Research on Lightweighting Methods for 3D Building Models Based on Semantic Constraints

Jia Wu[1], Tao Shen[1], Liang Huo[1]

[1] School of Geomatics and Urban Spatial Informatics, Beijing University of Civil Engineering and Architecture, No. 15, Yongyuan Road, Huangcun Town, Daxing District, Beijing, 100044, China;
wj19126444@163.com; shentao@bucea.edu.cn; huoliang@bucea.edu.cn

Keywords: Semantic Constraints, Multi-Level of Detail Models, Model Lightweighting, Triangle Mesh Simplification.

Abstract

Three-dimensional building models, as core data in Building Information Modeling, are extensively applied in various fields such as architectural design and urban planning. However, the geometric complexity and the vast amount of data involved pose significant challenges for storage, computation, and efficient application. Therefore, ensuring the geometric accuracy and semantic integrity of models while reducing data redundancy has become a critical issue in current research. To address this problem, this paper proposes a lightweighting method for 3D building models based on semantic constraints. The method combines face merging and face movement graphical simplification algorithms to simplify models from LOD3 to LOD1 in a layer-by-layer manner. In the transition from LOD3 to LOD2, a face merging algorithm is employed to analyze the semantic consistency of adjacent faces, ensuring that only semantically consistent faces are merged, thus generating an LOD2 model with semantic integrity. In the transition from LOD2 to LOD1, a concave-convex face movement and merging algorithm is utilized to reduce redundant data while maintaining geometric similarity and optimizing the model's topological structure, ultimately producing a lightweight LOD1 model. Experimental results demonstrate that the proposed method significantly reduces the model's storage requirements while effectively preserving its semantic information.

1. Introduction

With the rapid development of urban informatization and digital construction technologies, 3D building models have become one of the core elements in architectural design and management. These models not only provide an intuitive representation of geographic information (Zhu and Lin, 2004) but also offer highly realistic models for urban planning and related fields (Zhou et al., 2006). These 3D building models typically encompass rich geometric shapes and semantic information to describe multidimensional details, such as the spatial structure, functional zoning, and material characteristics of buildings. Building Information Modeling (BIM) is an interdisciplinary architectural design methodology based on the creation, management, and exchange of semantically rich 3D models (Eastman, 2011). The taxonomy of BIM information divides it into three categories: geometric, semantic, and topological information (Pratt-Hartmann, 2004). Geometric information directly relates to the shape and form of facilities, semantic information captures inherent attributes (such as function), while topological information describes the interrelationships between these objects.

The Level of Detail (LOD) model generation algorithm is one of the most common methods for lightweighting architectural models. LOD, a multi-scale model, can reflect various perspectives from macro to micro (Goetz, 2013). It describes the development of digital building models across different stages of the building's lifecycle, formalizing the progressive nature of the design process and improving decision-making quality (Hooper, 2015). The concept of LOD helps define the exchange requirements based on BIM (Li et al., 2019), with its data structure resembling a hierarchical tree, where each node represents a different LOD level. The root node contains the highest LOD mesh, and subsequent levels simplify progressively (Ge et al., 2024). LOD technology reduces geometric complexity and enhances processing efficiency by dynamically adjusting the display of models according to viewing distance and detail requirements. However, the traditional geometric element removal method, as a common LOD generation algorithm, although effective in reducing data volume, tends to overlook the semantic information of the model, leading to the loss of critical functional and structural data (Hoppe et al., 1993). The geometric element removal method simplifies models by deleting or collapsing the triangular faces (Wu and Xue, 2007), achieving the lightweighting goal. However, this simplification process neglects semantic information, which impacts the practical value of the model.

