Exploring State Space Models in LiDAR Point Cloud Segmentation

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Abstract

Mamba has achieved significant success in various fields due to its ability to efficiently model long-range dependencies with linear complexity. However, its application in LiDAR point cloud processing is still in its early stages, facing challenges such as unordered and irregular data structures. In this study, we investigated the performance of two existing Mamba-based algorithms, PointMamba and PointCloudMamba, on the aerial DALES LiDAR dataset for point cloud segmentation, and further explored the critical role of token serialization in influencing Mamba’s performance. To evaluate serialization quality, we proposed two novel indicators—Neighbor Preservation Ratio (NPR) and Sequence Jump Distance (SJD)—which quantify the ability of serialization methods to preserve spatial topology and geometric relationships. Our findings confirm the great potential of Mamba in LiDAR point cloud processing, and demonstrate that serialization significantly impacts Mamba’s performance, with better preservation of spatial and geometric relationships leading to higher segmentation accuracy. These results provide meaningful insights into improving Mamba’s performance in LiDAR point cloud processing and guiding the development of advanced serialization methods.

1. Introduction

LiDAR technology enables precise 3D mapping of real-world environments by densely sampling object surfaces, generating detailed point clouds containing spatial coordinates and attributes such as reflectance intensity. This versatility enables LiDAR to be a critical tool in remote sensing applications like urban planning [Wang et al., 2018], environmental monitoring [Xiao et al., 2023], and disaster management [Vetrivel et al., 2018]. For example, it supports the development of 3D building models for urban planning [Sun and Salvaggio, 2013] and facilitates biomass estimation [Yu et al., 2013] in ecological research.

Recently, Mamba [Gu and Dao, 2023], an advanced Structured State Space Model (SSM), has gained significant attention due to its remarkable ability to model long-range dependencies while maintaining linear computational complexity through its inherent recurrence relations. Mamba has been successfully applied in several domains, such as natural language processing and time-series forecasting, showcasing its potential for handling complex sequential data efficiently. Despite its growing adoption, the application of Mamba in LiDAR point cloud processing remains in its infancy, with only a limited number of studies exploring its use in this domain.

In this work, we focus on evaluating the effectiveness of Mamba-based methods for LiDAR point cloud processing, addressing the unique challenges posed by the sparse, unordered, and irregular nature of point clouds. Specifically, we investigated two recently proposed Mamba-based point cloud processing networks, PointMamba and PointCloudMamba, and analyzed their performance on a large-scale aerial LiDAR dataset, Dayton Annotated Laser Earth Scan (DALES) [Varney et al., 2020]. Furthermore, a key aspect of this study is the exploration of point cloud serialization, which plays a crucial role in enabling Mamba-based models to handle point cloud data effectively. Despite the importance of serialization in determining the performance of Mamba models, the impact of different serialization methods on point cloud processing remains underexplored. To address this gap, we investigated and compared several existing serialization techniques within the PointMamba framework. Our analysis not only examines their impact on Mamba’s performance but also investigates the underlying factors, aiming to provide valuable insights for future advancements in Mamba-based point cloud processing. By analyzing the interaction between serialization methods and Mamba-based networks, we aspire to contribute foundational knowledge to the field and offer guidance for designing more effective Mamba models tailored to LiDAR point cloud processing.

The main contributions of our work are summarized as follows:

- Compare and analysis the effectiveness of existing Mamba-based methods in LiDAR point cloud processing (investigating two representative Mamba works: PointMamba [Liang et al., 2024] and PointCloudMamba [Zhang et al., 2024] in our experiments).
- Taking PointMamba as the baseline, investigate and compare different point cloud serialization methods, exploring the impact of serialization on Mamba’s performance.
- Design novel evaluation indicators for assessing the quality of point cloud serialization, evaluating the preservation of the original spatial topology and geometric relationships in serialized data. The new indicators provides valuable insights for future advancements in Mamba-based point cloud processing.

