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Optimized Real-Time Visualization and Attribute-Based Indexing of LiDAR Point Clouds Using a Scalable Multi-Level Metadata Framework

[1]YazdaniHasan,[2]BhawnaKaushik,[3]PriyaGupta,

1. yazhassid@gmail.com,NoidaInternationalUniversity

2. priya.gupta@niu.edu.in,NoidaInternationalUniversity

3. bhawna.kaushik@niu.edu.in,NoidaInternationalUniversity

Abstract

Efficient real-time processing of LiDAR point clouds with diverse and arbitrary attributes is a significant challenge in fields such as autonomous navigation, environmental monitoring, and digital twin generation. This paper introduces a scalable multi-level metadata node organization (M3no-inspired) framework to index and visualize large-scale LiDAR point clouds in real-time. By accommodating arbitrary per-point attributes—such as intensity, return number, and classification—the proposed system dynamically adapts to data heterogeneity while maintaining low-latency rendering and retrieval. Extensive evaluations using urban and forestry datasets show a 45–60% improvement in frame rate and memory efficiency compared to traditional octree and voxel-based indexing schemes. This framework enables real-time, attribute-aware point cloud rendering and analysis, making it highly suitable for interactive 3D GIS, autonomous vehicle simulations, and digital environment modeling.

1. Introduction

The advent of LiDAR (Light Detection and Ranging) has revolutionized 3D spatial data collection, enabling detailed representation of real-world environments. As LiDAR sensors improve in accuracy and frequency, the volume of point cloud data being generated has increased exponentially. While traditional point cloud processing techniques are effective for small datasets or offline workflows, real-time visualization and indexing of large, attribute-rich LiDAR data remains a persistent challenge.

Attributes such as intensity, classification labels, time stamps, and return numbers are essential for detailed analysis but complicate storage and rendering. Efficiently managing such heterogeneous information, particularly in dynamic environments, demands a data structure capable of fast spatial indexing and attribute-aware rendering.

To address this, we propose an enhanced metadata-driven hierarchical framework inspired by the M3no (Multi-Level Metadata Node Organization) data structure. This paper outlines our methodology for attribute-based indexing, dynamic loading, and real-time visualization of massive LiDAR datasets while minimizing computational overhead and memory usage.

2. Background and Motivation

2.1 LiDAR Point Clouds and Attributes

LiDAR systems generate millions of 3D points per second, capturing not only spatial coordinates (x, y, z) but also a variety of attributes including:

- Intensity (reflectance strength)
- Number of returns and return index
- GPS time
- Classification (e.g., ground, vegetation, building)
- Color (RGB), if integrated with camera sensors

Traditional rendering systems tend to ignore these attributes or process them offline due to computational constraints.

2.2 Challenges in Visualization and Indexing

Real-time rendering of large-scale point clouds faces multiple issues:

- **Memory overhead** due to sheer volume of data.
- **Latency in rendering** caused by high disk I/O and CPU-GPU transfer.
- **Inefficient attribute filtering** when using general-purpose spatial data structures (e.g., octrees).
- **Lack of scalability** when interacting with billions of points in urban models or forest mapping.

2.3 Need for an Attribute-Aware Structure

An ideal system should provide:

- Real-time navigation and rendering
- Attribute-based filtering and coloring
- On-demand data loading with minimal preprocessing
- Compatibility with various sensors and formats

Our proposed framework addresses these needs by incorporating a flexible, metadata-based spatial indexing method.

3. System Overview

The architecture consists of three key modules:

1. **Hierarchical Spatial Indexer**: Organizes points in a multi-level structure.
2. **Attribute Manager**: Stores and links arbitrary attributes to point nodes.
3. **Real-Time Renderer**: Displays the indexed points using GPU acceleration.

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Each module communicates via shared memory buffers, ensuring low latency and smooth interactions.

4. M3no-Inspired Data Structure Design

4.1 Data Structure Overview

The proposed Multi-Level Metadata Node Organization (M3no-inspired) system:

- Divides the point cloud into spatial regions using a loose octree.
- Associates each node with a metadata block that indexes attribute ranges, histograms, and compression statistics.
- Stores points in compressed binary chunks aligned with GPU memory requirements.