Currently, the progress of LOD algorithms for 3D building models primarily focuses on geometric simplification. Li et al. (2019) proposed a continuous detail level topology data structure method, which optimizes the data structure of urban building models and combines a minimum feature face movement algorithm to address compatibility issues in layered expressions of lightweight models. Ge et al. (2024) introduced an LOD generation method using a rapid multi-level pyramid structure and adaptive tree organization, which excels in maintaining high precision, preserving multi-level structures, and optimizing texture map occupancy, thus enhancing high frame rates for LOD model construction. Xie et al. (2012) proposed rendering 3D building models at different levels of detail (LOD) while maintaining spatial geometric accuracy and human visual preferences, reducing data pressure in 3D city model applications. Among existing geometric simplification methods, Forberg (2005) simplified 3D building features based on mathematical morphology. Baig et al. (2013), Ge et al. (2017), and Li et al. (2016) simplified building model feature surfaces by restricting the number of edges, curves, and angles in the feature planes. He et al. (2024) proposed a lightweight processing method for real-world 3D models, which simplifies the model's topological structure through edge-collapse decimation algorithms. Zhang et al. (2023) reduced the number of triangular faces on the model surface using mesh simplification algorithms, minimizing model deformation while better maintaining its geometric features.

In recent years, researchers have increasingly focused on preserving semantic information during the lightweighting process of building models. Chen (2021) proposed a method based on the priority merging of components with the same attributes, which utilizes semantic consistency to guide geometric simplification, ensuring effective retention of the model's semantic information. Additionally, Zhu et al. (2021) introduced a semantic-based building model simplification approach, combining model simplification with semantic information at different levels. They proposed the s-LOD1 to s-LOD4 levels of detail and selected appropriate simplification strategies based on semantic information. Jia et al. (2016) presented the basic structure for the semantic description of geographic information, refining it into semantic granularity terms of different sizes to construct a model for the level of detail (LOD) expression of geographic information semantics. They also implemented quantitative calculations of geographic information semantic similarity based on matching relationships between semantic granularity terms. Fan et al. (2009) utilized semantic information for building model simplification, significantly improving the model's storage efficiency while effectively retaining critical model information. Isailović et al. (2020) proposed a semantic enhancement method for generating remaining BIM and damaged point cloud geometric reconstruction, along with the corresponding IFC model. They employed and evaluated multi-view classification to detect peeling damage features, thereby generating accurate AS-IS-IFC models that meet Building Maintenance System (BMS) inspection requirements.

This study, based on existing LOD generation algorithms and semantic-driven building model simplification techniques, proposes a multi-level building model lightweighting method that integrates geometric simplification with semantic information retention. The method involves several key aspects, particularly the use of LOD technology to adjust the level of geometric detail, thereby reducing the geometric complexity of the model. The primary focus of the study is on semantic information-driven model simplification, where the semantic information of the building model is leveraged to prioritize the retention of critical functional data during the simplification process. By performing semantic classification and analysis of building elements, the method ensures that semantic information is effectively preserved throughout the simplification process.

2. Related Work

2.1 Semantic Information of 3D Building Models

3D building models not only provide a visual representation of the geometric form of buildings but also integrate more semantic information related to the structure. This semantic information includes non-geometric data such as the functions, properties, materials of building components, and their relationships with the surrounding environment. It enriches the content of building models, making them more than just representations of geometric shapes and transforming them into valuable tools for practical applications. The application of semantic information in 3D building models is primarily reflected in aspects such as the functions and attributes of building components, descriptions of architectural spaces, and the relationship between the building and its environment. Semantic information allows for the identification of key components in general 3D models, enabling users to distinguish between walls, roofs, floors, and other surfaces (Yao et al., 2020).

2.2 Representation of Semantic Information in Building Models

In the construction industry, Industry Foundation Classes (IFC) serve as an open standard widely used in Building Information Modeling (BIM), aiming to provide a unified data exchange format for building information models (Liebich et al., 2013). The IFC standard describes the geometric, topological, and semantic information of building models by defining Entities, Attributes, and Relationships. It not only defines the geometric data of buildings in detail but also provides a comprehensive description of the semantic information of building components, including their functional types, material properties, spatial location, and other relevant attributes. Through this structured expression, the IFC standard encodes all components of a building and their attributes in a standardized way, offering a unified method for semantic description (Ding et al., 2020). Each IFC file contains unique identifiers for building elements (such as walls, doors, windows, beams, columns, etc.), along with details about their function, position, construction method, material, and other relevant attributes. The richness of semantic information in IFC makes the building model not just a geometric representation but a digital expression containing multi-layered information. In addition to the IFC standard, other standards are also widely used in building information modeling. For instance, CityGML is primarily used for city-level 3D modeling, supporting the representation of various geographic elements such as buildings, roads, and terrain (Biljecki et al., 2018). CityGML not only describes geometric forms but also includes semantic information, such as the functions and uses of buildings.