2. Methodology

This section introduces the frameworks of PointMamba [Liang et al., 2024] and PointCloudMamba [Zhang et al., 2024], fol-

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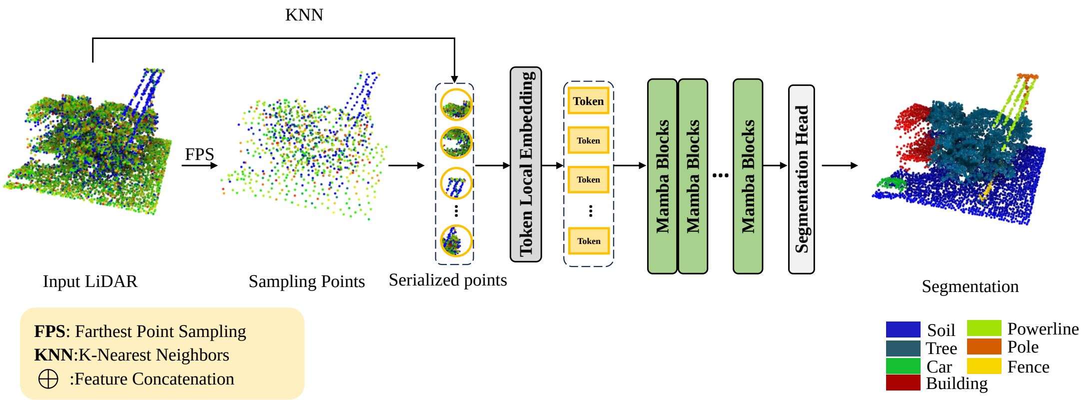

Figure 1. The overall framework of PointMamba [Liang et al., 2024].

lowed by an introduction to a series of existing point cloud serialization methods.

2.1 PointMamba

The framework of PointMamba [Liang et al., 2024] is shown in Fig. 1. PointMamba is a lightweight and effective Mamba-based framework for point cloud analysis, leveraging the power of Mamba's linear complexity and global modeling capabilities. The pipeline begins with Farthest Point Sampling (FPS) to select representative key points from the input point cloud. These key points are then serialized using Hilbert space-filling curves and its transposed variant, Trans-Hilbert, which preserve spatial locality and ensure meaningful sequential representations of the point cloud.

The serialized points are processed into tokens through a k-Nearest Neighbor (kNN)-based tokenization process, where local patches of neighboring points are aggregated using relative coordinates. A lightweight PointNet [Qi et al., 2017a] module is employed to map these patches to a feature space, producing serialized point tokens. To differentiate between Hilbert and Trans-Hilbert tokenizations, order indicators are introduced, embedding unique latent characteristics for each serialization strategy.

The serialized tokens are subsequently fed into a plain, non-hierarchical Mamba encoder, which stacks multiple Mamba blocks. Each block includes Selective State Space Modeling (SSM), layer normalization, depth-wise convolution, and residual connections, enabling efficient global context modeling. The design intentionally avoids complexity, adhering to the principle of simplicity for both efficiency and scalability.

PointMamba demonstrates superior performance across various synthetic point cloud datasets while maintaining significantly reduced computational costs compared to Transformer-based counterparts. Its simplicity and efficiency make it a promising baseline for future point cloud analysis tasks.

2.2 PointCloudMamba

As shown in Fig. 2, the PointCloudMamba (PCM) [Zhang et al., 2024] framework leverages the strengths of the Mamba architecture to efficiently process point cloud data while addressing the inherent challenges of sparsity, irregularity, and unordered structures in 3D point clouds. PCM introduces several novel design elements to adapt Mamba's state-space model (SSM) for point cloud processing.

PCM incorporates order prompts, which explicitly inform Mamba layers about the input sequence's structure. These learnable embeddings are strategically integrated into the model, allowing Mamba to effectively process data while adapting to the unique characteristics of point clouds. Additionally, PCM includes a positional embedding mechanism based on spatial coordinate mapping, which projects 3D coordinates into feature spaces, preserving critical spatial information more effectively than traditional positional encodings.

