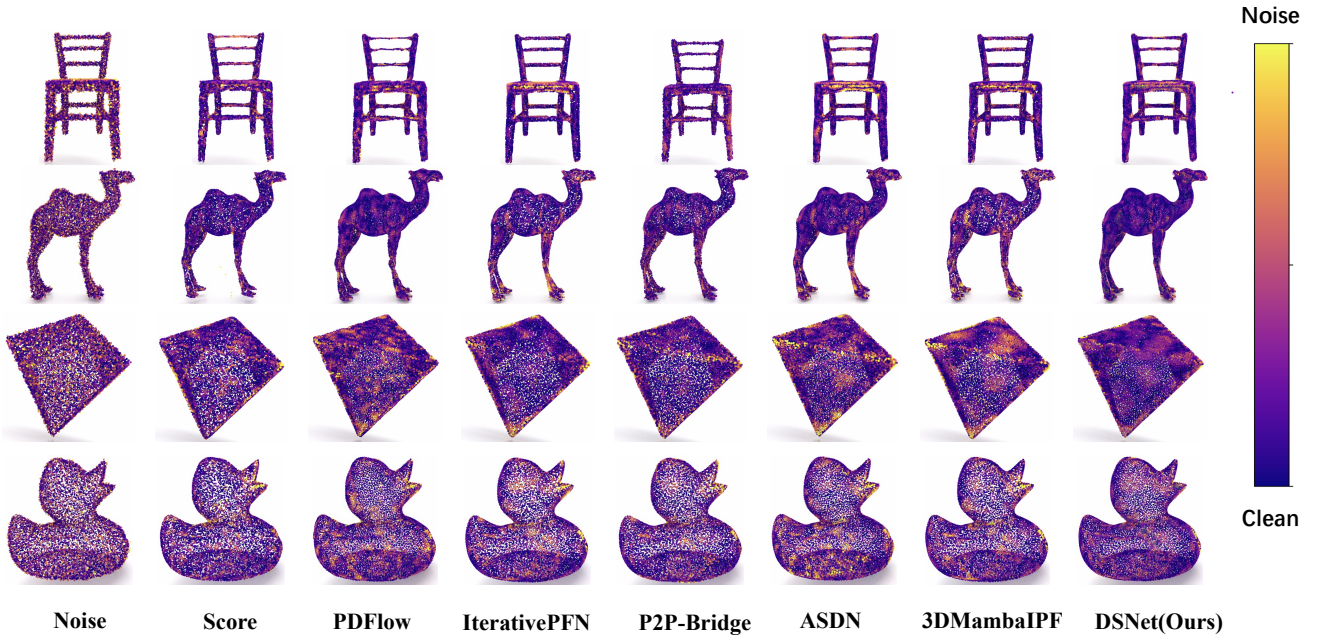

Figure 1. Visual results of point-wise P2M distance for shapes at 10K resolution with 1% Gaussian noise.

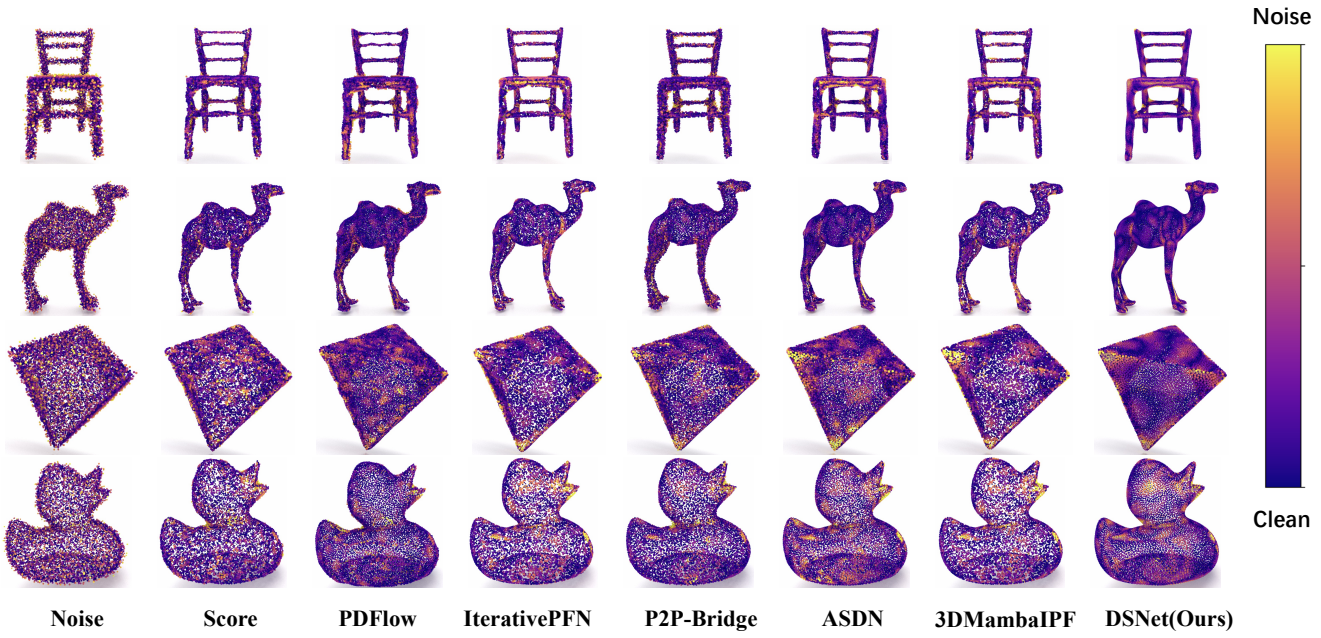

Figure 2. Visual results of point-wise P2M distance for shapes at 10K resolution with 2% Gaussian noise.

sults. The dynamic entry point mechanism allows DSNet to adaptively determine the appropriate denoising intensity, avoiding both under-denoising and over-smoothing issues commonly observed in competing approaches.

