Integrated Indoor and Outdoor Topological Modeling

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Abstract

With the rapid advancement of urbanization, the spatial structures of large-scale public venues such as transportation hubs and shopping malls have become increasingly complex. These venues often include diverse and flexible types of transitional spaces connecting them with their surrounding environments, which impose a significant cognitive burden on individuals navigating through them. However, traditional methods for constructing indoor and outdoor geospatial data for location-based services (LBS) are typically conducted independently. These approaches lack a unified topological characterization of transitional spaces, leading to several challenges in practical applications, such as the disconnection between indoor and outdoor spaces, difficulties in cross-scene transitions, and inaccurate topological correspondences between indoor and outdoor spaces. This highlights the critical need for an integrated indoor-outdoor topological modeling approach. To address these issues, this study proposes a systematic workflow for constructing an integrated indoor-outdoor topological model based on complete transitional spaces derived from indoor and outdoor point cloud data. This approach provides foundational support for subsequent applications, such as path navigation and emergency planning for unmanned aerial vehicles (UAVs).

1. Introduction

With the comprehensive advancement of the Real-Scene 3D China initiative, enhancing the capability of surveying and mapping geoinformation services to empower various applications has become a key research focus. This endeavor aims to provide robust support for the construction and implementation of Digital China. According to research, over 75% of the global population resides in towns and cities, and modern urban dwellers spend 80% to 90% of their time living and working inside buildings (EPA, 2009) , the frequency of movement between complex buildings and between indoor and outdoor spaces is steadily increasing. To meet the growing demand for diverse spatial services and facilitate the development of 3D city construction for public services, it is essential to advance integrated topological modeling of indoor and outdoor spaces.

The automated generation of topological spatial models is closely related to spatial structures, and earlier studies have highlighted the structural differences between indoor and outdoor spaces (Claridades and Lee, 2021). In the description of spatial topological features, the structural differences between indoor and outdoor scenes have led to diverse and independent expressions of their respective topological spatial models. Generally, outdoor topological models are typically represented using 2D structures, while indoor models are characterized by complex 3D network models with spatial depth. Research on outdoor topological models has achieved significant progress, greatly enhancing the convenience of daily production and life. However, despite the maturity of outdoor topological model applications, indoor models, particularly integrated indoor-outdoor topological spatial models, remain underexplored and underdeveloped (Basiri et al., 2017; Kang et al., 2014). The expression of indoor spatial topological features is highly diverse, including representations such as regular grids (Zhao et al., 2022) 、 irregular grids (Boguslawski et al., 2016) 、 node relationship diagrams (Yang et al., 2021) , as well as hybrid graphs (Lin et al., 2017; Yeh and Zhong, 2021) , among others.

Unlike outdoor spatial structures, indoor scenes feature complex spatial configurations and flexible topological characteristics, posing significant challenges in the construction of indoor topological spatial models. Currently, the creation of indoor navigation topological maps primarily relies on manual modeling. However, this approach is both time-consuming and labor-intensive (Liu et al., 2021), making it difficult to meet the demands of practical applications. Given the current limitations in the integration of semantics, geometry, and topology within indoor topological spatial models, as well as deficiencies in the expression and description of indoor spatial topological features, many scholars have increasingly focused on the automated construction of indoor topological models. These efforts aim to extract the geometric, semantic, and topological attributes of indoor spatial objects from geospatial data sources such as BIM, CityGML, CAD, and point clouds, and to model indoor spatial objects (Boguslawski et al., 2016; Chuang and Sung, 2021; Fu et al., 2020; Teo and Cho, 2016) . Significant progress has been made in this area. However, since indoor and outdoor topological models remain independent, location-based services, such as navigation and emergency rescue across indoor and outdoor scenes, inevitably face challenges such as data switching and global optimization verification (Yeh and Zhong, 2021). Consequently, the automatic generation of integrated indoor-outdoor topological models has gradually become a research hotspot (Teo and Cho, 2016; Yan et al., 2019; Yeh and Zhong, 2021) . These studies primarily focus on achieving integrated above-ground and below-ground representations and applications of indoor and outdoor spaces through semantic hierarchies of buildings and their surrounding scenes.