3. Methods

3.1 Data Preprocessing

During the data preprocessing stage, this study utilizes IFC parsing libraries (such as IfcOpenShell) to parse IFC files and extract geometric data (such as vertex coordinates and face indices) and semantic information (such as component types, materials, and functional spaces) of the building model. IfcOpenShell is an open-source IFC parsing library that supports multiple IFC versions and efficiently processes complex building model data. First, all building components in the IFC file (such as walls, roofs, slabs, doors, and windows) are sequentially read, and their geometric information is extracted. The geometric data in IFC files may be stored in various forms, such as Boundary Representation (B-Rep), Constructive Solid Geometry (CSG), or Swept Solid. To ensure uniform processing, this study converts geometric data into a triangulated representation (Tessellation), including vertex coordinates and face indices. Simultaneously, semantic information such as the type of each component (e.g., IfcWall, IfcRoof) is extracted. These type labels are assigned to each face and serve as conditions in subsequent simplification algorithms, such as face merging. Ultimately, the extracted geometric data and semantic information will be used in the subsequent LOD conversion process, providing the basis for face merging at this stage and ensuring that the simplified model remains consistent with the original model in both geometric and semantic aspects.

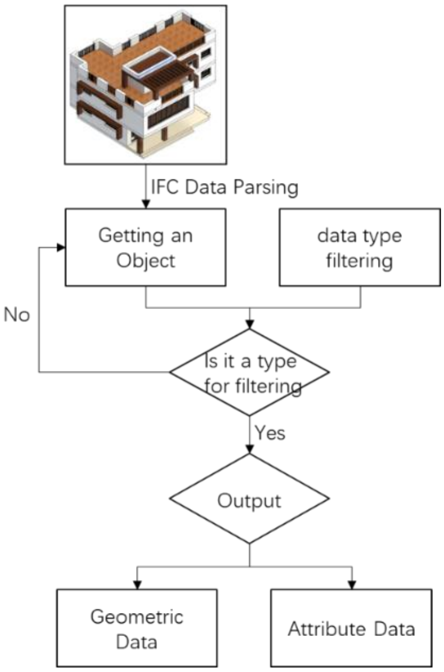

Figure 1. The IFC Data Parsing Process

3.2 Face Merging Method from LOD3 to LOD2

Before performing the face merging operation, it is essential to assess the semantic consistency of the faces. For two adjacent faces, f_1 and f_2, their corresponding semantic labels S_1 and S_2 are extracted. If $S_1 = S_2$, these two faces are considered to have the same semantic information, allowing for direct geometric analysis and subsequent merging. However, if $S_1 \neq S_2$, the semantic similarity between these two labels, denoted as $Sim(S_1, S_2)$, must be further calculated. In this study, the Jaccard similarity coefficient is used to measure this similarity. The Jaccard similarity is a widely used method for binary attribute datasets, which evaluates similarity by comparing the ratio of the intersection to the union of two sets. The formula is:

$$J(A, B) = \frac{|A \cap B|}{|A \cup B|}, \quad (1)$$

If the computed semantic similarity $Sim(S_1, S_2) > T_S$ (where the threshold T_S can be set to 0.9, for example), the two faces are considered to have sufficient semantic similarity and can proceed with the merging operation. Otherwise, they will not be merged.
To further ensure the accuracy of the merging process, this study introduces semantic constraints to guarantee that only faces with the same function are merged. For instance, an IfcWall can only be merged with another IfcWall, and an IfcRoof can only be merged with another IfcRoof. Semantic labels of adjacent faces are extracted from the IFC model and evaluated based on the aforementioned method to determine whether they meet the semantic consistency conditions. If all conditions are met, pairs of faces that satisfy the criteria are output for subsequent merging operations.
This method effectively filters out face pairs that meet semantic consistency conditions, ensuring the accuracy and reliability of the merging process. Once the faces satisfy both semantic and geometric conditions, the next step is to perform the merging operation to generate larger simplified faces. This process includes calculating the boundary of the new face, inheriting semantic information, and updating the topological structure.