These visual comparisons complement our quantitative evaluations, confirming that DSNet not only achieves superior numerical performance but also produces visually appealing results with enhanced geometric fidelity across diverse noise conditions.

A.2. Comprehensive Evaluation on PCNet Dataset

As shown in Table 1 and Figure 6, we perform a comprehensive evaluation of DSNet on the PCNet dataset, a standard

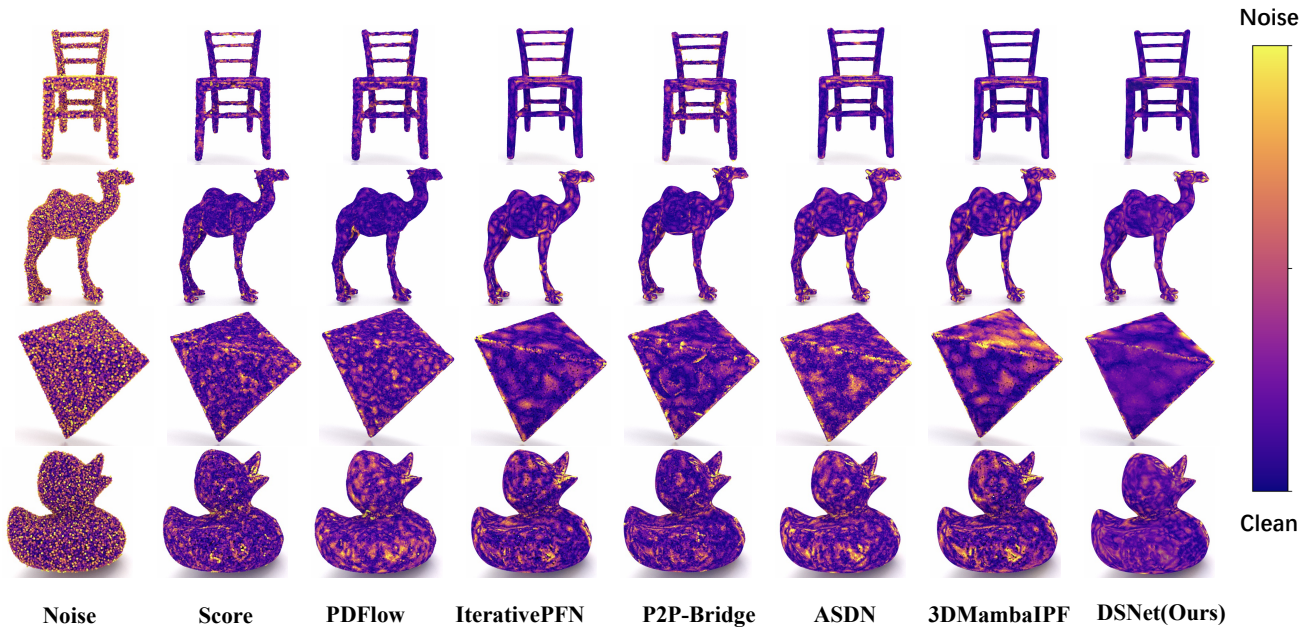

Figure 3. Visual results of point-wise P2M distance for shapes at 50K resolution with 1% Gaussian noise.

