Current State and Trends of Point Cloud Segmentation in Construction Research

Samuel A. Prieto[1], Eyob T. Mengiste [1], Uday Menon [1], and Borja García de Soto [1]

[1] S.M.A.R.T. Construction Research Group, Division of Engineering, New York University Abu Dhabi (NYUAD), Experimental Research Building, Saadiyat Island, P.O. Box 129188, Abu Dhabi, United Arab Emirates
samuel.prieto@nyu.edu, eyob.mengiste@nyu.edu, um2038@nyu.edu, garcia.de.soto@nyu.edu

Abstract –

The construction industry is witnessing a transformative shift with the integration of advanced technologies, especially in the topic of 3D segmentation. This study underscores the current state and challenges of 3D segmentation, with special emphasis on construction research, and provides an insightful understanding of the latest research developments and trends. The study also looks at the performance metrics of the most relevant techniques, as well as the main limitations and research gaps, highlighting the need for further research in highly-performing techniques based on Deep Learning for point cloud segmentation in construction applications.

Keywords –

3D Segmentation; Systematic Literature Review; Construction Industry; Point Cloud; Deep Learning

1 Introduction

The abundance of 3D point cloud data is increasing with the availability and advancement of laser scanning equipment and the democratization of 3D semantic data generation. The availability of 3D data generally boosts the possibility and efficiency of developing deep learning algorithms to segment and classify 3D information, which heavily relies on the volume of available training data [1]. The manufacturing industry, amongst others, has greatly benefited from the extensive research over the past 15 years in 2D and 3D segmentation [2]. This was possible due to the static scenarios present in said industries, making them reliable semi-controlled environments. However, the construction industry has not developed at the same pace due to its dynamic and unstructured nature [3]. Some researchers and companies are already providing the means for the construction industry to take advantage of this revolution, where several applications and companies employ 3D data acquisition systems and processing algorithms [4], especially in the field of Scan-to-BIM [5]. Nevertheless, segmentation algorithms are still behind.

In this review article, the recent advancements in 3D point cloud processing are explored, particularly in the segmentation and classification domain, comparing the trending techniques in all industries with a focus on construction. From that, current challenges and research gaps are highlighted. The rest of the paper is structured as follows: Section 2 explains in detail the scope of this review. Section 3 presents the methodology used for the acquisition and analysis of the presented data. Section 4 analyses the obtained data. Section 5 provides a discussion of some of the findings from the analyzed data. Section 6 comments on some of the limitations of this study and future work. Finally, Section 7 summarizes the main takeaways of the study.

2 Scope of review

The review focuses on segmentation and classification algorithms. These can be applied to either 2D or 3D data. With 2D being extensively studied already, this study particularly focuses on 3D data, particularly in point cloud segmentation. The study also explores applications in the construction industry and non-construction industry (e.g., manufacturing, medical, robotics perception, etc.), with special emphasis on the construction industry. Point cloud segmentation techniques can be generalized into three different categories:

1. *Traditional techniques:* Traditional techniques of point cloud segmentation do not include training or clustering. These techniques include voxel cloud connectivity segmentation or super voxel-based segmentation, region growing, edge detection, and model fitting-based techniques.
2. *Machine learning techniques:* This category is comprised of techniques that include automated classification of points based on features (unsupervised machine learning), including K-Nearest Neighbors (KNN), Gaussian Mixture Models (GMM), and shallow learning models such as Support Vector Models (SVM).

3. *Deep learning techniques:* This is the most advancing category of techniques. They can be sub-categorized as point-based, projection-based, and discretization.

3 Methodology

The methodology used followed a Systematic Literature Review (SLR) [6] to conduct a methodical and comprehensive examination of existing research literature on a specific topic aimed at identifying, evaluating, and summarizing the findings of relevant studies to address a defined research question. Unlike traditional literature reviews, which can be more narrative and subjective, an SLR provides a comprehensive and unbiased overview of the current state of research. To ensure reproducibility and comprehensiveness, SLR involves defined steps, such as (1) defining clear research questions, (2) setting inclusion and exclusion criteria, (3) extracting and analyzing data, and (4) reporting and presenting findings in a structured manner. The following subsections delve into each of these steps.