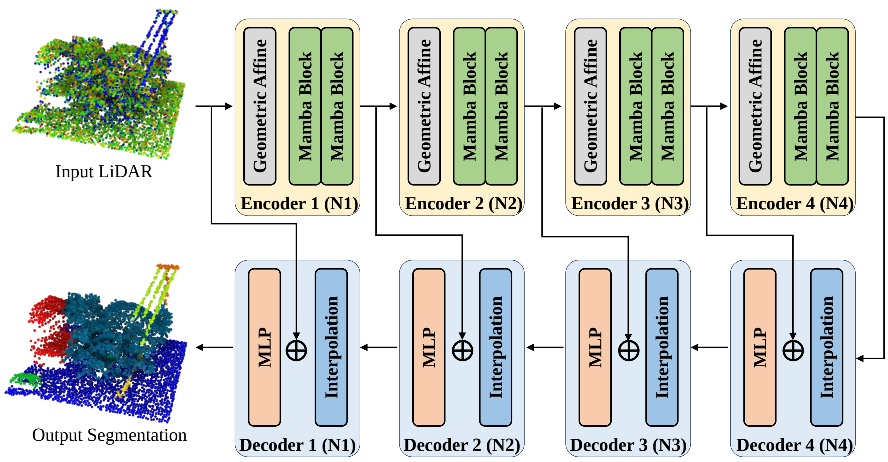

Figure 2. The overall framework of PointCloudMamba [Zhang et al., 2024].

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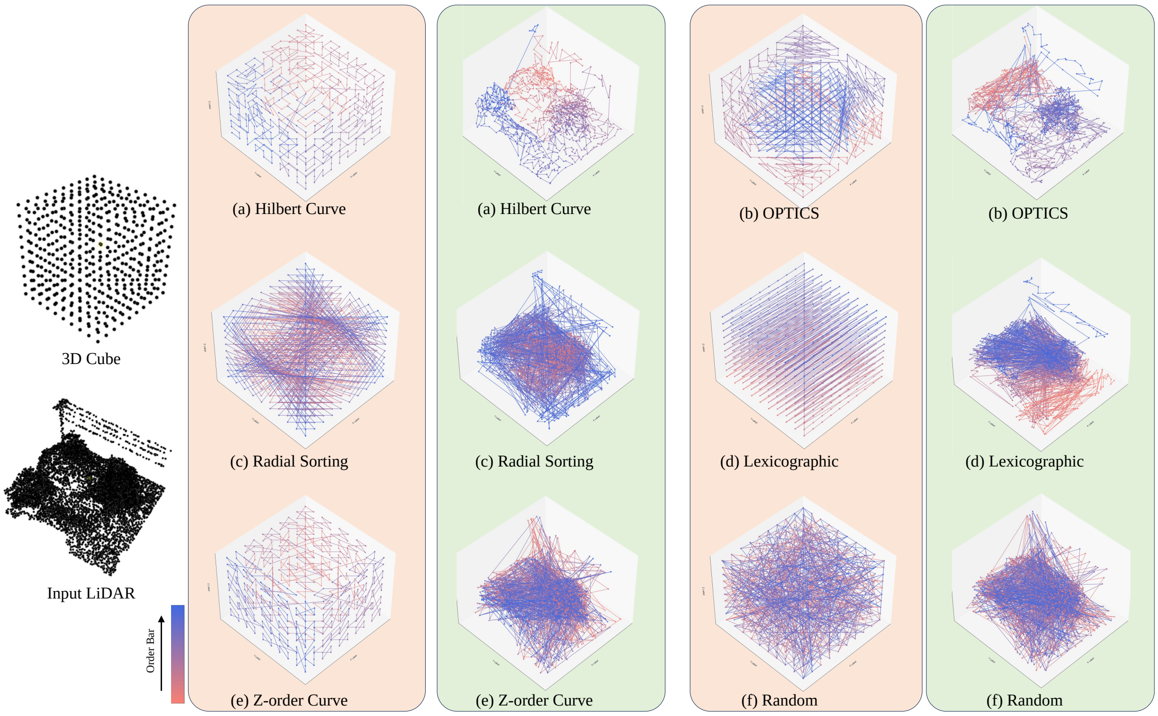


Figure 3. Serialization results of investigated method on the synthetic 3D cube and raw LiDAR point cloud in [Varney et al., 2020].

