Automatic Geometry Extraction from Design Drawings and Design Compliance Checking for Steel Scaffolds

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Abstract

Scaffolding accidents account for significant fatalities in the construction industry, with deviations between erected structures and approved design drawings being a leading cause. However, automated verification of scaffold compliance with design specifications remains an open challenge due to the difficulty of extracting geometric information from engineering drawings and matching them to as-built point cloud data. This paper presents a three-stage framework for automated design compliance checking of steel scaffolds that integrates multi-view drawing analysis with 3D point cloud verification. The first step extracts geometry from scaffold drawings using computer vision algorithms. The second step involves extracting geometry from as-built scaffolds based on point cloud analysis method. The third step verifies the existence of components by comparing the extracted as-built information with the design information. Validation experiments were conducted on a point cloud dataset acquired from a scaffold system in a construction site in Hong Kong. The results provided 100% detection accuracy for tubes and safety-critical components (toe-boards, platforms and stairs), with drawing-based geometric reconstruction accuracy achieving sub-centimeter precision (mean error: 1.94 mm for tube length). This work represents the first automated system for verifying scaffold adherence to design specifications, addressing a critical gap between code compliance and design compliance in construction safety automation.

Keywords –

3D point cloud; Design compliance checking; Drawing analysis; Scaffold; Construction automation; Computer vision

1 Introduction

Scaffolding is a critical yet potentially hazardous temporary structure in construction, often associated with severe accidents due to structural failures. While adherence to safety standards and design specifications during scaffold assembly is crucial for mitigating accident risks, deviations between erected scaffolds and approved safety drawings are frequently observed. These deviations include unauthorized changes to the structural configuration and improper installation of key components. Consequently, the verification of erected scaffolds against approved safety drawings is a routine and essential practice. However, manual design compliance check of scaffolds is slow, inaccurate, qualitative and dangerous. Frequent compliance checking of scaffolds is necessary as scaffolds are often taken down and rebuilt as the project moves forward. To address this challenge, there is a growing focus on developing automatic systems for compliance checking for scaffolds. The advancements in technologies such as computer vision, robot dogs, and unmanned aircraft can assist or replace workers in conducting efficient and safe compliance checks. Adopting automatic compliance checking for scaffolding is essential for advancing engineering management [1].

Recent studies on scaffold compliance checking have concentrated on component detection, including toe-boards [2], guard-rails [2,3], and work platforms [3]. Wang [2] analyzed the geometric attributes of platform-related components, though the scope remained limited. Kim et al. [3] relied exclusively on point cloud quantity to identify elements, overlooking critical geometric dimensions. Conversely, Luo et al. [4] fused imagery with point cloud data, utilizing Graph Neural Networks (GNNs) to evaluate structural metrics such as upright verticality and bottom runner clearance. However, reliance on single-image analysis renders such methods susceptible to occlusion, limiting their application to single-layer scaffolds. Currently, a comprehensive approach that leverages geometric characteristics to verify all scaffold component types is lacking. Furthermore, few studies address compliance checking against architectural drawings, despite the critical importance of ensuring consistency between the as-built scaffolding and the original design.

To address these limitations, this study aims to develop an automated framework for design compliance checking of scaffolds, specifically focusing on component presence verification. Unlike previous approaches, this research bridges the gap between 2D design documentation and 3D site data. The primary contributions are twofold: 1) a novel drawing analysis method is proposed to automatically extract component positions and geometric attributes from rasterized design drawings; and 2) a robust compliance checking algorithm is developed to verify component existence through geometric feature extraction.