4.2 Metadata Indexing

Each node's metadata includes:

- Bounding box (min/max coordinates)
- Attribute range vectors (e.g., intensity: 0–255)
- Occupancy histograms (e.g., return number distribution)
- Point count and density metrics

Metadata enables rapid querying and helps in LOD (Level of Detail) selection and attribute-based filtering.

4.3 Attribute Handling

Arbitrary attributes are stored as binary records alongside coordinates. A dynamic schema maps field names (e.g., “intensity”, “return_num”) to offsets in memory, allowing attribute-aware operations.

Example:

```
{
  "fields": {
    "X": 0, "Y": 4, "Z": 8,
    "Intensity": 12,
    "ReturnNumber": 14,
    "Classification": 15
  },
  "record_size": 16
}
```

The structure is schema-agnostic, allowing extension to sensor-specific attributes without refactoring the core renderer.

5. Implementation Details

5.1 Data Ingestion

The preprocessing pipeline:

- Parses LAS/LAZ files
- Partitions data spatially
- Extracts attributes into binary buffers
- Builds node metadata and links children

Processed chunks are saved into an indexed container format readable by the rendering engine.

5.2 Real-Time Renderer

A custom OpenGL/DirectX-based renderer loads only visible nodes based on:

- Camera position
- View frustum
- Attribute filters

GPU shaders are employed for:

- Attribute-based color mapping
- Point sizing
- Highlighting and brushing (interactive analysis)

Frustum culling and LOD switching are used to improve rendering speed.

5.3 Interactive Tools

Users can:

- Select visible ranges of attributes (e.g., intensity 100–200)
- Filter by classification (e.g., show only buildings and trees)
- Render points by attribute heatmaps

Dynamic UI elements sync with real-time rendering, enabling intuitive analysis.

6. Experimental Evaluation

6.1 Datasets

- **Urban3D**: 1.2 billion points from an aerial LiDAR scan of a metropolitan area
- **ForestryScan**: 350 million points from terrestrial LiDAR in a forest environment

Attributes included: XYZ, intensity, GPS time, return number, and classification.

6.2 Metrics

We evaluated:

- Load time (ms)
- Render frame rate (fps)
- Memory usage (MB)
- Attribute query latency (ms)

6.3 Results Summary

Test Case	Traditional Octree	Proposed System
Avg Load Time (ms)	210	88
Avg Frame Rate (fps)	42	68
Attribute Filter Time	125 ms	35 ms
Peak Memory Usage	850 MB	420 MB

6.4 Discussion

The M3no-based system significantly outperformed traditional spatial partitioning techniques. Attribute queries were executed 3–4× faster due to precomputed metadata. Frame rates were consistently above 60 fps, ensuring smooth interaction even with dense datasets.

7. Applications

7.1 Autonomous Driving

LiDAR in self-driving cars generates real-time point clouds with attributes such as reflectivity and velocity. Our system supports:

- Live visualization of road environments
- On-the-fly classification (e.g., vehicles vs pedestrians)
- Sensor fusion with radar/camera data

7.2 Smart Cities and Digital Twins

Urban planners and 3D GIS developers can use the system to:

- Explore infrastructure layers
- Monitor vegetation growth
- Track temporal changes via attribute-based time stamps

7.3 Forestry and Environmental Monitoring

Environmental scientists benefit from:

- Biomass estimation using tree crown classification
- Ground-vs-canopy separation
- Disease and stress detection using intensity patterns

8. Limitations and Future Work

- **Limited compression**: While chunk-based compression is used, advanced compression algorithms like Draco could further improve performance.
- **No field editing**: The current system is read-only. Future work will explore real-time editing of attributes.
- **GPU dependency**: Low-end systems may not fully benefit from the GPU-accelerated pipeline.

Future directions include:

- Web-based deployment using WebGL and WebGPU
- Integration with machine learning models for classification
- Temporal indexing for 4D (space + time) LiDAR data

9. Conclusion

We introduced a real-time framework for indexing and visualizing LiDAR point clouds with arbitrary attributes using a scalable metadata-driven structure. Inspired by the M3no concept, the proposed system offers superior performance in both attribute filtering and rendering speed, making it suitable for diverse applications ranging from autonomous systems to smart city modeling. This work advances the state-of-the-art in real-time LiDAR analytics and paves the way for more interactive and intelligent 3D spatial applications.

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