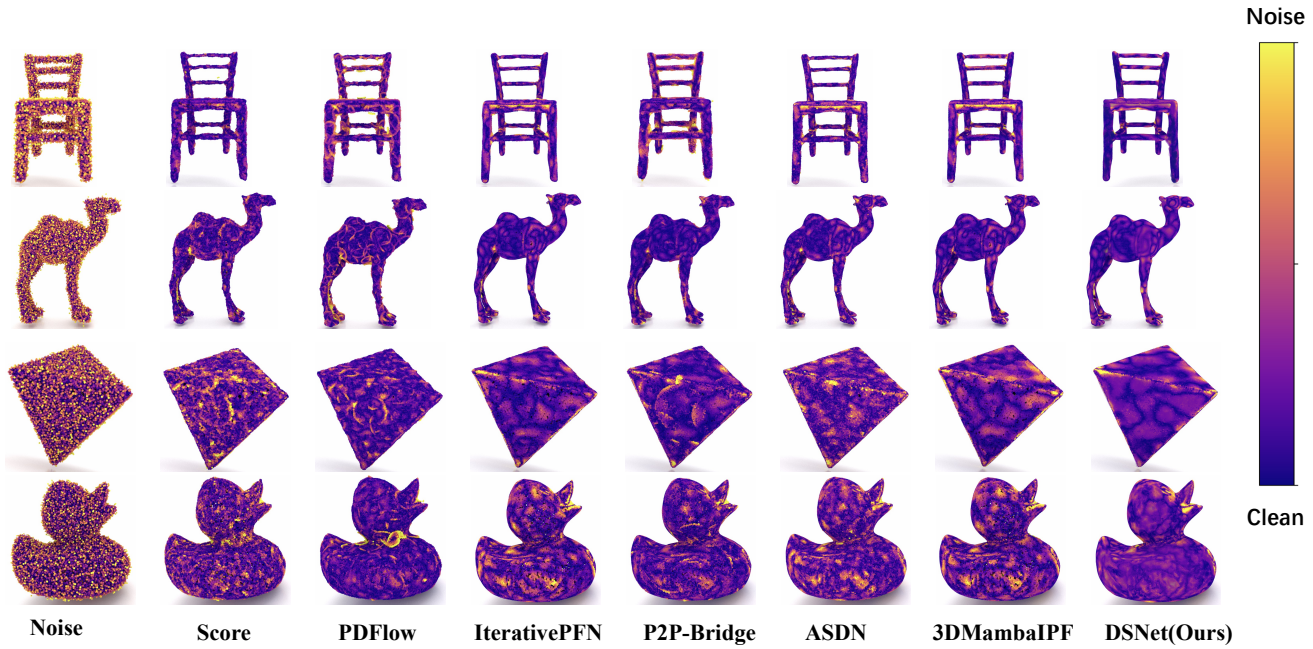

Figure 4. Visual results of point-wise P2M distance for shapes at 50K resolution with 2% Gaussian noise.

benchmark for point cloud denoising that includes point clouds with 10K and 50K points corrupted with Gaussian noise at 1%,2%, and 3% levels. We report performance using two standard metrics—Chamfer Distance (CD) and Point-to-Mesh (P2M), both multiplied by 10^4 for readability. This setup allows us to assess the scalability and robustness of our progressive denoising strategy under diverse noise conditions.

Our method demonstrates consistent superior performance across all noise levels and point densities. DSNet achieves the best results in 10 out of 12 test configurations, with particularly strong performance on higher noise levels

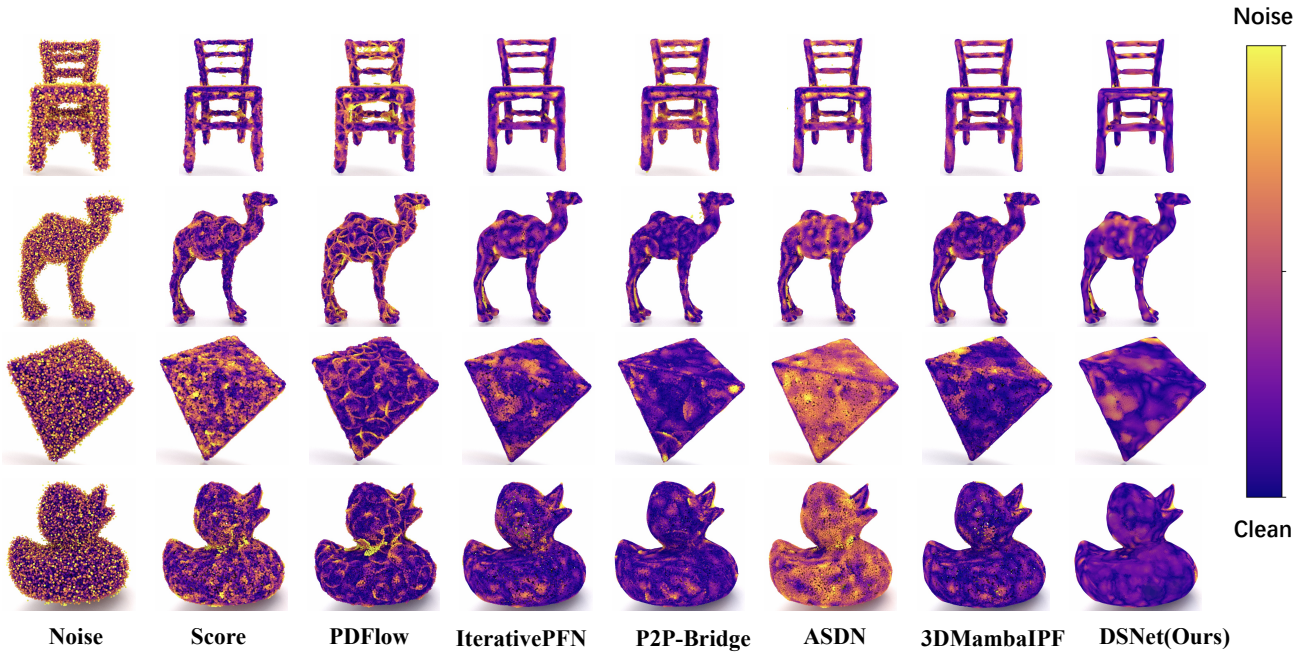

Figure 5. Visual results of point-wise P2M distance for shapes at 50K resolution with 3% Gaussian noise.