In existing research, most work has primarily focused on indoor topological spatial models and their construction methods (Flikweert et al., 2019; Tessema et al., 2019), with relatively simple topological representations. Additionally, although some

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studies have explored the integration of indoor and outdoor topological models, these efforts generally emphasize modeling and cartographic representation. Research on the automatic generation of integrated indoor-outdoor topological models remains relatively scarce, and most studies connect indoor and outdoor spaces via a single node (Tashakkori et al., 2015; Teo and Cho, 2016; Wang and Niu, 2018). While this approach is straightforward, it overlooks the spatial diversity and multi-level expression between buildings and outdoor roads, failing to fully reflect the real world and severely limiting navigation path planning.

Research has shown that certain spaces can be considered neither fully indoor nor fully outdoor, but rather as transitional zones between the two. These spaces challenge traditional spatial classifications and prompt a reevaluation of how they should be modeled and navigated in applications. Transitional spaces can act as buffers or circulation pathways between indoor and outdoor environments, such as building porches, lobbies, front yards, or plazas, facilitating smooth transitions from one space to another (Kray et al., 2013; Sabeen and Kim, 2020). Although some studies have investigated the construction of integrated indoor-outdoor models for transitional spaces, current research is limited to the horizontal aspects of transitional spaces, overlooking the vertical characteristics.

Compared to indoor and outdoor spaces, transitional spaces serve as a unique buffer zone, a function not only relevant to pedestrian path navigation but also significant in vertical scenarios. In special emergency situations such as fires, rescue devices like drones can access indoor spaces through the doors and windows of transitional spaces. This critical application and uniqueness of transitional spaces have not been adequately considered in prior research.

This study will construct corresponding topological models for indoor and outdoor point clouds, connecting them through the shared characteristics of transitional spaces. The final integrated indoor-outdoor topological model will ensure the coherence of location-based services across both indoor and outdoor environments.

2. Method

This paper proposes a method to integrate indoor and outdoor topological models by fully utilizing the entire three-dimensional transitional space. For indoor point clouds, an indoor topological model is constructed by segmenting and extracting features from point clouds of doors, windows, rooms, and floors, dividing the model into semi-indoor and other parts. For outdoor point clouds, an outdoor topological model is designed through door and window recognition and road point cloud extraction, catering to the needs of pedestrian movement and UAV navigation, and dividing it into semi-outdoor and other parts. The semi-indoor and semi-outdoor sections from both the indoor and outdoor topological models are merged to form the transitional space, and the integration of the indoor and outdoor topological models is achieved by connecting the nodes within the transitional space. The overall technical framework is shown in Figure 1.

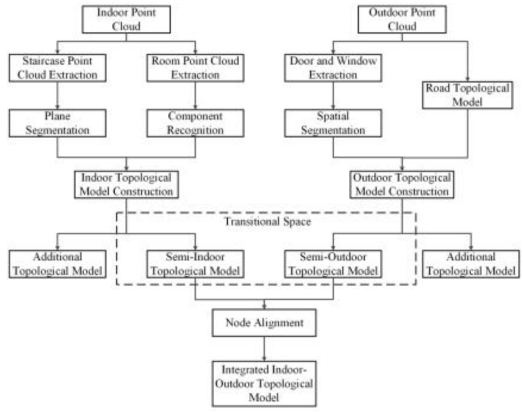

Figure 1. Technical Framework for Integrated Indoor-Outdoor Topological Modeling.

2.1 Indoor Topological Model Construction

2.1.1 Indoor Point Cloud Spatial Segmentation: From the perspective of indoor spatial partitioning, floor space is a composite space, typically divided into individual floors for processing using methods like elevation histograms. The first step is to segment the unstructured scanned point cloud into individual floors and extract the permanent structures (such as stairs). Subsequently, spatial segmentation is performed separately for each floor and the stairs.

