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Automated Extraction of Indoor Structural Information from 3D Point Clouds

[1]Sujitha Kurup, [2]Dr. Archana Bhise

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Abstract: In numerous smart city applications, including building information modeling (BIM), spatial location applications, energy consumption prediction, and signal simulation, accurate 3D modeling of interior environments is crucial. Rapid and stable reconstruction of three-dimensional models from point clouds has attracted considerable interest, but the creation of accurate three-dimensional models in complex interior environments remains a formidable challenge. This study presents a novel method for autonomously recreating 3D models by combining linear structures with three-dimensional geometric surfaces. Using 3D point clouds, the proposed method recognizes indoor structural frameworks. It uses a combination of Principal Component Analysis (PCA) variables, such as curvature, anisotropy, and verticality, to accurately detect and extract building structures. To evaluate the efficacy of the method, a dataset of real-world 3D point cloud scans is employed, and the results demonstrate its capacity to recognize structural frameworks with low Chamfer and Hausdorff distances. Doors, windows, and pillars are accurately reconstructed, allowing for an Indoor Structural Information model to be generated. This model can considerably improve building information modeling, construction planning, and maintenance tasks by automating BIM modeling. This method has the potential to improve the accuracy and efficacy of 3D reconstruction in smart city applications, allowing for more accurate building information modeling and streamlining construction and maintenance processes.

***Keywords**: structural elements, 3D reconstruction, PCA, indoor modelling, point cloud, wire framework*

1. Introduction

Due to its numerous applications in industries including design, construction, and building management, the extraction of internal building structure from 3D point clouds has become an important area of research in recent years [1]. Indoor building structure extraction is the technique of collecting relevant information from 3D point clouds, such as walls, doors, and furniture, for use in building design, facility management, and even virtual reality [2-4]. Traditional techniques, such as manual measurements and questionnaires, are labor-intensive, error-prone, and frequently insufficient. On the other hand, invasive testing procedures, like drilling and excavation, can be expensive, disruptive, and inappropriate for all structures.

3D scanning technology has enabled the capture of high-resolution 3D point cloud data of indoor spaces, enabling precise visualization of structures like position, form, and size [2]. However, detecting structural frameworks remains a challenge due to time and skill requirements [5-6]. The need for accurate building design, facility management, and virtual reality applications has led to the development of an automatic and unsupervised method for recognizing interior structural frameworks from 3D point clouds [7-8]. This approach saves time, and resources to produce more accurate and trustworthy outcomes, contributing to the sector's efficiency and precision in building design, facilities management, and virtual reality applications.

This research aims to develop an unsupervised automated method for recognizing interior structure frameworks from 3D point clouds. The proposed technique should be able to recognize and extract structural features such as beams, columns, and walls without requiring prior knowledge or human supervision to produce a line framework for a variety of applications. In addition, the proposed method must be adaptable to a variety of interior environment scenarios, point cloud densities, and occlusion levels. The following are the primary contributions of this study:

Developing an unsupervised automated system for recognizing and extracting indoor structural frameworks from 3D point clouds using a combination of feature extraction approaches and clustering algorithms. The evaluation of the proposed method uses a database of 3D point cloud images from the real world, representing a range of building types and point cloud density and occlusion levels.

The remaining sections of the paper are organized as follows. The following section of the paper provides an overview of the pertinent literature, while the third section provides a detailed explanation of the developed method, which uses indoor point clouds as input.

Department of Electronics and Telecommunication Engineering, Mukesh Patel School of Technology Management & Engineering NMIMS University, Mumbai, India
[1]ORCID:0000-0003-3396-5549,sujithaskurup@gmail.com
[2]ORCID:0000-0002-7913-791X, Archana.Bhise@nmims.edu

Section 3 describes the extraction of PCA-based geometric descriptors to define the structural geometry of an interior environment, whereas Section 4 evaluates the developed method using existing datasets. Section 5 discusses the experimental outcomes, including advantages, disadvantages, and potential future optimization of the experimental procedure. Section 6 concludes the paper by summarizing its entirety and looking ahead to future research.