2 Literature Review

Some studies proposed automatic metal scaffolding inspection methods through analyzing point cloud data. Wang [2] proposed an automated technique utilizing 3D point cloud data to extract scaffold platforms and verify the regulatory compliance of toe-boards and guard-rails. Most studies employ rule-based approaches which have limited general applicability, while a small portion uses learning-based methods due to the scarcity of data. Kim, et al. [3] developed an automated scaffold inspection methodology integrating terrestrial laser scanner data acquisition and RandLA-Net-based 3D segmentation. However, the practical implementation of these systems faces two significant hurdles: the scarcity of large-scale, labeled scaffold datasets for model training, and the substantial degradation of prediction performance when processing sparse point cloud data [5]. To address the limitations regarding point cloud scarcity and non-uniformity in large-scale scaffold monitoring, Kim, et al. [5] proposed a reconstruction method that utilizes synthetic datasets for semantic segmentation and an upsampling adversarial network to generate 3D CAD models. Some researchers apply advanced robotic technologies to automate data collection. Chung, et al. [6] developed a fully automated point cloud acquisition system using a quadruped robot that autonomously executes a three-stage workflow of initial site exploration, SLAM-based scan plan generation, and scanning execution without requiring prior information. Due to the height restrictions of robot dogs, the collected point cloud data contains missing and omitted parts. Johansen, et al. [7] employed specialized UAVs to autonomously capture point cloud data from the building exterior during inactive hours using optimized flight paths derived from digital safety plans. Furthermore, there have been few studies on the geometric quality assessment of scaffolding. Therefore, this study proposes a method to extract geometric features from point cloud data.

3 Methodology

The proposed framework consists of three integrated modules (Figure 1): (1) Multi-view Drawing Analysis, which extracts 3D geometric information from 2D raster drawings, (2) Component Detection, which extracts 3D geometric information from point cloud data, (3) Design Compliance Checking, which verifies component existence by comparing as-built component information against extracted design information.

3.1 Multi-view Drawing Analysis

This module extracts 2D information from multiple views and then matches and reasons to obtain 3D coordinates and geometry. Table 1 shows the data extracted from the drawings, and the different elements (tube, toe-board, platform, and stair) are described in the following subsections.

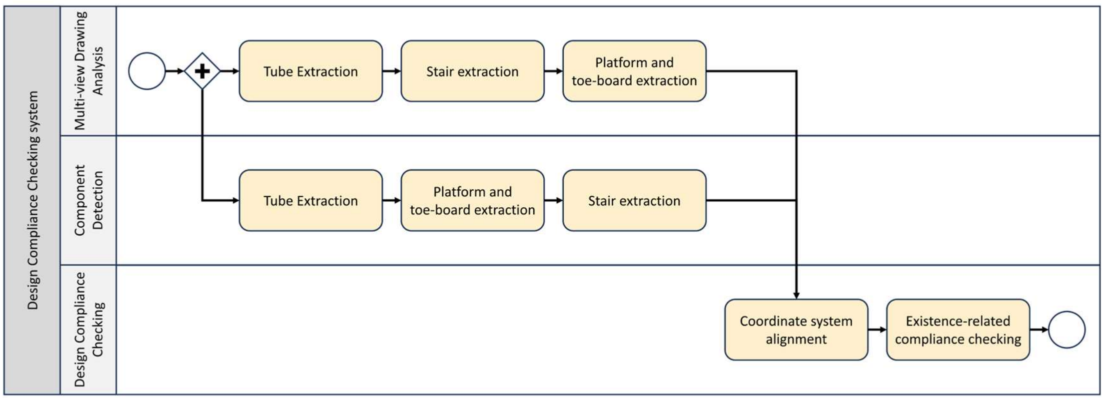

Figure 1. Proposed framework for design compliance checking of scaffolds

3.1.1 Tube Extraction

Scaffolding is defined as a temporary framework structure composed of tubes, with other types of components functioning as attachments to these tubes. Based on chromatic features, various components are extracted from the drawings, encompassing tubes, boards, and stairs. The Canny edge detector and Hough transform are utilized to identify and extract line segments representing the tubes. Given that a single tube in scaffold drawings may be represented by either a rectangle or a line segment, the detected segments are merged. Subsequently, the method of least squares is applied to perform linear fitting and generate definitive line segments. Finally, the starting and ending coordinates of each line segment are extracted to serve as the basis for subsequent analysis. When poor drawing quality compromises line segment extraction accuracy, the lengths and positions of the segments are calibrated by matching numerical annotations to the corresponding segments based on relative positions.

To integrate data extracted from different views, a unified coordinate system must be established. Scaffold drawings typically lack the axis lines and labels previous studies relied on to establish coordinate systems. Optical Character Recognition (OCR) techniques are employed to extract annotations from each view and filter for numerical annotations representing dimensions. These dimensional annotations are then matched with the corresponding tubes based on their coordinates. The scale ratio is calculated by dividing the annotated physical length by the pixel length of the tubes, which subsequently allows for the calculation of the actual tube lengths and 3D coordinates. Since image detection algorithms typically define the top-left corner of the image as the coordinate origin, a coordinate transformation is necessary to map image coordinates to the world coordinate system. When the world coordinate system is projected to form individual views, it is equivalent to retaining only two dimensions from the three-dimensional coordinates. An inverse operation is performed to restore the coordinates from all views to the world coordinate system with one dimension remains indeterminate at this stage. The origin of the world coordinate system is defined by the minimum coordinate values found among the start and end points of all detected tubes.

