Transformation of Point Clouds to Images for Safety Analysis of Scaffold Joints

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Abstract –

Structural flaws in scaffolds can lead to fatal accidents on construction sites, and the installation status of scaffold joints is crucial for the safety of scaffolds. However, manual inspection of scaffold joints can be challenging due to their small size and large quantity. This paper presents a scaffold joint inspection mechanism using a Terrestrial Laser Scanner (TLS) to address the challenge of inspecting large numbers of scaffold joints for structural flaws. Scaffold members are first extracted from the TLS-acquired point clouds using a 3D segmentation model to generate scaffold joint image sets. Then, a rule-based classifier is used on the image sets to identify the installation status of each joint. Our experiment showed 82.1% accuracy in scaffold joint safety analysis and successfully localized the unsafe joints on the 3D point cloud data.

Keywords –

Deep learning; Scaffold; Point-to-Image; Safety analysis; Terrestrial Laser Scanning

1 Introduction

Point cloud data obtained through Terrestrial Laser Scanner (TLS) is more accurate than that obtained through photogrammetry due to its high sensor accuracy and the simplicity of static scan registration. Furthermore, depending on the scanner, it is also possible to obtain RGB or intensity information, allowing for the acquisition of texture information as well. Due to the advantages of TLS-acquired data, TLS is frequently used in construction site quality control research. Wang et al. [1] extracted information for rebar quality assessment by performing automated rebar position estimation using the (x, y, z) coordinate information and (r, g, b) color information of the point clouds obtained by TLS. Erkal and Hajjar [2] used texture-mapped 3D data obtained with a camera-integrated TLS to detect damages on building surfaces.

The unstable state of scaffolds is a major cause of fatalities at construction sites. According to the Korean Ministry of Employment and Labor [3], 53% (341 cases) of occupational fatalities occurred in the construction industry in 2022. Among them, 208 fatalities were related to accidents that occurred in temporary structures; the statistic shows the importance of monitoring the safety condition of temporary structures. Typical causes of scaffold incidents include lack of fall protection, instability of the scaffold structure, overloading, and being struck by falling tools [4].

A previous study [5] investigated the detachment status of various components of scaffolds by directly processing the point clouds obtained by TLS. In the case of attached scaffold components, joint inspection is required to ensure proper installation. However, with large-scale construction site data, determining the presence of extremely small objects like the pins of a ringlock scaffold through direct processing of point clouds is computationally inefficient. On the other hand, Paik et al. [6] were able to efficiently solve the joint safety analysis task through the use of UAV-acquired images. However, since the image data do not include location or depth information, the automatic localization of the detected joint is challenging.

Various studies have utilized the fusion of 3D point clouds and 2D images. Nguyen et al. [7] employed images to effectively detect small features such as cracks in 3D data. They concatenated the image pixel features with low-density point clouds of the crack area and performed upsampling. Yang et al. [8] proposed Mem3D for effective 3D object reconstruction using a single-view image. For training Mem3D, the correspondence of the image-voxel pair of the dataset was used, including the memory network.

Motivated by the limitations of previous studies, we propose a methodology that combines the advantages of 3D point cloud data and 2D image data. The proposed method involves generating images from point cloud data, processing the generated images, and re-projecting the information processed from the image onto the 3D point clouds. This method allows us to use the rich data quality of point clouds and the efficiency of image processing to effectively locate the unsafe joints in the scaffold.

2 Methodology

In this research, the semantic segmentation through RandLA-Net [9] and then post-processing for the desired information were based on the method proposed in [5]. Therefore, this paper describes the three parts after the semantic segmentation: Point-to-Image translation, object detection, and joint safety analysis. The overall framework is shown in Figure 1.

2.1 Point-to-Image

By using the algorithm from [5], we can obtain representative (x, y, z) coordinates of the "upright" and the "guard rail" in a scaffold. Combining these two information resulted in the intersection points of "upright" and "guard rail," which is equal to the center coordinate of every joint. Afterwards, each joint coordinate is used as a center to crop a 20×20×20 (cm) sized bounding box from the point clouds, in order to extract the point cloud data for each joint. The joint extraction framework is shown in Figure 2. Then, the open-source library Open3D's [10] Visualizer function is utilized to save the compressed appearance in the required viewpoint vector direction as an image for each joint point clouds. The required viewpoint vector varies depending on the type of joint. As shown in Figure 3, parallel joint (Figure 3(b)) generates one image from one viewpoint, while corner joint (Figure 3(c)) generates two images from two viewpoints.

2.2 Object detection

Images generated through the Point-to-Image algorithm are fed into the YOLOv5 [11] model trained to detect "ledger end" and "tail" of the joint (Figure 4). The generated images are in the form of a white background with "upright" passing in the middle and "ledger end" and "tail" on sides of the "upright." The two components' information is sufficient to inspect the safety status of a joint. "Ledger end" indicates that there is a joint that should be inspected in that location, and "tail" is only visible when the pin is properly inserted into the corresponding "ledger end."