2. Related Works

With the recent development of laser technology and digital photogrammetry, a 3D point cloud model can restore the true appearance of an object. Point clouds are simple to visualize because they consist of clusters of points without attribute information. Consequently, their use in drawings is problematic for designers. Errors in drawings can be decreased if the point cloud can be segmented [9]. In addition, point cloud attributes can facilitate semi-automatic or fully automated modeling.

The advent of 3D scanning technologies in recent years has revolutionized the capture and analysis of indoor environments. With the ability to acquire high-resolution 3D point clouds representing the geometric details of architectural spaces, researchers have actively pursued automated methods to extract useful structural information from these data. The extraction of such information, including walls, floors, ceilings, and other important architectural elements, has enormous potential for use in architectural modeling, building inspection, and virtual reality. Unsupervised learning methods offer advantages in automated 3D point cloud structural information extraction, as they learn patterns directly from unlabelled data, reducing manual annotation and scalability. These methods capture complex relationships and variations, making them suitable for diverse environments [6]. The line framework of interior structures has been extracted from point cloud data using a variety of unsupervised techniques.

RANSAC (Random Sample Consensus) is a robust algorithm utilized in computer vision and geometric modelling to estimate the parameters of a mathematical model from a collection of observed data. RANSAC's resistance to outliers and noise makes it well-suited for dealing with unstructured point clouds, where data flaws are prevalent [10-11]. One study proposed a semi-automatic method involving the detection of plane components based on RANSAC segmentation, which enhanced modelling productivity in terms of time consumption and facilitated precise object sketching by operators [12]. However, additional automation was necessary to finish 3D modelling. While another semi-automatic method involving the segmentation, classification, and reconstruction of walls and slabs was able to generate a BIM file that allowed for simple integration with BIM software [13]. This method also accelerated the processing time by using Principal Component Analysis(PCA). Using RANSAC to detect concealed edges and corners [14], it was determined that contour point clouds offer benefits in terms of the interior geometry complexity of a building.

Unsupervised approaches also use probabilistic models, such as Gaussian Mixture Models (GMM) or Hidden Markov Models (HMM), to represent the underlying structure of the point cloud data in model-based procedures for point cloud analysis [5]. Construction and fitting of probabilistic models, such as Gaussian Mixture Models and Hidden Markov Models, can be computationally expensive and requires careful parameter calibration. In practice, the model's efficacy is highly dependent on selecting the optimal number of components or states. Analyzing and processing graphs can be computationally intensive, especially for large-scale point cloud datasets. Graph-based models often require graph traversal, clustering, or optimization algorithms, which may pose scalability challenges and hinder real-time or interactive applications. Graph-based models, including Graph Neural Networks (GNNs) and Graph Convolutional Networks (GCNs), also contribute to the generation of wireframe structures from unstructured point clouds [15-16]. Each point in the unstructured point cloud is converted into a node in the resulting graph representation. Certain criteria, such as proximity or connectivity between points, are utilized to establish the edges between nodes. Each node in the graph is allocated additional features that capture information about the local geometry or characteristics of the corresponding point in the point cloud. These attributes may consist of position coordinates, normal vectors, or other descriptive characteristics. The inherent connectivity and local relationships between the unstructured point cloud's elements are captured and utilized to infer the wireframe structure.

Unsupervised feature extraction techniques such as Principal Component Analysis (PCA) or Normal Estimation were used to extract geometric descriptors from the point cloud data. These descriptors encapsulate the local geometric properties and can be used to identify and extract the indoor line framework [17-18]. PCA is a popular unsupervised technique for extracting features from point cloud data, but it has limitations in terms of sensitivity to data scaling, linear projection, and robustness against anomalies.This study introduces a new method for autonomously constructing a three-dimensional indoor model from point clouds by combining line structures and three-dimensional surface geometry. Preserving structural information, the method segments unstructured point clouds using Principle Component Analysis (PCA) and Local Manifold Clustering (LMC) techniques. LMC overcomes the limitations of PCA by providing data scaling robustness, nonlinear projection robustness, outlier robustness, and local feature extraction. KD-tree computes nearest neighbors, whereas DBCSAN computes wireframes directly from point clouds. The Local Mean Curvature (LMC) technique recreates 3D structured models, yielding superior geometric attribute derivation results compared to PCA-based frameworks.