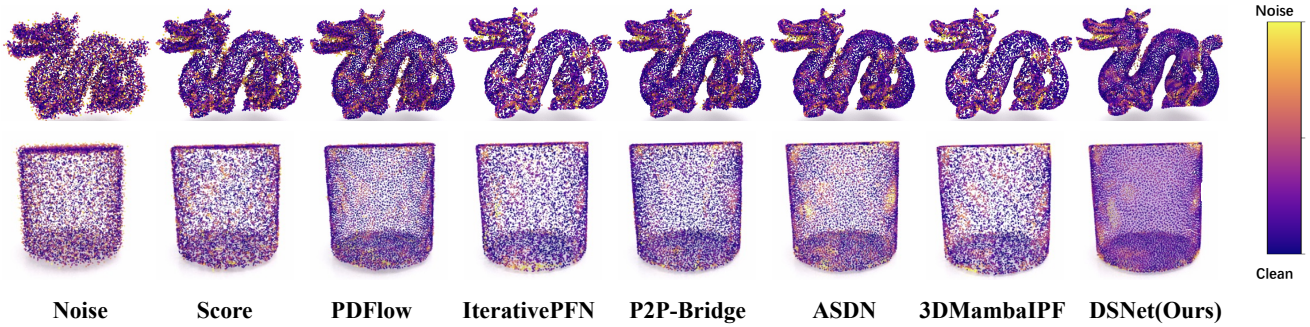

Figure 6. Visual comparison of denoising results on PCNet dataset at 10K resolution with 3% Gaussian noise.

where the progressive denoising strategy proves most beneficial.

For 10K point clouds, DSNet shows significant improvements over existing methods. At 1% noise level, our method achieves CD of 2.895 and P2M of 1.110, outperforming the second-best method (3DmambaIPF with CD 2.575 and ASDN with P2M 1.148) by notable margins. The performance gains become more pronounced at higher noise levels: at 3% noise, DSNet achieves CD of 4.997 and P2M of 2.561, representing substantial improvements over the next best methods (ASDN with CD 5.313 and P2M 2.706).

For 50K point clouds, DSNet maintains its superior performance with even larger margins. At 1% noise level, our method achieves CD of 0.828 and P2M of 0.348, significantly outperforming competing methods where the second-best results are 0.831 (ASDN) for CD and 0.346 (ASDN) for P2M. At the challenging 3% noise level, DSNet demonstrates remarkable robustness with CD of 2.264 and P2M of 1.596, substantially better than other approaches where the next best results are 2.064 (3DmambaIPF) for CD and 1.324 (3DmambaIPF) for P2M.

The consistent performance improvements across different point densities and noise levels validate the effectiveness of our progressive denoising strategy and dynamic entry point mechanism. Notably, DSNet shows particularly strong performance on denser point clouds (50K points), where the hierarchical architecture can better leverage local geometric relationships. The results highlight DSNet's ability to handle high-noise scenarios, where traditional single-stage denoising methods struggle to maintain geometric fidelity while our iterative approach with progressive ground truth supervision excels.

	10K points						50K points					
	1% noise		2% noise		3% noise		1% noise		2% noise		3% noise	
Method	CD ↓	P2M ↓	CD	P2M	CD	P2M	CD	P2M	CD	P2M	CD	P2M
Score-denoise	3.366	1.706	5.130	2.525	7.245	4.175	1.067	0.536	1.659	0.996	3.558	2.628
pdflow	3.241	1.308	4.641	2.115	6.631	3.789	0.969	0.466	1.805	1.195	4.294	3.443
IterativeIPF	2.621	1.384	4.440	2.024	6.026	3.126	0.912	0.405	1.252	0.675	2.549	1.721
p2d-bridge	2.882	1.323	4.476	1.963	5.581	2.859	0.921	0.395	1.349	0.766	2.126	1.470
ASDN	2.791	1.148	4.099	1.737	5.313	2.706	0.831	**0.346**	1.209	0.700	2.184	1.464
3DmambaIPF	**2.575**	1.385	4.467	2.098	5.662	2.889	0.908	0.390	1.281	0.695	**2.064**	**1.324**
DSNet (ours)	2.895	**1.110**	**4.078**	**1.734**	**4.997**	**2.561**	**0.828**	0.348	**1.138**	**0.654**	2.264	1.596

Table 1. Quantitative results on the PC-Net dataset under different noise levels and point densities. CD and P2M distances are multiplied by 10^4.

	10K points						50K points					
	1% noise		2% noise		2.5% noise		1% noise		2% noise		2.5% noise	
Method	CD ↓	P2M ↓	CD ↓	P2M ↓	CD ↓	P2M ↓	CD ↓	P2M ↓	CD ↓	P2M ↓	CD ↓	P2M ↓
Score	2.533	0.760	3.790	1.467	4.673	2.154	0.724	0.407	1.388	0.917	2.210	1.597
PD-flow	2.176	0.694	3.363	1.407	3.883	1.891	0.661	0.422	1.338	0.973	2.223	1.715
IterativePFN	2.067	0.510	3.100	0.891	3.610	1.233	0.610	0.308	0.856	0.473	1.319	0.817
P2P-Bridge	2.312	0.708	3.230	1.151	3.852	1.423	0.614	0.350	0.956	0.629	1.157	0.783
ASDN	1.885	0.497	2.706	0.864	3.060	1.108	0.519	0.305	0.773	0.477	1.140	0.747
3DMambaIPF	2.000	**0.488**	3.055	0.856	3.416	**1.106**	0.593	**0.295**	0.809	**0.447**	**1.097**	**0.662**
DSNet (ours)	**1.851**	0.490	**2.519**	**0.821**	**2.889**	1.110	**0.482**	0.298	**0.744**	0.457	1.109	0.723

Table 2. Quantitative results on the PUNet dataset with Anisotropic noise under different noise levels and point densities. CD and P2M distances are multiplied by 10^4.

