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Original Article

Refining Line Frame Construction from 3D Point Clouds: DBSCAN and Alpha Shape Approach

Sujitha Kurup[1], Archana Bhise[2]

[1,2]*Department of Electronics and Telecommunications Engineering, Mukesh Patel School of Technology Management & Sciences, NMIMS University, Vile Parle, Mumbai, Maharashtra, India.*

[1]*Corresponding Author : sujithaskurup46@gmail.com*

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Abstract *- The application of 3D point cloud data has gained significant traction in the field of advanced building and manufacturing. This paper presents a comprehensive methodology for refining line frame construction from indoor 3D point clouds directly. The proposed methodology integrates edge detection methods and Alpha Shape computation to achieve an accurate representation of indoor structural geometry. Extensive analyses of several scenarios of indoor scene environments have demonstrated the usefulness and robustness of the methods. The study evaluates this methodology across three distinct datasets, denoted as Cases A, B, and C, each representing varying degrees of indoor room complexity. The edge identification approach uses PCA-based geometric descriptors in conjunction with DBSCAN clustering to accurately locate and segment edge points, resulting in the creation of full wireframe models. The utilization of the Rolling Ball Pivoting algorithm in the computation of the Alpha Shape facilitates the enhancement of the wireframe structure, hence enabling accurate representation. Our evaluation demonstrates exceptional adaptability and performance across scenarios, with Case C showcasing remarkable Precision (0.914) and Recall (0.941), leading to an impressive F1 score of 0.927. This research contributes to advancing indoor scene reconstruction, offering a robust methodology for precise structural representation within interior spaces.*

Keywords *- 3D point cloud, PCA, Indoor modeling, Line frame construction, Alpha shape, Clustering.*

1. Introduction

The rapid advancement of technology in recent years has revolutionized various industries, including civil engineering. One transformative method that has emerged is the utilization of point cloud data, which has become instrumental in capturing and modeling indoor environments due to the escalating demand for accuracy and efficiency in construction and interior design [1-5]. Point clouds, comprising dense collections of three-dimensional (3D) points acquired through laser scanning or photogrammetric techniques, have demonstrated their indispensability in generating precise representations of real-world spaces [6-8]. However, despite the potential of point cloud data, the precise extraction of edges and corners remains a critical challenge in the process of converting raw 3D point clouds into meaningful geometric models [9-12]. Traditionally, identifying edges and corners within indoor environments relied heavily on manual measurements, which are not only laborious and time-consuming but also susceptible to human error, especially in the case of complex structures. Consequently, there exists a pressing need to address these challenges by developing more efficient and accurate methods for extracting edges and corners from point cloud data. This study addresses this research gap by proposing a novel approach for extracting edges and corners from point cloud data, with a particular focus on its applicability to civil and interior construction projects. By leveraging techniques such as DBSCAN and Alpha shape, this approach aims to enhance the efficiency and accuracy of edge and corner extraction, thereby facilitating precise measurements and aiding in the planning and execution of building and interior design projects through the provision of detailed 3D models highlighting key structural features. The novelty of this work lies in its integration of DBSCAN and Alpha shape algorithms to refine line frame construction from 3D point clouds, offering a systematic and automated solution to the challenges associated with manual edge and corner extraction. By automating this process, the proposed approach not only reduces the reliance on labor-intensive manual methods but also improves the accuracy and reliability of the resulting geometric models, thus advancing the state-of-the-art in point cloud processing for civil and interior construction applications. The subsequent sections of this paper are organized as follows: Section 2 provides an overview of the relevant literature, highlighting existing approaches and their limitations. Section 3 presents a detailed explanation of the proposed method, including the implementation of DBSCAN and alpha shape algorithms. In Section 4, the effectiveness of the developed technique is evaluated using existing datasets, followed by a discussion of the experimental results. Finally, Section 5 concludes the paper with a comprehensive summary and outlines directions for future research.

2. Related Works

2.1. Point Cloud Data

Point cloud data is used in civil engineering and interior design to capture comprehensive 3D representations of indoor settings. Acquired via laser scanning or photogrammetry, point clouds consist of vast arrays of 3D points that, when combined, accurately depict the surfaces and features of real-world scenes. Researchers and experts may create realistic indoor settings using point clouds to reconstruct buildings, rooms, and architectural spaces [12-14]. The technique entails extracting structural features from point cloud data, such as walls, floors, ceilings, doors, and windows, to construct accurate and parametric building models. These models are fundamental components of Building Information Modelling (BIM) applications, which are extensively used in the construction and design sectors [15]. The study conducted by [16] primarily centered on the automated reconstruction of parametric architectural models using indoor point clouds. The authors emphasized the significance of edge extraction in the process of recognizing and delineating structural components, such as walls and columns, within point cloud data. The approach employed by the researchers effectively extracted edges, so facilitating the production of parametric models. This, in turn, enabled efficient architectural design and refurbishment processes through the utilization of Building Information Modelling (BIM) technologies by introducing novel algorithms for the detection and reconstruction of 3D surface point cloud boundaries and edges. Utilizing advanced computational methods, their research sought to improve the precision and performance of edge extraction techniques. The increased accuracy of edge detection enabled more refined indoor scene reconstructions, resulting in high-quality BIM models that more accurately reflected the underlying architectural spaces.