In the floor division process, this study relies on prior knowledge to partition the floors, assuming that the floor of each level lies on the same elevation plane, with the ceiling height being consistent. When the sampled point cloud is evenly distributed, the point clouds on the upper and lower surfaces of the floor exhibit distinct peaks on the elevation histogram. This characteristic allows for the determination of floor height, as well as the elevation of the floor and ceiling, based on the point cloud's height histogram.

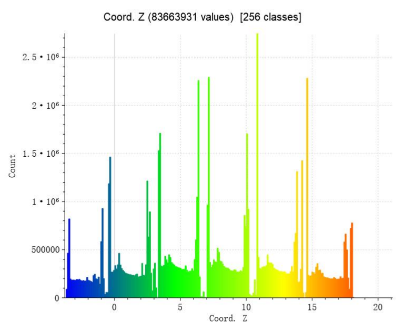

Figure 2. Floor Height Histogram.

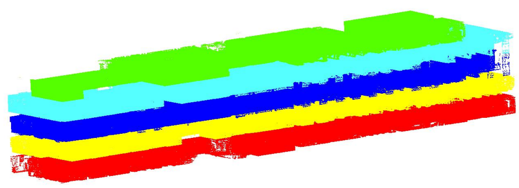

Figure 3. Floor Segmentation Results.

Near the ceiling height, the point clouds between rooms are usually disconnected. Therefore, for single-floor point clouds, the ceiling height is also determined using the elevation histogram method. The point cloud is then sliced based on the ceiling height, which facilitates the subsequent segmentation of individual rooms.

To represent the point cloud as an image, the first step is to partition the point cloud into a 2D virtual grid. Based on the minimum and maximum values of the point cloud's bounding box along the x-axis and y-axis, as well as the grid cell dimensions dx and dy, the 2D virtual grid is defined as follows:

$$2D_{grid} = \{Cell(u, v)\} \quad (1)$$

In the equation, u and v represent the 2D coordinates of the image pixels. $0 \leq \mathrm{u} \leq \mathrm{INT}\left(\frac{\mathrm{X_{max}}-\mathrm{X_{min}}}{\mathrm{dx}}\right)$, $0 \leq \mathrm{v} \leq \mathrm{INT}\left(\frac{\mathrm{Y_{max}}-\mathrm{Y_{min}}}{\mathrm{dy}}\right)$, Where $(X_{\max}, Y_{\max})$, (X_{min}, Y_{min}) represent the maximum and minimum coordinates of the point cloud's 2D projected bounding box, respectively, dx and dy represent the horizontal and vertical resolution, respectively. According to the definiton of a room, a single room is a closed space, which, in a 2D plane, is surrounded by a closed contour. Therefore, by performing a connected component analysis on the binary image, each room will be segmented into a separate region, allowing for the quick extraction of the point cloud for each individual space.

2.1.2 Door and Window Extraction: We start with existing mature 2D image-based object detection algorithms to perform object detection on 3D point clouds. The segmented room point cloud is processed using the RANSAC algorithm (Schnabel et al., 2007) for plane extraction, where vertical walls are retained based on their normal direction. A colored composite image of the wall surface is generated through point cloud projection. Simultaneously, the correspondence between the pixel points in the 2D image and the 3D indoor point cloud is maintained.

After obtaining the image containing doors and windows, object detection is applied to identify them. The colored wall image synthesized from the point cloud is input into the YOLO neural network (Farhadi and Redmon, 2018). This allows the extraction of bounding boxes for doors and windows, providing a rough estimate of their location. By utilizing the correspondence between the 2D and 3D data, a rough extraction of the indoor door and window point clouds can be achieved. Then, using the α-shape algorithm (Edelsbrunner and Mücke, 1994) for contour extraction, the method assumes that a circle with radius α rolls around the point set S. As α varies, the circle moves around the inside and outside of the point set, and the trace left by the rolling circle forms the convex hull of the point set S. When the points in S are evenly distributed and α is appropriately chosen, the inner and outer boundaries of the point set S can be obtained.