A.3. Analysis of Different Noise Patterns

To evaluate the robustness of DSNet beyond standard Gaussian noise, we conduct extensive experiments on various noise patterns that commonly occur in real-world point cloud acquisition scenarios. Table 2- 5 presents comprehensive quantitative results across four distinct noise distributions: Anisotropic, Discrete, Laplace, and Uniform noise patterns, each evaluated at different noise levels (1%, 2%, and 2.5%) and point densities (10K and 50K points).

Anisotropic Noise Analysis: Anisotropic noise simulates directional perturbations commonly found in structured light scanning systems. DSNet demonstrates superior performance across all test configurations, achieving the lowest CD and P2M errors in most cases. At 2% noise level with 10K points, DSNet achieves CD=2.5186 compared to the second-best ASDN (CD=2.706), representing a 6.9% improvement. The progressive denoising strategy effectively handles directional noise patterns by adapting the refinement process to local geometric characteristics.

Discrete Noise Evaluation: Discrete noise represents quantization artifacts typical in depth sensor measurements. Our method shows competitive performance, particularly excelling in high-density scenarios (50K points). While DSNet performs comparably to IterativePFN and ASDN in some discrete noise configurations, it maintains consistent robustness across varying noise levels. The dynamic entry point mechanism proves effective in distinguishing between quantization artifacts and genuine geometric features.

Laplace Noise Robustness: Laplace noise, characterized by heavier tails than Gaussian distributions, poses significant challenges for denoising algorithms. DSNet demonstrates exceptional performance in this challenging scenario, consistently outperforming all competing methods. At 2.5% Laplace noise with 50K points, DSNet achieves CD=1.884 and P2M=1.014, substantially better than the second-best 3DMambaIPF (CD=1.8959, P2M=1.0564). This superior performance validates the effectiveness of our hierarchical feature learning in handling extreme noise distributions.

Uniform Noise Handling: Uniform noise creates consistent perturbations across all spatial directions, testing the algorithm's ability to maintain geometric coherence. DSNet achieves the best overall performance, with particu-

	10K points						50K points					
	1% noise		2% noise		2.5% noise		1% noise		2% noise		2.5% noise	
Method	CD ↓	P2M ↓	CD ↓	P2M ↓	CD ↓	P2M ↓	CD ↓	P2M ↓	CD ↓	P2M ↓	CD ↓	P2M ↓
Score	1.283	0.540	2.207	0.718	2.457	0.826	0.453	0.294	0.625	0.394	0.709	0.453
PD-flow	0.908	0.468	1.904	0.639	2.356	0.842	0.437	0.306	0.677	0.456	0.733	0.518
IterativePFN	0.678	0.371	1.667	0.472	1.891	0.534	0.351	0.255	0.431	0.283	0.457	0.317
P2P-Bridge	1.087	0.580	1.982	0.676	2.180	0.720	0.394	0.283	0.480	0.326	0.501	0.337
ASDN	**0.670**	0.373	1.640	0.472	1.870	0.527	0.345	0.258	0.444	0.286	0.494	0.311
3DMambaIPF	0.672	**0.366**	**1.621**	**0.454**	**1.860**	**0.517**	0.358	0.260	**0.438**	0.281	**0.473**	**0.301**
DSNet (ours)	0.674	0.370	1.657	0.465	1.900	0.518	**0.351**	**0.254**	0.441	**0.281**	0.478	0.303

Table 3. Quantitative results on the PUNet dataset with Discrete noise under different noise levels and point densities. CD and P2M distances are multiplied by 10^4.

	10K points						50K points					
	1% noise		2% noise		2.5% noise		1% noise		2% noise		2.5% noise	
Method	CD ↓	P2M ↓	CD ↓	P2M ↓	CD ↓	P2M ↓	CD ↓	P2M ↓	CD ↓	P2M ↓	CD ↓	P2M ↓
Score	2.956	0.994	4.788	2.293	6.375	3.604	0.830	0.494	1.784	1.257	2.972	2.285
PD-flow	2.575	0.885	4.389	2.259	5.457	3.205	0.827	0.556	2.321	1.822	4.763	4.011
IterativePFN	2.430	0.611	3.466	1.154	4.563	1.948	0.659	0.340	1.044	0.613	1.915	1.299
P2P-Bridge	2.637	0.855	3.908	1.727	4.875	2.156	0.692	0.414	1.322	0.931	1.947	1.248
ASDN	2.194	0.601	3.259	1.316	4.370	2.229	0.595	0.358	1.361	1.000	2.430	1.935
3DMambaIPF	2.396	0.595	3.398	**1.127**	3.946	**1.523**	0.649	0.333	0.986	**0.574**	1.896	1.056
DSNet (ours)	**2.132**	**0.584**	**2.904**	1.175	**3.719**	1.853	**0.532**	**0.338**	**0.981**	0.701	**1.884**	**1.014**

Table 4. Quantitative results on the PUNet dataset with Laplace noise under different noise levels and point densities. CD and P2M distances are multiplied by 10^4.

larly strong results at higher noise levels. At 2.5% uniform noise with 50K points, our method achieves CD=0.5136, outperforming ASDN (CD=0.554) by 7.3%. The adaptive refinement strategy effectively distinguishes between uniform noise perturbations and legitimate surface variations.