PCM adopts a four-stage encoder-decoder architecture, where the encoder alternates between geometric affine modules for local feature extraction and Mamba layers for global context modeling. The decoder employs a streamlined design with point interpolation and Multi-Layer Perceptrons (MLPs) to reconstruct and classify point cloud features. The multi-stage encoding ensures comprehensive representation learning across different spatial resolutions, enabling the model to capture both local and global point cloud features.

By combining these innovations, PCM achieves State-Of-The-Art (SOTA) performance on various benchmark datasets. It significantly outperforms transformer- and point-based methods while maintaining Mamba’s linear computational complexity, making it a powerful and efficient framework for point cloud analysis.

2.3 Existing Point Cloud Serialization Methods

Several point cloud serialization methods are examined in this study, each offering unique strategies for ordering 3D point cloud data in a one-dimensional sequence. The methods are described as follows.

Hilbert Curve Serialization. The Hilbert curve is a recursive fractal that traverses every point in a 3D space within a predefined grid. By repeatedly subdividing the space into smaller cubes and connecting points in a continuous path, the Hilbert curve ensures that spatially close points in the 3D space remain adjacent in the serialized 1D sequence. This characteristic of spatial locality preservation makes it a widely used method for reducing the dimensionality of multidimensional data while retaining geometric proximity.

Z-order Serialization. The Z-order curve, also known as the Morton curve, converts 3D coordinates into a one-dimensional sequence by interleaving the binary representations of the x, y, and z coordinates. This interleaving generates a unique scalar value for each point, referred to as the Morton code. Sorting the points based on their Morton codes produces an ordering that partially preserves spatial locality, making it effective for organizing 3D data in a structured, single-dimensional representation.

Radial Distance Ordering. Radial ordering arranges points based on their Euclidean distances from a central reference point. In this work, the geometric centroid of the point cloud is used as the reference. Points are sorted in ascending order of their radial distances, ensuring that points closer to the center appear earlier in the sequence. This method is particularly useful for analyzing spatial relationships relative to a central position.

Coordinate-Based Lexicographic Sorting. This method arranges points hierarchically based on their Cartesian coordinates (x,y,z). The sorting prioritizes one coordinate at a time: initially by the x-coordinate, followed by the y-coordinate if the x-values are identical, and finally by the z-coordinate for points with identical x and y values. This simple dictionary-like approach is easy to implement and ensures a deterministic sequence of points.

OPTICS-based Serialization. Based on the principles of the OPTICS (Ordering Points To Identify the Clustering Structure) algorithm, this method generates an ordering of points that reflects their relative densities. Each point is assigned a core distance and a simplified reachability distance (assuming all points are core points). The resulting order prioritizes points in dense regions, placing them consecutively in the sequence, while points in sparser areas appear later. This density-aware approach is particularly beneficial for tasks requiring an understanding of local point cloud density variations.

Random Ordering. Random ordering serves as a baseline for evaluating the impact of structured serialization methods. Points are assigned a completely random sequence, disregarding their spatial or geometric properties. This approach ensures

Table 1. Performance comparison (%) of different methods on the DALES dataset, including OA, mIoU, and latency(ms).

Methods	input points	OA	mIoU
PointNet++ [Qi et al., Dec. 2017b]	8192	95.7	68.3
KPConv [Thomas et al., 2019]	8192	96.9	72.4
DGCNN [Wang et al., Nov. 2019]	8192	96.1	66.4
PointCNN [Li et al., 2018]	8192	97.2	58.4
SPG [Landrieu and Simonovsky, 2018]	8192	95.5	60.6
ConvPoint [Boulch, 2020]	8192	97.2	67.4
PointTransformer [Zhao et al., 2021]	8192	97.1	74.9
SuperCluster [Robert et al., 2024]	8192	-	77.3
PReFormer [Akwensi et al., 2024]	8192	92.9	70.9
PointMamba [Liang et al., 2024]	8192	96.3	73.3
PointCloudMamba [Zhang et al., 2024]	8192	97.0	74.7

no inherent bias in the ordering and provides a reference for assessing the significance of spatially informed serialization.