3.1 Research Questions

Given the emphasis of the study on 3D data segmentation in the construction industry and its evolution, especially with the development of Machine Learning and Deep Learning approaches, the following research questions have been formulated for this review:

1. Which techniques are used in the construction industry to segment and/or classify point clouds from the construction sites?
2. What techniques are adopted to segment and/or classify non-construction site point clouds?
3. What are the common metrics used to measure the efficiency of the techniques?
4. What are the common challenges of the best-performing techniques in the construction domain?

3.2 Databases and Search Engines

For this review, the Scopus (ScienceDirect) database has been chosen. Scopus is one of the largest abstract and citation databases, covering a broad spectrum of disciplines. Its extensive coverage of peer-reviewed scientific journals makes it a suitable choice for this review. Scopus includes papers published in reputable and relevant journals to the research topic evaluated in this paper, such as Automation in Construction, and proceedings of equally relevant and reputable conferences, such as the International Symposium on Automation and Robotics in Construction (ISARC). To ensure we did not miss any relevant ISARC publication, we also used the ISARC proceedings database available in the publication section of the IAARC website [7].

3.3 Search Strategy

For this review, the keywords shown in Table 1 were identified based on their relevance to 3D data segmentation in the construction industry and the previously established classification. The set of keywords is comprised of the different techniques and other pertinent terms that, based on the initial search and to the authors' knowledge, fall within the different categories.

Table 1. Set of keywords used for literature search, based on the different categories.

Category	Sub-category	Keywords
1. Traditional	1.1 Supervoxel-based techniques	VCCS; Seed Growing; Graph-based; Mean shift-based; Normalized cuts; Random walks; Hierarchical diffusion
	1.2 Region growing-based techniques	Region growing; Octree based; RG
	1.3 Model fitting-based techniques	RANSAC; Hough transform; Region growing with model fitting; Expectation-Maximization; EM
2. Machine Learning	2.1 Unsupervised learning techniques	KNN; GMM; K-means
	2.2 Shallow learning techniques	SVM; Decision trees; Random Forests; Density-based spatial clustering; DBSCAN
3. Deep Learning	3.1 Point-based techniques	PointNet; PointNet++; PointCNN; DGCNN; KPConv; PointConv; Point Transformer; ShellNet; PointBERT; CurverNet; Self Organizing Network
	3.2 Projection-based techniques	Spherical Projection; Voxel Grid projection
	3.3 Discretization-based techniques	3D CNN; VoxNet; Submanifold Sparse CNNs

To maximize the scope of the search and ensure all relevant literature is captured, the keywords were combined using the Boolean operators "AND" and "OR".

An example of the search query used in the database for subcategory 1.2 (region growing-based techniques) combining the keywords mentioned above with all the different inclusion and exclusion criteria is shown below:

TITLE-ABS-KEY ((("region growing" OR "octree" OR "RG") AND ("3D data") AND ("construction industry" OR "AEC"))) AND PUBYEAR>2007 AND PUBYEAR<2025 AND (LIMIT-TO(DOCTYPE,"ar") OR LIMIT-TO(DOCTYPE,"cp") OR LIMIT-TO(DOCTYPE,"re")) AND (LIMIT-TO(LANGUAGE, "English"))

In this typical structure of the query, *region growing*, *octree* and *RG* represent the list of keywords in Table 2. The terms *3D data*, *construction industry* and *AEC* were used to limit the search to construction and related domains. Moreover, *ar*, *cp*, and *re* are document types representing 'article', 'conference paper', and 'review', respectively. The use of these operators allows for a more refined search, ensuring that the results are closely aligned with the research questions. The results from this search criteria are available in [8].

3.4 Inclusion and Exclusion Criteria

To ensure the relevance and consistency of the literature selected for this review, the following criteria were established:

- Focus on techniques related to 3D data processing. The data processing is conducted in two separate streams for construction and non-construction domains.
- Papers that have appeared in recognized journals or conference proceedings.
- Papers published after 2008 for a broader overview of the topic, with a specific emphasis on those published after 2018 to evaluate the most recent and cutting-edge techniques.
- Papers written in English.
- Exclusion of non-peer-reviewed papers, such as opinion pieces, editorials, or news articles.
- Exclusion of papers not related to 3D data processing.
- To evaluate techniques, specific research is conducted by specifying the data as laser scan or LiDAR and Photogrammetry.

3.5 Data extraction and synthesis

For this review, the following data were extracted from each paper: Authors, Publication year, Journal or conference, Keywords, Abstract, Methodology, and Findings.