To generate the boundary of the merged face, this study employs the Convex Hull Algorithm. The specific steps are as follows:
Given two adjacent faces f_1 and f_2 that meet the semantic consistency criteria, all their vertices are first combined into a single set. Then, the convex hull algorithm is applied to compute the minimal convex polygon enclosing this set. The formula for this operation is:

$$f_{new} = ConvexHull(f_1 \cup f_2), \quad (2)$$

Through this method, we obtain a new face f_{new}, whose boundary is the minimal convex polygon encompassing all the vertices of the original faces f_1 and f_2. During the merging process, it is crucial to appropriately inherit semantic information. Depending on semantic consistency and similarity, different strategies are adopted:
1.Complete Consistency: If the semantic labels of the two faces are completely identical (i.e., $S_1 = S_2$), the semantic information is directly inherited:

$$S_{new} = S_1 = S_2, \quad (3)$$

2.Partial Similarity: If the semantic labels of the two faces are partially similar but not entirely identical, the merged face's semantic information is determined based on the dominant semantic category or the material with the highest proportion.
After the merging process, the model's topology needs to be updated to maintain data consistency and integrity. The specific steps include:
1.Remove Redundant Faces: The original faces f_1 and f_2 are deleted from the model to prevent data redundancy.
2.Recalculate Adjacency Relationships: Since the merging operation may alter the original adjacency relationships of the faces, it is necessary to recalculate and update these relationships. Specifically, for each newly generated face f_{new}, its new adjacency relationships with surrounding faces must be determined and the corresponding connectivity information updated.
The final output is a LOD2-level building model with fully preserved semantic information.

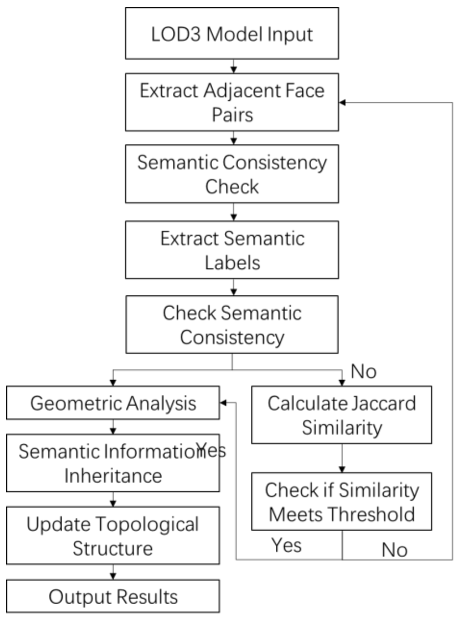

Figure 2. Face Merging Method from LOD3 to LOD2

3.3 Face Moving Method from LOD2 to LOD1

Before performing face movement and merging, functional consistency and material consistency must be assessed to ensure that the merged faces maintain semantic integrity. Functional Consistency Check: If the faces belong to the same functional region, they can be directly moved or merged. If the faces have different functional uses, the decision is based on the proportion of window and door areas: If the window/door area is less than 10%, these faces are directly removed. If the window/door area exceeds 10%, they are retained and merged into the wall surface. The final output consists of face pairs that meet semantic consistency conditions, ensuring accurate and reliable merging operations. To merge detailed faces (e.g., windows and doors) with larger structural elements, the centroid of the faces is first computed. Based on the centroid positions, faces are translated accordingly. Finally, the convex hull algorithm is used to generate the merged face.

