ABSTRACT

To achieve point cloud denoising, traditional methods heavily rely on geometric priors, and most learning-based approaches suffer from outliers and loss of details. Recently, the gradient-based method was proposed to estimate the gradient fields from the noisy point clouds using neural networks, and refine the position of each point according to the estimated gradient. However, the predicted gradient could fluctuate, leading to perturbed and unstable solutions, as well as a long inference time. To address these issues, we develop the momentum gradient ascent method that leverages the information of previous iterations in determining the trajectories of the points, thus improving the stability of the solution and reducing the inference time. Experiments demonstrate that the proposed method outperforms state-of-the-art approaches with a variety of point clouds, noise types, and noise levels. Code is available at: https://github.com/IndigoPurple/MAG.

Index Terms— point cloud denoising, point cloud processing, 3D vision

1. INTRODUCTION

Point cloud denoising aims to restore clean point clouds from noise-corrupted ones. Due to the inherent limitations of acquisition devices or matching ambiguities in the 3D reconstruction, noise inevitably degrades the quality of scanned or reconstructed point clouds, for which point cloud denoising is favored. Moreover, the quality of point clouds affect the performance of downstream 3D vision tasks, e.g., detection and segmentation. Therefore, point cloud denoising offers crucial preprocessing for relevant 3D vision applications.

Unlike image and video denoising [1], point cloud denoising is challenging because of the intrinsic unordered characteristic of point clouds. Point clouds consist of discrete 3D points irregularly sampled from continuous surfaces. Perturbed by noise, the 3D points can deviate from their original positions and yield the wrong coordinates. To tackle this issue, both traditional [2, 3, 4, 5, 6, 7] and deep learning [8, 9, 10, 11] methods have been explored but show limited performance. Recently, Luo and Hu propose score-based denoising (Score) [12] to iteratively update the point positions according to the estimated gradient fields. However, the predicted gradients can fluctuate, leading to perturbed and unstable solutions, as well as a large inference time.

To improve the performance and efficiency of the gradient-based method, as Figure 1 shows, we propose a novel iterative...
2. RELATED WORK

To perform point cloud denoising, traditional methods [2, 3, 4, 5, 6, 7] heavily rely on geometric priors but show limited performance. Deep learning-based approaches break the performance limit of the point cloud denoising. Among them, some [8, 9, 10, 11, 14] denoise by estimating the deviation of noisy points from the clean surface, but often results in outliers due to the coarse one-step estimation. Others [15] predict the underlying manifold of a noisy point cloud for reconstruction, which loses details in the downsampling stage.

Recently, Score [12] is proposed to tackle the aforementioned issues by iteratively updating the point position in implicit gradient fields learned by neural networks. However, the predicted gradients suffer fluctuation, leading to perturbed and unstable solutions, as well as a large inference time. Moreover, once its estimated gradient deviates from the correct direction, the gradient estimation errors could be accumulated and result in serious outliers.

3. METHOD

Given a noisy point cloud $X = \{x\}_{i=1}^N$, we first implement a network that inputs noisy point clouds and outputs point-wise gradients, and then utilize the estimated gradients to denoise point clouds by momentum ascent, as Figure 2 shows.

3.1. Neural Network and Loss Function

The network aims at estimating the gradient in the neighborhood space around $x_i$, denoted as $\hat{g}_i(x)$. We adopt the network and loss function reported in Score [12], which inputs point coordinates $x \in \mathbb{R}^3$ surrounding $x_i$, learns point-wise features $f_i$, and outputs the estimated gradient $\hat{g}_i(x)$:

$$
\hat{g}_i(x) = G(x - x_i, f_i),
$$

where $G(\cdot)$ is the gradient estimation network implemented by a multi-layer perceptron. Then the loss function [12] is

$$
\mathcal{L} = \frac{1}{N} \sum_{i=1}^{N} \mathcal{L}_i = \frac{1}{N} \mathbb{E}_{x \sim N(x_i)} [ ||g(x) - \hat{g}_i(x)||_2^2 ],
$$

where $N(x_i)$ is a distribution concentrated in the neighborhood of $x_i$ in $\mathbb{R}^3$ space, $g(x)$ is a vector from $x$ to the ground truth clean surface. Following Score [12], the ensemble gradient is calculated as

$$
z_i(x) = \frac{1}{k} \sum_{j} \hat{g}_j(x), \quad x_j \in H(x_i; k), \; x \in \mathbb{R}^3,
$$

where $H(x_i; k)$ is the k-nearest neighborhood of $x_i$.