3. Proposed Methodology

The proposed methodology for extracting indoor structural information from 3D point clouds is outlined in Fig. 1. The flowchart provides a comprehensive overview of the step-by-step process employed in this research. The methodology encompasses a series of key stages, including data acquisition, pre-processing, segmentation, structural wireframe generation, and results visualization.

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In the pre-processing stage, various techniques are applied to the acquired point cloud data to enhance its quality and prepare it for subsequent analysis. This subsection focuses on two key pre-processing steps: Statistical Outlier Removal and Voxel Down-sampling. Statistical Outlier Removal is a technique for denoising point cloud data by removing deviating points, and removing noise, artifacts, and incorrect elements.

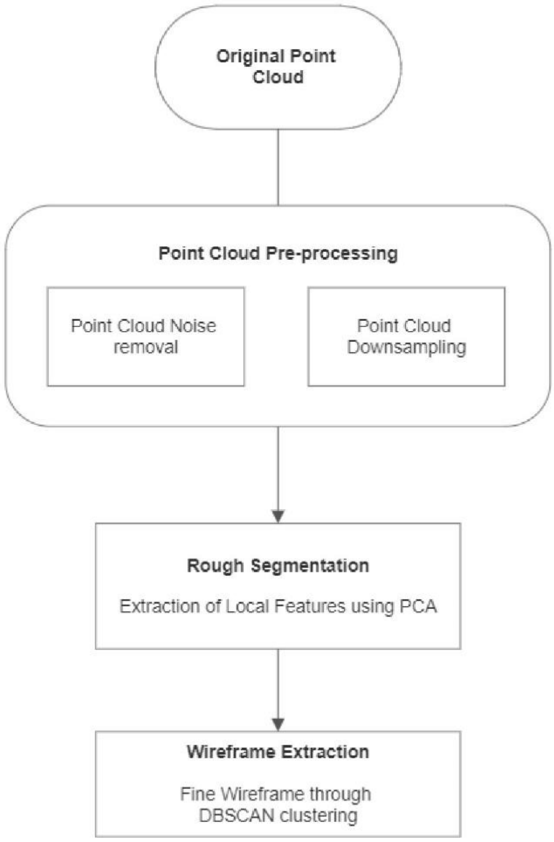


Fig. 1 Flowchart of the proposed methodology

This improves accuracy and reliability for modeling and analysis, eliminating spurious points caused by sensor noise, environmental interference, or scanning artifacts. Voxel downsampling reduces the density and size of point clouds by dividing them into 3D grids called voxels and selecting representative points. This technique increases efficiency, reduces noise, preserves structural information, and reduces data size, resulting in more refined and comprehensive representations of fundamental geometry.

Table 1. Definition of Geometric Descriptors

Descriptor	Definition
Eigen Values	$d_v^g = \lambda_v$ with $v \varepsilon 1, 2, 3$
Sum of Eigen Values	$d_4^g = \sum_1^v \lambda_v$
Linearity	$d_5^g = (\lambda_1 - \lambda_2)/\lambda_1$
Planarity	$d_6^g = (\lambda_2 - \lambda_3)/\lambda_1$
Sphericity	$d_7^g = \lambda_3/\lambda_1$
Anisotropy	$d_8^g = (\lambda_1 - \lambda_3)/\lambda_1$
Omnivariance	$d_9^g = \sqrt[3]{(\lambda_1.\lambda_2.\lambda_3)}$
Eigentropy	$d_{10}^g = -\sum \lambda_v . \ln(\lambda_v)$
Parallelity_x	$d_{11}^g = 1 - \lvert u_x.e_3 \rvert$
Parallelity_y	$d_{12}^g = 1 - \lvert u_y.e_3 \rvert$
Parallelity_z	$d_{13}^g = 1 - \lvert u_z.e_3 \rvert$

The objective of the rough segmentation block is to comprehend the structural geometry of unstructured point cloud data by extracting global- and local-level features using Principal Component Analysis (PCA). Using PCA based on eigenvalues and eigenvectors, the geometric features of the point cloud are computed.

