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Research on Urban 3D Data Management and Representation Method Based on BeiDou Grid Code

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Abstract:
With the advancement of urbanization and digital twin city development, urban 3D data are characterized by large volume, heterogeneity, and structural complexity. Traditional spatial data management methods face limitations in hierarchical organization, retrieval efficiency, and redundancy control, and the lack of a unified spatial coding system hinders multi-source data integration. This paper proposes a method for urban 3D data management and representation based on BeiDou grid coding and adaptive voxel modeling. The method converts point cloud data from local coordinates to the 2000 National Geodetic Coordinate System, applies 36-bit 3D BeiDou grid coding, performs adaptive octree voxel partitioning based on point cloud density, elevation variation, and class entropy, and binds spatial, geometric, and semantic attributes at the voxel level. Using the SensatUrban dataset, the method is compared with fixed-resolution voxel modeling, latitude-longitude indexing, and R-tree indexing in terms of voxel quantity, data storage, and retrieval time. Results show that it reduces voxel count by 28.1% and storage volume by 13.6% while maintaining high-precision representation, and the BeiDou grid-based indexing significantly improves query efficiency and stability. The proposed approach balances visualization quality and computational efficiency, providing an effective solution for large-scale urban 3D data management.

1. Introduction

With the continuous advancement of urbanization, urban spatial structures have become increasingly complex, and the demand for refined management and intelligent applications has grown significantly. The development of digital twin cities and high-precision spatial data acquisition technologies has led to the rapid accumulation of urban 3D data, such as terrestrial laser scanning point clouds, photogrammetric models, and multi-source imagery, which have become essential foundations for urban planning, infrastructure management, and spatial analysis. However, when facing large-scale and heterogeneous 3D data, traditional spatial data management methods still exhibit evident limitations in hierarchical organization, retrieval efficiency, and data redundancy control. Meanwhile, the lack of a unified spatial coding system has, to some extent, constrained the integration and efficient management of multi-source data.
In response to the above challenges, researchers both domestically and internationally have conducted extensive studies in multi-source data fusion, 3D modeling, and spatial data organization. In terms of multi-source data fusion and 3D modeling, Youn et al. [6] integrated mobile mapping, LiDAR, and photogrammetric data to construct high-precision urban 3D scenes and employed lightweight mesh structures to achieve efficient data organization. Dreščєk et al. [1] proposed a spatial ETL method based on photogrammetric point clouds to generate semantic building models at LOD2 that conform to the CityGML standard, thereby improving the standardization and structuring of urban 3D data.

Regarding large-scale data storage and indexing, existing studies mainly rely on distributed computing frameworks and spatial coding methods to enhance data management capabilities. Feng [2] constructed a distributed spatial data storage system based on HBase and achieved efficient indexing by combining quadtree and Hilbert curve encoding. Ma [4] utilized GeoSOT coding and the Spark framework to realize unified management and rapid retrieval of multi-source remote sensing imagery and point cloud data. Zhang [7] designed a spatial data management system based on the Hadoop platform and improved data access efficiency through customized indexing mechanisms. Although these methods have improved the storage and query performance of massive urban 3D data to a certain extent, they still show limitations in unified coding and multi-scale representation.

In terms of spatial organization models and unified representation, research has gradually evolved toward multi-model integration and unified coding. Lu [3] proposed a method that integrates voxel models with global grid systems to address the difficulty of unified representation of voxel data under different coordinate systems. Ren [5] constructed an association model of urban components and events based on global grid coding, enabling unified encoding of spatial, temporal, and semantic information, and improving the organization and analysis capability of multi-dimensional data. In addition, Zhou [8] achieved efficient organization and semantic segmentation of large-scale point cloud data by optimizing point cloud sampling and feature encoding methods.

Overall, existing studies have made certain progress in multi-source data fusion, distributed storage, and semantic modeling; however, there are still deficiencies in unified spatial coding, multi-scale data organization, and efficient indexing mechanisms. To address these issues, this paper proposes a method for urban 3D data management and representation based on BeiDou grid coding and adaptive voxel modeling. By constructing a unified spatial coding system and a multi-resolution data structure, the proposed method achieves efficient organization, rapid retrieval, and refined representation of large-scale urban 3D data.