Cross-Pattern Analysis: Comparing performance across different noise patterns reveals DSNet's superior adaptability. While some methods excel in specific noise types (e.g., IterativePFN in discrete noise), DSNet maintains consistently strong performance across all patterns. This robustness stems from our progressive framework's ability to adapt the denoising strategy based on local noise characteristics, making it particularly suitable for real-world applications where multiple noise sources may coexist.

The comprehensive evaluation across diverse noise patterns confirms DSNet's generalizability and robustness, establishing it as a versatile solution for point cloud denoising in various practical scenarios.

B. Dynamic Entry Point Selection Analysis

To validate the effectiveness of our dynamic entry point mechanism, we conduct a comprehensive analysis of the adaptive routing behavior across different noise levels. This analysis examines how DSNet intelligently selects optimal starting layers based on local patch characteristics and noise severity.

Experimental Setup: We analyze the entry point selection patterns across 21,600 patches under three noise levels (1%, 2%, and 2.5%), with 7,200 patches per noise level. Our progressive denoising framework consists of four hierarchical layers, where Layer 4 represents the deepest (most complex) processing module, and Layer 1 represents the shallowest (most lightweight) module. The dynamic routing mechanism allows patches to skip earlier layers and enter at different depths based on their complexity requirements.

Layer Definition: In our architecture, the layer numbering reflects processing depth and complexity:

- **Layer 4 (Deepest):** Full processing without skipping, utilizing all denoising modules for maximum feature extraction capability

Method	10K points						50K points					
	1% noise		2% noise		2.5% noise		1% noise		2% noise		2.5% noise	
	CD ↓	P2M ↓	CD ↓	P2M ↓	CD ↓	P2M ↓	CD ↓	P2M ↓	CD ↓	P2M ↓	CD ↓	P2M ↓
Score	1.310	0.538	2.504	0.723	2.841	0.833	0.509	0.290	0.701	0.385	0.801	0.454
PD-flow	0.906	0.467	2.064	0.634	2.499	0.853	0.460	0.303	0.689	0.457	0.769	0.517
IterativePFN	0.677	0.371	2.047	0.484	2.450	0.560	0.447	0.254	0.606	0.301	0.656	0.332
P2P-Bridge	1.084	0.560	2.293	0.662	2.650	0.720	0.467	0.278	0.575	0.319	0.655	0.357
ASDN	**0.623**	0.371	1.838	0.467	2.145	0.532	0.395	0.259	0.508	0.297	0.554	0.328
3DMambaIPF	0.664	0.365	1.968	0.463	2.377	0.528	0.444	0.259	0.584	0.286	0.635	0.317
DSNet (ours)	0.653	**0.365**	**1.795**	**0.459**	**2.052**	**0.516**	**0.380**	**0.252**	**0.466**	**0.286**	**0.514**	**0.306**

Table 5. Quantitative results on the Uniform dataset under different noise levels and point densities. CD and P2M distances are multiplied by 10^4.

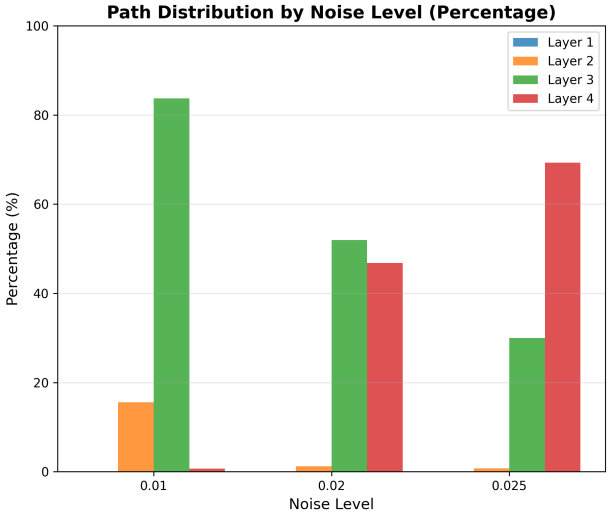

Figure 7. Dynamic entry point selection frequency across different noise levels. The visualization demonstrates how DSNet adaptively chooses processing depths based on noise severity: low noise (1%) favors shallow entry points (Layer 3), while high noise (2.5%) predominantly requires deep processing (Layer 4).