Principal Component Analysis (PCA) is a statistical method for analyzing data and identifying significant patterns using eigenvalues and eigenvectors. PCA enables the extraction of geometric features that characterize the shape and orientation of objects or surfaces within a point cloud in the context of point cloud analysis.PCA is applied locally to the preprocessed point cloud to compute the eigenvalues and eigenvectors of each point's surrounding neighborhood. These local characteristics provide information about the geometry and orientation of the point cloud at the local level. PCA is also used on a global scale to capture the geometry characteristics of the point cloud as a whole. By contemplating the entire point cloud or larger regions, global-level characteristics reveal the structural geometry at a larger scale. PCA reduces dimensionality in point cloud data, capturing dominant variations and identifying principal axes. LMC analyzes local geometric properties, capturing fine-grained details and local structures. Combining PCA and LMC offers a global overview, capturing dominant patterns and local geometric details, resulting in more comprehensive and accurate geometric descriptors for further analysis or applications.

The PCA eigenvalues and eigenvectors are utilized to extract the pertinent geometric features. These characteristics may include ratios of eigenvalues, sums of eigenvalues, anisotropy, verticality, and others as listed in Table. 1. They serve as descriptions of the structural characteristics of the point cloud.

From the unstructured point cloud data, valuable geometric information is extracted using PCA during the initial segmentation stage. The extracted global-level and local-level features enhance comprehension of the point cloud's structural geometry, laying the groundwork for subsequent analysis and segmentation procedures.

DBSCAN (Density-Based Spatial Clustering of Applications with Noise) is later employed to improve the wireframe derived from the geometric descriptors. DBSCAN is a density-based clustering algorithm that efficiently identifies dense regions within the point cloud, thereby contributing to the refinement of the wireframe representation.

DBSCAN clustering enhances wireframe refinement by grouping densely connected points, identifying significant structures and segments, filtering out noise and anomalies, and identifying critical cluster boundary locations for wireframe reconstruction. Its adaptability to varying densities in the point cloud enables flexible parameter settings, making it suitable for complex indoor environments with variable data densities.

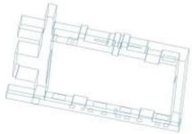
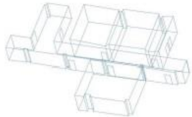
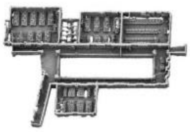
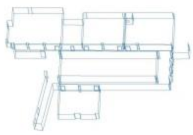
By applying DBSCAN clustering to the wireframe generated from the geometric descriptors, the wireframe representation is enhanced by removing noise, identifying meaningful clusters, and determining precise boundary lines. This improved wireframe model provides a more trustworthy basis for subsequent analysis, reconstruction, and visualization duties.

4. Experimental Results

4.1 Dataset

The dataset chosen for evaluation is the ISPRS Benchmark on Multisensory Indoor Mapping and Positioning and the Navvis dataset[19] whichis a colored point clouds that capture the structure of indoor spaces withhigh spatial resolution. The ISPRS Benchmark on Multisensorial IndoorMapping And Positioning (MiMAP) project provided a common frameworkfor the evaluation and comparison of LiDAR-based SLAM, BIM feature extraction, and smartphone-based indoor positioning methods [20-21].TheBIM feature extraction dataset contains data from three indoor scenes with varying complexity. For each of the scenes, raw data (point cloud in LAS format) and corresponding BIM line framework (in OBJ format) are provided.Table. 2 contains a description of the employed dataset.