For two faces f_1 and $f_2$2, the centroid C is computed using an area-weighted average formula:

$$C = \frac{|f_1|C_1 + |f_2|C_2}{|f_1| + |f_2|}, \quad (4)$$

Where C_1 and C_2 are the centroids of the faces f_1 and f_2, and $|f_1|$ and $|f_2|$ are their respective areas. To align the faces f_1 and f_2, the distance vector $d(f_1, f_2)$ between them is calculated, a f_2 is translated to its new position:

$$f_2' = f_2 + \mathrm{d}(f_1, f_2), \quad (5)$$

Here, $d(f_1, f_2)$ is the translation vector calculated based on the centroid positions. Subsequently, the convex hull algorithm is used to compute the boundary of the merged face, ensuring that the new face has a simplified geometric shape and continuous topology.

$$f_{new} = ConvexHull(f_1 \cup f_2), \quad (6)$$

During the merging process, redundant vertices and edges are removed to ensure the geometric and topological consistency of the face. The final output is the simplified merged face, which retains the main geometric features and semantic information of the original faces. To further simplify the building model, invalid faces with too small an area are removed, and the boundary relationships between adjacent faces are optimized. For each face f, its area $A(f)$ is calculated. If the area is smaller than the preset threshold A_{min}, the face is marked as redundant and deleted.

$$if\ A(f) < A_{min},\ then\ delete\ f, \quad (7)$$

After deleting redundant faces, the boundary relationships between adjacent faces are recalculated to ensure that the polygons are closed and non-overlapping. A geometric repair algorithm is used to optimize the boundaries of the faces, ensuring the geometric consistency and topological continuity of the model. The final output is an LOD1 building model, retaining only the building's exterior facade while preserving the complete semantic information. Through the above methods, the LOD2-level IFC model can be effectively simplified to an LOD1-level model.

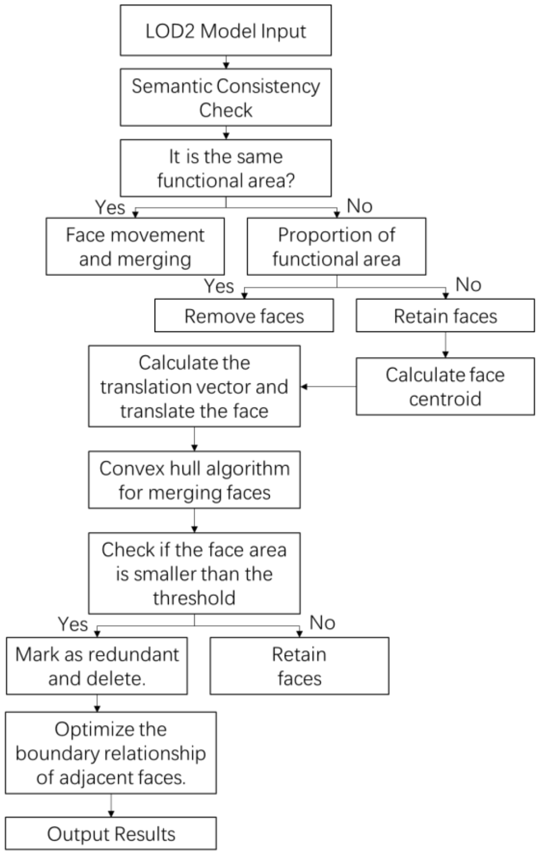

Figure 3. Face Moving Method from LOD2 to LOD1

4. Experiments and Analysis

4.1 Experimental Data

The experiment used the IfcOpenShell library for IFC file parsing and geometric data extraction, the Python programming language for algorithm implementation, and the Open3D library for 3D model rendering and visualization. Key parameters used in the experiment include the semantic similarity threshold $T_S = 0.9$ and the area threshold $A_{min} = 0.1\ m^2$. The data used in the experiment consists of IFC format data for various types of building models, as shown in the figure.