Following the extraction, the data were synthesized to provide a comprehensive overview of the current state of 3D data processing in the construction industry. The synthesis process involves analyzing the extracted data to identify patterns, trends, and key insights.

4 Analysis of the data

The number of publications found for each category is shown in Figure 1. The values shown indicate the number of papers obtained using the criteria specified in Section 3 and the classification and keywords provided in Table 1. The gradient provides a visualization of the number of papers per category (from low (light background) to high (dark background)). The search also distinguished among the different sub-categories (i.e., techniques) applied to the construction industry and those applied to non-construction industries. This distinction helps to identify how the construction industry is catching up with other fields.

From Figure 1, it can be seen that fitting-based segmentation techniques (Category 1.3), such as RANSAC, Hough transform, region growing with model fitting and EM, are the most frequently implemented and researched. Overall, the adoption of these techniques has been on a constant increase in the past 15 years. Figure 2 shows a significant increase in the use of these techniques in the construction industry in 2012 and 2017. However, in other industries, their usage has been steadily growing, with a slight decrease observed in 2020.

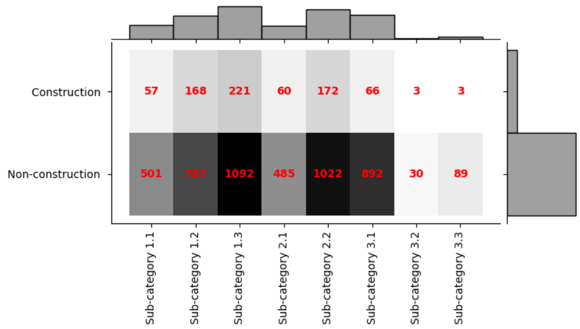
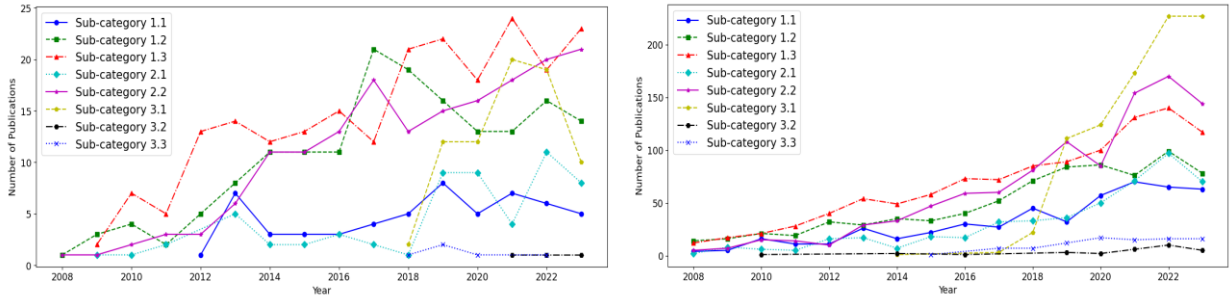


Figure 1. Number of publications for each sub-category.

Figure 1 also shows that the second most frequently used set of techniques is Category 2.2. This category encompasses shallow learning techniques like SVM, decision trees, Random Forests (RF), and DBSCAN. Until 2012, the application of these techniques was limited across various domains, including construction.