Existing two-view matching algorithms, utilizing either feature engineering or deep learning, prove ineffective for the three-dimensional reconstruction of scaffolding from engineering drawings. This ineffectiveness stems from the orthogonal projection of such drawings, where a 90-degree angular disparity often causes a structural member in one view to degenerate into a single node in another. To address this geometric ambiguity, the 'Two-View Matching with Third-View Validation' technique is employed to recover the missing spatial dimensions of individual tubes. The algorithm matches the endpoints of extracted line segments across two selected views and subsequently validates these candidates against a third view. However, this methodology inherently generates redundant line segments, thereby necessitating manual intervention for their removal.

3.1.2 Stair Extraction

The graphical representation of stair stringers and railings is morphologically similar to that of tubes. The location of the staircase and the quantity of steps are derived based on the position of the stringers. In the frontal view of the staircase, stringers are rendered as paired line segments perpendicular to the ground or as rectangles with their major axes aligned vertically. Conversely, in the lateral view of the staircase, the stringers manifest as inclined line segments or rectangles with tilted major axes due to projection and occlusion effects. The steps are depicted as short straight lines or rectangles that bridge the stringers and are horizontally relative to the ground. The Hough transform was utilized to extract stringers from both front and side views. The orientation of the staircase was determined based on the quantity of these detected stringers, which subsequently determined whether the identified geometric features represented the step length or width. Finally, the precise spatial position and dimensions of the staircase were derived using the coordinate transformation and 3D reconstruction methodologies previously applied to the tubes.

3.1.3 Platform and Toe-board Extraction

Scaffolding platforms are horizontal planar surfaces designed to support loads of personnel, tools and materials, represented in the plan view as shaded, colored or hatched rectangles. By extracting the minimum bounding rectangle from the top view, the actual x and y coordinates of the platforms within the world coordinate system are derived using the same transformation logic as tube detection. These rules stipulate that: 1) platforms must be located at the head and foot of staircases; 2) upper platforms require a minimum of four horizontal tubes for structural support; and (3) these supporting tubes must form a ground-parallel rectangular configuration.

Toe-boards are vertical plates positioned along platform perimeters to prevent slips and falls. Their extraction follows the platform methodology but utilizes front and side views. The final spatial coordinates of the toe-boards are determined by referencing the boundary coordinates of the underlying platforms.

Table 1. Component categories and checking items of the inspected scaffolds

Checking item	Extracted data from drawings				Extracted data from point cloud data			
	Tube	Toe-board	Platform	Stair	Tube	Toe-board	Platform	Stair
Number	√	√	√	√	√	√	√	√
Position	√	√	√	√	√	√	√	√
Orientation	√	√			√	√		
Length	√	√	√		√	√	√	
Width		√	√			√	√	
Thickness						√	√	
Radius					√			
Straightness					√			
Number of steps				√				√

3.2 Component Detection

3.2.1 Tube Extraction

Scaffolding tubes are typically composed of circular steel tubes, which are classified into various types based on their position and function, such as upright tubes, transverse horizontal tubes, and cross bracing. The Hierarchical Density-Based Spatial Clustering of Applications with Noise (HDBSCAN) algorithm considering principal direction and cylindricity is employed to perform the initial clustering of the point cloud. The principal direction is initially estimated using Principal Component Analysis (PCA) and subsequently refined through line fitting via the Maximum Likelihood Estimation Sample Consensus (MLESAC) algorithm within the vicinity of the principal axis [8]. Due to high noise levels, non-uniform density, and the presence of numerous irregularly shaped connectors within the scaffolding point cloud, HDBSCAN tends to segment the data into multiple fragments. To address this, these fragments are merged based on collinearity and spatial distance to generate nearly complete point cloud clusters for individual tubes.