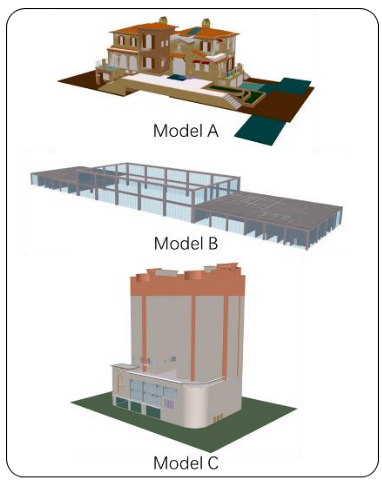

Figure 4. Experimental Data

4.2 Building Model Lightweighting Results

Table 1. LOD3 to LOD2 Model Lightweighting and Semantic Consistency Comparison Table

Model Name	LOD3 Face Count	LOD2 Face Count	LOD3 Semantic Labels	LOD2 Semantic Labels	Semantic Label Retention Rate	Semantic Similarity
Model A	364,584	218,750	'IfcStair', 'IfcColumn', 'IfcOwnerHistory', 'IfcPlate', 'IfcWallStandardCase', 'IfcStairFlight', 'IfcLocalPlacement', 'IfcDoor', 'IfcMember', 'IfcWall', 'IfcSpace', 'IfcWindow', 'IfcRoof', 'IfcProductDefinitionShape', 'IfcBuildingElementProxy', 'IfcRailing', 'IfcSlab'	'IfcStair', 'IfcColumn', 'IfcWall', 'IfcRoof', 'IfcMember', 'IfcWindow', 'IfcDoor', 'IfcSlab', 'IfcRailing', 'IfcWallStandardCase', 'IfcSpace'	85%	0.92
Model B	135898	85,634	IfcWallStandardCase', 'IfcLocalPlacement', 'IfcProductDefinitionShape', 'IfcPlate', 'IfcBeam', 'IfcDoor', 'IFC', 'IfcColumn', 'IfcWindow', 'IfcCurtainWall', 'IfcSlab', 'IfcOwnerHistory	'IfcWall', 'IfcSlab', 'IfcBeam', 'IfcColumn', 'IfcCurtainWall', 'IfcDoor'	80%	0.85
Model C	177,976	106,786	'IfcSpace', 'IfcWindow', 'IfcColumn', 'IfcDoor', 'IfcRailing', 'IfcStair', 'IfcSlab', 'IfcWall', 'IfcCurtainWall', 'IfcOwnerHistory', 'IfcPlate', 'IfcLocalPlacement', 'IfcProductDefinitionShape', 'IFC', 'IfcStairFlight', 'IfcBuildingElementProxy', 'IfcWallStandardCase', 'IfcRoof'	'IfcSpace', 'IfcWindow', 'IfcColumn', 'IfcDoor', 'IfcRailing', 'IfcStair', 'IfcSlab', 'IfcWall', 'IfcCurtainWall', 'IfcPlate', 'IfcRoof'	88%	0.94

Table 2. LOD2 to LOD1 Model Lightweighting and Semantic Consistency Comparison Table

Model Name	LOD2 Face Count	LOD1 Face Count	LOD2 Semantic Labels	LOD1 Semantic Labels	Semantic Label Retention Rate	Semantic Similarity
Model A	218,750	10,856	'IfcStair', 'IfcColumn', 'IfcWall', 'IfcRoof', 'IfcMember', 'IfcWindow', 'IfcDoor', 'IfcSlab', 'IfcRailing', 'IfcWallStandardCase', 'IfcSpace'	'IfcWall', 'IfcRoof', 'IfcSlab', 'IfcSpace', 'IfcWallStandardCase'	75%	0.85
Model B	85,634	55,327	'IfcWall', 'IfcSlab', 'IfcBeam', 'IfcColumn', 'IfcCurtainWall', 'IfcDoor'	'IfcWall', 'IfcSlab', 'IfcColumn', 'IfcCurtainWall'	75%	0.8
Model C	106,786	45,961	'IfcSpace', 'IfcWindow', 'IfcColumn', 'IfcDoor', 'IfcRailing', 'IfcStair', 'IfcSlab', 'IfcWall', 'IfcCurtainWall', 'IfcPlate', 'IfcRoof'	'IfcWall', 'IfcSlab', 'IfcRoof', 'IfcSpace'	70%	0.87

The LOD3 to LOD2 model simplification method based on face merging and semantic consistency proposed in this study effectively simplifies the geometric structure of building models while retaining semantic information to the greatest extent. The experimental results show that through face merging operations, the retention rate of semantic labels is between 85% and 88%, and the semantic similarity is maintained between 0.85 and 0.94, ensuring semantic consistency during the simplification process. Especially in models with higher complexity, semantic consistency is well preserved, indicating that this method can effectively balance geometric simplification and semantic retention while simplifying the building model, laying a solid foundation for further simplification from LOD2 to LOD1.