This combined 2D-3D approach improves both extraction efficiency and accuracy, preventing errors caused by holes due to occlusion by indoor clutter.

2.1.3 IndoorGML Topological Model Construction: In IndoorGML, the topological structure between "cells" is derived through the use of Poincaré duality, which maps the layout of indoor spaces. According to Poincaré duality theory, a k-dimensional object in the N-dimensional primal space is mapped to an (N-k)-dimensional object in the dual space. For example, a cell (such as a room within a building) in the three-dimensional primal space is mapped to a node (0-dimensional) in the dual space. The common 2D surface shared by two adjacent cells is transformed into an edge (1-dimensional) in the dual space, connecting the two adjacent nodes. Figure 4 illustrates the dual transformation in both two-dimensional and three-dimensional primal spaces.

To construct the IndoorGML topological model, we first extract the contour points from the room point cloud and the door/window point cloud. For the room point cloud, we slice the Offset region (an additional spatial area defined outside the ceiling height range, which allows including points slightly below the ceiling height) to obtain the contour point cloud. The extracted contour point cloud is then normalized, and the centroids of each region are calculated as the State points of the topological model. The normalized contour is used to define the shape of the cell.

IndoorGML also provides specific definitions for components such as doors and windows. If a door is represented as a gml: Curve in two-dimensional space, it can be mapped to the <IndoorNavi::ConnectionBoundary> or <IndoorNavi::Anchor-Boundary> in the indoor navigation extension module, which is known as the "thin door model. " If a door is represented as a gml:Solid in three-dimensional space, it can be mapped to the < IndoorNavi::ConnectionSpace> or <IndoorNavi::AnchorSpace> in the indoor navigation extension module, which is known as the "thick door model. " Since all doors and windows in this study are assumed to be navigable, they are set as thick door and thick window models. During topological relationship reco-nstruction, it is assumed that all doors and windows are connect ed to the room nodes by default.

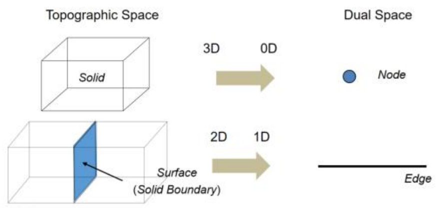

Figure 4. Transformation Relationship Between Primal and Dual Spaces Based on Poincaré Duality (Lee, 2004) .

2.2 Outdoor Topological Model Construction

In this paper, outdoor spaces are divided into semi-outdoor and other parts (such as roads), and separate outdoor topological models are constructed for each. Following the definition by Yan (Yan et al., 2019) , we extend the definition of semi-outdoor space, where the entire area from the exterior building wall to the bottom step of the staircase connected to the building exit is defined as the semi-outdoor space. Given the absence of point cloud data for the semi-external space, we adopt a spatial division approach. This involves dividing the space extending outward from the building's external walls by a specified distance. The RANSAC algorithm is then employed to extract the main façade of the building's exterior walls. Based on the orientation of this main façade, we extend outward to construct the semi-external space's CellSpace. The preliminary spatial division is subsequently refined through a secondary division based on the floor height obtained in section 2. 1. 1, resulting in the construction of subspaces.

Next, it is essential to identify and extract traversable components on the building’s external walls. Compared to interior walls, the external walls are less obstructed, allowing for the use of hole extraction methods to detect doors and windows. This algorithm constructs an irregular triangular mesh through triangulation, extracting longer edge points which are then clustered. The edge points belonging to the same hole are marked, and the adjacency relationships between inner and outer boundary triangles are analyzed to distinguish between the internal and external edges of the hole. This process ultimately enables the extraction of the contours of windows or other openings (Pu and Vosselman, 2007). The algorithm constructs an irregular triangular mesh through triangulation, extracting longer edge points which are then clustered. Edge points belonging to the same hole are marked, and the adjacency relationships between inner and outer boundary triangles are analyzed to distinguish between the internal and external edges of the hole. This enables the extraction of the contours of windows or other openings. However, considering the large volume of outdoor building point cloud data and the relatively slow speed of triangular mesh construction, we employ the same 2D-3D cross-data method used for interior detection for window and door detection.