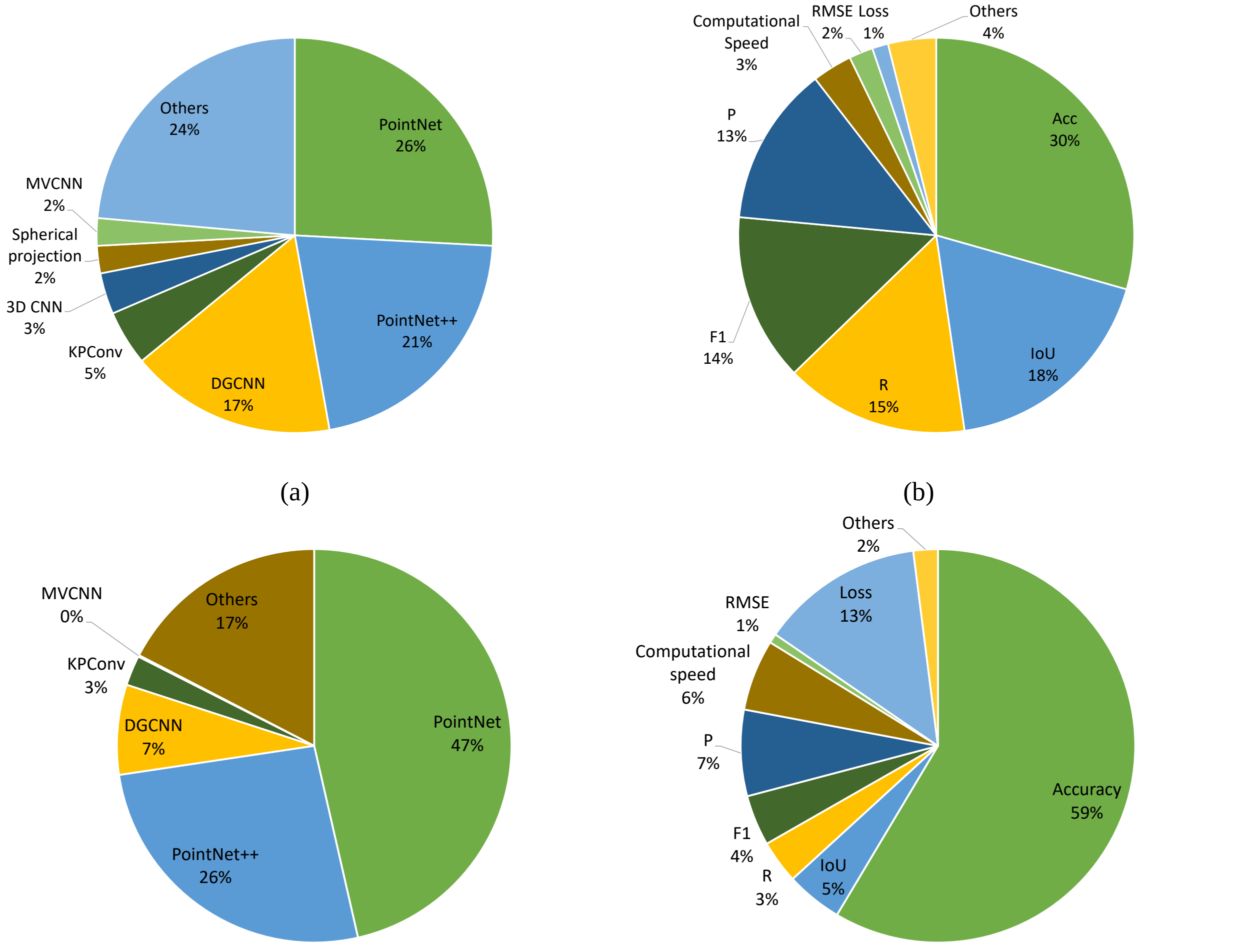
However, from 2012 to 2014, there was a significant increase in the number of construction industry publications. The usage of these techniques continued to rise with relative consistency until 2017, followed by a sudden decline. In the non-construction sector, a drop was observed in 2020.

Focusing on Category 3, the distribution of the different techniques and metrics from the 72 construction-related publications (66 from 3.1, 3 from 3.2 and 3 from 3.3) and 1,011(892 from 3.1, 30 from 3.2 and 89 from 3.3) from non-construction related are summarized in Figure 3.



(a) (b)

Figure 2. Number of publications for each sub-category in (a) the construction industry and (b) non-construction industries versus time (from 2008 until November 2023).



(a) (b)

(c) (d)

Figure 3. Distribution of papers related to Category 3 for (a) techniques and (b) metrics used in construction publications and (c) techniques and (d) metrics used in non-construction publications.
Legend: P = Precision; R = Recall, OA = Overall Accuracy, Acc = Accuracy; IoU = Intersection over Union, CM = Confusion Matrix, MAE = Mean Absolute Error, RMSE = Root mean squared error.
Others for techniques include: PointConv, depth image estimation, 3DAGN, FPSnet, SOnet, Point Transformer, ShellNet, ResPointNet++, SEP network, GLSNet, DbNet, 3DLEB-Net, RandLA-Net, IAGMLP, RFFS-Net, TriangleConv, DSNet, SPGraph, PointCNN, IBPCS, CNN. Others for metrics include: Support, MAE, FLOPs, Success, R^2, CM

In summary, it can be seen that the use of point-based techniques, part of Deep Learning (Category 3 in Table 1), is growing the most. Due to space constraints, this paper focuses on Deep Learning techniques as it is expected to be more relevant in future construction research.

