Integrated Framework for Scaffold Monitoring: From Point Cloud Acquisition to Anomaly Detection

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Abstract –

Scaffolding safety is a critical challenge in the construction industry, often compromised by accidents caused by improper assembly and missing components. This study introduces an automated pipeline for scaffold safety monitoring, integrating robot-assisted point cloud data acquisition, deep learning-based segmentation, scaffold component detection, and safety verification. A quadruped robot equipped with terrestrial LiDAR is utilized to acquire point cloud data, which is then segmented using a deep learning model. The scaffold components are detected through a patch-based algorithm, followed by 3D transformation, clustering, and Delaunay triangulation. The process culminates in the generation of a 3D CAD model, enabling safety evaluations to identify issues such as missing platforms and improperly installed horizontal members. The experimental results demonstrated high performance in CAD model generation and successfully identified structural anomalies in scaffolds, with the proposed method achieving an F1 score of 97.44% in CAD modeling. This approach shows substantial potential for improving scaffolding safety through effective monitoring and early hazard detection.

Keywords –

Scaffold Monitoring; Robotic Data Acquisition; Point Cloud Data; Deep Learning; 3D CAD Modeling; Safety Evaluation

1 Introduction

Scaffolds are vital temporary structures in construction sites, ensuring worker safety while enhancing operational efficiency. However, accidents occurring during the installation of scaffolds remain a significant safety concern, often attributed to missing components or improper assembly [1]. To prevent such accidents, safety guidelines are established to regulate scaffold installation, but ensuring compliance remains a challenge [2]. In practice, adherence to these guidelines relies heavily on manual inspections by supervisors, making it difficult to consistently enforce strict safety protocols. To address these issues, there is a growing demand for the development of automated technologies that can monitor scaffolding conditions and evaluate their safety.

Recent studies have highlighted the potential of using 3D point cloud data for scaffold safety monitoring. With its ability to provide precise spatial information about structures, 3D point cloud data can serve as a valuable tool for detecting and analyzing scaffold components. Luo et al. [3] applied least-squares fitting and random sample consensus (RANSAC) to scaffold point clouds acquired through mobile laser scanning (MLS) to extract scaffold pipes and monitor their deformation. Wang [4] utilized algorithms such as clustering, RANSAC, and m-estimator sample consensus to extract scaffold components from point clouds and verify compliance with installation regulations. Advancements in deep learning have further improved the accuracy of scaffold recognition. Kim et al. [5] developed a scaffold monitoring pipeline that includes data acquisition using a quadruped robot equipped with MLS, deep learning-based point cloud segmentation, and 3D CAD model generation. Kim et al. [6] proposed an algorithm that leverages deep learning techniques to interpret terrestrial laser scanning (TLS) point cloud data and performed regulation checks on scaffold installations.

However, there has been a lack of comprehensive research for scaffold safety monitoring presenting a complete pipeline that encompasses all stages, from data acquisition to 3D model generation and anomaly detection. Furthermore, existing methods for scaffold component detection have often demonstrated reduced performance when applied to different scaffold sites. In previous studies, scaffold component detection methods projected point clouds into 2D before applying techniques such as RANSAC and peak finding. However, this approach results in the loss of 3D geometric information of the components. A patch-based detection approach could offer a more effective alternative by preserving and utilizing the 3D structure of the components.

This study addresses these limitations by proposing a robust pipeline specifically designed for scaffold monitoring. As shown in Figure 1, the proposed approach integrates efficient point cloud data acquisition using a quadruped robot, deep learning-based point cloud segmentation, scaffold component detection, 3D CAD model generation, and automated anomaly detection into a unified framework. Notably, the method enhances robustness in scaffold component detection through processes such as 3D transformation, patch-based component detection, and Delaunay triangulation for scaffold unit identification.

During the scaffold installation phase, major factors contributing to scaffold accidents include errors in falsework design, incorrect connections, missing components, and improper assembly [7]. However, this study focuses on automatically detecting missing components and improper assembly. The proposed method detects these anomalies by segmenting scaffold point clouds, identifying structural components, and verifying their geometric correctness within the 3D CAD model. By addressing improper assembly and missing components, the framework ensures proactive safety monitoring, enabling early detection of hazardous scaffold conditions. If further refined, the proposed method is expected to contribute significantly to preventing accidents and improving safety conditions in construction environments.

