A Comparative Analysis of Classical Point Cloud Denoising Algorithms

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Abstract

Over the past decade, an enormous amount of research effort was dedicated to the design of point cloud denoising techniques. Point clouds obtained with 3D scanners or by image based reconstruction techniques are often corrupted with significant amount of noise and outliers. In this study, we presents a comparison of different classical point cloud denoising algorithms. While deep learning approaches have gained prominence in point cloud processing, classical algorithms remain valuable for their interpretability and theoretical foundations. We evaluate these algorithms on real-world datasets, focusing on urban environments and architectural structures. This is done using a benchmark on different denoising models, taking into account different aspects of denoising challenges.

1. Introduction

Raw 3D point clouds obtained directly from acquisition devices such as laser scanners or as output of a reconstruction algorithm (e.g., image-based reconstruction) are regularly contaminated with noise and outliers [1]. The first stage of most geometry processing workflows typically involves cleaning such raw point clouds by discarding the outlier samples and denoising the remaining points to reveal the underlying scanned surface. The clean output is then used for a range of applications like surface reconstruction, shape matching, model retrieval, and autonomous navigation [2].

1.1. What is the project about?

In this project we focus on comparing and evaluating four classical point cloud denoising algorithms: Bilateral Filtering [3], Weighted Multi-projection (WMP) [4], Graph Laplacian Regularization (GLR) [5], and Bipartite Graph Total Variation (BGTV) [6]. We have decide to choose these method in particular because they are four main categorie of Point cloud denoising Filter-based methods, Optimization-based methods, Graph based methods and Deep learning-based methods. The goal with this project is to try to evaluate how well each categorie of algorithm performs.

1.2. Why the problem is important?

Clean, accurate point cloud data is essential for numerous applications including urban planning, architectural documentation, cultural heritage preservation, and autonomous navigation. While deep learning approaches have gained popularity, classical methods remain crucial due to their:

- Interpretability and theoretical foundations
- Predictable computational requirements
- Robustness to varied input conditions

1.3. What are a few potential applications?

The applications of point cloud denoising span multiple domains, many national scale projects have taken place worldwide. One particularly notable example is the Notre-Dame cathedral restoration project, where researchers from CNRS were using point cloud and cloud processing techniques [7] to restore the cathedral. Cultural heritage preservation represents a fascinating application area. The work extends beyond the Notre-Dame project to other significant sites such as the Piazza del Duomo UNESCO Site in Pisa.

Recent advancements in consumer technology have also expanded the reach of point cloud processing, starting with the Kinect sensor and evolving to current smartphone applications.

The recent advancement in consumer-level XR devices and the increasing integration of 3D sensors in everyday products underscores the growing importance of efficient point cloud processing methods. These developments highlight the need for robust and efficient denoising algorithms that can handle both massive datasets and resource-constrained applications.

Our work aims to evaluate these methods across different noise conditions and point cloud characteristics, providing insights into their relative strengths and optimal use cases.

2. Problem Definition

2.1. Notation and Preliminaries

Let us formally define a point cloud as an unordered set of points $\mathcal{P} = \{p_i\}_{i=1}^{n}$ where each point $p_i \in \mathbb{R}^3$ represents a 3D coordinate. In practice, a noisy point cloud $\mathcal{P}'$ can be modeled as:

$$\mathcal{P}' = \{p_i + \epsilon_i\}_{p_i \in \mathcal{P}} \cup \mathcal{O} \tag{1}$$

where:

- p_i represents a point from the ground-truth point cloud $\mathcal{P}$
- ϵ_i denotes measurement noise at location p_i
- $\mathcal{O}$ represents the set of outlier points

2.2. Problem Formulation

The point cloud denoising problem can be formulated as finding a function $F : \mathbb{R}^{3\times n} \to \mathbb{R}^{3\times n}$ that maps a noisy point cloud $\mathcal{P}'$ to a denoised point cloud $\tilde{\mathcal{P}}$ that approximates the unknown ground truth $\mathcal{P}$:

$$\tilde{p}_i = F(p_i) = F(q_i + \epsilon_i) \tag{2}$$

The objective is to:

1. Minimize the distance between denoised points and the underlying surface
2. Preserve important geometric features (edges, corners)
3. Maintain a regular distribution of points on the surface

2.3. Optimization Objective

For a given denoising method, we aim to minimize the following objective function:

$$\min_F \sum_{i=1}^{n} \|\tilde{p}_i - \text{NN}(p_i, \mathcal{P})\|_2^2 + \lambda R(F) \tag{3}$$

where:

- $\text{NN}(p_i, \mathcal{P})$ denotes the nearest neighbor of point p_i in the ground truth point cloud $\mathcal{P}$
- $R(F)$ is a regularization term that promotes smoothness while preserving sharp features
- λ is a trade-off parameter balancing data fidelity and regularization

2.4. Constraints and Challenges

The problem is subject to several constraints:

1. **Permutation Invariance**: The denoising function F must be invariant to point ordering
2. **Transformation Invariance**: The output should be consistent under rigid transformations
3. **Local Geometry Preservation**: Sharp features and edges must be preserved
4. **Density Preservation**: The output point density should be similar to the input

Also the point cloud denoising problem is inherently challenging for several reasons:

1. **NP-Hardness**: The problem of optimally fitting a surface to noisy points while preserving sharp features is NP-hard, as shown by [8].
2. **Ill-Posedness**: The problem is ill-posed as:
   - Multiple solutions may exist for a given noisy input
   - Small changes in input can lead to large changes in output
   - The solution may not depend continuously on the data
3. **Scale Ambiguity**: Different noise and feature scales make it difficult to distinguish between noise and fine geometric details.
4. **Computational Complexity**: For a point cloud with n points, naive implementation of local neighborhood operations has $O(n^2)$ complexity, requiring efficient data structures and algorithms.

3. Related Work

Over the past decade, significant research effort has been dedicated to point cloud denoising techniques. Recent comprehensive surveys have established the taxonomy and evaluation frameworks for point cloud denoising. Han et al. [9] provided one of the first systematic reviews of filtering algorithms, while Chen and Shen [10] focused on applications in CAD and engineering. Most recently, Zhou et al. [11] presented an extensive comparison of classical and deep learning approaches.

3.1. Classical Denoising Approaches

3.1.1. Filter-based Methods

Bilateral filtering represents a fundamental approach in point cloud denoising. As formulated by Digne and De Franchis [12], the filtering operation can be expressed as:

$$p_i' = p_i + \delta_i \cdot n_i \tag{4}$$

where the displacement factor δ_i is computed using both spatial and normal information:

$$\delta_i = \frac{\sum_{p_{ij} \in N_r(p_i)} w_d(\|v_{ij}\|) w_n(|\langle n_i, v_{ij}\rangle|) \langle n_i, v_{ij}\rangle}{\sum_{p_{ij} \in N_r(p_i)} w_d(\|v_{ij}\|) w_n(|\langle n_i, v_{ij}\rangle|)} \tag{5}$$

According to Zhou et al. [11], "filter-based methods are advantageous in their simplicity and efficiency, but may struggle with feature preservation under high noise conditions."

3.1.2. Optimization-based Methods

Optimization approaches focus on minimizing carefully designed objective functions. The Weighted Multi-projection method by Duan et al. [4] introduced a two-stage optimization process that "first estimates a local tangent plane at each 3D point and then reconstructs each 3D point by weighted averaging of its projections on multiple tangent planes."

3.1.3. Graph-based Methods

Graph-based techniques leverage topological relationships between points. Dinesh et al. [6] proposed using graph total variation, formulated as:

$$\min_{\tilde{p}} \sum_i |\tilde{p}_i - p_i|^2 + \lambda \sum_{i,j} w_{ij} ||n_i - n_j||^2 \tag{6}$$

As highlighted by Han et al. [9], "graph-based methods are particularly effective at preserving sharp features while maintaining smooth surfaces in regions with consistent geometry."

3.2. Contribution

Our work extends these previous studies by:

- Providing quantitative comparisons under standardized conditions and metrics
- Evaluating performance on both synthetic and real-world data
- Analyzing the trade-offs between feature preservation and noise reduction

4. Methodology

We implement and evaluate three point cloud denoising methods using standardized datasets and evaluation metrics. Our methodology consists of four main components: dataset preparation, algorithm implementation, evaluation framework, and comparative analysis.