2. Methods

To address the challenges of large volume, complex structure, and multi-source heterogeneity in large-scale urban 3D data, traditional 3D data organization methods generally suffer from low spatial indexing efficiency, fragmented semantic information, and difficulties in multi-source data integration. These limitations hinder the efficient storage, rapid retrieval, and integrated management of 3D data in scenarios such as smart cities, digital twins, and natural resource monitoring. To this end, this paper proposes a unified 3D spatial representation method that integrates BeiDou grid coding with adaptive voxel modeling. This method uses multi-source heterogeneous point cloud data as the core input and performs preprocessing procedures including noise point filtering, coordinate system unification, and block slicing to standardize and normalize the multi-source data. Based on this, leveraging the globally unified, hierarchical, and multi-scale spatial coding system of the BeiDou Grid Code, it accomplishes full-domain 3D spatial coding and positional anchoring. By combining multi-indicator complexity analysis with an octree structure, the method achieves dynamic adaptive voxel partitioning and fine-grained modeling. Finally, through voxel-level semantic encoding, spatial positions, geometric features, and semantic attributes are deeply bound, forming a 3D data organization model that provides both efficient spatial indexing and complete semantic representation. This framework offers a unified technical solution for integrated storage, rapid retrieval, and intelligent applications of large-scale urban 3D data. The overall workflow is shown in Figure 1 and comprises the following key components:

(1) Transformation from local coordinates to a unified geodetic coordinate system;
(2) Three-dimensional spatial encoding based on the BeiDou grid;
(3) Octree-based adaptive voxel partitioning and modeling based on multi-indicator complexity analysis;
(4) Voxel-level binding and unified representation of spatial–geometric–semantic attributes.

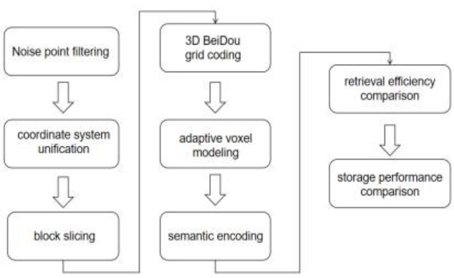


Figure 1. Technical Methodology

2.1 Coordinate Unification

To ensure the consistency and standardization of spatial data, the CGCS2000 geodetic coordinate system is adopted as the unified spatial reference, and urban point cloud data are transformed from a local engineering coordinate system (ENU) to the geodetic coordinate system. Let the local coordinates be (x,y,z), and the reference origin be (L_0, B_0, H_0) . The transformation formulas for the target point in geodetic coordinates (L,B,H) are as follows:

$$\Delta B = \frac{y}{M_0}, \quad B = B_0 + \Delta B_\omega \tag{1}$$

$$\Delta L = \frac{x}{N_0 \cos B_0}, \quad L = L_0 + \Delta L_\omega \tag{2}$$

$$H = H_0 + z \tag{3}$$

where M_0 and N_0 denote the meridional radius of curvature and the prime vertical radius of curvature, respectively. This model realizes the unified transformation between local coordinates and the national geodetic coordinate system, providing standardized input for subsequent spatial encoding.

2.2 Three-dimensional BeiDou grid encoding

The BeiDou Grid Code is a global geospatial grid coding model, derived from the GeoSOT hierarchical grid partitioning. It provides a method for discrete, multi-scale hierarchical, and unified positional identification and representation, which can be used to specify locations of spatial regions worldwide. Compared with the traditional latitude-longitude system, the BeiDou Grid Code addresses a series of challenging issues related to multi-scale representation, uniqueness, hierarchical correlation, and object information expression in large-scale spatial data. It can assign a globally unique one-dimensional integer code to grids of various sizes on Earth and can be associated with any physical object to establish correspondence with spatial locations. Within the same spatial region, the BeiDou Grid Code enables convenient identification and management of spatial information.