Fig. 3 illustrates the serialization results of the discussed methods, applied to both a synthetic evenly distributed point cloud cube and a raw LiDAR point cloud scene from the DALES dataset [Varney et al., 2020]. The results highlight that the Hilbert and OPTICS algorithms effectively preserve local geometric structures in both synthetic and real-world LiDAR point clouds. In contrast, methods such as coordinate-based lexicographic sorting and Z-order sorting, while performing adequately on planar point clouds, struggle to maintain consistent and meaningful orderings in complex LiDAR datasets. This inconsistency undermines their effectiveness in LiDAR point cloud processing and analysis tasks.

3. Experiments

This section presents the comparative results of various Mamba-based methods on the DALES dataset, along with an evaluation of different point cloud serialization methods within the PointMamba framework [Liang et al., 2024].

3.1 Implementation Details

PointMamba [Liang et al., 2024] and PointCloudMamba [Zhang et al., 2024] were implemented using PyTorch and executed on NVIDIA Tesla V100 GPUs. The models were trained using the SGD optimizer with a momentum of 0.9 and a weight decay of 0.0001. The initial learning rate was set to 0.01 and adjusted throughout the training process using a cosine annealing schedule. Each model underwent training for a total of 200 epochs on the DALES dataset.

Table 2. Comparison Results (%) of investigated serialization methods on DALES. The highest scores are shown in bold.

Methods	DALES	
	mIoU	OA
Random Ordering	71.1	96.1
Z-order Curve	71.2	96.1
Radial Ordering	71.6	96.2
Lexicographic Ordering	72.4	96.3
OPTICS Ordering	73.3	96.4
Hilbert Curve	**73.3**	**96.3**

3.2 Datasets and Metrics

The Dayton Annotated LiDAR Earth Scan (DALES) dataset, introduced by [Varney et al., 2020], is a comprehensive aerial LiDAR dataset containing over 500 million points spanning an area of 10 square kilometers. The dataset is annotated into eight distinct object categories: Ground, Vegetation, Cars, Trucks, Powerlines, Fences, Poles, and Buildings. Aerial Laser Scanner point clouds, such as those in DALES, present unique challenges due to their scale and sparsity while offering diverse applications.

The dataset is divided into 40 regions, each covering 0.5 km^2 and containing approximately 12 million points with detailed class annotations. Each point is characterized by four attributes: spatial coordinates (XYZ) and intensity. For consistency and fair comparisons, we subsampled the dataset using a 10 cm grid, then partitioned it into $20m \times 20m$ blocks, each containing 8,192 points after sampling. These blocks were used as the training and testing samples.

To evaluate performance, we utilized standard metrics, including mean Intersection over Union (mIoU), Overall Accuracy (OA), and the average F_1 score.

3.3 Performance Comparison

Table 1 shows the comparison results of PointMamba and PCM, as well as previous deep learning methods. From the results, these two Mamba-based point cloud processing methods surpasses the traditional deep learning methods such as PointNet++ [Qi et al., Dec. 2017b] and KPConv [Thomas et al., 2019], achieving competitive performance with current SOTA methods such as PReFormer [Akwensi et al., 2024]. The comparison results demonstrate the superiority and great potential of Mamba in LiDAR point cloud processing. In addition, due to comprehensive representation of point features by combining both local and global feature modeling, PCM achieves better results than PointMamba.

Furthermore, we also reported the comparison results of the investigated serialization method introduced in Section 2.3. PointMamba [Liang et al., 2024] represents a purely Mamba-based network, relying solely on the strengths of Mamba's global modeling capabilities without incorporating additional components. Therefore, we chose PointMamba as the baseline to investigate the impact of different serialization methods on Mamba's performance. Table 2 shows the related comparison results. Among the evaluated methods, the Hilbert curve and OPTICS ordering achieved the highest scores, as reflected by their superior mIoU (73.3%) and average F_1 score (81.9%). Random ordering and Z-order curve exhibit the lowest performance, suggesting that these methods are less effective at maintaining the spatial coherence of complex LiDAR point clouds, leading to

Table 3. Comparison results measured by NPR and SJD for investigated serialization methods on the DALES dataset.