Table 2. Description of MiMaP BIM Feature Extraction dataset

Name	Size	Description	Point Cloud	Ground Truth
Scene 1	14.2 MB	Closed loop corridor		
Scene 2	105 MB	Corridor and rooms		
Scene 3	237 MB	Corridor and rooms		

4.2 Point Cloud Pre-processing

After applying the SOR filter with the specified parameters, a denoised point cloud containing 281,765 points was obtained after effectively eliminating points from the original point cloud, of 307,484 points, designated as outliers or noise, resulting in a more accurate and reliable representation of the underlying structural data. Denoising with the SOR filter is essential for producing point cloud data for modeling and reconstruction. It improves the accuracy and reliability of the subsequent analysis by reducing noise and outliers, resulting in more accurate structural information extraction from the point cloud data.

Table 3. Voxel Downsampling of denoised point cloud

Voxel Size	0.03	0.05	0.1
No of points	12336 / 281765	47815 / 281765	124119 / 281765
Time	0.022 sec	0.032 sec	0.077 sec

In the voxel downsampling phase, the previously obtained denoised point cloud is downsampled using variable voxel grid sizes. The point cloud is specifically downsampled at three distinct voxel grid sizes: 0.1, 0.03, and 0.05 as shown in Table. 3.The resolution at which the point cloud is represented after downsampling is determined by the voxel grid size. A reduced voxel grid size increases the level of detail and preserves the point cloud's finer-grained features. A larger voxel grid size, on the other hand, reduces the level of detail but can simplify the point cloud representation. It is essential to choose a voxel grid size based on the application's specific requirements and the intended balance between level of detail and computational efficiency. To assure optimal results for the extraction of indoor structural information from the downsampled point cloud, the voxel grid size of 0.05 was chosen in accordance with the goals of the subsequent modeling and reconstruction steps.

4.3 Framework generation

In this study, PCA-based geometric features were applied to indoor scene point cloud data in order to obtain insight into the overall structural geometry. These characteristics allowed for a comprehensive comprehension of the efficacy of comprehending structural geometry. To discern the fine geometry of the structure, it was essential to comprehend the neighborhood specifics. To accomplish this, local characteristics were extracted from the k-valued neighborhoods of coordinates. This method provided valuable information about the neighborhood-level properties of coordinates. Again, PCA and LMC analysis was utilized to comprehend the neighborhood-level characteristics. Two conspicuous characteristics of the local neighborhood were identified.

The surface curvature of edge points and corner points was found to be greater than that of points on level surfaces. This distinction is due to the more diverse orientations and reduced variation in the local region of edge and corner points. The anisotropy values of edge points and corner points were low due to their typical location at the boundaries of distinct surfaces.

Table 4. Line Framework Generation on Navvis Dataset

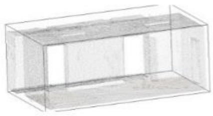
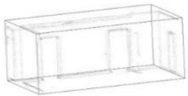
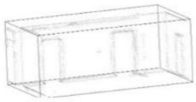
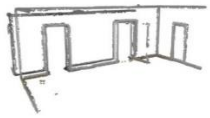
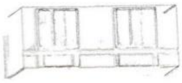
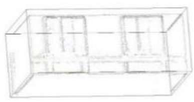
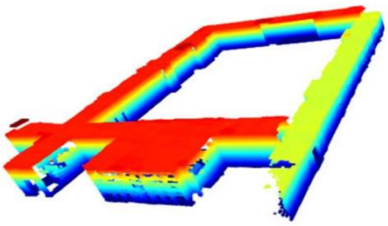
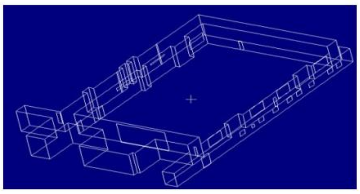
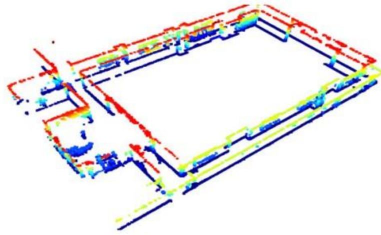
Original Point Cloud	Surface Curvature	Anisotropy	Line Framework
			
			

Table 5. Line Framework Generation on MiMaP dataset.