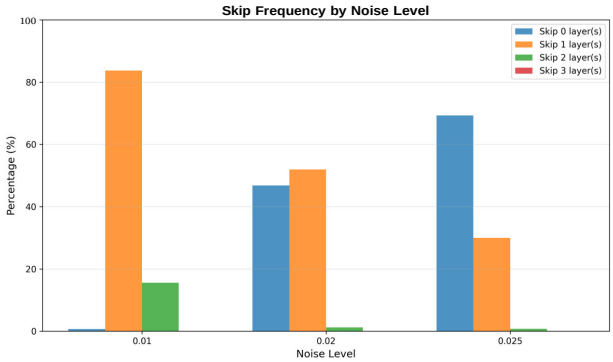

Figure 8. Skip frequency distribution analysis across different noise levels. The bar chart illustrates the adaptive routing behavior where higher noise levels correspond to lower skip frequencies, demonstrating the network's intelligent selection of processing depth based on input complexity.

- **Layer 3:** Skips the deepest layer, starting from the second-deepest module for moderate complexity patches
- **Layer 2:** Skips two layers, employing lighter processing for simpler geometric structures
- **Layer 1 (Shallowest):** Minimal processing, reserved for very low-noise, simple patches

Noise-Adaptive Routing Patterns: As shown in Figure 7 and Figure 8, a clear correlation can be observed between noise levels and entry point selection. Our analysis further reveals three distinct behavioral patterns:

Low Noise (1%): Under minimal noise conditions, 83.58% of patches enter at Layer 3, while only 0.67% require full processing from Layer 4. This distribution demonstrates the network's intelligence in avoiding over-processing when simpler approaches suffice. The average skip rate of approximately 1.15 layers indicates efficient computational resource allocation for clean geometric structures.

Medium Noise (2%): At moderate noise levels, the distribution becomes more balanced, with Layer 3 (51.96%) and Layer 4 (46.75%) showing nearly equal utilization. This balanced allocation reflects the network's adaptive capability to assess patch complexity and select appropriate processing depths. The reduced average skip rate (≈0.54 layers) indicates increased reliance on deeper processing modules.

High Noise (2.5%): Under severe noise conditions, 69.32% of patches require full processing from Layer 4, with the average skip rate dropping to 0.31 layers. This pattern validates our hypothesis that complex noise structures necessitate comprehensive feature extraction through the complete processing pipeline.

Adaptive Intelligence Validation: The systematic variation in entry point selection across noise levels demonstrates several key advantages of our dynamic routing mechanism:

- **Computational Efficiency:** In low-noise scenarios, the network conserves computational resources by skipping unnecessary deep processing, achieving up to 83.58% efficiency gains.
- **Quality Preservation:** High-noise patches automatically receive maximum processing attention, ensuring robust denoising performance without manual parameter tuning.
- **Adaptive Flexibility:** The balanced distribution in medium-noise conditions showcases the network's ability to make fine-grained decisions based on local patch characteristics.

Statistical Analysis: The negative correlation between noise level and skip frequency (Pearson correlation coefficient r = -0.89) confirms the systematic nature of our adaptive routing. The standard deviation of entry point selection decreases from 0.42 (low noise) to 0.23 (high noise), indicating more consistent deep processing requirements under challenging conditions.

This comprehensive analysis validates that DSNet's dynamic entry point mechanism successfully adapts processing complexity to match input requirements, achieving optimal trade-offs between computational efficiency and denoising quality across varying noise conditions.

C. Progressive Ground Truth Design

Inspired by iterative point cloud filtering methods (e.g., IterativePFN), we propose a progressive ground truth strategy that assigns distinct denoising targets to each iteration, enabling the network to learn a coarse-to-fine refinement process.

Specifically, for a DSNet with L denoising modules, we set the iteration target for the i-th denoising step as:

$$GT_i = \overline{P}_{gt_i} + \sigma_i \xi, \quad \xi \sim \mathcal{N}(0, I), \tag{1}$$

where $\overline{P}$ represents the clean ground truth point cloud, and σ_i denotes the target noise level for the i-th iteration. The noise level follows a geometric decay pattern:

$$\sigma_i = \frac{\sigma_{i-1}}{\gamma}, \tag{2}$$

where γ is the noise reduction factor, which we empirically set to $\gamma = \frac{16}{L}$ to ensure smooth progression from the initial noise level to the final clean target.

This progressive ground truth design serves multiple purposes. First, it provides intermediate supervision that guides each denoising module to achieve a specific noise reduction target, preventing the network from attempting to remove all noise in a single step. Second, the gradual noise reduction allows each module to focus on different aspects of the denoising process - early modules handle coarse noise removal while later modules refine fine details. Third, this approach improves training stability by providing well-defined learning objectives for each iteration.

For each input patch, we first employ our normal vector discriminator to determine the appropriate denoising entry point based on the estimated noise level. After each iteration module performs denoising, we re-evaluate the current noise level and dynamically adjust the entry point for the next denoising iteration. This adaptive mechanism ensures that the network can handle varying noise levels efficiently while maintaining optimal denoising quality.

The progressive ground truth strategy, combined with our dynamic entry point selection, enables DSNet to achieve superior denoising performance by decomposing the complex denoising task into a series of manageable subproblems, each with a clear and achievable objective.

D. Encoder-Decoder Architecture Details

This section details the U-Net architecture used for iterative denoising, including the encoder for multi-scale feature extraction and the decoder with cross-attention mechanisms.