Constrained by scanner positioning and occlusions, the resulting scaffolding point clouds often appear as partial cylinders. Thus, the principal direction calculated directly via PCA exhibits significant deviation and renders direct cylinder fitting methods ineffective. Therefore, an iterative slicing approach to determine the centerline is adopted [9]. First, the point cloud is sliced equidistantly along the initial principal direction calculated by PCA. Circles are fitted to each slice using Least Squares to extract centers and diameters. Slices with highly reliable fitted circles within a preset diameter threshold are selected. Then, Random Sample Consensus (RANSAC) is employed to fit a straight line through their centers. This process is repeated iteratively until the angular difference between two consecutive centerlines falls below a specified threshold, at which point the fitted line is defined as the final centerline. The final diameter is determined by averaging the diameters of the valid slices.

3.2.2 Platform and Toe-board Extraction

The positions and geometric dimensions of the platforms and toe boards are determined by extracting planes from the point cloud. For platform detection, local normal vectors are calculated based on the eight nearest neighbors of each data point to filter for approximately horizontal points within the entire point cloud dataset. A Z-value histogram with a bin width of 0.1 m is computed for all data points. Bins positioned above ground level, containing a point count exceeding three times the average of all bins, are identified as potential working platform locations. Consecutive bins are merged, and the M-estimator Sample Consensus (MSAC) algorithm is employed to fit the planes. The extracted platforms are projected onto the xy-plane, and DBSCAN clustering is utilized to separate distinct planes located at the same elevation but spatially disconnected. However, in practical scaffolding scenarios characterized by high noise levels, erroneous planes may be generated from connected surfaces at identical heights, such as stair treads or the upper surfaces of tubes affected by noise. To mitigate this, a grid coverage-based platform segmentation method is proposed. First, the minimum bounding rectangle (MBR) of the extracted plane is computed and discretized into 5 cm rectangular grids. Coverage rate for each row and column is determined based on the point count within the grid. If two consecutive rows or columns fail to meet the coverage threshold, indicating a potential gap, then a split point is established to segment the point cloud. This segmentation process is iterated until all platform fragments meet the coverage criteria. The principal directions of these fragments are fitted using RANSAC to determine their MBRs. After excluding outliers via histogram statistics, the length and width of each platform fragment are calculated. Fragments meeting the defined minimum size thresholds are retained as extracted platforms.

Finally, toe boards are searched for within a range of 10 cm inward and outward from the platform boundaries. Planar fragments are extracted using a method similar to that used for the platforms. The proposed grid coverage-based segmentation method is also applied to eliminate the interference of guardrails located above the toe boards.

3.2.3 Stair Extraction

Based on the positions of the uprights and the platform, the potential region of the staircase is identified. The point cloud within this area is subsequently segmented and subjected to planar projection. The Probabilistic Hough Transform is utilized to detect short line segments parallel to the ground, while DBSCAN is employed to cluster similar height values to preliminarily determine the number of steps. Because staircase steps typically share uniform dimensional specifications with identical lengths and widths, these dimensions are applied as constraints for filtering during the extraction process. Finally, the position of the staircase is defined by the geometric centroid of the identified steps.

3.3 Design Compliance Checking

3.3.1 Coordinate System Alignment

To enable subsequent position-based component matching for compliance checking, the drawing coordinate system is aligned with the scanner coordinate system using the coordinates of the uprights. The upright detection pipeline begins by extracting horizontal slices and segmenting points via region growing to fit circles based on radius and root-mean-squared error constraints [2]. The spatial distribution of the resulting centers is converted into a binary density map, facilitating the construction of a convex hull that identifies the precise centroid coordinates of the uprights [2]. To determine the alignment, two upright centroids from the drawing analysis and two from the point cloud are selected. Assuming a correspondence between these pairs, the Singular Value Decomposition (SVD) method is employed to solve for the rigid body transformation matrix. Transformed point cloud upright centroids that fall within a specified distance threshold of the drawing upright centroids are classified as inliers. An Exhaustive Search is performed to iterate through all possible combinations. The transformation matrix maximizing the inlier count is selected as the optimal solution. If several solutions have equal inliers, the one with the matrix with the lowest Root Mean Square Error (RMSE) is selected. Finally, this optimal transformation matrix is applied to the raw 3D point cloud to achieve global alignment.