2.3 Joint safety analysis and localization

The safety status of each joint is inspected through the information of "ledger end" and "tail" detected through YOLOv5 in each image. If "ledger end" does not exist in an image (Figure 5(c)), the image is excluded from inspection because it does not have a joint. If "ledger end" exists, it indicates that a joint exists in the image and the number of detected "tail" and that of "ledger end" are compared. If the number of detected "tail" is less than that of "ledger end," it is judged as unsafe because the "tail" is not visible (Figure 5(b)); there is a risk of accident due to incorrect insertion of pins and loose joints. In the case of a corner joint, if either of the two images of a single joint is classified as unsafe, then the joint is considered unsafe. The scenarios of safe, unsafe, and no joint are presented in Figure 5. The flowchart of the rule-based joint safety classifier is shown in Figure 6.

In order to localize the unsafe joint images onto the point cloud map, we included the index of the corresponding joint in the file name format generated during the Point-to-Image algorithm. Through the index number, we were able to easily determine the (x, y, z) coordinates of the detected joint.

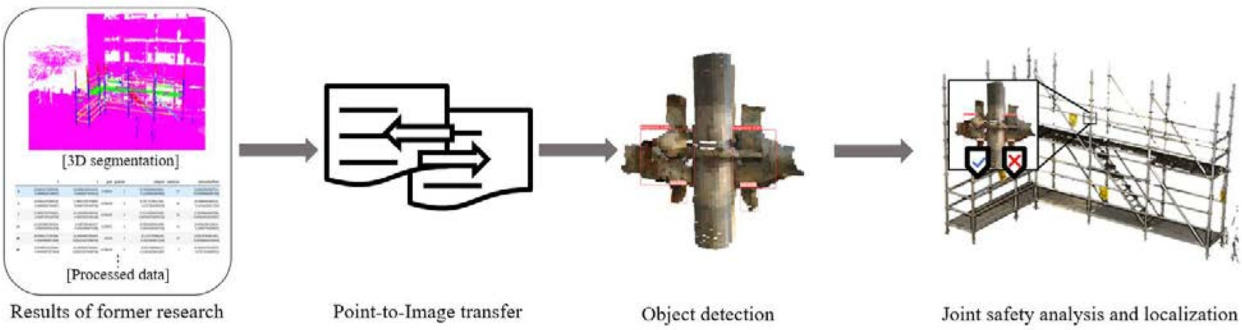

Figure 1. Overall framework.

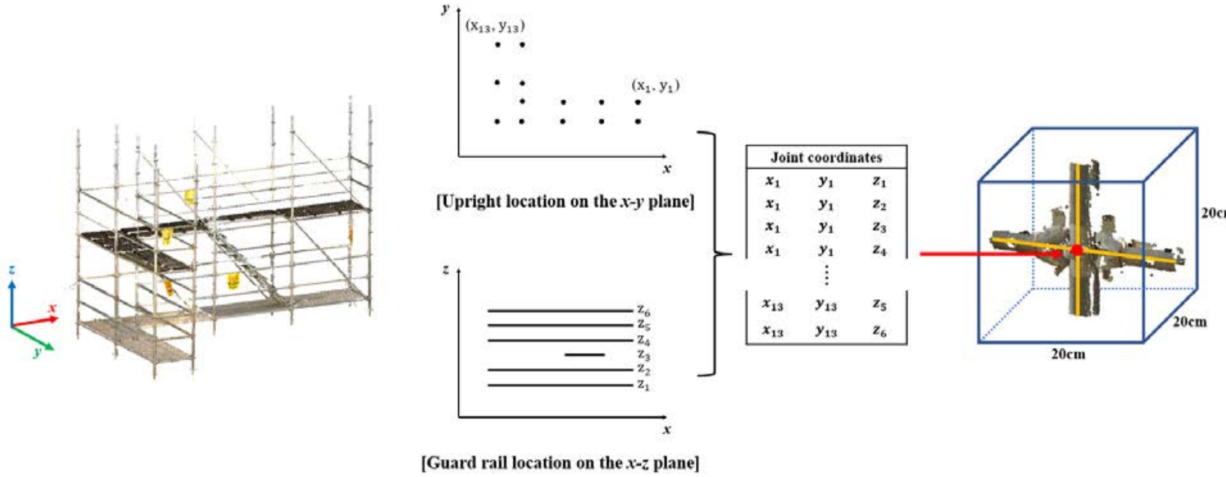

Figure 2. Joint extraction framework.