A thorough analysis of the most up-to-date methods for building reconstruction using point clouds is provided in references [17]. In the realm of research on building reconstruction techniques, it has been observed that there are significant limitations in how they are developed [18,19]. These limitations pertain to concerns regarding the efficiency and effectiveness of the techniques, their applicability to various scenarios, their robustness in the face of disturbances, and the constraints imposed by the methods used for data acquisition [20,21]. It is crucial to prioritize the resolution of these constraints and problems to make progress in the field of building reconstruction using point clouds. This will ultimately facilitate the advancement of methodologies that are more effective, adaptable, and robust, enabling their practical application in a wide range of real-world situations.

2.2. Edge Detection Techniques

The research uses unsupervised learning to identify significant patterns and structures from raw point cloud data without labeled samples, making it more scalable and adaptable to varied real-world contexts. This minimizes the need for labor-intensive manual annotations and expands the applicability of the procedures to a wide range of building kinds and configurations, which could revolutionize building reconstruction. Edge extraction in point cloud data helps identify and delineate structural components like walls, floors, doors, and windows in interior and outdoor environments. These methods provide accurate and comprehensive 3D models for civil engineering, architecture, interior design, and robotics. Clustering-based unsupervised edge detection from point clouds is powerful and efficient. 3D modelling, scene segmentation, and robotics use their capacity to distinguish clusters of points indicating edges and boundaries [22]. These approaches cluster close points in the point cloud by spatial proximity or other similarity metrics, recognizing scene edges and surfaces. A modified DBSCAN clustering technique to find boundaries and planes in 3D point clouds was introduced in [23], which uses 3D space to pick candidate samples and detect valid fitting planes. The suggested method improves the standard DBSCAN clustering algorithm to detect boundaries and segment planes in point clouds, making it viable for 3D modeling and scene reconstruction. In [24], new algorithms for edge and corner recognition in unorganized 3D point clouds evaluated symmetry in a small neighborhood and used an adaptive density-based threshold to discriminate 3D edge points. The new corner recognition algorithm clusters curvature vectors and leverages geometrical characteristics to identify corners. The algorithms are tested on RGB-D semantic segmentation, ShapeNet 3D washer models, and robotic welding weld seam identification.

Geometric shape-based methods provide a potent approach for unsupervised edge extraction from point clouds, yielding valuable insights into the structural elements of the scene and facilitating numerous applications in 3D modelling, scene understanding, and robotics [25]. These methods use geometric properties and characteristics of the point cloud, such as surface normals, curvatures, and local surface orientations, to detect abrupt surface changes indicative of edges or corners. [26] present a method to automatically detect contours in large-scale outdoor point clouds, which are crucial intermediary elements for organizing point clouds and creating high-quality surface or solid models. The method addresses contour extraction as a two-stage discriminative learning problem. It can process point clouds with more than 10^7 points in a matter of minutes, vastly outperforming existing line detection algorithms. In [27,28], methods for processing point cloud data using voxel-based feature engineering that seek to improve the characterization of point clusters and provide substantial assistance in both supervised and unsupervised classification tasks were proposed. The strategy proposed by [29] offers a method for effectively segmenting point clouds of historical buildings, a task of significant relevance in the fields of engineering and construction. The methodology integrates the Hierarchical Watershed Transform and curvature analysis techniques to derive optimal seed points. The effectiveness of this approach was assessed using data collected from both aerial drones and terrestrial laser scanners. Geometric-based methodologies exhibit susceptibility to noise and changes in point density due to their dependence on local geometric attributes of the point cloud. Clustering-based methodologies demonstrate efficacy in the grouping of proximate points and identification of clusters. However, they may exhibit limitations in accurately segmenting intricate scenes with overlapping structures or variations in point density. To address the constraints above, the present study introduces a novel methodology that integrates DBSCAN clustering and geometric form-based methods. Subsequently, the alpha shape algorithm is employed to enhance the precision of edge and corner detection within indoor environments. The integration of DBSCAN clustering enhances the method's ability to accurately detect clusters that correspond to potential edges and boundaries inside the point cloud. The use of surface normals, curvatures, and local orientations in the geometric shape-based approach serves to enhance the accuracy and robustness of the edge extraction procedure for the discovered clusters. The alpha shape method, in conclusion, offers a concave hull surrounding the point cloud data, facilitating the creation of a precise and intricate depiction of the edges and corners within the indoor environment.

3. Materials and Methods

The objective of the proposed methodology is to derive the structural geometry of an indoor room scene using unstructured point cloud data. The input to the procedure consists of an unstructured point cloud that represents the indoor room scene. The methodology has three primary stages: Pre-processing, Edge Detection, and Edge refining, as seen in Figure 1. A comprehensive explanation of each stage is provided below.