Methods	NPR				SJD
	$K = 1$	$K = 10$	$K = 30$	$K = 50$	
Hilbert Curve	**0.1981**	**0.5126**	**0.5601**	**0.5869**	**0.1644**
OPTICS Ordering	0.0431	0.3061	0.4098	0.4447	0.3732
Lexicographic Ordering	0.0257	0.1460	0.2580	0.3236	0.7271
Radial Ordering	0.0125	0.0817	0.1592	0.2118	1.0178
Z-order Curve	0.0043	0.0292	0.0681	0.1080	1.0657
Random Ordering	0.0020	0.0195	0.0587	0.0978	1.1102

reduced segmentation quality. The quantitative comparison results are also consistent with the visual serialization results of these methods shown in Fig. 3.

4. Discussion and Analysis

To further explore the intrinsic factors affecting the serialization method on Mamba performance, we designed novel indicators to evaluate the quality of point cloud serialization. When converting 3D point clouds into 1D sequences, our primary concern is whether the spatial topology and geometric relationships of the point cloud are adequately preserved. Therefore, our proposed indicators focus on measuring a serialization method's ability to retain these critical properties. Specifically, we employ two evaluation indicators as follow.

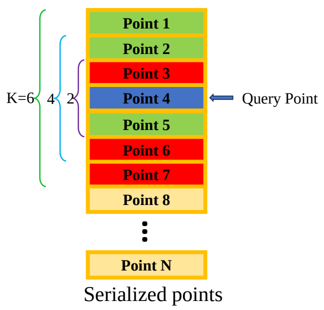


Figure 4. Illustration of the definition of NPR, where the green points represents common neighbor points in both the serialized neighborhood and the original spatial neighborhood.

Neighbor Preservation Ratio (NPR). NPR represents the proportion of original neighbors preserved in the serialized neighborhood, which can be expressed as:

$$\text{NPR} = \frac{1}{N}\sum_{i=1}^{N}\frac{|N_K^{\text{serialized}}(p_i) \cap N_K^{\text{original}}(p_i)|}{K}, \tag{1}$$

where K represents the number of nearest neighbors, $N_K^{\text{serialized}}(p_i)$ and $N_K^{\text{original}}(p_i)$ represent the set of K-nearest neighbors of the query point p_i in the serialized 1D sequence and original 3D space, respectively, $|N_K^{\text{serialized}}(p_i) \cap N_K^{\text{original}}(p_i)|$ represents the number of neighbors that are common between the serialized neighborhood and the original spatial neighborhood. A higher NPR value indicates better preservation of the original spatial topology, as more neighbors from the original 3D space are retained in the serialized neighborhood. In extreme cases, if NPR equals 1, it means the serialization perfectly preserves the spatial locality for all points. Fig. 4 provides a clear illustration for the definition of NPR.

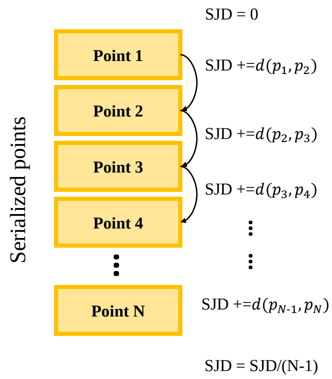


Figure 5. Illustration of the definition of SJD.