In this study, a 36-bit 3D BeiDou Grid Code is employed to perform standardized and unified coding of massive urban spatial data, enabling high-precision spatial positioning across the entire urban area and establishing a standardized coding foundation for the subsequent organization, storage, and retrieval of urban 3D data. The 36-bit 3D BeiDou Grid Code adopts a hierarchical coding structure, consisting of a 24-bit horizontal code and a 12-bit vertical code. The specific conversion and calculation formulas for this coding scheme are presented below, and the implementation mechanisms of the horizontal and vertical codes are illustrated in Figures 2 and 3, respectively.

$$a_g = \frac{(\lambda_{lng} - \lambda_{L-1})}{\Delta\lambda} + 1 \tag{4}$$

$$b_g = \frac{(\phi_{Lat} - \phi_{L-1})}{\Delta\phi} + 1 \tag{5}$$

$$n = \frac{\theta_0}{\theta}\left(\log_{(1+\theta_0)}\left(\frac{H + r_0}{r_0}\right)\right) \tag{6}$$

Among them, the two-dimensional code is obtained by calculating the row and column numbers (a_g, b_g) of the target longitude and latitude $(\lambda_{lng}, \phi_{Lat})$ relative to the grid's starting corner point$(\lambda_{L-1},\phi_{L-1})$. Meanwhile, the 12-bit height code n is used to ensure high-precision division in the vertical direction. This code is derived by applying a logarithmic mapping to the absolute elevation H.

Code Position	Level / Information	Value Range	Core Function
Digit 1	Hemisphere	N (Northern Hemisphere), S (Southern Hemisphere)	Determines global hemisphere location
Digits 2-4	Level 1 Grid	Digits 2-3 (Longitude): 01–60; Digit 4 (Latitude): A–V	Corresponds to 1:1,000,000 map scale, macro-level positioning
Digits 5-6	Level 2 Grid	Digit 5 (Longitude): 0–B (12 values); Digit 6 (Latitude): 0–7 (8 values)	Refines to 30′ × 30′ region
Digit 7	Level 3 Grid	0–5 (6 values, Z-order encoding)	Represents 15′ × 10′ grid, suitable for 1:50,000 maps
Digits 8-9	Level 4 Grid	Digit 8 (Longitude): 0–E (15 values); Digit 9 (Latitude): 0–9 (10 values)	Locates 1′ × 1′ region
Digits 10-11	Level 5 Grid	Digit 10 (Longitude): 0–E; Digit 11 (Latitude): 0–E (15 values each)	Refines to ~123.69 m resolution
Digit 12	Level 6 Grid	0–3 (4 values, Z-order encoding)	Locates ~61.84 m resolution
Digits 13-14	Level 7 Grid	0–7 (8 values each)	Refines to ~7.73 m resolution
Digits 15-16	Level 8 Grid	0–7 (8 values each)	Locates ~0.97 m resolution (≈1 m accuracy)
Digits 17-18	Level 9 Grid	0–7 (8 values each)	Refines to ~12 cm resolution
Digits 19-20	Level 10 Grid	0–7 (8 values each)	Locates ~1.5 cm resolution (highest precision)

Figure 2. Schematic diagram of the horizontal encoding mechanism

Height Code Position (Digits 21–32)	Vertical Level	Value Range	Core Function
Digit 21 (a0)	Initial Vertical Grid (Above/Below Surface)	0 (Above Ground), 1 (Underground)	Defines vertical reference (positive/negative direction)
Digits 22–23 (a1–a2)	Level 1 Vertical Grid	00–63 (64 values)	Coarse height partition (~445.28 km resolution)
Digit 24 (a3)	Level 2 Vertical Grid	0–7 (8 values)	Refines Level 1 (~55.66 km resolution)
Digit 25 (a4)	Level 3 Vertical Grid	0–1 (2 values)	Refines Level 2 (~27.83 km resolution)
Digit 26 (a5)	Level 4 Vertical Grid	0–9, A–E (15 values)	Refines Level 3 (~1.85 km resolution)
Digit 27 (a6)	Level 5 Vertical Grid	0–9, A–E (15 values)	Refines Level 4 (~123.69 m resolution)
Digit 28 (a7)	Level 6 Vertical Grid	0–1 (2 values)	Refines Level 5 (~61.84 m resolution)
Digit 29 (a8)	Level 7 Vertical Grid	0–7 (8 values)	Refines Level 6 (~7.73 m resolution)
Digit 30 (a9)	Level 8 Vertical Grid	0–7 (8 values)	Refines Level 7 (~0.97 m resolution ≈ 1 m accuracy)
Digit 31 (a10)	Level 9 Vertical Grid	0–7 (8 values)	Refines Level 8 (~12.1 cm resolution)
Digit 32 (a11)	Level 10 Vertical Grid	0–7 (8 values)	Refines Level 9 (~1.5 cm resolution, highest precision)