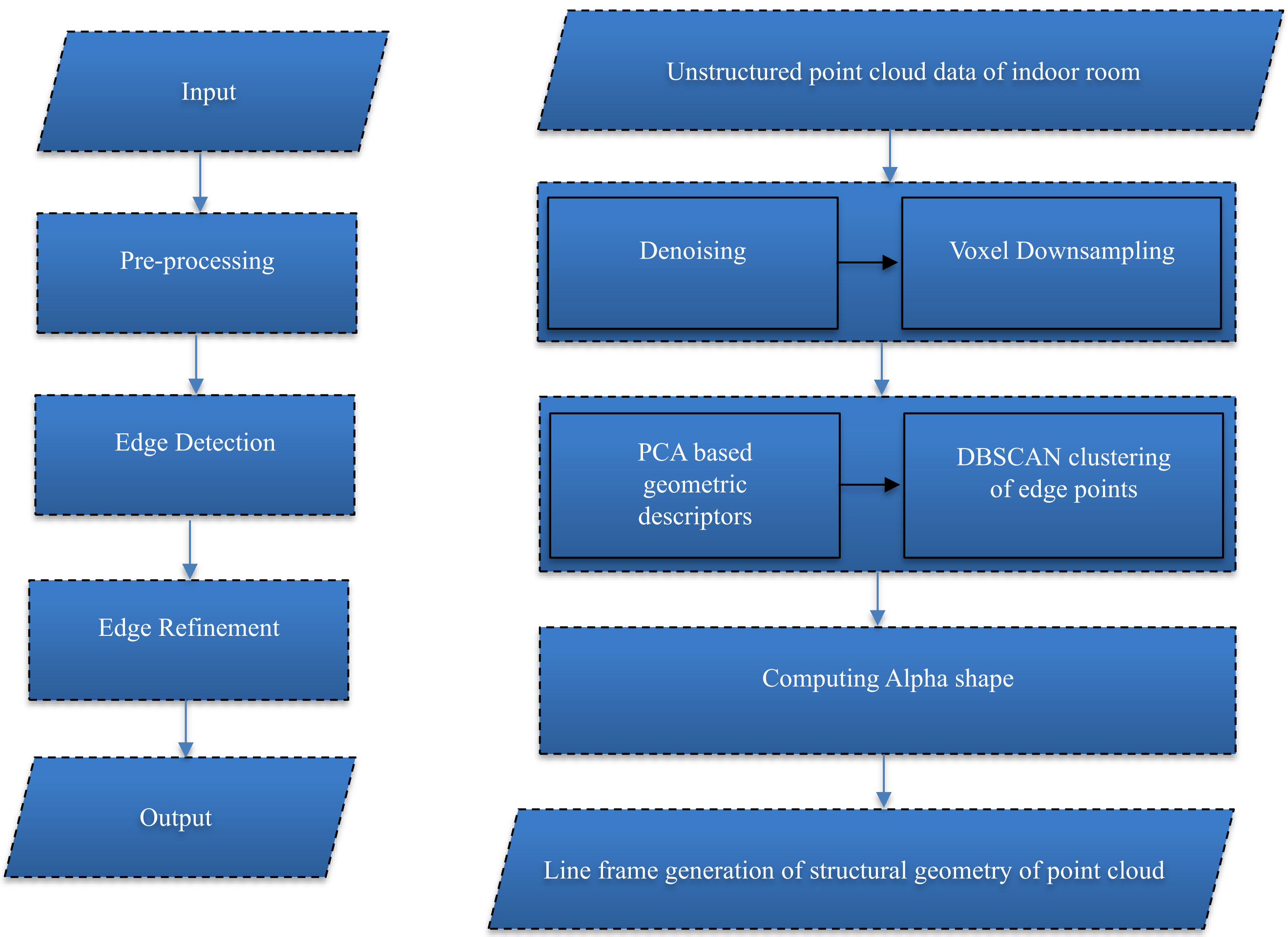


Fig. 1 Flowchart of the proposed methodology

During the pre-processing stage, the point cloud data is subjected to an initial phase of data cleaning and simplification to enhance the quality of the data and decrease the computing complexity. The approach consists of two fundamental sub-steps: Denoising utilizing Statistical Outlier Removal and Voxel Down-sampling. The process of denoising serves to effectively remove unwanted noise and outliers present in the point cloud data, hence enhancing its quality. On the other hand, Voxel Down-sampling is employed to decrease the density of the point cloud while preserving its fundamental structural characteristics.The third stage is Edge Detection, which is concerned with the identification of the edges pertaining to the structural geometry of the indoor room. The process entails the computation of Principal Component Analysis (PCA)-based geometric descriptors [30] for the local neighborhood of each point, considering a set of 10 neighboring points. Surface curvature and anisotropy are two significant descriptors utilized at this stage. Locations that have surface curvature values that surpass a certain threshold and locations that have anisotropy values below a separate criterion are recognized as potential edge points. The potential edge points undergo DBSCAN clustering to extract the contour of the space's structural geometry. This technique effectively isolates the edges and improves the representation of the architectural aspects within the room.