In the LOD2 to LOD1 simplification process, although the number of faces significantly decreases, the retention rate of semantic labels remains between 70% and 75%, and the semantic similarity ranges from 0.8 to 0.87, indicating that the loss of semantic information is limited. For example, in Model A, the retention rate of semantic labels reaches 75%, and the semantic similarity is 0.85, showing that semantic consistency is still well preserved while significantly reducing the number of faces. Overall, the face movement and merging method adopted in this study not only effectively reduces the model size but also retains key semantic information as much as possible, ensuring the usability and accuracy of the LOD1 model. This result indicates that the proposed simplification method performs excellently in the LOD conversion of building models, particularly in maintaining the basic semantics of building functions and structures.

5. Conclusions

Overall, the lightweighting method for 3D building models based on semantic constraints proposed in this study effectively reduces model complexity while ensuring the retention of critical semantic information, thus preserving the model's usability and

https://doi.org/10.5194/isprs-archives-XLVIII-G-2025-1565-2025

accuracy. This method successfully facilitates the conversion of building models across different Levels of Detail (LOD), while maintaining the fundamental semantic integrity of architectural functions and structures, thereby enhancing both the storage and processing efficiency of the models. Experimental results demonstrate that the proposed lightweighting approach excels in LOD conversion, particularly in its ability to maintain semantic consistency. This study lays a solid foundation for future research in building model simplification methods, with significant implications for the preservation of semantic information and its application in practical settings.

References

Baig, S.U.; Rahman, A.A. A Three-Step Strategy for Generalization of 3D Building Models Based on CityGML Specifications. GeoJournal 2013, 78, 1013 – 1020, doi:10.1007/s10708-013-9475-0.

Biljecki, F.; Kumar, K.; Nagel, C. CityGML Application Domain Extension (ADE): Overview of Developments. Open Geospatial Data, Software and Standards 2018, 3, 13, doi:10.1186/s40965-018-0055-6.

Chen, B. Research on a 3D Building Simplification Method Considering Both Mesh Structure and Building Structures. Master's Thesis, Nanjing University, Nanjing, China, 2021.

Ding, X.; Yang, J.; Liu, L.; Huang, W.; Wu, P. Integrating IFC and CityGML Model at Schema Level by Using Linguistic and Text Mining Techniques. IEEE Access 2020, 8, 56429–56440, doi:10.1109/ACCESS.2020.2982044.

Eastman, C.M. BIM Handbook: A Guide to Building Information Modeling for Owners, Managers, Designers, Engineers and Contractors; John Wiley & Sons, 2011; ISBN 0-470-54137-7.

Fan, H.; Meng, L.; Jahnke, M. Generalization of 3D Buildings Modelled by CityGML. In Advances in GIScience; Sester, M., Bernard, L., Paelke, V., Eds.; Lecture Notes in Geoinformation and Cartography; Springer Berlin Heidelberg: Berlin, Heidelberg, 2009; pp. 387–405.

Forberg, B. Generalization of 3D Building Data. In Proceedings of the 22nd International Cartographic Conference, A Coruña, Spain, 9–16 July 2005.

Ge, L.; Wu, F.; Li, J.; Ma, Z. A Feature Analysis Approach in Simplification of 3D Building with Complex Flat Roof. 2017, 53, 1–7, doi:10.13209/j.0479-8023.2016.111.

Ge, Y.; Xiao, X.; Guo, B.; Shao, Z.; Gong, J.; Li, D. A Novel LOD Rendering Method With Multilevel Structure-Keeping Mesh Simplification and Fast Texture Alignment for Realistic 3-D Models. IEEE Transactions on Geoscience and Remote Sensing 2024, 62, 1–19, doi:10.1109/TGRS.2024.3457796.