Figure 3 Schematic diagram of the vertical (height) encoding mechanism

2.3 Adaptive voxel modeling

Based on spatial complexity features, an adaptive voxel subdivision model was designed. This model uses three core criteria within each voxel—point cloud density, elevation variation, and class entropy—to dynamically identify local complexity characteristics in three-dimensional space. It supports voxel units to be further subdivided down to a minimum resolution of 0.25 meters, effectively mitigating the spatial redundancy problem inherent in fixed-resolution modeling. The modeling results at different voxel resolutions are shown in Figure 4. The definitions of the above three spatial complexity evaluation metrics are described as follows:

$$\begin{cases} \rho = \dfrac{N}{V_s{}^3} \\ \sigma = \dfrac{\sqrt{\sum_{i=1}^{N}(z_i - \bar{z})^2}}{N}, \quad \bar{z} = \dfrac{\sum_{i=1}^{N} z_i}{N} \\ H = -\sum_{k=1}^{M} p_k \log_2(p_k) \end{cases} \tag{7}$$

Among them, ρ is used to measure the degree of point aggregation, σ characterizes the complexity of surface undulation, and H reflects the degree of semantic information mixture, serving as a key factor for achieving semantic-driven adaptive subdivision.

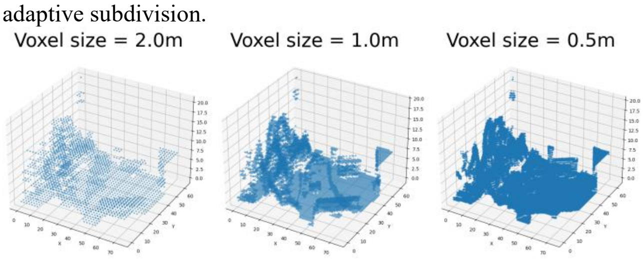


Figure 4 Comparison of 3D modeling effects under different voxel resolutions

2.4 Adaptive Voxel Subdivision Strategy

Based on the complexity evaluation results, an octree-based recursive subdivision strategy is adopted to perform adaptive voxel refinement. When the voxel complexity exceeds a predefined threshold, the voxel is subdivided according to the following formula:

$$s_{child} = \frac{S_{parent}}{2} \tag{8}$$

where s_{parent} and s_{child} denote the edge lengths of the parent voxel and the child voxel, respectively.
The subdivision process terminates when the minimum voxel size or the maximum hierarchy level is reached. Through this strategy, high-resolution voxels are generated in complex regions, while larger voxels are preserved in simple regions, thereby achieving a balance between representation accuracy and computational efficiency.

2.5 Attribute binding and semantic representation

Each voxel stores three categories of attribute information — spatial, geometric, and semantic — and integrates them through attribute fusion to form a unified "space–geometry–semantics" voxel unit, thereby enhancing semantic retrieval and three-dimensional representation capabilities.

3. RESULTS AND ANALYSIS

3.1 Experimental Data and Experimental Setup

The experimental data used in this study are derived from the SensatUrban large-scale urban point cloud dataset, which covers typical urban features such as buildings, roads, and vegetation, and can fully reflect the heterogeneity and structural complexity of urban three-dimensional space. All experiments were conducted under a unified hardware environment to ensure the fairness and comparability of performance evaluation results.
In this study, the proposed adaptive voxel modeling method based on BeiDou grid codes is taken as the experimental group, while the traditional fixed-resolution voxel modeling method, the latitude–longitude indexing method, and the R-tree indexing method are selected as control groups. Three core evaluation metrics, including the number of voxel units, data storage volume, and retrieval response time, are designed for performance validation. The retrieval performance tests include typical scenarios such as spatial range queries and semantic joint queries. Multiple repeated experiments are conducted and averaged to ensure the reliability of the results.

3.2 Analysis of Raw Data and Voxel Modeling Representation Results

In this study, the raw point cloud data are first preprocessed through coordinate unification and noise removal. The preprocessed experimental data are shown in Fig. 5. The processed data retain the complete spatial characteristics of typical features such as buildings, roads, and vegetation, providing a standardized data foundation for subsequent voxel modeling.
The adaptive voxel modeling results based on BeiDou grid codes are shown in Fig. 6. This method determines voxel complexity using point density, elevation variation, and category entropy as core indicators, and performs adaptive subdivision through octree-based recursive partitioning. The modeling representation performance is significantly better than that of the traditional fixed-resolution voxel modeling method. In complex spatial regions such as building edges and densely vegetated areas, the method automatically generates high-resolution voxels, accurately restoring the spatial distribution characteristics and detailed morphology of features. In simple regions such as roads and flat open areas, low-resolution voxels are adopted, significantly simplifying

data organization while ensuring the completeness of spatial representation.