5 Discussion

5.1 Techniques

As depicted in Figure 2, in the non-construction sector, despite limited mentions of Deep Learning techniques in earlier years since 2010, the number of publications incorporating these techniques began to increase significantly since 2016. Publications in the construction sector using Deep Learning techniques under Categories 3.1 and 3.3 began in 2018, while Category 3.2 started in 2021. The clear difference in the Category 3 popularity between the construction and non-construction sectors is affected by the fact that Deep Learning techniques heavily rely on the quality and quantity of the training data. The construction sector is challenging, dynamic, and often restricted by policies that do not allow the data to go public. This has prevented the widespread of training datasets related to construction, which has directly affected the usage of Deep Learning techniques in the construction field.

Among the Deep Learning techniques, Category 3.1, which includes point-based techniques such as PointNet, PointNet++, PointCNN, DGCNN, KPConv, PointConv, Point Transformer, ShellNet, PointBERT, CurverNet, and Self Organizing Network, is dominant compared to the other categories identified for Deep Learning. Since 2018, the adoption of these techniques has increased more significantly in non-construction sectors, making them the most widely used techniques in recent years, particularly since 2021. However, in the construction sector, Category 1.3 (model fitting-based techniques) and Category 2.1 (techniques like SVM, decision trees, random forests, and DBSCAN) continue to be predominant. Meanwhile, the frequency of publications mentioning Category 3.1 techniques has decreased by ten since 2022 in the construction domain. Figure 3(a) illustrates that from techniques grouped in Category 3, the field of construction research frequently employed PointNet, PointNet++, and DGCNN. Moreover, MVCNN, Spherical projection and 2D CNN were each utilized in more than 2 articles. The publications in the non-construction sector have a similar tendency to use PointNet and PointNet++ more frequently than the remaining techniques, with a greater usage of PointNet over PointNet++ and a 10% reduction in utilization of DGCNN. On the other hand, other techniques including PointConv, depth image estimation, 3DAGN, FPSnet, SOnet, Point Transformer, ShellNet, ResPointNet++, SEP network, GLSNet, DbNet, 3DLEB-Net, RandLA-Net, IAGMLP, RFFS-Net, TriangleConv, DSNet, SPGraph, PointCNN, IBPCS and CNN were used in about 24% of reviewed publications in the construction field, and 17% for non-construction fields.

5.2 Metrics

Figure 2 (b) highlights that recent techniques have mostly employed metrics like Precision, Recall, F1-Score, and Intersection over Union (IoU) to assess performance. Accuracy, measured as a ratio of correct predictions to the total number of predictions, is a dominant metric used in the Category 3 papers published in the construction domain, where it is used in 30% of the reviewed publications. IoU was utilized to measure efficiency in 18% of these construction-related publications. Precision, Recall and F1 score were employed in an average of 14% of the publications for Category in the construction field.

In the case of the non-construction domain, there is an increased reliance on Accuracy, with 59% of the reviewed papers using this metric to evaluate the performance of their algorithms. Unlike the construction domain, research in non-construction fields utilized Recall, Precision and F1 scores in about 5% of the reviewed publications. In general, compared to the construction-related research, there is a similar utilization of the metrics that are grouped as others (Support, MAE, FLOPs, Success, R2, CM) in the non-construction.

5.3 Challenges

Despite providing highly accurate results, Deep Learning techniques have limitations. For instance, they heavily rely on the diversity and completeness of the initial training dataset for them to produce accurate results, as well as correctly labeled training datasets [9]. Hu et al. [10] demonstrated the negative impact of training a model on a dataset that contains geometries that are different from those in the scan location. Their segmentation technique utilizing ResPointNet++ was successful in scoring mean IoU (mIoU) values greater than 90% across all the classes. However, the mIoU for the segmentation of points belonging to chairs was 62.55%. The authors note that this low mIoU can be attributed to the dataset used for training the model. The dataset contained data for a specific kind of chair, whereas the scan site had chairs with different geometries. In order to account for this, the geometries of the building components could be identified before the scan, and the model could be trained on a dataset that contains information on the geometries of commonly occurring classes in a scan location. Alternatively, a more robust approach could include training datasets that are comprised of various generic chairs that have a higher probability of being found on a scan site.