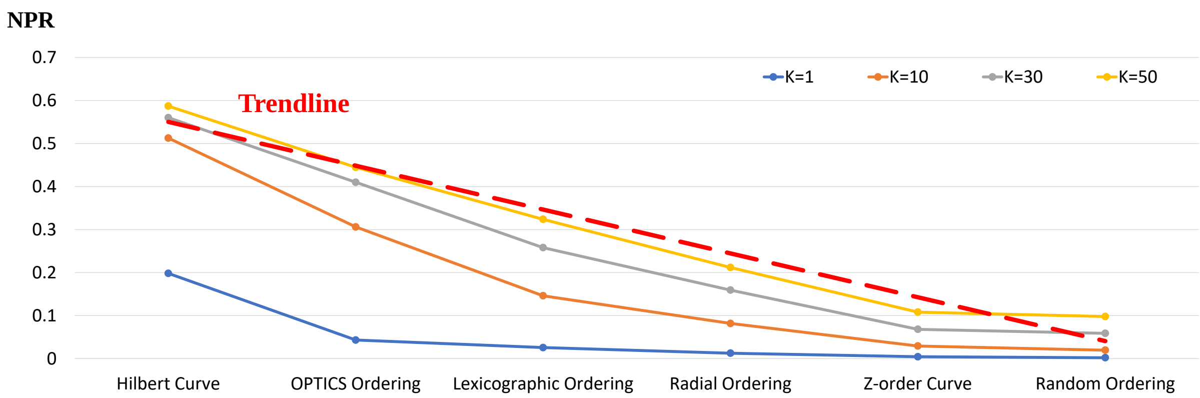
Sequence Jump Distance (SJD). SJD is defined as the average 3D spatial distance between sequentially adjacent points in the serialized 1D sequence. It quantifies how well the original spatial locality of points in the 3D point cloud is preserved after serialization. Mathematically, it can be expressed as:

$$\text{SJD} = \frac{1}{N-1}\sum_{i=1}^{N-1} d(p_i, p_{i+1}), \tag{2}$$

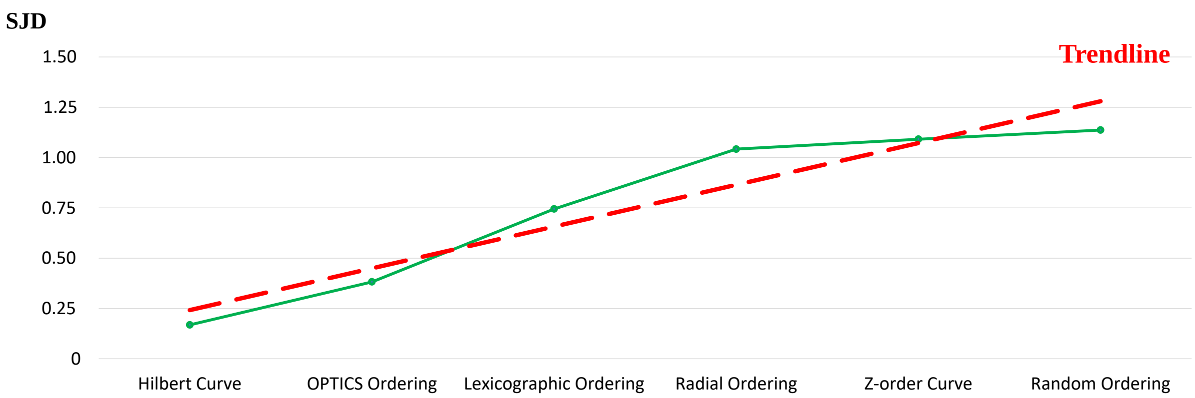
where N represents the total number of points, p_i and p_{i+1} represent consecutive points in the serialized sequence, $d(p_i, p_{i+1})$ represents the Euclidean distance between the two points in 3D space. A lower SJD value indicates better preservation of spatial proximity, as points that are close in 3D space remain close in the serialized sequence. Fig. 5 provides a clear illustration for the definition of SJD.

We applied the NPR and SJD indicators to evaluate the investigated serialization methods and summarized their performance on the DALES test set, as shown in Table 3. To comprehensively assess the effectiveness of different serialization methods, we calculated NPR at various K values. The results indicate that the Hilbert curve consistently outperforms other methods across all K-values, achieving the highest NPR scores. This demonstrates that the Hilbert serialization effectively preserves the original spatial neighborhoods, leading to superior retention of the local geometric and topological structures of the point cloud. Additionally, Hilbert achieves the lowest SJD score, reflecting its ability to maintain spatial continuity with minimal distortion in the serialized sequence.