Meanwhile, through voxel-level fusion and binding of spatial–geometric–semantic attributes, an integrated representation of urban 3D data is achieved, enabling each voxel unit to simultaneously possess a unique spatial identifier, accurate geometric parameters, and explicit semantic information, thereby providing a foundation for subsequent spatial analysis and data applications.

Figure 5. Preprocessed raw point cloud data

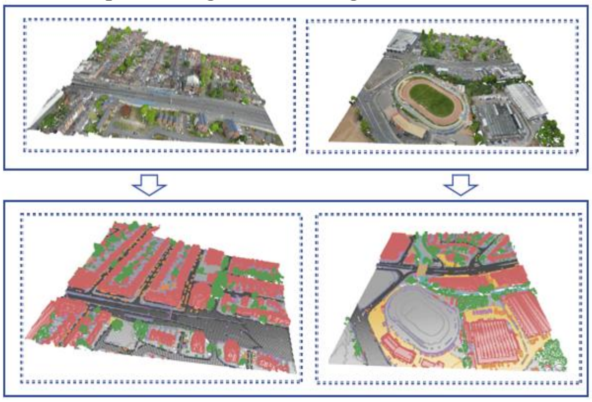


Figure 6. Adaptive voxel modeling results based on BeiDou grid code

3.3 Analysis of Voxelized Data Organization Results

The overall data organization results of the adaptive voxel modeling method based on BeiDou grid codes are shown in Fig. 7. This method constructs an integrated data organization framework of "BeiDou grid coding – geometric attributes – semantic attributes," transforming the preprocessed point cloud data into voxel units with unique spatial codes and achieving efficient conversion from point cloud data to structured voxel data.

Each voxel unit is uniquely bound to a 36-bit three-dimensional BeiDou grid code, which integrates high-precision spatial location information in both planar and elevation dimensions. At the same time, it is associated with geometric attributes such as voxel size and geographic coordinates, as well as semantic attributes such as primary and secondary feature categories, forming a hierarchical and comprehensive three-dimensional data organization structure. This data organization model not only realizes the unique spatial identification of voxel units but also completes the integrated association of multi-dimensional attributes, addressing the problem of separation among spatial, geometric, and semantic information in traditional 3D data organization, and improving the structured management level of urban 3D data.

Longitude	Latitude	Height	main_class	sub_class	voxel_size	semantic_code	beidou_code
-1.872572	52.497093	166.3309	Natural Elements	Vegetation	0.25	010256691006853	N30N870799C226715056000000105407
-1.87256	52.498535	165.56117	Natural Elements	Vegetation	0.25	010268253600649	N30N870799D332170156000000105324
-1.8725612	52.498043	165.09097	Natural Elements	Ground	1	0101728972591961	N30N870799D233067442000000105265
-1.8725997	52.497368	166.09146	Natural Elements	Ground	0.5	0101500316592639	N30N870799C322404507000000105367
-1.8723124	52.497383	155.4855	Natural Elements	Ground	0.5	0101305155593139	N30N870799C362524460000000104071
-1.8721472	52.497356	155.52321	Engineering Facilities	Parking	0.5	0204597409366560	N30N87079AC111075313000000104074
-1.8721507	52.49735	155.43349	Engineering Facilities	Parking	0.5	0204891908366662	N30N87079AC111061473000000104066
-1.8721253	52.49657	156.16057	Engineering Facilities	Wall	0.35	0202614543733747	N30N87079AB116341721000000104146
-1.8721472	52.497356	155.52321	Engineering Facilities	Wall	0.35	0202855288733861	N30N870799C223605357000000105250
-1.8725592	52.497066	162.33345	Engineering Facilities	Street Furniture	1	0205978567387776	N30N870799C235161032000000104775
-1.872549	52.496525	164.14745	Engineering Facilities	Street Furniture	1	0205963523400140	N30N870799B335272560000000105167
-1.8725764	52.497856	163.54152	Engineering Facilities	Building	0.25	0201482505462342	N30N870799D221701747000000105117
-1.87262	52.49725	164.15523	Engineering Facilities	Building	0.25	0201165631484041	N30N870799C320231130000000105167
-1.8726265	52.497246	161.50804	Engineering Facilities	Building	0.25	0201152858488052	N30N870799C320123523000000104707
-1.8723212	52.497375	156.41304	Transportation Vehicles	Car	0.3	0304264594579866	N30N870799C370370715000000104125
-1.872634	52.497013	163.97833	Transportation Vehicles	Car	0.3	0304091572579961	N30N870799C362414550000000104167