Additionally, a common limitation that has been identified is the computational load required for segmentation [11]. The effects of high computational load can be mitigated through the utilization of voxelization [12] and octrees [13]. By reducing the access time for each data point and the number of data points, these techniques were capable of increasing computational efficiency.

Based on the construction-related publications that were considered, four key limitation categories have been identified in Table 2. First, some techniques' effectiveness is contingent on the quality of the point cloud; factors like point cloud density can significantly influence segmentation outcomes. The impact of noise and occlusion is another concern, as some algorithms are severely affected by these elements.

The second key limitation is the ability to handle complex geometry. While certain techniques perform well in segmenting planar objects or familiar shapes like furniture and vehicles, they are limited when segmenting objects on construction sites. The primary reason for this is that construction often involves irregular shapes, such as cylindrical forms or structures with unconventional geometry, like unfinished elements or formwork systems. The capability to accurately segment undefined shapes is crucial in construction applications. Many techniques are effective in specific scenarios but require extensive testing and fine-tuning when dealing with complex shapes.

The third limitation category is the dependence on synthetic point clouds, predominantly from BIM. Although BIM offers a detailed representation of element geometry, it usually does not align with real-world scenarios, especially in terms of texture and the geometric presence of unfinished or temporary objects on construction sites. For example, casting concrete requires formwork, and if the concrete element is elevated, it will require scaffoldings. These elements (i.e., formworks and scaffoldings) need to be accurately represented in the BIM to achieve an accurate representation of the construction site using a synthetic point cloud generated from the BIM. Moreover, this becomes even more pronounced when the specific surface texture of materials is relevant to explaining the status of the construction. This is because the renderings from the BIM are not sufficiently close to the texture of the real material at a given time. Therefore, a synthetic dataset might not be comprehensive enough to be used on the construction site.

The last category is a limitation related to the manual intervention requirements. Given the complexity of construction, complete automation would be beneficial to bypass time-consuming data processing steps. Hence, the need for manual intervention during segmentation is considered a significant limitation.

6 Limitations and future work

Despite having provided a comprehensive and systematic review of the different techniques used for point cloud segmentation, the methodology presents some limitations. Given the volume of handled data, the study had to be based on keyword extraction and evaluation of the abstract and author-provided keywords, which in most cases is sufficient to provide an overall idea of the study's objective and methodology. But in some cases, said keywords are not going to be well defined, and it could lead to mislabeling said studies. A more in-depth analysis would be needed for more accurate results.

Table 2. Summary of the 4 categories identified for the challenges.

No.	Categories	Challenges	References
1	Point cloud quality	Dependence on point cloud density	[14], [15]
		Handling and effect of noise	[16]
		Handling and effect of occlusion	[17], [18]
2	Complex geometries	Limited to common geometric shapes	[10], [19]
		Limited to planar surfaces	[12], [13], [20], [21]
		Not experimented with complex shaped elements	[22], [23], [24]
		Technique trained for specific objective and set of elements	[25]
3	Based on synthetic data		[26], [27]
4	Manual intervention required		[26], [28]

This study revealed the main challenges in current point cloud segmenting methods for applications in the construction domain. In practice, despite the increasing adoption of technology in construction sites, there is still a significant reliance on manual and hybrid (semi-automated) construction information processing. Therefore, there is still more work to do in reshaping the proposed methods to be feasible for construction industry utilization. In addressing the challenges, recent advancements in generative algorithms, such as Large Vision Language modeling, and spatial computing technologies, such as Neural Radiance Fields and Gaussian Splatting, could offer solutions to many of the challenges outlined in Table 2. Future research should specifically investigate these methods for practical applications in construction sites, evaluate whether the limitations are adequately addressed, and recommend directions for future work.

Given the space limitations, not all the required data for a detailed comparison could be added to the study. For future work, a more extensive study will be done, providing a more detailed comparison and description of the different evaluated techniques, including a comparison of their effectiveness, especially in real-world construction scenarios and providing technical differences between the techniques and their mean performance/evaluation metrics, an objective comparison is provided.