2 Methodology

2.1 Point Cloud Acquisition and Segmentation

As shown in Figure 1(a), a mobile laser scanning system was constructed by mounting a TLS LiDAR (FARO Focus M70) and a mini PC (Intel NUC 11) onto a quadruped robot (Unitree Aliengo). The robot was remotely controlled for movement and point cloud data acquisition. Figure 1(b) illustrates the analysis of the acquired point cloud data using RandLA-Net [8], a deep learning-based 3D segmentation model. The model classifies the point cloud data into seven categories: vertical members, horizontal members, platforms, stairs, rakers, bracings, and background.

2.2 Scaffold Component Detection

In the scaffold component detection step illustrated in Figure 1(c), vertical members, horizontal members, and platforms are extracted from the segmented point clouds. These three components are essential elements of scaffolds and are therefore subject to safety verification; other components are excluded from the assessment as they do not directly affect structural stability.

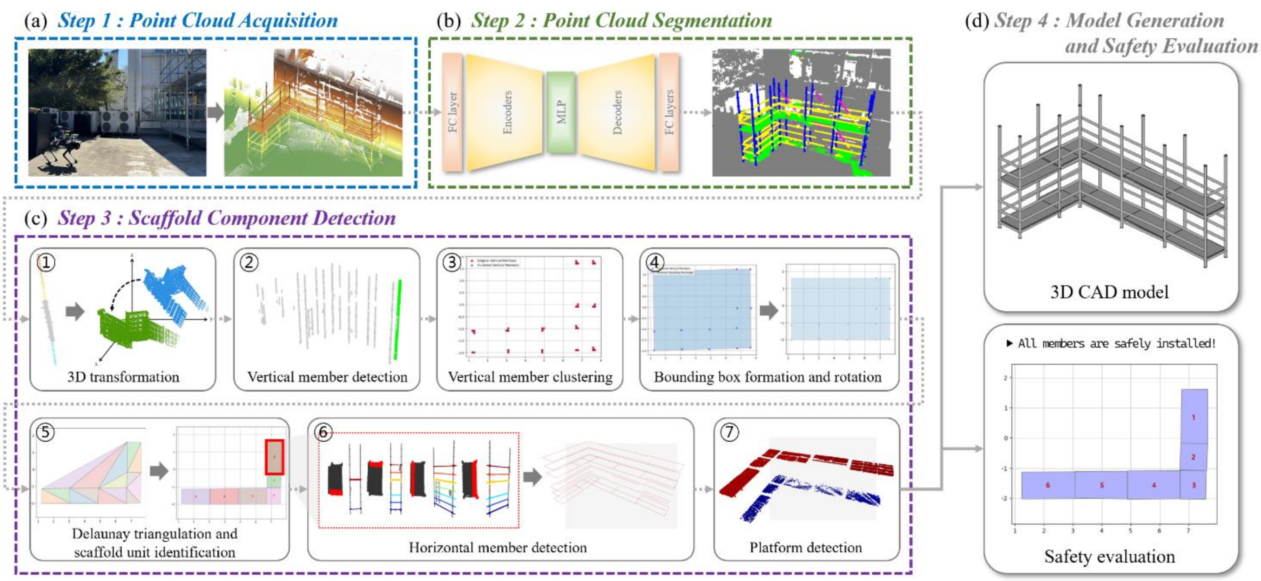
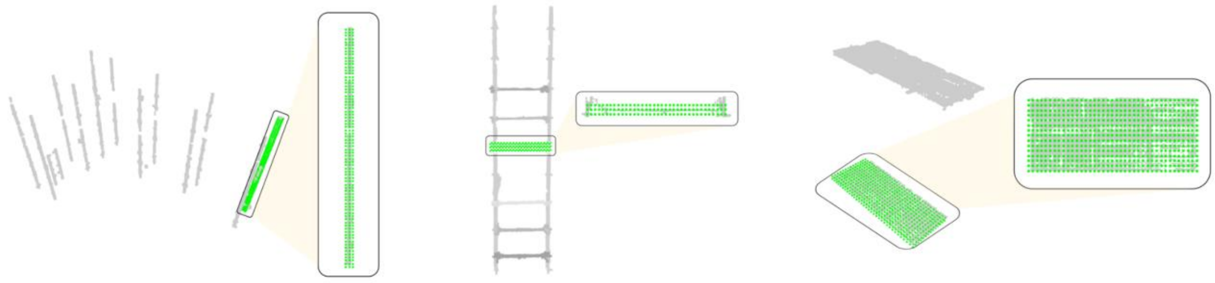