The process of edge refining plays a crucial role in the methodology by improving the accuracy of structural elements obtained from 3D point clouds. This ensures a more precise depiction of the physical surroundings. The last stage of Edge refining involves the utilization of the Alpha Shape generation process [31], notably Rolling Ball Pivoting, to acquire a more precise line frame model of the structural geometry within the interior room. The Rolling Ball Pivoting (RBP) algorithm [32] efficiently computes a point cloud's Alpha Shape by envisioning a rolling ball pivoting over its surface. From a seed triangle, the algorithm grows the ball's radius until it reaches another point, generating tetrahedra and testing the Delaunay circumsphere property.

The Alpha Shape is filled with triangles until all points are included, representing the point cloud's shape, including convex and concave regions. This revised Alpha Shape is useful for line frame models for indoor room scene structural geometry [33]. The Alpha Shape algorithm can capture both convex and concave regions, so offering a thorough depiction of the structural edges and corners within the room. The line frame model obtained from the computed Alpha Shape provides a comprehensive and precise depiction of the structural geometry of the indoor room. The methodology presented demonstrates a high level of effectiveness in capturing the complex characteristics of the room, so facilitating more accurate measurements and providing valuable support for a range of civil engineering and interior works applications.

4. Results and Discussion

4.1. Dataset

To evaluate the efficacy of the suggested methodology, experiments were conducted utilizing point cloud data, a dataset of colored point clouds with high spatial resolution, which represents interior situations well. The input dataset for this study comprises a colored point cloud captured using a NavVis Laser scanner. This point cloud represents an entire floor of a building and is stored in the last format.

With a total of 4,244,416 points, this dataset provides a detailed and comprehensive representation of the entire floor, including multiple rooms with varying interior geometries. These rooms may differ in size, shape, and layout, making the dataset particularly valuable for various analyses and applications within the study. The methodology's capabilities and restrictions are better assessed using colored point clouds in real-world circumstances. Within the NavVis dataset, three specific use case scenarios, labelled as Cases A, B, and C, were created.

These scenarios were designed to assess and confirm the effectiveness of the algorithm's methodology, as shown in Figure 2. The number of points present in each point cloud scenario is detailed in Table 1. These cases serve as representative testbeds for evaluating the algorithm's efficacy and dependability in various architectural settings. Case A displays a point cloud depicting a wall with two distinct doorways. The presence of numerous doorways within a single structural element poses a challenge to the algorithm's ability to capture and analyze architectural features precisely.

In Case B, the point cloud represents a wall configuration characterized by the presence of three windows. The varying window sizes and positions introduce complexities that enable us to evaluate the algorithm's ability to distinguish and delineate architectural components accurately. Case C presents us with a wall containing two distinct doors, with beams serving as architectural elements separating them. This scenario tests the algorithm's ability to recognize and differentiate structural elements despite the spatial complexities introduced by beams. The analysis of these three use cases not only demonstrates the adaptability of our proposed methodology but also offers valuable insights into its applicability in a variety of architectural contexts.

4.2. Pre-processing

In this section, the pre-processing stage of the proposed methodology is elaborated, including two essential sub-steps for improving the quality of point cloud data. Initial denoising exploiting the Statistical Outlier Removal (SOR) algorithm is utilized to enhance the precision and dependability of subsequent analyses by reducing noise and outliers. Denoising point cloud data increases structural information extraction, making the process more robust.

Table 1. Indoor scenarios used as the use case for the proposed methodology

Dataset	No of points	Scenario	No of points	Description
NavVis Scanner indoor dataset	4 244 416	Case A	224 423	Room wall with one open and one closed door
		Case B	297 172	Room wall with three windows and a beam across them.
		Case C	193 267	Room wall with one open door and one closed door with a pillar separating the doors.