Based on the results of the window and door extraction, the nodes of the windows and doors are extended outward along the wall's normal direction to define semi-external subspace State nodes. In constructing the outdoor portion, we not only consider pedestrian accessibility but also integrate emergency path planning into the unified model. For example, in the event of a fire or other emergencies, this feature can assist drones and other devices in entering the building through all accessible passages. To ensure model compatibility, we account for both scenarios in the construction requirements, ensuring path planning flexibility in both horizontal and vertical directions. Thus, all adjacent nodes are connected using transitions in both vertical and horizontal directions.

As the IndoorGML model is more oriented towards indoor building representations, the outdoor road network is modeled using different formats. Currently, the outdoor models known to connect to the IndoorGML model through anchor nodes include CityGML, GDF, and PNspec. In this study, we adopt the CityGML model as the standard for the outdoor portion. This model not only effectively represents the geometric information of three-dimensional urban space but also offers rich semantic layers, enabling detailed descriptions of the attributes and relationships of elements such as buildings, roads, and green spaces. This provides strong support for integrated indoor-outdoor modeling.

2.3 Construction of an Integrated Indoor-Outdoor Topological Model Based on Transitional Spaces

Transitional spaces not only physically connect the indoor and outdoor environments but also provide necessary buffer zones functionally. These spaces facilitate both the physical connection between indoor and outdoor areas and the multi-route accessibility for entry and exit. In this study, we aim to integrate the indoor and outdoor topological models based on the model proposed by Claridades (Claridades and Lee, 2021).

The Transfer_Link is a data model connection method introduced by the authors, designed to establish spatial relationships between indoor and outdoor navigation networks. It utilizes unique identifiers and connection information of indoor and outdoor network nodes to achieve seamless connectivity between different datasets and database schemas, eliminating the need for data conversion or complex implementations. This approach supports continuous navigation activities of agents across indoor and outdoor spaces. Moreover, since roads or sidewalks may have multiple access points, multiple Transfer_Links are permitted within the transitional space, thus avoiding the single-point connection issue seen in the IndoorGML model (as shown in Figure 5).

By leveraging the model's advantage of enabling multi-point connections, all nodes within the vertical region of the transitional space can be utilized for integrated indoor-outdoor connectivity. The semi-indoor and semi-outdoor topological models must remain consistent at transitional components, such as doors and windows, which is a key factor in achieving integration. Thus, we treat the window and door nodes in the semi-indoor topological model as connection points for the indoor topological model, while the semi-outdoor subspace nodes serve as connection points for the outdoor topological model. By using Transfer_Link, we establish a connection between the two models, constructing an integrated indoor-outdoor topological model (as shown in Figures 6 and 7).

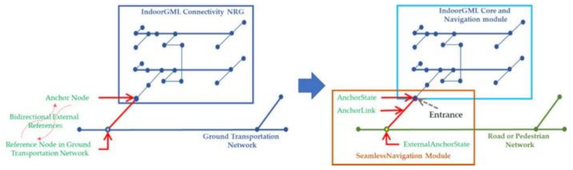

Figure 5. Definition of AnchorNode in the SeamlessNavigation Module of the IndoorGML Model.

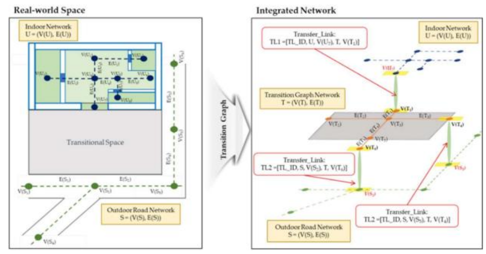

Figure 6. Network Representation of the Generated Transitional Space (Claridades and Lee, 2021).