Figure 1. Overview of the scaffold safety monitoring pipeline; (a) robot-assisted point cloud data acquisition, (b) point cloud segmentation using a deep learning-based model, (c) scaffold component detection, and (d) 3D CAD model generation and scaffold safety evaluation.



(a) (b) (c)

Figure 2. 3D patch representation of scaffold components; 3D patches for (a) vertical members, (b) horizontal members, and (c) platforms.

Vertical members, horizontal members, and platforms are identified using a patch-based component matching algorithm proposed by Kim et al. [9]. A 3D patch similar in size and shape to each component is generated and traverses across the target region within the point cloud. If the distance between the points in the patch and the target point cloud is below a predefined threshold, the presence of the component is confirmed. Figures 2(a), 2(b), and 2(c) show green points representing the generated 3D patches for vertical members, horizontal members, and platforms, respectively.

Once the point cloud data are segmented, the largest cluster of vertical member points is identified using density-based spatial clustering of applications with noise (DBSCAN). The entire point cloud is then aligned through a 3D transformation to ensure that the largest vertical member cluster is perpendicular to the XY plane (Figure 1(c), Step 1). This alignment effectively handles tilted scaffold point cloud data. The patch-based component matching algorithm is then applied to the segmented vertical member points to detect vertical components (Figure 1(c), Step 2), using patches measuring 0.1 m × 0.1 m × 4 m. Overlapping vertical members are merged through DBSCAN clustering (Figure 1(c), Step 3). Subsequently, a bounding box is created around the projected vertical member points on the XY plane, and the points are rotated so that the bounding box aligns with the X and Y axes (Figure 1(c), Step 4). Delaunay triangulation is applied using the X and Y coordinates of the vertical members to partition the space. From the partitioned areas, regions forming right-angled rectangles are identified as individual scaffold units (Figure 1(c), Step 5). This scaffold unit identification method is robust and performs effectively regardless of the scaffold's shape or size. Finally, within each scaffold unit, horizontal members and platforms are detected using patches (Figure 1(c), Steps 6 and 7). The dimensions of the patches used to detect these components are determined based on the size of the corresponding scaffold unit, with a patch thickness set at 0.1 m.

2.3 Model Generation and Anomaly Detection

As shown in Figure 1(d), once the scaffold components are detected, their positional information is extracted to generate a 3D CAD model. For example, in Step 6 of Figure 1(c), if a horizontal member is detected using a patch measuring 0.1 m × 0.1 m × 1 m, a pipe with a length of 1 m is created at the corresponding position. The CAD model is automatically generated using the FreeCAD modeler with a Python-based script. The detected vertical and horizontal members are represented as cylindrical CAD objects in FreeCAD, while platforms are modeled as rectangular box-shaped objects. The final CAD model is then exported in FCStd format.

This model can serve as a visual resource for site managers to monitor the installation status of scaffolds and facilitate structural stability analysis. The obtained component information can also be used to directly evaluate the safety of the scaffold. In this study, the presence of platforms and the abnormal lengths of horizontal members in each scaffold unit are identified.

3 Experiments and Results

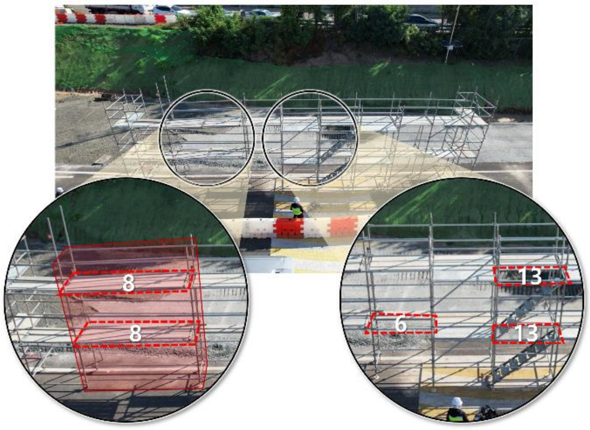
3.1 Datasets

In this study, the RandLA-Net model pretrained on the dataset from Kim et al. [6] was used for point cloud data segmentation. To validate the proposed method, point cloud data were acquired from an actual scaffold site. Figures 3(a) and 3(b) show the scaffold site where the data were acquired and the quadruped robot used for data acquisition, respectively. A total of 23 point cloud datasets were acquired as the robot moved across the site, and these datasets were registered using FARO SCENE software.