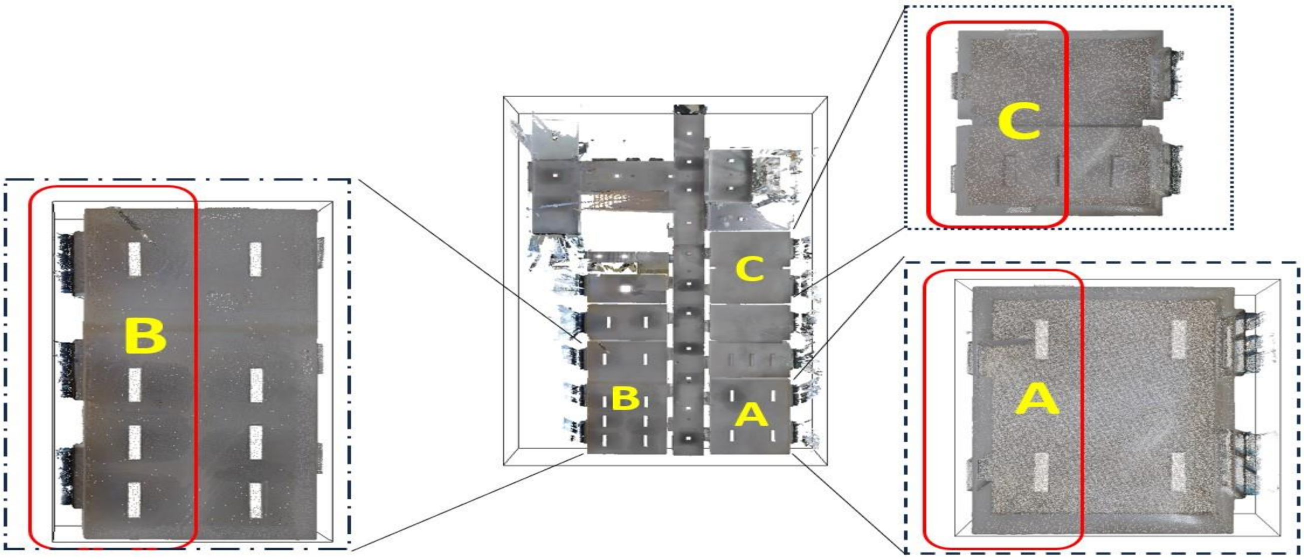


Fig. 2 NavVis Dataset - Three distinctive architectural cases (A, B, and C)

The point cloud is voxel downsampled using grid sizes of 0.1, 0.03, and 0.05 after denoising. A smaller voxel grid size preserves fine-grained properties, while a larger size simplifies point cloud representation. After conducting a series of trials and evaluations, it was determined that a voxel grid size of 0.03 is the optimal choice for extracting indoor structural data in the context of modelling and reconstruction. This grid size was found to minimize data loss while still achieving satisfactory results. These rigorous pre-processing methods prepare point clouds to extract accurate and complete interior structural elements.

4.3. Edge Detection

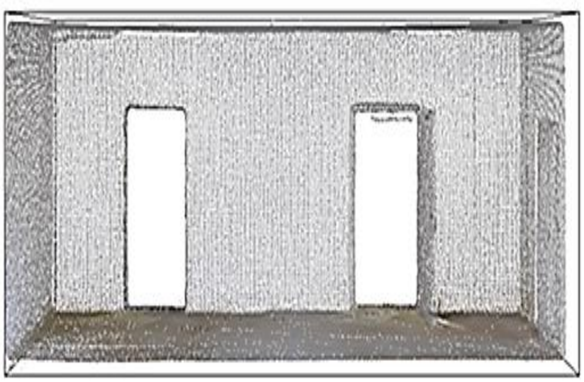
This section presents the edge detection algorithm used to extract structural edges from the pre-processed point cloud data. The approach uses Principal Component Analysis (PCA) to compute eigenvalues and extract geometric descriptors, including verticality, anisotropy, and surface curvature, inside a localized region consisting of 10 points closest to one another.PCA is applied to each point in the pre-processed point cloud to determine eigenvalues, which represent the local curvature direction and magnitude. Among the derived descriptors, anisotropy and surface curvature are determined to be the most important characteristics for edge detection. The method determines threshold values by utilizing the mean values of anisotropy and surface curvature descriptors. The results of edge detection on Cases A, B and C are shown in Figures 3(b), 4(b) and 5(b). Points that have anisotropic values below a certain threshold are categorized as anisotropic points, which suggests the existence of edge features. On the other hand, sites with surface curvature values that are beyond the threshold are identified as curvature points, highlighting possible edge positions. After the detection of edge points, the algorithm proceeds to utilize the Density-Based Spatial Clustering of Applications with Noise (DBSCAN) technique for the purpose of clustering the discovered edge points [24-25]. The DBSCAN algorithm is utilized to aggregate adjacent edge points into clusters, considering a predefined distance threshold. The choice of an epsilon value in the DBSCAN algorithm is determined through a thoughtful analysis of the desired spatial resolution and the density of edge points in the specific context. The objective is to accurately identify significant clusters while minimizing the impact of noise and appropriately grouping edge points. The clusters that are obtained from the edge framework serve to define the structural edges of the indoor scene environment accurately.

4.4. Edge Refinement

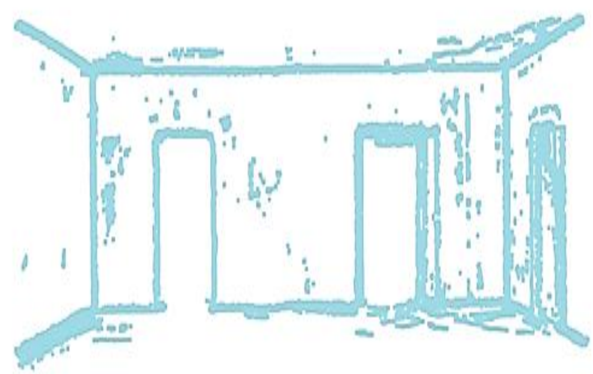
The method of refining the wireframe for the indoor scene involves the computation of the Alpha Shape using the Rolling Ball Pivoting (RBP) algorithm [19]. Alpha Shape is a comprehensive representation of the interior scene's structural geometry, capturing both convex and concave regions and refining the wireframe model with enhanced details. The alpha radius determines the Alpha Shape algorithm's detail and sensitivity. The alpha radius defines the size of the ball used to probe point cloud data. A small alpha radius decreases the probing ball. The alpha form will capture finer point cloud features and geometric aspects in this case, resulting in a more sophisticated data representation. Using a larger alpha radius will result in a larger probing orb. Larger alpha forms smooth out smaller point cloud details. Data that is more significant and in coarser forms is recorded.