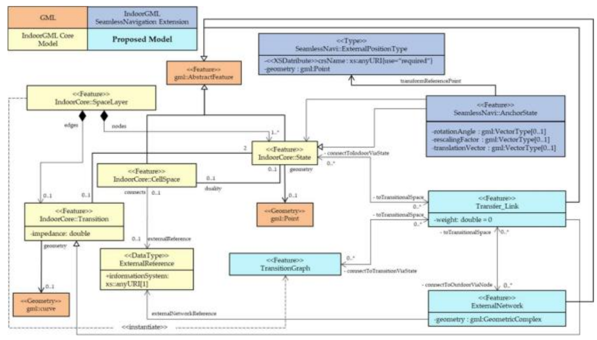

Figure 7. UML Class Diagram of the Proposed Data Model.

3. Experimental Results

We selected integrated indoor-outdoor point cloud data from a company in Beijing, China, to conduct experiments on the construction of the integrated indoor-outdoor topological model, with the outdoor road network connected directly through an existing road topology model. First, we processed the indoor point cloud data. To analyze the impact of spatial resolution on room partitioning, tests were conducted with spatial resolutions of 0.1 m, 0.2 m, 0.3 m, and 0.4 m. Among these, a spatial resolution of 0.2 m yielded the best results. Figure 8 shows the indoor point cloud segmentation results achieved through distance transform at a spatial resolution of 0.2 m, while Table 2 presents the room segmentation accuracy data for different floors.

Data	Number of Points($\times 10^6$)	Area(m^2)
Floor1	14. 865166	1836
Floor2	16. 462953	1836
Floor3	16. 740668	1836
Floor4	16. 089905	1836
Floor5	16. 385180	1836

Table 1. Point Cloud Information for Each Floor of the Building.

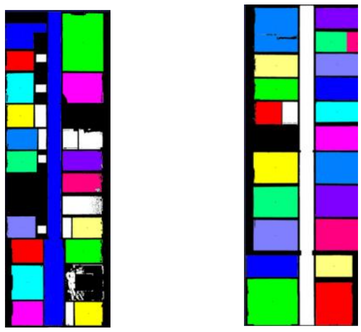

Figure 8. Indoor Space Partitioning Results.

Floor	Precision(%)	Recall(%)
F1	89. 4	95. 6
F2	88. 3	93. 7
F3	81. 0	74. 2
F4	85. 1	88. 2
F5	88. 5	94. 1

Table 2. Spatial Partitioning Accuracy for Different Floors.

The same method using the YOLO neural network was applied to extract doors and windows in both indoor and outdoor environments. We created 2, 000 indoor and outdoor point cloud color composite images for training, enabling coarse extraction of doors and windows. The fine extraction was then performed using the α-shape method. Figure 9 shows the results of our door and window extraction, where the first column displays the detection results from the point cloud color composite images, the second column shows the coarse extraction based on 2D-3D relationships, and the third column illustrates the fine extraction results.
The error calculation requires the true locations of the door and window feature corner points. In this study, we manually annotated the sample data to obtain the true positions, and then used the calculated results from the algorithm to assess the effectiveness of the proposed method by comparing the maximum and average errors between the computed values and the true values. These two functions are defined as:
Maximum error function:

$$e_{max} = \max\{\|g_i - c_i\|, i = 1, \ldots, N\} \tag{2}$$

Average Error Function:

$$e_{avg} = \frac{\sum_{i=1}^{N} \|g_i - c_i\|}{N} \tag{3}$$

Where $\|\cdot\|$ denotes the Euclidean distance between two points, g represents the set of true feature points, and c denotes the set of computed points.

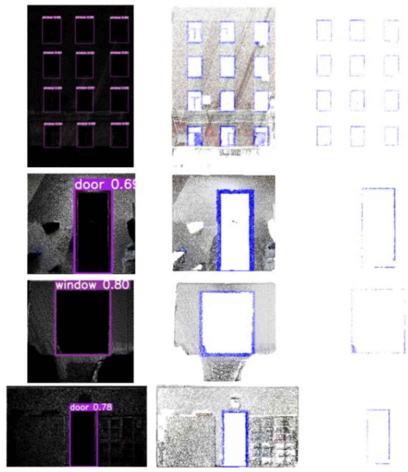

Figure 9. Door and Window Extraction Results from Coarse to Fine.