(a) (b)

Figure 3. Data acquisition at the scaffold site; (a) scaffold site where point cloud data were acquired, and (b) quadruped robot used for data acquisition.

To evaluate the performance of the proposed method for scaffold safety verification, components were deliberately installed incorrectly at the scaffold site depicted in Figure 3. As shown in Figure 4(a), the horizontal members of scaffold Unit 8 were installed with an abnormally long length, and their platforms were improperly secured and tilted. Additionally, as shown in Figure 4(b), platforms were missing from scaffold Units 6 and 13.



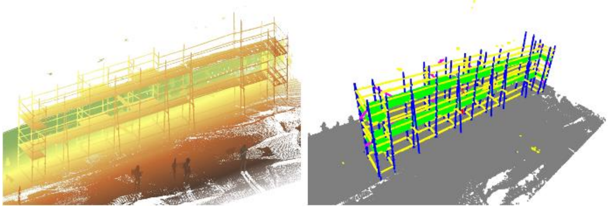
(a) (b)

Figure 4. Examples of structural anomalies in scaffolds; (a) improperly installed horizontal members and tilted platforms in scaffold Unit 8, and (b) missing platforms in scaffold Units 6 and 13.

3.2 Experimental Results

3.2.1 3D Semantic Segmentation Results

Figure 5(a) shows the registered point cloud data of scaffolds acquired using the robot. The acquired point cloud data were segmented using a deep learning-based approach, as shown in Figure 5(b). As indicated in Table 1, the segmentation achieved an average F1 score of 91.08%.



(a) (b)

Figure 5. Scaffold point cloud registration and segmentation; (a) registered scaffold point cloud data acquired using the robot, and (b) segmentation results based on the deep learning-based approach.

Table 1. Segmentation performance for scaffold point cloud data.

Scaffold component	Precision	Recall	F1 score
Vertical member	83.14%	99.44%	90.56%
Horizontal member	96.24%	70.46%	81.36%
Platform	88.40%	97.16%	92.57%
Background	99.77%	99.92%	99.84%
Average	91.89%	91.75%	91.08%

3.2.2 Scaffold Component Detection Results

Patch-based detection was performed on the segmented point cloud data to identify points corresponding to vertical members (Figure 6(a)). The detected vertical members were consolidated through clustering (Figure 6(b)) and then rotated to align with the X and Y axes (Figure 6(c)). Using the X and Y coordinates of the vertical members as reference points, Delaunay triangulation was applied to partition the space (Figure 6(d)). From the partitioned areas, scaffold units were estimated (Figure 6(e)). For each scaffold unit, horizontal members and platforms were detected using the patch-based approach (Figures 6(f) and 6(g)).