Original Point Cloud	Ground Truth	Line Framework
		

Therefore, edge points and corner points exhibited reduced anisotropy. By collecting the finer details of the point cloud data, these local features significantly contributed to a more thorough comprehension of the structural geometry. These two characteristics were used to extract the generated wireframe, which was then clustered using the DBSCAN clustering mechanism. This algorithm was evaluated on both experimental datasets. The results for the Navvis dataset are depicted in Table. 4 and that of Scene 1 in the MiMAP dataset is depicted in Table. 5.The results indicate that the derived features from the Navvis dataset defined a detailed line framework model. However, when applied to the MiMaP dataset, which consisted of a long corridor and multiple interconnected rooms, the generated framework exhibited insufficient detail.

4.4 Evaluation metrics

To quantify the difference between point clouds, numerous evaluation metrics are employed to provide objective measures of dissimilarityand enable comparisons between distinct algorithms or methods. Various metrics, such as Chamfer distance and Hausdorff distance, allow for the evaluation of how closely a reconstructed point cloud aligns with ground truth data.

Table 6. Evaluation of the proposed method on the MiMaP dataset

MiMaP Dataset	Point Cloud (points)	Pre-processing (points)	Processing Time (minutes)	Line Framework (points)	Chamfer Distance	Hausdorff Distance
Scene 1	2 098 121	641 936	69.71	38 829	1.938	7.72
Scene 2	3 451 281	876 459	78.11	45 643	1.874	7.87
Scene 3	3 893 452	883 876	79.62	46 652	1.883	7.54

Chamfer distance measures the average distance between points in one point cloud and the point in the other point cloud that is closest to them. It is symmetric and takes distances between points in both clouds into consideration. In Table. 6., for scene 1, the chamfer distance was determined to be 1.938, indicating that each original point cloud point is approximately 1.938 units from its closest point in the ground truth point cloud. A smaller Chamfer distance indicates greater similarity between the two point clouds. While the

Hausdorff distance measures the error between two point clouds, it also evaluates the distances between points in one cloud and the closest point in the other cloud. It has a high sensitivity to outliers and large deviations. A 7.72 Hausdorff distance indicates that the two clouds are more closely aligned.

5. Conclusion

The proposed method extracts the line framework from point cloud data using PCA-based geometric descriptors, as evaluated on the Navvis and MiMaP Benchmark Dataset. The procedure effectively reduces the number of points in the original point cloud, allowing for more efficient data representation and processing. Despite the reduction in point cloud size, the method exhibits reasonable computation times, with the processing time for the evaluated scenes ranging from 69.71 to 79.62 minutes. The line frameworks generated by the method are compared to the ground truth data to demonstrate the method's ability to capture the fundamental characteristics of the scene's line structures. The use of evaluation metrics such as the Chamfer distance and Hausdorff distance provides quantitative measures of the efficacy of a method, enabling objective comparisons and benchmarking. However, the method depends on PCA-based geometric descriptors, which may limit its performance when the line structures have complex geometries that are not well captured by LMC. The efficiency of the method is affected by the precision of the extracted line framework, which is dependent on the quality of the preprocessing phase. While the method's performance on the MiMaP Benchmark Dataset is promising, its performance on other datasets or in real-world scenarios may vary. To assess its generalizability, additional testing on various data sets is required. The proposed method provides benefits such as reduced point cloud size, reasonable computation times, and precise line framework extraction. Nonetheless, its reliance on PCA, sensitivity to pre-processing, and limited generalizability must be taken into account. These limitations could be addressed through additional research and experimentation, thereby expanding the method's applicability in a variety of contexts.

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