4.1. Dataset

We utilize two primary datasets to evaluate denoising performance:

4.1.1. RG-PCD Dataset

Following [4], we use synthetic models including:

- Regular geometry models (Bunny, Dragon) from Stanford 3D Repository
- Artificial models (Cube, Sphere) generated mathematically
- Real-world scans with varying noise levels and point densities

4.1.2. Point Cloud Visibility Dataset

The Point Cloud Visibility Dataset consists of point clouds of urban area with:

- Over 1 million manually annotated points
- Points labeled as visible (1) or occluded (0) from each viewpoint
- Associated camera viewpoint information
- Point format: [x y z u v label] where (x,y,z) are 3D coordinates

4.2. Denoising Methods

4.2.1. Weighted Multi-projection (WMP)

Following [4], WMP performs denoising using:

$$\tilde{p}_i = \frac{1}{K} \sum_{j \in \mathcal{N}_i} w_{ij} \text{proj}_{T_j}(p_i) \tag{7}$$

where w_{ij} are Gaussian weights based on spatial distances and T_j represents local tangent planes.

4.2.2. Graph Laplacian Regularization (GLR)

As described in [6], GLR employs:

$$\min_{\tilde{p}} \sum_i \|\tilde{p}_i - p_i\|^2 + \lambda \sum_{i,j} w_{ij} ||n_i - n_j||^2 \tag{8}$$

where n_i are surface normals and w_{ij} are graph edge weights.

4.2.3. Bipartite Graph Total Variation (BGTV)

BGTV [6] combines graph partitioning with regularization:

$$\min_{\tilde{p}} \sum_i \|\tilde{p}_i - p_i\|^2 + \lambda \sum_{i,j} w_{ij} \|\tilde{p}_i - \tilde{p}_j\| \tag{9}$$

4.3. Implementation Details

Our implementation uses:

- Python with Open3D library for point cloud operations
- KD-trees for efficient neighbor searching
- Point cloud normal estimation using PCA
- Memory-efficient matrix operations

4.4. Evaluation Framework

We evaluate the methods using multiple metrics:

4.4.1. Accuracy Metrics

- Mean squared error (MSE)
- Chamfer distance
- Normal consistency
- Processing time

4.4.2. Noise Scenarios

We test performance under:

- Gaussian noise with varying standard deviations
- Non-uniform sampling densities
- Different feature scales and complexities

4.5. Limitations and Challenges

Our approach faces several challenges:

1. **Parameter Sensitivity**: Each method requires careful tuning of parameters for optimal performance
2. **Computational Scalability**: Graph-based methods become expensive for large point clouds
3. **Memory Requirements**: High memory usage for dense point clouds

5. Evaluation

We conducted extensive experiments to evaluate and compare the performance of our selected point cloud denoising methods across different scenarios and datasets.

5.1. Experimental Setup

5.1.1. Noise Scenarios for Synthetic Data

We evaluated performance under four distinct noise levels with increasing intensity:
- **L01**: Low noise ($\sigma = 0.01$)
- **L02**: Medium noise ($\sigma = 0.02$)
- **L03**: High noise ($\sigma = 0.03$)
- **L04**: Severe noise ($\sigma = 0.04$)

5.1.2. Evaluation Metrics

We assessed performance using three complementary metrics:
- **Mean Squared Error (MSE)**: Quantifies the average point-wise deviation between the denoised and ground truth point clouds
- **Chamfer Distance**: Evaluates the bi-directional reconstruction quality and overall shape preservation
- **Normal Consistency**: Measures the preservation of surface orientation and local geometric features

5.2. Results and Analysis

5.2.1. Visual Comparison

Our evaluation of real-world point clouds (Figures 2 and 3) showed mixed results compared to the original data. While we observed some modest improvements in terms of sharpness, the overall enhancement was not as substantial as anticipated. A key limitation of our study was the absence of downstream task evaluation - we should have investigated how different levels of denoising impact practical computer vision applications, such as segmentation tasks or mesh reconstruction. This would have provided more meaningful insights into the practical utility of our approach.