Goetz, M. Towards Generating Highly Detailed 3D CityGML Models from OpenStreetMap. International Journal of Geographical Information Science 2013, 27, 845 – 865, doi:10.1080/13658816.2012.721552.

Hooper, M. Automated Model Progression Scheduling Using Level of Development. Construction Innovation 2015, 15, 428–448, doi:10.1108/CI-09-2014-0048.

Hoppe, H.; DeRose, T.; Duchamp, T.; McDonald, J.; Stuetzle, W. Mesh Optimization. In Proceedings of the Proceedings of the 20th Annual Conference on Computer Graphics and Interactive Techniques; Association for Computing Machinery: New York, NY, USA, 1993; pp. 19–26.

Isailović, D.; Stojanovic, V.; Trapp, M.; Richter, R.; Hajdin, R.; Döllner, J. Bridge Damage: Detection, IFC-Based Semantic Enrichment and Visualization. Automation in Construction 2020, 112, 103088, doi:10.1016/j.autcon.2020.103088.

Li, S.; Li, W.; Lin, Z.; Yi, S. Method for 3D City Building Continuous Transformation Based on an Improved LOD Topological Data Structure. ISPRS International Journal of Geo-Information, 2019, 8(11), 504.

Li, Y.; Hu, Q.; Wu, M.; Liu, J.; Wu, X. Extraction and Simplification of Building Façade Pieces from Mobile Laser Scanner Point Clouds for 3D Street View Services. ISPRS International Journal of Geo-Information 2016, 5, doi:10.3390/ijgi5120231.

Pratt-Hartmann, I. Fragments of Language. Journal of Logic, Language and Information 2004, 13, 207 – 223, doi:10.1023/B:JLLI.0000024735.97006.5a.

Wu, H.X., Xue, H.F., 2007. Research on a hybrid data structure model for 3D GIS based on block models. Comput. Appl. Res. (10), 273–275.

Xie, J.; Zhang, L.; Li, J.; Wang, H.; Yang, L. Automatic Simplification and Visualization of 3D Urban Building Models. International Journal of Applied Earth Observation and Geoinformation 2012, 18, 222 – 231, doi:10.1016/j.jag.2012.01.014.

Yao, S.; Ling, X.; Nueesch, F.; Schrotter, G.; Schubiger, S.; Fang, Z.; Ma, L.; Tian, Z. Maintaining Semantic Information across Generic 3D Model Editing Operations. Remote Sensing 2020, 12, doi:10.3390/rs12020335.

Zhu, J.; Wu, P.; Anumba, C. A Semantics-Based Approach for Simplifying IFC Building Models to Facilitate the Use of BIM Models in GIS. Remote Sensing 2021, 13, 4727, doi:10.3390/rs13224727.

Zhu, Q.; Lin, H. Digital City Geographic Information System: A Preliminary Study of Three-Dimensional Urban. Model. In Virtual City Environment; Wuhan University Press: Wuhan, China, 2004.

Zhou, Y.; Zhu, Q.; Huang, Z. LOD of complex buildings for 3DCM. Sci. Surv. Mapp. 2006, 31, 74–77.

He, J.; Guo, J.; Liu, T.; He, H.; Wang, X. Real-World 3D Model Lightweighting Technology Based on Edge Collapse Simplification. Surveying and Mapping Bulletin 2024, 53-56+190, doi:10.13474/j.cnki.11-2246.2024.S111.

Zhang, Y.; Wang, S.; Zheng, Q.; Zhang, H. 3D Mesh Model Lightweighting Algorithm for Preserving Geometric Features. Journal of Computer Applications 2023, 43, 1226–1232.

Jia, X.; Ai, T.; Peng, Z.; Wang, G. LOD Representation and Similarity Measurement of Geographic Information Semantics.

Journal of Wuhan University (Information Science Edition) 2016, 41, 1299–1306, doi:10.13203/j.whugis20140711.

Liebich, T.; Adachi, Y.; Forester, J.; Hyvarinen, J.; Richter, S.; Chipman, T.; Weise, M.; Wix, J. Industry foundation classes IFC4 official release, Online: <http://www.buildingsmart-tech.org/ifc/IFC4/final/html>, 2013.