3.3.2 Existence-related Compliance Checking

Component presence is validated by contrasting the position and geometric attributes derived from the drawings against those from the point cloud. Platforms and toe-boards are matched via centroid distance, with subsequent assessments of their length, width, and orientation. Since the uprights were already filtered by diameter during the extraction process, they are matched based on the orientation and position of their centerlines. The presence of the component is confirmed by a successful match. Finally, stairs are validated by directly comparing their position and the number of steps. The component categories and checking items of the inspected scaffolds are presented in Table 1.

4 Case study

4.1 Data collection

A scaffold system located at a construction site in Hong Kong was selected for this case study. The scaffold system consisted of 42 tubes, 4 toe-boards, 1 platform and 1 staircase with 8 steps. The design drawings for the scaffold system are stored as color raster images, as illustrated in Figure 2. Point cloud data of a scaffold system was acquired using a high-resolution SHARE SLAM S20 handheld 3D LiDAR scanner. During data acquisition, the scanner was maneuvered slowly around the scaffold, continuously emitting laser pulses and recording the reflected signals. The built-in SLAM algorithm within the SHARE PointCloud Studio software was then utilized to generate a high-density point cloud, which was exported in plain text format for subsequent analysis. Finally, manual pre-processing was performed using CloudCompare to remove extraneous environmental data. The resulting pre-processed point cloud is illustrated in Figure 3.

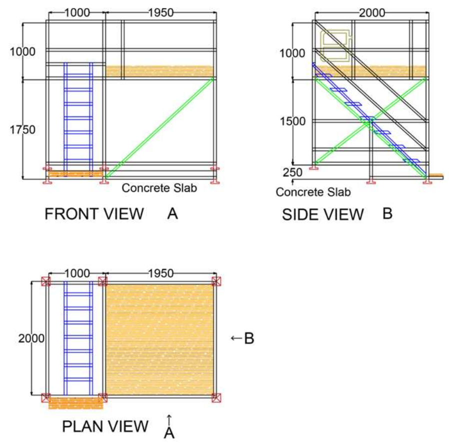

Figure 2. Scaffolding design drawing

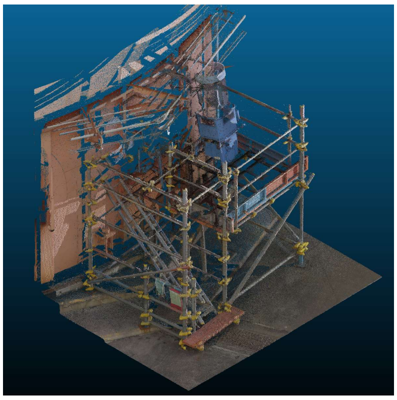

Figure 3. Collected and preprocessed scaffolding point cloud

4.2 Results

4.2.1 Geometry Extraction from Design Drawings

In the drawing analysis, the discrepancies between the measured values and the ground truth values for scaffold tubes were minimal. Figure 4 shows the spatial distribution of errors between the extracted scaffold tube measurements and the ground truth in three dimensions. Each tube is visualized in its 3D location, and its color indicates the magnitude of error according to the corresponding color bar (green = low discrepancy, red = high discrepancy). The position difference heatmap (left) highlights where centerline or endpoint localization deviates from the reference, the length difference heatmap (middle) shows segment-wise deviations in tube length, and the angle difference heatmap (right) summarizes orientation errors. For all three metrics, most tubes appear in green tones, indicating small discrepancies throughout the structure. Using a scale of 4 mm per pixel, the average discrepancies were 8.334 mm for position, 1.935 mm for length, and 0 for angle, confirming minimal deviation from ground truth and high geometric consistency in the drawing-based scaffold analysis. Overall, discrepancies remain low across the scaffold geometry, indicating close agreement between the measured results and the ground truth. However, the extraction errors for platforms and toe-boards were slightly higher (Table 2). Position errors ranged from 8.77 mm (platform) to 49.56 mm (toe-board 3), meaning toe-boards were harder to localize accurately than the platform. Length errors were similar for all components (−72 to −74 mm). Width errors were small and consistent for toe-boards (−8.00 mm), but much larger for the platform (−74.00 mm). The angle error was 0° for every component, showing that orientation was correctly preserved. These differences mainly come from the use of color segmentation, where filled regions start at the tube edges, while the drawing dimensions are referenced to the tube centerlines. Therefore, the deviations are systematic and acceptable for scaffold modeling.