7 Conclusion

This study provides a review of the literature on point cloud segmentation techniques with a focus on construction applications. The study examined the popularity of specific techniques over time and evaluated the implementation trends in the construction industry and non-construction sectors. A key observation is the rapid advancement of deep learning techniques in non-construction applications in recent years, while construction-related applications still predominantly rely on shallow learning or fitting-based techniques. Based on the reviewed construction publications, PointNet, PointNet++ and DGCNN are found to be dominant in deep learning-based techniques. This study also has revealed that out of the 72 reviewed construction-related articles, 30% employed Accuracy, 18% utilized IoU, 15% applied Recall, 14% used the F1 score, and 13% relied on Precision. Finally, the study presented a summary of limitations in the considered set of construction-related publications. The limitations were classified into four main areas such as working with low-quality point clouds, the necessity for manual intervention, reliance on synthetic data, and the capability to segment complex geometries, such as the elements in the construction site.

Acknowledgment

This work was partially supported by the Sand Hazards and Opportunities for Resilience, Energy, and Sustainability (SHORES) Center, funded by Tamkeen under the NYUAD Research Institute Award CG013. This work also benefited from the collaboration with the NYUAD Center for Interacting Urban Networks (CITIES), funded by Tamkeen under the NYUAD Research Institute Award CG001.

References

[1] K. Mirzaei, M. Arashpour, E. Asadi, H. Masoumi, Y. Bai, and A. Behnood, “3D point cloud data processing with machine learning for construction and infrastructure applications: A comprehensive review,” *Advanced Engineering Informatics*, vol. 51, p. 101501, Jan. 2022, doi: 10.1016/j.aei.2021.101501.

[2] Q. Wang, Y. Tan, and Z. Mei, “Computational Methods of Acquisition and Processing of 3D Point Cloud Data for Construction Applications,” *Arch Computat Methods Eng*, vol. 27, no. 2, pp. 479–499, Apr. 2020, doi: 10.1007/s11831-019-09320-4.

[3] Q. Wang and M.-K. Kim, “Applications of 3D point cloud data in the construction industry: A fifteen-year review from 2004 to 2018,” *Advanced Engineering Informatics*, vol. 39, pp. 306–319, Jan. 2019, doi: 10.1016/j.aei.2019.02.007.

[4] “Matterport. Capture, share, and collaborate the built world in immersive 3D.” Accessed: Dec. 01, 2023. [Online]. Available: https://matterport.com/

[5] B. P. Maldonado, N. W. Hayes, and D. Hun, “Automatic point Cloud Building Envelope Segmentation (Auto-CuBES) using Machine Learning,” presented at the 40th International Symposium on Automation and Robotics in Construction, Chennai, India, Jul. 2023. doi: 10.22260/ISARC2023/0009.

[6] B. Kitchenham, “Procedures for Performing Systematic Reviews”.

[7] “The International Association for Automation and Robotics in Construction (ISARC) publications database.” Accessed: Mar. 11, 2024. [Online]. Available: https://www.iaarc.org/publications/search-php

[8] “SMART@NYUAD Github database.” Accessed: Dec. 06, 2023. [Online]. Available: https://github.com/SMART-NYUAD/ISARC2024_lit_review_data/tree/main

[9] Y. Chen, S. Kim, Y. Ahn, and Y. K. Cho, “A Framework of Reconstructing Piping Systems on Class-imbalanced 3D Point Cloud Data from Construction Sites,” presented at the 40th International Symposium on Automation and Robotics in Construction, Chennai, India, Jul. 2023. doi: 10.22260/ISARC2023/0058.

[10] D. Hu, V. J. L. Gan, and C. Yin, “Robot-assisted mobile scanning for automated 3D reconstruction and point cloud semantic segmentation of building interiors,” *Automation in Construction*, vol. 152, p. 104949, Aug. 2023, doi: 10.1016/j.autcon.2023.104949.

[11] Y. Yajima, S. Kim, J. D. Chen, and Y. Cho, “Fast Online Incremental Segmentation of 3D Point Clouds from

Disaster Sites," presented at the 38th International Symposium on Automation and Robotics in Construction, Dubai, UAE, Nov. 2021. doi: 10.22260/ISARC2021/0048.

[12] G. Cheng, J. Liu, D. Li, and Y. F. Chen, "Semi-Automated BIM Reconstruction of Full-Scale Space Frames with Spherical and Cylindrical Components Based on Terrestrial Laser Scanning," *Remote Sensing*, vol. 15, no. 11, 2023, doi: 10.3390/rs15112806.

[13] F. Poux and R. Billen, "Voxel-based 3D Point Cloud Semantic Segmentation: Unsupervised Geometric and Relationship Featuring vs Deep Learning Methods," *IJGI*, vol. 8, no. 5, p. 213, May 2019, doi: 10.3390/ijgi8050213.