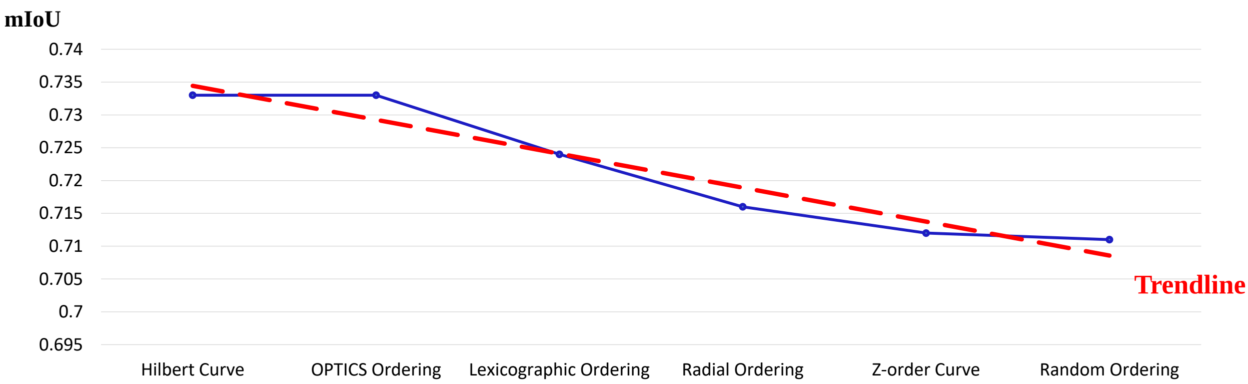
The results also reveal a clear correlation between the evaluated serialization methods' accuracy on the DALES dataset and their performance on the proposed indicators. As shown in Fig. 6, higher NPR scores are strictly positively correlated with greater



(a) Comparison results of investigated serialization methods, measured by NPR with different K values (K = 1, 10, 30, 50)



(b) Comparison results of investigated serialization methods, measured by SJD



(c) Comparison results of investigated serialization methods, measured by mIoU

Figure 6. Comparison results of investigated serialization methods, measured by NPR (a), SJD (b), and mIoU (c), respectively. From the results, there is a strict correlation between the proposed indicators and the model accuracy.

accuracy (measured by mIoU), while lower SJD scores exhibit a strict negative correlation. This alignment underscores the reliability of the proposed indicators in quantifying serialization quality. Moreover, the consistency of NPR across different K-values for the investigated methods highlights the robustness of the indicators.

Overall, these comparative results demonstrate the validity and robustness of our indicators in assessing serialization quality. They further confirm that preserving the spatial topology and geometric relationships in serialized point clouds is a critical factor influencing Mamba's performance. This provides valuable insights for future efforts to enhance Mamba's capabilities and guides the design of more effective serialization methods for point cloud processing.

5. Conclusion

This study demonstrates the effectiveness and significant potential of Mamba-based models in LiDAR point cloud processing. Through evaluating two representative Mamba-based algorithms, PointMamba and PointCloudMamba, we confirmed their capability to handle the challenges posed by unordered and irregular point cloud data while achieving promising results in segmentation tasks. These findings highlight Mamba's suitability for processing complex point cloud data, reinforcing its potential for broader applications in the field. Additionally, we conducted an in-depth analysis of token serialization and its impact on Mamba's performance. By introducing two novel indicators—Neighbor Preservation Ratio (NPR) and Sequence Jump Distance (SJD)—we provided a comprehensive framework to evaluate serialization quality. The results revealed that serialization plays a critical role in preserving spatial topology and geometric relationships, which are essential for enhancing Mamba's performance. Methods like Hilbert and OPTICS were shown to excel in maintaining these relationships, resulting in improved segmentation accuracy.

Overall, this work not only underscores the potential of Mamba-based models for LiDAR point cloud processing but also provides meaningful insights into the importance of serialization strategies. These findings offer valuable guidance for optimizing Mamba's performance and designing more effective serialization methods to unlock its full potential in point cloud analysis.

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