Extensive experimentation revealed that in the context of our use cases A, B, and C, an alpha radius value of 0.08 proved to be a highly effective parameter for modulating the level of detail and sensitivity in the alpha shape computation process. This specific alpha radius value was empirically determined to strike the optimal balance, enabling us to capture the most important architectural features present in the point cloud data while effectively filtering out noise and preserving computational efficiency. The selection of alpha radius was consistent across all three use cases, demonstrating its robustness and applicability across a variety of architectural scenarios. This parameter selection was crucial to improving the precision and interpretability of our alpha shape-based analysis. From the dataset, Case A is a wall with two door openings, as shown in Figure 3(a). The algorithm demonstrates its efficacy in accurately representing the structural limits of the space, including the door openings, as illustrated in Figures 3(b) and (c). Nevertheless, it is apparent that the detection of the door frame was not fully comprehensive. The constraint might be ascribed to the comparatively diminished quantity of data points that depict the door frame inside the input point cloud. The limited availability of data points pertaining to the door frame poses a challenge for the algorithm in accurately discerning and reconstructing the entirety of the door frame structure. Resolving this matter necessitates the implementation of approaches aimed at improving the process of acquiring point cloud data.

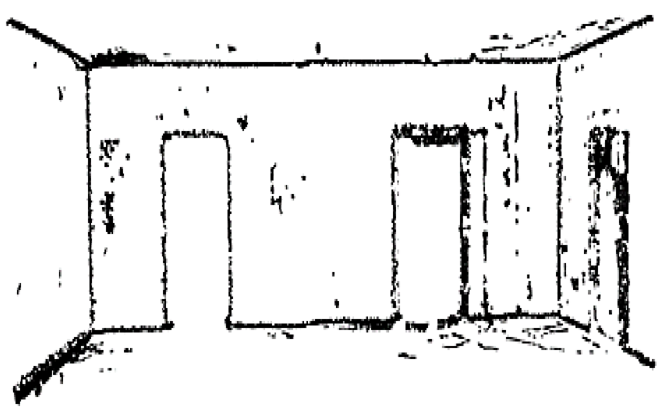
The present study assessed the efficacy of the proposed methodology through the examination of Case B, which serves as a representative subset of an interior room scene featuring three windows, as shown in Figure 4(a). The wireframe successfully depicted the structural elements of the room, such as the windows, thus indicating the efficacy of the proposed methodology in precisely representing the room's structural characteristics. However, the representation of the beam between the windows and floor remained incomplete, as depicted in Figures 4(b) and (c).



a) Original Point cloud



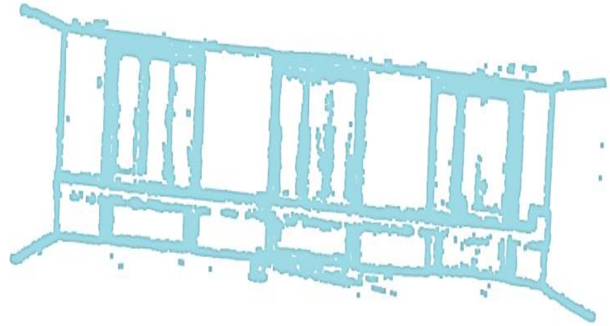
b) Edges Detected



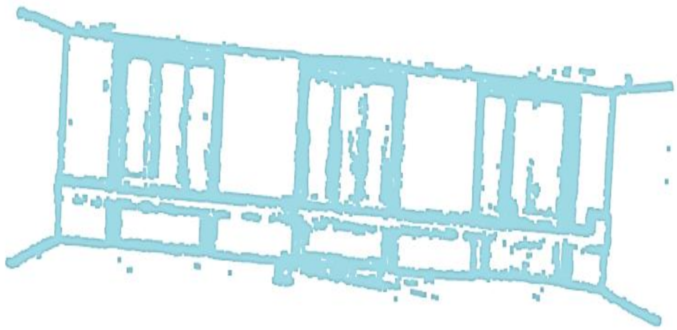
c) Generated Line frame

Fig. 3 Results obtained for Case (A)