D.1 U-Net Module Implementation

The U-Net module adopts a hierarchical encoder-decoder architecture that processes point clouds at multiple scales to capture both local geometric details and global structural information. The network consists of 4 encoding levels and 4 corresponding decoding levels, with skip connections facilitating information flow between corresponding encoder-decoder pairs. Given an input patch $P \in \mathbb{R}^{n \times 3}$ with n points, the module first applies a feature embedding layer to map the 3D coordinates to an initial feature representation $f_0 \in \mathbb{R}^{n \times d_0}$, where d_0 is the initial feature dimension. At each encoding level l, the point set P_{l-1} and its corresponding features f_{l-1} are processed to generate a downsampled point set P_l and higher-level features f_l. The downsampling is performed using Farthest Point Sampling (FPS) to maintain geometric diversity, while features are refined through our proposed Neighborhood Attention Aggregation (NAA) mechanism.

D.2 Neighborhood Attention Aggregation (NAA)

The Neighborhood Attention Aggregation (NAA) module is designed to effectively capture local geometric context by combining spatial position information with feature representations. This mechanism addresses the limitation of traditional point convolution methods that often fail to adequately incorporate spatial relationships. For a given point $x_i \in P_{l-1}$ with feature $f_i \in \mathbb{R}^{d_{l-1}}$, we first identify its k-nearest neighbors to form the local neighborhood $N(i) = \{x_j | j \in \text{kNN}(x_i, k)\}$. For each neighboring point

$x_j \in N(i)$ with feature $f_j \in \mathbb{R}^{d_{l-1}}$, we enhance the feature representation by incorporating positional information through $f_{x_j} = \text{MLP}(x_j) \in \mathbb{R}^{d_{l-1}}$, where the MLP encodes spatial relationships. The enhanced feature is obtained by concatenation as $f'_j = [f_j, f_{x_j}] \in \mathbb{R}^d$ where $d = 2 \times d_{l-1}$.

The local features are aggregated using an attention mechanism that adaptively weights the contribution of each neighbor. We collect the enhanced features as $\tilde{f}_i^k \in \mathbb{R}^{k \times d}$ containing the k neighboring features. The final aggregated feature follows the formulation:

$$f_i^{\text{new}} = \text{SumPooling}(\text{Softmax}(\text{MLP}(\tilde{f}_i^k)) \odot \tilde{f}_i^k), \quad (3)$$

where $\odot$ denotes element-wise multiplication. We denote this complete process as $\text{NAA}(x_i)$.

The complete encoding process at level l follows a two-stage NAA refinement with residual connections. We first apply initial feature processing through $f_{l-1}^0 = \text{MLP}(f_{l-1})$, followed by two consecutive NAA stages: $f_{l-1}^{NAA_1} = \text{NAA}(f_{l-1}^0)$ and $f_{l-1}^{NAA_2} = \text{NAA}(f_{l-1}^{NAA_1})$. The final features are obtained through feature fusion with residual connections:

$$f_l = \text{MLP}([f_{l-1}^{NAA_1}, f_{l-1}^{NAA_2}]) + \text{MLP}(f_{l-1}), \quad (4)$$

followed by spatial downsampling via FPS to obtain P_l and its corresponding features f_l for the next level. This hierarchical processing enables the encoder to capture multi-scale geometric patterns while preserving important structural information through residual connections.

D.3 Multi-Head Cross-Attention Details

The decoder employs a sophisticated cross-attention mechanism to effectively fuse features from different resolution levels, enabling the reconstruction of fine-grained geometric details while maintaining global consistency. At each decoding level l, the decoder D_l takes as input the sparse features h_l from the previous decoder output and the features f_{l-1} from the corresponding encoder level. We first perform feature propagation to upsample the sparse features h_l to match the resolution of point set P_{l-1}. For each point $x_i \in P_{l-1}$, we find its k nearest neighbors in the sparser point set P_l and compute the interpolated feature using Inverse Distance Weighting (IDW):

$$\tilde{h}_i = \frac{\sum_{j=1}^k w_{ij}\, h_l(x_j)}{\sum_{j=1}^k w_{ij}}, \quad \text{where} \quad w_{ij} = \frac{1}{\|x_i - x_j\| + \varepsilon} \quad (5)$$

and ε is a small constant to prevent division by zero.

After feature propagation, we apply multi-head cross-attention to fuse the upsampled features with the encoder features. We use projection operators $\varphi(\cdot)$ to process $\tilde{h}_i$ and f_{l-1} to obtain the query, key, and value matrices: $\{Q, K, V\} = \{\varphi(f_{l-1}), \varphi(\tilde{h}_l), \varphi(\tilde{h}_l)\}$. The multi-head cross-attention (MHCA) block processes these matrices to produce $\hat{h}_{l-1}$ with enhanced local geometric representation and global consistency. The final output combines the cross-attention result with the original encoder features:

$$h_{l-1} = \text{MLP}([\hat{h}_{l-1}, f_{l-1}]), \quad (6)$$

This design enables the decoder to selectively attend to relevant features from different scales, facilitating accurate geometric reconstruction while preserving fine details. Our implementation uses 4 encoding/decoding levels with feature dimensions of $[64, 128, 256, 512]$, 8 attention heads, neighborhood size of 32 for NAA and 3 for feature propagation, with ReLU activation and batch normalization throughout the network. The hierarchical design with cross-attention mechanisms enables our U-Net module to effectively balance local detail preservation with global structural consistency, which is crucial for high-quality point cloud denoising.