[14] T. Xia, J. Yang, and L. Chen, "Automated semantic segmentation of bridge point cloud based on local descriptor and machine learning," *Automation in Construction*, vol. 133, p. 103992, Jan. 2022, doi: 10.1016/j.autcon.2021.103992.

[15] R. Pierdicca *et al.*, "Point Cloud Semantic Segmentation Using a Deep Learning Framework for Cultural Heritage," *Remote Sensing*, vol. 12, no. 6, p. 1005, Mar. 2020, doi: 10.3390/rs12061005.

[16] Y. Xu, S. Tuttas, L. Hoegner, and U. Stilla, "Voxel-based segmentation of 3D point clouds from construction sites using a probabilistic connectivity model," *Pattern Recognition Letters*, vol. 102, pp. 67–74, Jan. 2018, doi: 10.1016/j.patrec.2017.12.016.

[17] M. Kamari and Y. Ham, "Vision-based volumetric measurements via deep learning-based point cloud segmentation for material management in jobsites," *Automation in Construction*, vol. 121, p. 103430, Jan. 2021, doi: 10.1016/j.autcon.2020.103430.

[18] Z. Chen, E. Che, F. Li, M. Olsen, and Y. Turkan, "Web-based Deep Segmentation of Indoor Point Clouds," *presented at the 36th International Symposium on Automation and Robotics in Construction*, Banff, AB, Canada, May 2019. doi: 10.22260/ISARC2019/0074.

[19] J. Grandio, B. Riveiro, M. Soilán, and P. Arias, "Point cloud semantic segmentation of complex railway environments using deep learning," *Automation in Construction*, vol. 141, p. 104425, Sep. 2022, doi: 10.1016/j.autcon.2022.104425.

[20] P. Wei, L. Yan, H. Xie, and M. Huang, "Automatic coarse registration of point clouds using plane contour shape descriptor and topological graph voting," *Automation in Construction*, vol. 134, p. 104055, Feb. 2022, doi: 10.1016/j.autcon.2021.104055.

[21] W. Yue, J. Lu, W. Zhou, and Y. Miao, "A new plane segmentation method of point cloud based on mean shift and RANSAC," in *2018 Chinese Control And Decision Conference (CCDC)*, Shenyang: IEEE, Jun. 2018, pp. 1658–1663. doi: 10.1109/CCDC.2018.8407394.

[22] J. Martens and J. Blankenbach, "VOX2BIM+ - A Fast and Robust Approach for Automated Indoor Point Cloud Segmentation and Building Model Generation," *PFG - Journal of Photogrammetry, Remote Sensing and Geoinformation Science*, vol. 91, no. 4, pp. 273–294, 2023, doi: 10.1007/s41064-023-00243-1.

[23] R. Zeng, J. J. S. Shi, C. Wang, and T. Lu, "Integrating as-built BIM model from point cloud data in construction projects," *ECAM*, Jul. 2023, doi: 10.1108/ECAM-12-2022-1196.

[24] F. Poux, C. Mattes, Z. Selman, and L. Kobbelt, "Automatic region-growing system for the segmentation of large point clouds," *Automation in Construction*, vol. 138, p. 104250, Jun. 2022, doi: 10.1016/j.autcon.2022.104250.

[25] J. S. Lee, J. Park, and Y.-M. Ryu, "Semantic segmentation of bridge components based on hierarchical point cloud model," *Automation in Construction*, vol. 130, p. 103847, Oct. 2021, doi: 10.1016/j.autcon.2021.103847.

[26] H. X. Zhang and Z. Zou, "Quality assurance for building components through point cloud segmentation leveraging synthetic data," *Automation in Construction*, vol. 155, p. 105045, Nov. 2023, doi: 10.1016/j.autcon.2023.105045.

[27] J. W. Ma, T. Czerniawski, and F. Leite, "Semantic segmentation of point clouds of building interiors with deep learning: Augmenting training datasets with synthetic BIM-based point clouds," *Automation in Construction*, vol. 113, p. 103144, May 2020, doi: 10.1016/j.autcon.2020.103144.

[28] C. Fotsing, N. Menadjou, and C. Bobda, "Iterative closest point for accurate plane detection in unorganized point clouds," *Automation in Construction*, vol. 125, p. 103610, May 2021, doi: 10.1016/j.autcon.2021.103610.