Though Score [12] uses the ensemble gradient for robustness, it still suffers in fluctuated gradients. Moreover, once its estimated gradient deviates from the correct direction, the errors could be accumulated and result in serious outliers.

3.2. Momentum Ascent Denoising Algorithm

To alleviate those problems faced by previous gradient-based methods, we propose to perform point cloud denoising by updating point coordinates with momentum gradient ascent. At the beginning of point cloud denoising, we initialize the coordinate for each point according to the input point cloud:

$$
x_i^{(0)} = x_i, \quad x_i \in X.
$$
To leverage past gradients, we introduce an auxiliary vector, which is initialized as zero and updated with a leaky average over past gradients:

$$v_i^{(t)} = \alpha z_i(x_i^{(t-1)}) + (1 - \alpha)v_i^{(t-1)}, \quad t = 1, \ldots, T,$$

where $t$ is the iterative step, $\alpha$ is the momentum weight, $v_i$ serves to relieve gradient variance and obtain more stable directions of ascent. Finally, the point cloud is denoised by updating point coordinates with momentum gradient ascent:

$$x_i^{(t)} = x_i^{(t-1)} + \beta \gamma^t v_i^{(t)}, \quad t = 1, \ldots, T,$$

where $t$ is the iterative step, $T$ is the total number of iteration steps, $\beta$ is the step size, $\gamma^t$ is the decay coefficient decreasing towards 0 to ensure convergence. While Score requires a relatively large number of total steps $T = 30$ to conduct their experiments, our method applies momentum gradient ascent, thus reducing the step number to $T = 15$ while achieving better performance.

As Figure 3 shows, compared to classical gradient ascent, momentum gradient ascent leverages the information of previous iterations in determining the trajectories of points, thereby benefiting solution stability and inference time.

| # Points | 1% 10K (Sparse) | 2% 10K (Sparse) | 3% 10K (Sparse) | 1% 50K (Dense) | 2% 50K (Dense) | 3% 50K (Dense) |
|----------|----------------|----------------|----------------|----------------|----------------|----------------|
| Type     | Method         | CD P2M         | CD P2M         | CD P2M         | CD P2M         | CD P2M         |
| Gaussian | GLR [17]       | 3.232 1.211    | 4.751 2.090    | 7.977 4.773    | 0.962 0.374    | 3.269 2.325    |
|          | PCNet [11]     | 4.616 1.940    | 11.082 7.218   | 20.981 15.922  | 1.190 0.458    | 2.854 1.866    |
|          | DMR [15]       | 4.600 1.811    | 5.441 2.469    | 6.918 3.714    | 1.243 0.537    | 1.881 1.077    |
|          | Score [12]     | 2.915 0.674    | 4.601 1.799    | 6.332 3.271    | 0.823 0.231    | 1.658 0.869    |
|          | Ours           | 2.887 0.669    | 4.521 1.754    | 6.237 3.257    | 0.816 0.212    | 1.648 0.857    |
| Laplace  | GLR [17]       | 1.850 1.015    | 2.948 1.052    | 3.400 1.109    | 0.485 0.071    | 0.656 0.132    |
|          | PCNet [11]     | 1.205 0.337    | 3.378 1.018    | 5.044 1.995    | 0.806 0.228    | 1.064 0.358    |
|          | DMR [15]       | 4.307 1.640    | 4.445 1.693    | 4.685 1.857    | 1.064 0.391    | 1.159 0.464    |
|          | Score [12]     | 1.277 0.248    | 2.467 0.418    | 3.079 0.654    | 0.506 0.047    | 0.690 0.129    |
|          | Ours           | 1.243 0.239    | 2.404 0.397    | 3.052 0.638    | 0.487 0.045    | 0.679 0.122    |

Table 1: Point cloud denoising comparisons on the PU-Net dataset [18]. CD and P2M are multiplied by 10^4.