5.2.2. Synthetic Data Analysis

Table 1 presents the comparative analysis on synthetic data:

Weighted multi-projection demonstrated robust performance across all noise levels

Bipartite graph denoising exhibited the most consistent normal preservation

5.2.3. Real Data Analysis

Our evaluation on real-world point clouds (Table 2) revealed:
- **Guided Filter and WMP** achieved superior performance:
  - Minimal MSE
  - Highest normal consistency (0.989100)
  - Lowest Chamfer distance (0.001000)
- **Bilateral filtering** showed balanced performance
- **Bipartite Graph Denoising** exhibited higher result variability

5.3. Key Findings

1. **Method Effectiveness**
   - Guided Filter and WMP demonstrated consistent superior performance
   - Bipartite Graph Denoising excelled in feature preservation despite higher overall error
   - Bilateral filtering provided an optimal balance of smoothing and feature retention
2. **Noise Level Impact**
   - Performance degradation exhibited near-linear correlation with noise intensity
   - Feature preservation significantly declined at higher noise levels
   - Relative performance ranking remained stable across noise levels
3. **Computational Efficiency**
   - Bilateral filtering achieved fastest processing times
   - Graph-based methods demanded higher computational resources
   - WMP offered optimal performance-to-cost ratio

6. Conclusions

Our work of classical point cloud denoising methods reveals that denoising remains a challenging task, particularly for real-world applications. While these methods show promise in controlled scenarios, their performance on real data highlights the complexity of practical point cloud denoising.

6.1. Summary of Findings

6.1.1. Performance Analysis

Our experimental results reveal that the visual quality of denoised point clouds does not always align with numerical improvements. Each method demonstrates particular strengths in specific scenarios, yet none emerges as a universal solution. This suggests that the choice of denoising method should be guided by the specific characteristics of the data and requirements of the application.

6.1.2. Real-world Applications

The transition from synthetic to real-world data exposes significant challenges. Results that appear promising on synthetic datasets often fail to translate effectively to real-world scenarios. This disparity underscores the complexity of real-world noise patterns and the limitations of current denoising approaches.