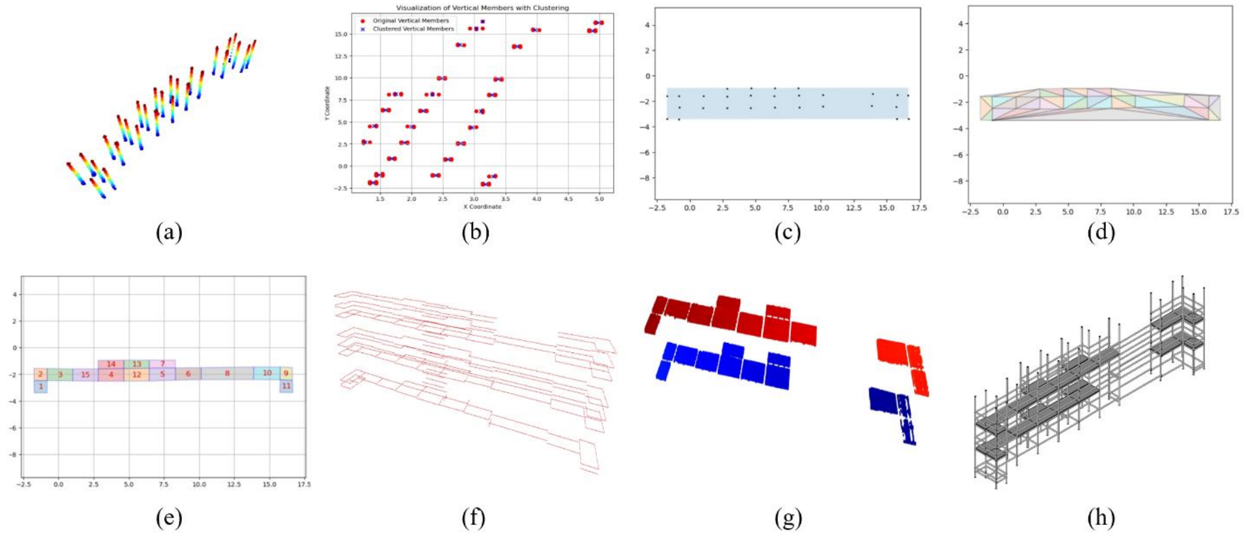


Figure 6. The process of scaffold component detection; (a) patch-based vertical member detection in the segmented point cloud, (b) clustering of detected vertical members, (c) rotation of vertical members to align with the X and Y axes, (d) Delaunay triangulation for space partitioning based on vertical member coordinates, (e) estimation of scaffold units from partitioned areas, (f) horizontal member detection in scaffold units, (g) platform detection in scaffold units, and (h) 3D CAD model generation.

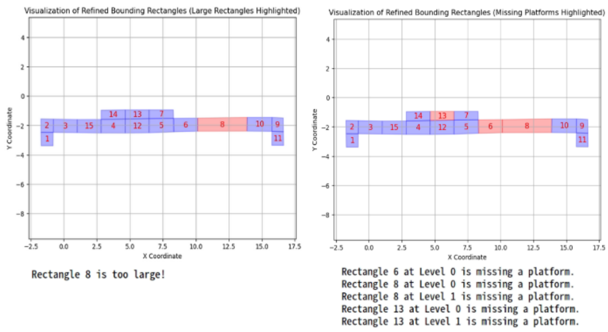
3.2.3 3D CAD Model Generation and Anomaly Detection Results

Figure 6(h) shows the 3D CAD model generated based on the detected scaffold component information. As shown in Table 2, the scaffold components were represented in the 3D CAD model with an F1 score of 97.44%. Although the segmentation of the scaffold point cloud achieved lower performance (Table 1), the modeling accuracy improved by utilizing the raw point cloud data within the scaffold units during the extraction of horizontal members and platforms.

Table 2. Performance of 3D model generation for scaffold components.

Scaffold component	Precision	Recall	F1 score
Vertical member	100%	100%	100%
Horizontal member	95.71%	98.05%	96.87%
Platform	100%	91.30%	95.45%
Average	98.57%	96.45%	<u>97.44%</u>

Figure 7 shows the evaluation and visualization of the scaffold's safety status based on the component information. As shown in Figure 7(a), the algorithm successfully detected the abnormally long horizontal members in scaffold Unit 8. An abnormally long horizontal member must be detected in advance, as it compromises structural stability and increases the risk of collapse. Additionally, Figure 7(b) demonstrates that the algorithm accurately identified the missing platforms in scaffold Units 6 and 13. As shown in Figure 7(b), the platforms in scaffold Unit 8 were abnormally installed at a tilt and were therefore detected as missing.



(a) (b)

Figure 7. Evaluation and visualization of scaffold safety status; (a) detection of abnormally long horizontal members, and (b) identification of missing platforms.

3.3 Discussion

3.3.1 Challenges in CAD Modeling Accuracy

Figure 8(a) highlights the factors that led to the decreased precision in horizontal member representation within the CAD modeling results (Table 2). As shown in the figure, multiple horizontal members at the lowest level were incorrectly detected. This issue arose because noise points acquired near the ground were misclassified as horizontal members. To address this, a preprocessing step to filter out ground noise points could be introduced.