Figure 7. Structured attribute table of voxel units based on BeiDou grid code

3.4 Comparison Results of Retrieval Performance

The comparison results of retrieval performance for different indexing methods are shown in Fig. 8. In this study, the latitude–longitude indexing method and the R-tree indexing method are selected as controls to verify the retrieval efficiency advantages of the BeiDou grid code-based indexing method.

The experimental results indicate that the retrieval method based on BeiDou grid codes significantly outperforms the traditional latitude–longitude indexing method and the R-tree indexing method in terms of retrieval speed. The traditional latitude–longitude indexing method requires point-by-point traversal and matching of coordinate information, and its retrieval time increases linearly with the data volume, resulting in the lowest retrieval efficiency. Although the R-tree indexing method provides certain optimization for spatial retrieval, it is prone to redundancy in index hierarchy under complex multi-condition joint query scenarios, leading to unstable retrieval performance. In contrast, the BeiDou grid code adopts a multi-level recursive subdivision encoding structure, enabling structured representation of spatial locations and voxel-level unique indexing. The retrieval process can rapidly filter target regions through hierarchical code matching, significantly reducing data traversal. It maintains stable and high-speed retrieval performance in both simple spatial queries and complex joint query scenarios, demonstrating its advantages in large-scale urban 3D data retrieval.

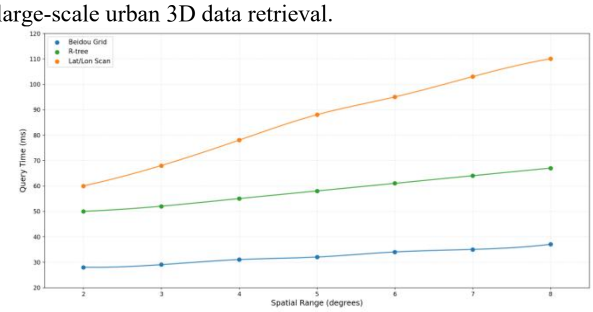
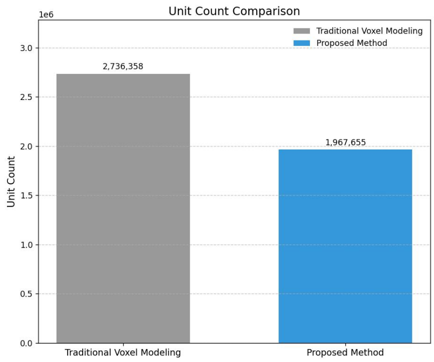


Figure 8. Retrieval efficiency comparison

3.5 Comparison Results of Storage Performance

The comparison results of the number of voxel units and data storage volume are shown in Fig. 9. In this study, the storage performance of the proposed adaptive voxel modeling method is quantitatively compared with that of the traditional fixed-resolution voxel modeling method.

The experimental results show that the adaptive voxel modeling method based on BeiDou grid codes is significantly superior to the traditional method in terms of storage efficiency. In terms of the number of voxel units, through accurate complexity evaluation and differentiated subdivision, the proposed method achieves a 28.1% reduction in voxel quantity compared with the traditional method while maintaining representation accuracy, thereby significantly reducing the basic storage burden caused by redundant voxel units. In terms of data storage volume, by leveraging the integrated spatial indexing design of BeiDou grid codes, spatial location information is embedded into unique codes, eliminating the need to store detailed voxel coordinate information separately. Combined with the reduction in voxel quantity, a total storage reduction of 13.6% is achieved. The dual reduction effect significantly improves the overall storage efficiency of urban 3D data, effectively alleviates the storage pressure of large-scale point cloud data, and is more suitable for long-term storage and management of massive urban-level 3D data.