4. EXPERIMENT

**Experiment Setting.** The commonly used PU-Net dataset [18] is adopted for training and testing following previous works [11, 12, 15]. Moreover, we use the real-world dataset Paris-rue-Madame [19] for qualitative evaluation. We utilized a single model trained on the PU-Net training set to conduct both synthetic and real-world experiments. Two traditional methods, bilateral filtering [16], GLR [17], and three deep-learning-based approaches including PCNet [11], DMR [15] and Score [12] are used for comparison. Two commonly used metrics are adopted for quantitative evaluation, the Chamfer distance (CD) [20] and point-to-mesh distance (P2M) [21].

**Quantitative and Qualitative Results.** As Table 1 shows,
our model significantly outperforms previous methods bi-
lar filtering [16], PCNet [11], DMR [15], and surpasses
GLR [17], Score [12] in the majority of cases. To further il-
lustrate the effectiveness of our method, we compare the
qualitative performance with the competitive baseline Score [12].
As Figure 4 shows, Score takes 30 steps to achieve the
denoising results and suffers in outliers, while ours takes only
15 steps and outputs results with fewer outliers and smoother
outlines. In Figure 5, compared to Score [12], our denoised
point clouds feature fewer outliers, better structures and
smoother outlines in all the iterative steps. In Figure 6, Score
results in cracks, while ours effectively reduces the outliers,
maintains cleaner and smoother outlines.

**Inference Time.** As Table 2 shows, Score requires a longer
inference time. In contrast, our method utilizes previous gra-
dients to seek promising directions to move forward, thus re-
ducing inference time by approximately 25% ~ 40%.

**Ablation Study.** We investigate hyper-parameters of the pro-
posed algorithm formulated in Equation 5, 6. Other implement-
eation details, including learning rates, decay coefficient
\( \gamma \), etc., are the same as the classical gradient-based method
Score [12]. According to Table 3, we recommend the setting
\( T = 15 \), \( \alpha = 0.9 \), and \( \beta = 0.2 \), which is used in this paper.

### Table 2: Average inference time per point cloud in minutes

| # Points | 10K (Sparse) | 50K (Dense) |
|----------|--------------|-------------|
| Score [12] | 0.66 | 6.27 |
| Ours | 0.40 | 4.76 |

### Table 3: Ablation study w.r.t. hyper-params \( T, \alpha, \beta \) on sparse point clouds from PU-Net [18]. CD & P2M multiplied \( 10^4 \).

| Gaussian Noise | 1% | 2% | 3% |
|----------------|-----|-----|-----|
| \( T \) | \( \alpha \) | \( \beta \) | CD | P2M | CD | P2M | CD | P2M |
| 15 | 0.9 | 0.2 | 2.498 | 0.459 | 3.629 | 1.054 | 4.686 | 1.923 |
| 15 | 0.9 | 0.2 | 2.858 | 0.695 | 5.665 | 2.576 | 7.905 | 4.676 |
| 15 | 0.9 | 0.2 | 2.489 | 0.453 | 3.998 | 1.283 | 4.906 | 2.038 |
| 15 | 0.9 | 0.2 | 2.488 | 0.453 | 3.784 | 1.137 | 4.725 | 1.938 |
| 15 | 0.9 | 0.2 | 2.508 | 0.463 | 3.702 | 1.091 | 4.696 | 1.940 |
| 15 | 0.9 | 0.2 | 2.522 | 0.468 | 3.683 | 1.084 | 4.705 | 1.940 |

In this paper, we propose point cloud denoising via mo-
momentum ascent in gradient fields. To improve the previous
gradient-based method, we propose a simple yet effective
iterative paradigm of point cloud denoising, which leverages
past gradients to seek promising directions to move forward.
Our method effectively prevents outliers that are much more
likely to occur for previous methods. Moreover, our method
accelerates optimization and reduces the inference time of the
previous gradient-based method. On both synthetic and real-
world datasets, extensive experiments demonstrate that our
method outperforms state-of-the-art methods with a variety
of point clouds, noise types and noise levels.

### 5. CONCLUSION
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