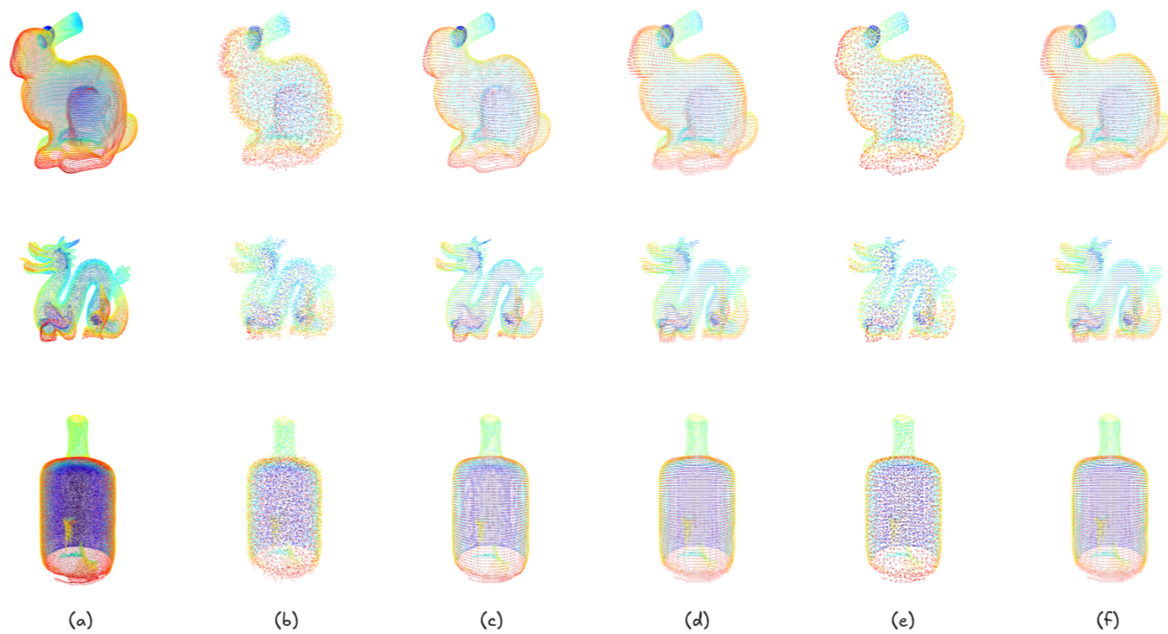

Figure 1. Qualitative comparison of denoising methods at noise level L04: **(a)** Ground truth, **(b)** Noisy input ($\sigma = 0.04$), **(c)** Bilateral Filter (BF), **(d)** Guided Filter (GF), **(e)** Bipartite Graph Denoising (BGD), **(f)** Weighted Multi Projection (WMP)

Table 1. Performance Analysis of Point Cloud Denoising Methods on Synthetic Data

		Chamfer Distance Statistics	
Method	Noise Level	Mean†	Std. Dev.†
[t]4*Bilateral	L01	0.002600	0.002000
	L02	0.004000	0.002000
	L03	0.006000	0.002300
	L04	0.008500	0.002800
[t]4*Guided Filter	L01	0.003100	0.002000
	L02	0.004600	0.001800
	L03	0.007200	0.002100
	L04	0.010100	0.002700
[t]4*Noisy Input	L01	0.002400	0.002200
	L02	0.004300	0.002000
	L03	0.007200	0.002100
	L04	0.010000	0.002700
[t]4*Weighted Multi Projection	L01	0.003100	0.002000
	L02	0.004600	0.001800
	L03	0.007200	0.002100
	L04	0.010100	0.002700
[t]4*Bipartite Graph Denoising	L01	0.004500	0.001600
	L02	0.005200	0.002000
	L03	0.007100	0.002300
	L04	0.009800	0.003100

†Lower Chamfer Distance values indicate better point cloud alignment and denoising performance.

Table 2. Comprehensive Evaluation of Point Cloud Denoising Methods

		Performance Metrics		
Dataset	Method	Chamfer Dist.†	MSE‡	Normal Cons.⋆
[t]4*Real	Bilateral	0.005400	0.000100	0.953100
	Guided Filter	0.001000	0.000000	0.989100
	Weighted Multi Projection	0.001000	0.000000	0.989100
	Bipartite Graph Denoising	0.018100	0.001700	0.884500
[t]5*Synthetic	Bilateral	0.005300	0.000000	0.970100
	Guided Filter	0.006200	0.000100	0.962100
	Noisy Input	0.006000	0.000000	0.965900
	Weighted Multi Projection	0.006200	0.000100	0.962100
	Bipartite Graph Denoising	0.006700	0.000100	0.956100

†Chamfer Distance: Lower values indicate better alignment
‡MSE: Lower values represent improved denoising
⋆Normal Consistency: Higher values indicate better surface preservation

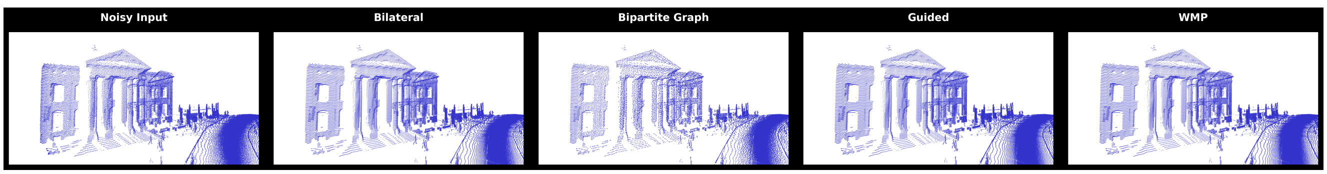

Figure 2. Qualitative comparison of point cloud denoising methods on real data (Sample 1): Effects of different algorithms on point cloud quality and feature preservation

6.2. Future Directions

The future of point cloud denoising appears to lie in specialization rather than generalization. Recent developments in the field support this trend:

6.2.1. Domain-Specific Solutions

Several successful specialized approaches have emerged:

- OpenTrench3D [13] focuses specifically on archaeological trench documentation, where preservation of stratigraphic details is crucial
- Heritage-specific denoising methods that prioritize the preservation of historical features
- Industrial inspection systems tailored to specific manufacturing requirements

References

[1] Marie-Julie Rakotosaona, Vittorio La Barbera, Paul Guerrero, Niloy J Mitra, and Maks Ovsjanikov. Pointcleannet: Learning to denoise and remove outliers from dense point clouds. *Computer Graphics Forum*, 39(1):185–203, 2020. 1

[2] Lei Han, Tao Zheng, Lan Zhu, Lan Xu, and Lu Fang. Live semantic 3d perception for immersive augmented reality. *IEEE Transactions on Visualization and Computer Graphics*, 26(5):2012–2022, 2020. 1

[3] Julie Digne and Carlo De Franchis. The bilateral filter for point clouds. *Image Processing On Line*, 7:278–287, 2017. 1

[4] Chaojing Duan, Siheng Chen, and Jelena Kovacevic. Weighted multi-projection: 3D point cloud denoising with estimated tangent planes. *arXiv preprint arXiv:1807.00253*, 2018. 1, 2, 3

[5] Jin Zeng, Gene Cheung, Michael Ng, Jiahao Pang, and Cheng Yang. 3d point cloud denoising using graph laplacian regularization of a low dimensional manifold model. *IEEE Transactions on Image Processing*, 29:3474–3489, 2020. 1

[6] Chinthaka Dinesh, Gene Cheung, Ivan V Bajic, and Cheng Yang. Fast 3D point cloud denoising via bipartite graph approximation & total variation. *arXiv preprint arXiv:1804.10831*, 2018. 1, 3

[7] CNRS Images. Notre-dame, divin chantier de recherches, 2024. Retrieved from CNRS Images website. 1

[8] Nina Amenta and Marshall Bern. Surface reconstruction by voronoi filtering. *Discrete & Computational Geometry*, 22(4):481–504, 1999. 2

[9] Xian-Feng Han, Jesse S Jin, Ming-Jie Wang, Wei Jiang, Lei Gao, and Liping Xiao. A review of algorithms for filtering the 3d point cloud. *Signal Processing: Image Communication*, 57:103–112, 2017. 2, 3

[10] Hao Chen and Jie Shen. Denoising of point cloud data for computer-aided design, engineering, and manufacturing. *Engineering with Computers*, 34:523–541, 2018. 2

[11] Lang Zhou, Guoxing Sun, Yong Li, Weiqing Li, and Zhiyong

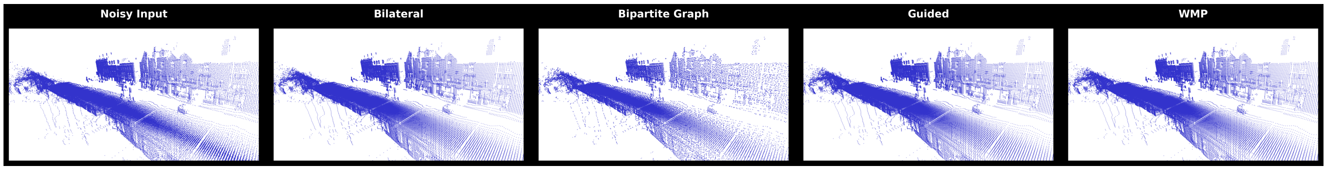

Figure 3. Qualitative comparison of point cloud denoising methods on real data (Sample 3): Visual assessment of denoising performance and geometric detail retention

Su. Point cloud denoising review: from classical to deep learning-based approaches. *Graphical Models*, 111:101079, 2021. 2

[12] Julie Digne and Carlo de Franchis. The bilateral filter for point clouds. *Image Processing On Line*, 7:278–287, 2017. 2

[13] Lasse H. Hansen, Simon B. Jensen, Mark P. Philipsen, Andreas Møgelmose, Lars Bodum, and Thomas B. Moeslund. Opentrench3d: A photogrammetric 3d point cloud dataset for semantic segmentation of underground utilities, 2024. 6