(a) Original Point cloud

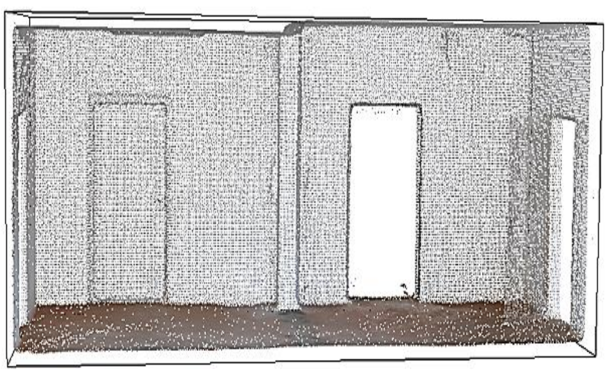


(b) Edges Detected



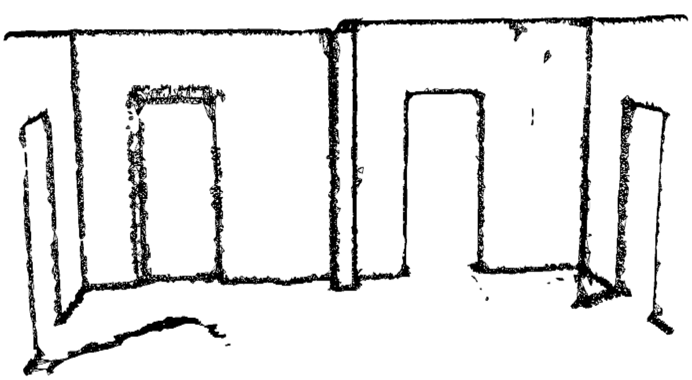
(c) Generated Line frame

Fig. 4 Results obtained for Case (B)



(a) Original point cloud

(b) Edges Detected



(c) Generated Line frame

Fig. 5 Results obtained for Case (C)

Table 2. Quantitative analysis of processing time and point cloud metrics across methodology stages

Dataset		Pre-Processing		Edge Detection			Edge Refinement		
Scene	No of Points	Processing Time (sec)	No of points	Epsilon Value	Processing Time (sec)	No of points	Alpha radius	Processing Time (sec)	No of points
Case A	224 423	0.08	90 652	0.06	63.44	21 794	0.8	177.55	18 238
Case B	297 172	0.11	123 556	0.05	80.77	20 622	0.8	356.29	18 837
Case C	193 267	0.11	77 659	0.06	45.20	11 204	0.8	93.24	10 482

Within the dataset, Case C presents a complex scenario characterized by the presence of a wall with two distinct doors that are divided by a central pillar. Notwithstanding the intricacy of this arrangement, our proposed approach exhibited exceptional abilities in reconstructing the structural geometry of the space. The depiction successfully encompasses the fundamental components of the scenario, encompassing both the doors and the pillar, as shown in Figure 5(a). Nevertheless, it is important to acknowledge that although our methodology demonstrated exceptional proficiency in reconstructing the intended structural characteristics, it also inadvertently restored several undesired components.

The discoveries provide essential perspectives for the continued improvement and enhancement of our methodology, guaranteeing its resilience and precision in complex situations, as shown in Figures 5(b) and (c). Case C serves as a demonstration of the efficacy of our methodology in addressing intricate real-world problems, hence facilitating advancements in spatial reconstruction techniques across diverse applications.

The proposed methodology is thoroughly evaluated by providing a complete analysis of the processing time and the number of points in the point cloud at different crucial stages of the reconstruction process. This analysis, summarized in Table 2, provides valuable insights into the efficiency and performance of our approach. The table displays the duration of each step in the methodology, encompassing pre-processing, epsilon, edge detection, processing, and edge refinement. It additionally displays the total points before and after each phase.

In Case A, the pre-processing time is 0.08 seconds, resulting in a reduction of the number of points from 224,423 to 63,444. This indicates that the pre-processing stage can substantially decrease the number of points in the point cloud without incurring a lengthy duration. Similar trends are observed in Cases B and C, with varying numbers of points and processing times at each stage. The approach showcases efficiency through its accelerated processing speeds at different phases. This attribute highlights its capacity for prompt implementation in real-world contexts. Furthermore, the methodology maintains the intrinsic three-dimensional characteristics of the data during the reconstruction process. This technology preserves geographical information without requiring the conversion of point cloud data into two-dimensional representations. The high level of accuracy to the original data structure is especially beneficial for applications that heavily rely on precise three-dimensional representation, such as object recognition or segmentation. This feature improves the methodology's suitability and significance in situations when accurate spatial comprehension is crucial. In summary, the data shown in the table indicates that the methodology under evaluation is a highly efficient technique for handling 3D point cloud data. It possesses high speed and effectiveness and maintains the integrity of the 3D data. These improvements are significant when compared to an approach that involves converting 3D point cloud data into 2D, conducting edge detection, and then converting it back to 3D.

The evaluation procedure generated the following key performance indicators:

4.4.1. True Positives (TP)

The number of correctly identified and matched structural elements as line segments in the reconstructed framework.

4.4.2. False Positives (FP)

The number of line segments in the reconstructed framework that are not supported by structural elements in the point cloud data.