Figure 8(b) illustrates the factors contributing to the decreased recall in CAD modeling of horizontal members. The figure shows Unit 8 of the scaffold, where an abnormally long horizontal members were installed. The installation caused a slight tilt, leading to the failure of the patch-based component matching algorithm. Since the patches move parallel to the X or Y axes, they are less effective in detecting tilted components.

The causes of the reduced recall in platform modeling are demonstrated in the example shown in Figure 8(c). Although platforms were present, they were installed at an angle, similar to the situation in Figure 8(b), and therefore were not detected. However, such improper platform installation poses a significant risk of falls, making the detection of these anomalies in the safety evaluation results meaningful.

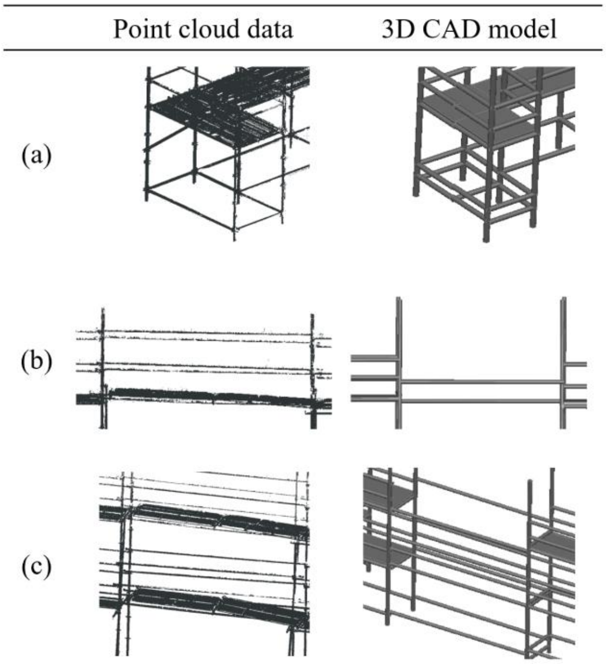


Figure 8. Analysis of false detection issues in CAD modeling for scaffold components; (a) incorrect detection of horizontal members, (b) undetected horizontal members, and (c) undetected platforms.

3.3.2 Future Directions

To achieve comprehensive structural monitoring of scaffolds, it is essential to detect not only improper assembly and missing components but also incorrect connections, such as base plates and joints. However, since these connections are highly localized features, they are difficult to segment using point cloud data alone. Therefore, future studies could explore a sensor fusion approach that integrates image and point cloud data to enable more accurate connection monitoring.

In this study, scaffold safety monitoring was conducted by detecting improper assembly and missing components. The proposed method was validated using abnormally long horizontal members as an example of improper assembly and missing platforms as an example of missing components. However, many additional subcategories exist. For instance, the improper assembly category could include tilted components or elements installed with irregular spacing. Similarly, the missing component category could be expanded to include missing horizontal and vertical members. To enhance the practical applicability of the proposed method, future research will apply and validate the method on scaffolds with a wider range of defects.

Although the proposed method was validated in a testbed environment, future studies should focus on applying and refining the method in real construction sites. This would require acquiring a larger and more diverse scaffold point cloud dataset to further improve 3D segmentation performance. Additionally, to address real-world challenges such as noise and occlusion in point cloud acquisition, techniques such as noise removal and point cloud upsampling should be integrated into the workflow.

4 Conclusion

This study proposed a comprehensive pipeline for scaffold safety monitoring, consisting of robot-assisted point cloud data acquisition, deep learning-based point cloud segmentation, scaffold component detection, CAD model generation, and safety evaluation. Experimental results confirmed that the proposed method effectively detected scaffold components, and generated high-accuracy 3D CAD models. Furthermore, the method successfully detected missing platforms and abnormal horizontal member installations in scaffold units, contributing to the visual assessment of safety conditions. However, the false detection cases of some components suggest the need for further research into noise point cloud preprocessing and the improvement of tilted component detection. For the generalization of the method, further improvement is needed through its application to construction sites with a wider variety of scaffold shapes and sizes. The proposed method has significant potential for effectively monitoring the installation status and verifying the safety of scaffolds, and is expected to play a key role in improving safety conditions at construction sites.

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