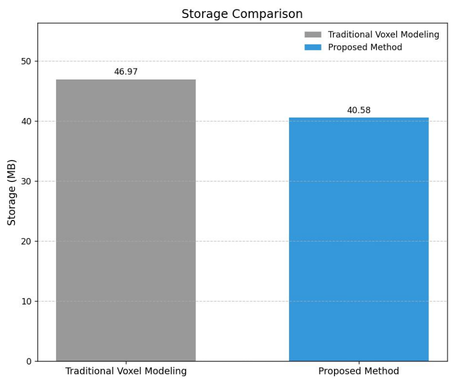


Figure 9. Storage performance comparison

3.6 Summary of This Chapter

This study takes the SensatUrban dataset as the experimental basis and conducts multi-dimensional performance comparisons between the proposed adaptive voxel modeling method based on BeiDou grid codes and traditional methods under a unified experimental environment. Combined with the results shown in Fig. 5 to Fig. 9, the effectiveness and superiority of the proposed method are fully verified.

First, the method completes standardized preprocessing of raw point cloud data and achieves a balance between high-precision representation in complex regions and data simplification in simple regions through an adaptive voxel subdivision strategy. At the same time, it realizes integrated representation of spatial–geometric–semantic information through attribute fusion, improving the representation capability and structural level of urban 3D data.

Second, an integrated data organization framework based on BeiDou grid codes is constructed, which resolves the problem of information separation in traditional 3D data and achieves unique spatial identification and multi-dimensional attribute association of voxel units.

Third, the indexing mechanism based on BeiDou grid codes significantly outperforms traditional methods such as latitude–longitude indexing and R-tree indexing in retrieval speed, with more pronounced advantages in complex query scenarios, meeting the requirements for rapid retrieval of large-scale 3D data.

Finally, while ensuring representation accuracy, the method achieves a dual reduction of 28.1% in voxel quantity and 13.6% in storage volume, thereby improving data storage efficiency. Overall, the proposed method effectively addresses the limitations of traditional urban 3D data management in terms of representation accuracy, data organization, retrieval efficiency, and storage load, and provides a feasible solution for the efficient management and application of large-scale urban 3D data.

4. Conclusions

This paper proposes a method for urban 3D data management and representation based on BeiDou grid coding and adaptive voxel modeling. Experimental results show that, compared with traditional spatial indexing and fixed-resolution voxel methods, the proposed approach reduces data storage while maintaining high representation accuracy in complex regions and achieving better retrieval efficiency in spatial queries. By introducing a unified three-dimensional spatial coding mechanism, each voxel is assigned a unique spatial identifier. Combined with a semantic-driven adaptive subdivision strategy, the method preserves detailed representations in regions of interest while reducing redundancy in simple areas, effectively balancing visualization quality and computational efficiency. This is of great significance for improving the management and application efficiency of large-scale urban 3D data. In future work, we will further explore the application of this method to larger-scale urban datasets and investigate mesh simplification and distributed computing techniques to further reduce data volume and enhance processing performance.

Although this paper proposes a three-dimensional spatial indexing method based on the BeiDou grid code, which demonstrates certain innovations in urban 3D data management and adaptive voxel modeling, several limitations remain. First, the review of related work is not comprehensive. The discussion mainly focuses on two-dimensional indexing techniques, and does not adequately compare with mainstream three-dimensional indexing structures (e.g., octree, 3D R-tree, space-filling curves, and three-dimensional extensions of GeoHash), making it difficult to clearly demonstrate the advantages of the proposed method in terms of 3D spatial query performance, storage efficiency, and scalability. Second, the experimental evaluation primarily concentrates on data storage and retrieval efficiency, while systematic quantitative analysis of key metrics, such as 3D spatial representation accuracy, the impact of semantic-driven voxels on modeling quality, and improvements in accuracy, is lacking, resulting in insufficient validation. In addition, the actual effect of semantic-driven voxels on improving model representation accuracy has not been fully revealed, which makes the advantages of the method less intuitive in certain scenarios. Finally, the paper does not clearly articulate the specific research gap being addressed or the substantive contribution of the method, and the experimental design and evaluation metrics require further refinement to more directly demonstrate the effectiveness and applicability of the approach. Future work can focus on improving the review of related work, designing multi-dimensional evaluation metrics, introducing comparative experiments, and more explicitly quantifying the role of semantic-driven voxels, thereby comprehensively verifying the advantages of the method in large-scale urban 3D data management.

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