4.4.3. False Negatives (FN)

The number of structural elements in the point cloud data that are not correctly designated as line segments in the reconstructed framework. For each case, the evaluation metrics Precision, Recall, and F1 score were calculated using True Positives (TP), False Positives (FP), and False Negatives (FN), as shown in Table 3. Precision is determined by calculating the proportion of correctly identified line segments among the total number of identified line segments.

$$Precision = \frac{TP}{TP + FP} \quad (1)$$

Recall quantifies the completeness of the reconstruction by evaluating the proportion of correctly identified line segments among all actual structural elements in the point cloud dataset.

$$Recall = \frac{TP}{TP + FN} \quad (2)$$

Table 3. Evaluation metrics of the proposed methodology

Dataset	Evaluation Metrics		
	$Precision = \frac{TP}{TP+FP}$	$Recall = \frac{TP}{TP+FN}$	$F1\ score = \frac{2 * Precision * Recall}{Precision + Recall}$
Case A	0.81	0.772	0.791
Case B	0.875	0.724	0.792
Case C	0.914	0.941	0.927

The F1 score harmonizes precision and recall into a single metric, providing a balanced evaluation of the reconstruction's accuracy and completeness. It is calculated as 2 * (Precision * Recall) / (Precision + Recall).

$$F1\ score = \frac{2 \times (Precision \times Recall)}{Precision + Recall} \quad (3)$$

The evaluation of the proposed methodology for 3D reconstruction from indoor point cloud data encompassed three distinct structural geometry cases. Case A, representing a single wall with a door opening, achieved a commendable balance between Precision (0.81) and Recall (0.772), resulting in an F1 score of 0.791. In Case B, a complex indoor scene featuring three windows on a wall and a beam was considered, yielding a higher Precision of 0.875 but with a slightly lower Recall of 0.724, resulting in an F1 score of 0.7923. Case C, depicting a single wall with two doors and a pillar, showcased exceptional performance, with a Precision of 0.914 and a Recall of 0.941, resulting in an impressive F1 score of 0.927. These results emphasize the methodology's adaptability to varying structural geometries, with Case C emerging as particularly promising for reconstructing complex indoor scenes.

However, the choice among cases may still hinge on specific application requirements, carefully considering the precision-recall trade-off. The assessment of the proposed strategy for 3D reconstruction using indoor point cloud data provides vital insights into its effectiveness in bridging the research gap and overcoming the inherent difficulties involved with accurate geometric modelling. The methodology demonstrated remarkable performance metrics across three different structural geometry examples, suggesting its capacity to adapt to different complexities inside indoor situations. In Case A, which is defined by a simple arrangement consisting of only one wall with a door opening, the technique exhibited a harmonious equilibrium between Precision and Recall, leading to a favorable F1 score. This result indicates that the methodology has the potential to effectively identify and define essential structural elements with a high level of dependability. In Case B, which had a complex indoor environment with many windows and a beam, the methodology showed improved Precision but slightly lower Recall. However, the F1 score obtained was still competitive, which suggests that the methodology is effective in dealing with complex structural geometries. Case C, which depicted a scenario featuring only one wall, two doors, and a pillar, presented convincing proof of the methodology's improved performance. The approach demonstrated its high level of proficiency in successfully reconstructing complex indoor scenes with excellent fidelity, as both Precision and Recall exceeded 0.9. In summary, our findings highlight the importance of the methodology in filling the research gap by providing a systematic and automated approach to 3D reconstruction using point cloud data. The methodology overcomes the constraints of standard manual reconstruction methods by obtaining strong performance in a wide range of structural difficulties, especially in scenarios with many pieces and sophisticated geometries. However, carefully choosing the appropriate circumstances requires a thorough evaluation of the individual requirements of the application to properly balance precision and recall and meet the needs of various use cases.

5. Conclusion and Future Scope

Using 3D point cloud data directly, the study introduces a novel technique for the refinement of line frame constructions within interior room environments. Three distinct datasets, denoted as Cases A, B, and C, were used to conduct a comprehensive evaluation of the proposed methodology. These datasets were carefully chosen to represent a variety of indoor room scenarios with differing degrees of complexity. Utilising a series of pre-processing techniques, edge recognition algorithms, and Alpha Shape calculations, the method generates accurate and detailed representations of interior structural geometry. Pre-processing procedures, including Statistical Outlier Removal (SOR) denoising and Voxel downsampling, significantly improved the quality of point cloud data, enabling more precise structural information extraction. Utilising PCA-based geometric descriptors and DBSCAN clustering, the edge detection method effectively detected and segmented edge points, resulting in highly accurate edge extraction. By combining the Alpha Shape and Rolling Ball Pivoting techniques, the methodology produced enhanced line frame models capable of accurately depicting convex and concave interior features. Importantly, the proposed method excelled at accurately representing interior room environments' structural boundaries, door apertures, and windows. Despite the positive results, some shortcomings were found during the review process, particularly in the detection of missing portions in wireframe representations. These constraints highlight the need for additional research and optimization to resolve these challenges effectively. Nonetheless, the proposed method has numerous advantages, such as the provision of accurate structural geometry representations, support for interior civil engineering applications, and facilitation of precise measurements. In conclusion, this study establishes a solid foundation for advancing the refinement of line frame constructions in interior room environments, with potential applications in a variety of disciplines. Continued research is encouraged to resolve identified limitations and further improve the robustness and accuracy of the methodology. Potential future research might prioritize the enhancement of door frame detection and the investigation of automated line frame refining methods for intricate indoor environments. The inclusion of semantic information and the improvement of the algorithm's performance have the potential to expand the versatility and practical usability of the methodology. In general, the suggested technique presents novel opportunities for interior civil works, architectural planning, and interior design applications, providing useful insights for data-informed decision-making within the field of civil engineering.

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