Index	e_{max}	e_{avg}
1	0. 045	0. 023
2	0. 044	0. 019
3	0. 038	0. 019
4	0. 036	0. 020
5	0. 039	0. 026

Table 3. Door and Window Recognition Accuracy.

Figure 10 shows the final constructed integrated indoor-outdoor topological model, where the yellow portion represents the indoor topological model, the gray area represents the transitional space topological model, and the green lines indicate the spatial unit connections in the IndoorGML model. The white circles represent the spatial unit nodes, and the blue lines represent the outdoor road topology model. The enlarged view on the left side of the image illustrates the specific connections within the transitional space, where the red geometric cubes represent the thick door models, and the yellow geometric cubes represent the thick window models.
This study uses two metrics for model evaluation: the proportion of floor points included in the floor surface (Floor Coverage) and the proportion of wall points included in the wall surface (Wall Coverage). These metrics indicate that the reconstructed model closely matches the original data and effectively reflects the true structure of the building. To demonstrate that the integrated topological model fully utilizes the advantages of the vertical transitional space, we conducted an unmanned aerial vehicle (UAV) flight path planning experiment, where the shortest route from a designated outdoor node through the transitional space to a designated indoor node was calculated. This confirms that the model is applicable in scenarios such as emergency response.

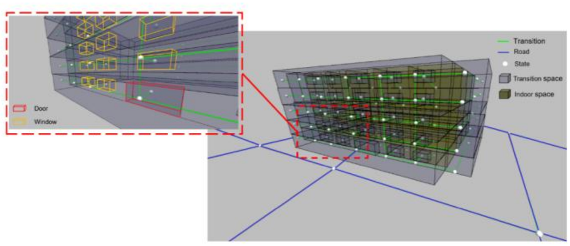

Figure 10. Integrated Indoor-Outdoor Topological Model.

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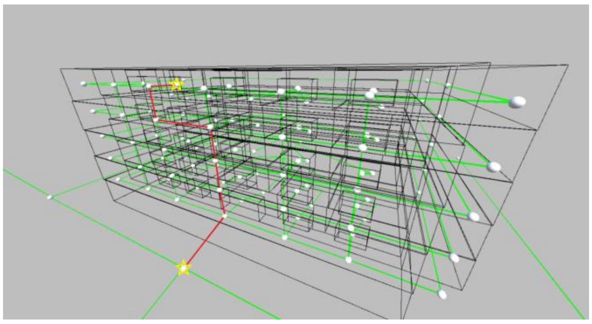

Figure 11. UAV Path Planning (with the red line representing the planned flight path).

Data	Floor Coverage	Wall Coverage
Floor1	0. 955	0. 944
Floor2	0. 968	0. 952
Floor3	0. 974	0. 945
Floor4	0. 975	0. 954
Floor5	0. 969	0. 956

Table 4. Model Construction Accuracy.

4. Conclusion

To meet the demands of cross-scenario navigation and emergency UAV flight, this study proposes a topological modeling method for integrated indoor-outdoor spaces based on transitional spaces. By revisiting the definition of transitional spaces, we redefined semi-indoor and semi-outdoor spaces, and established node connections between indoor door/window nodes and the semi-outdoor space, addressing the limitations of single-point connections that fail to meet navigation requirements. This led to the construction of the final integrated indoor-outdoor topological model.

The topological model developed in this study not only considers ground-level scenario navigation but also fully incorporates the vertical aspects of transitional spaces, extending the outdoor topological model from a two-dimensional to a three-dimensional application. The integrated indoor-outdoor model not only satisfies routine pedestrian path planning needs but can also serve as an offline model for emergency scenarios such as UAV path planning during fires and escape route planning for trapped individuals, offering significant practical applications.

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