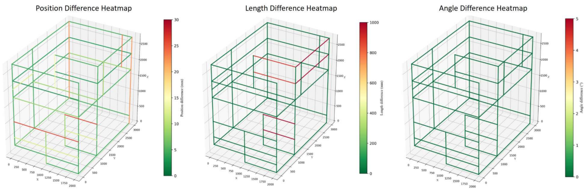

Figure 4. 3D discrepancy heatmaps comparing the measured scaffold tube parameters against ground truth

Table 2. Discrepancies between measured and ground truth values for scaffold toe-board and platform components

Component	Position difference (mm)	Length difference (mm)	Width difference (mm)	Angle difference (deg.)
Toe-board 1	41.42	-72.00	-8.00	0
Toe-board 2	47.97	-74.00	-8.00	0
Toe-board 3	49.56	-72.00	-8.00	0
Toe-board 4	47.97	-74.00	-8.00	0
Platform	8.77	-72.00	-74.00	0

4.2.2 Design Compliance Checking

Table 3 presents the results of the existence-related compliance checking for the case study. A total of 42 tubes, 1 staircase, 1 platform and 4 toe-boards were successfully detected. Compared with the design drawings, an additional stair step was constructed in the as-built scaffold.

Table 3. Results of existence-related design compliance checking of the case study

	Quantity in drawing	Quantity in point cloud data	Detected quantity
Tube	42	42	42
Platform	1	1	1
Toe-board	4	4	4
Stair	1	1	1
Steps of stair	7	8	8

5 Discussion

During tube detection, due to total or partial occlusion and the co-linear superposition of boundaries, segment endpoints or the vertices of overlapping rectangles become indistinguishable, rendering actual geometric attributes indeterminate. This inherent metric ambiguity affects both human and computational systems, necessitating expert knowledge or top-down semantic constraints for its resolution. As a result, certain short line segments situated within the interior of the scaffold structure may be erroneously extracted as longer segments, leading to the generation of redundant tubes during the 3D reconstruction process. In this study, we manually remove redundant tubes. Future research can incorporate stronger structural and semantic priors into the tube reconstruction pipeline, including scaffold connectivity rules, topological constraints, and the functional roles of the components.

A limitation of this study is that the method was validated on only one small dataset containing 42 tubes. Although the overall framework is not inherently constrained by scaffold size, scaling to larger and more complex scaffolds is expected to introduce additional challenges, including heavier occlusion, denser tube arrangements, repeated structural patterns, and error propagation from local line extraction to global 3D reconstruction. These factors may increase ambiguity in tube interpretation and lead to more redundant tube instances. In future work, we will evaluate the method on larger and more diverse datasets.

In addition, the quality of the Point Cloud Data (PCD) requires further improvement. Primarily, constraints related to scanner elevation and layout, along with the inherent complexity of the scaffolding structure, lead to non-negligible incompleteness in the captured point clouds. Specifically, the numerous support tubes beneath the platforms often generate excessive noise in the undersurface data. Despite deploying handheld mobile scanners carried up the stairs manually, the point clouds of the platform's upper surface remain fragmented due to occlusions caused by other equipment located on the platform. While the proposed grid coverage-based platform segmentation method mitigates the effects of point cloud sparsity and uneven distribution to a certain extent, the accuracy of platform dimension extraction remains compromised. Moreover, regarding scaffolding positioned adjacent to walls, spatial inaccessibility results in blind spots on the back of the structure. Similarly, lower-level components often obstruct the line of sight to higher scaffolding tiers. To address these limitations, future work should employ more flexible devices, such as Unmanned Aerial Vehicles (UAVs), to scan the target range from various angles and heights. Furthermore, developing appropriate point cloud completion methods to increase data density and completeness without altering the geometric characteristics of the components serves as a potential solution.

6 Conclusion

This paper proposed a framework for automated design compliance checking of steel scaffolds, addressing a critical gap in construction safety automation. By integrating multi-view drawing analysis with 3D point cloud verification, the proposed method enables quantitative comparison between as-built conditions and approved design specifications. Specifically, this study has two main contributions: 1) proposes a multi-view drawing analysis method that can effectively extract information and enables 3D reconstruction, and 2) enables effective scaffold design compliance checking. While current results are promising, limitations include occlusion-related false negatives, assumption of approximate positional correctness, and single case study validation. Future work should integrate multi-modal data sources (photogrammetry, BIM) and validate across diverse scaffold configurations.

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