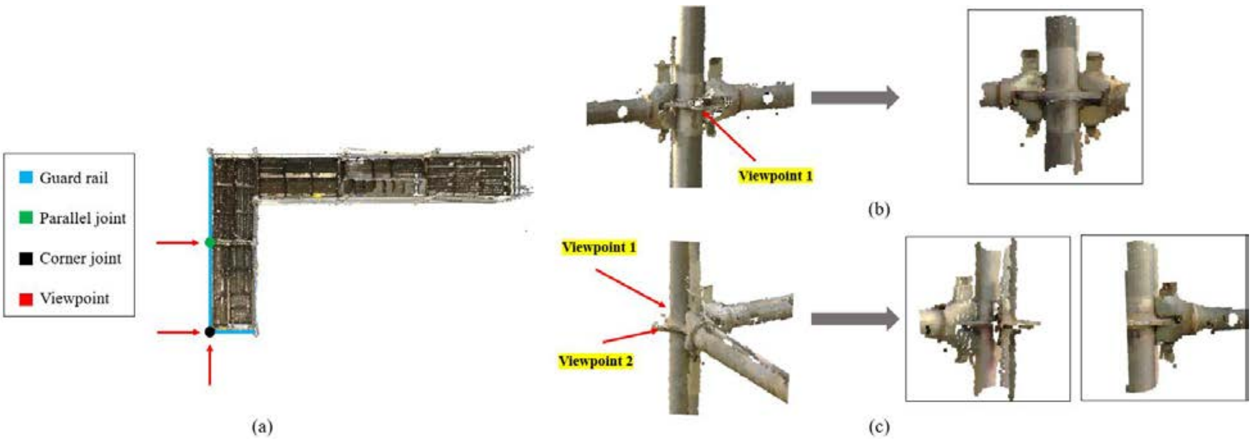

Figure 3. Two types of joints and the images generated from each type; (a) bird-eye view of a scaffold, (b) an example of parallel joint (left: point clouds, right: generated image), (c) an example of corner joint (left: point clouds, right: generated image).

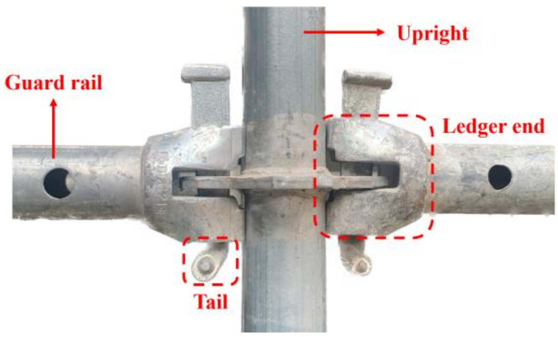

Figure 4. Image of a scaffold joint.

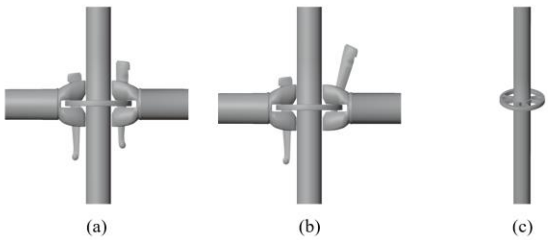

Figure 5. Scenario of joint safety status; (a) safe, (b) unsafe: tail is not visible on the right pin, (c) no joint: ledger end is not visible.

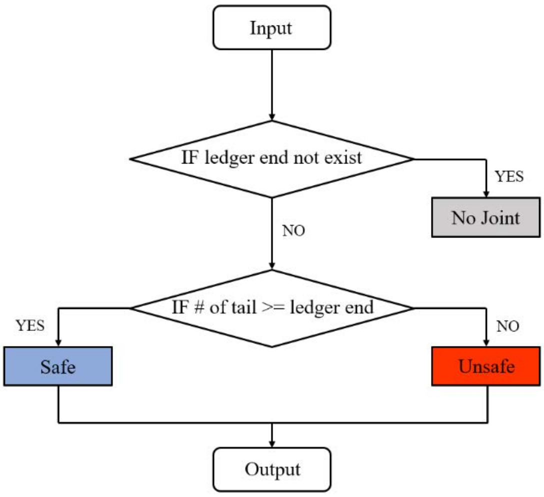

Figure 6. Rule-based joint safety classifier.

3 Experiments and Results

In this section, we present detailed information about the data used in the experiments and the evaluated results. We also discuss the current limitations and challenges revealed through the results of the experiments.

3.1 Dataset specification

The data used in this study were acquired from a total of three construction sites with ringlock scaffolds. In the point cloud data of site A shown in Figure 7, 239 joint images were acquired. These 239 images were augmented to 478 images by applying the gaussian blur method; to smoothen the variation in the images made by point size difference without breaking the geometry of the joint. In site B, a total of 90 joint images were acquired from the point cloud data. This study targets to inspect the structural safety of the scaffold after it is erected and before it is disassembled. Therefore, image data were acquired at the upper part of the scaffold without safety nets at site B. The images obtained from site A were used as the training dataset for YOLOv5, while the images obtained from site B were used as the validation dataset for YOLOv5. Point cloud data acquired from site C were used as test data.

All sites did not have actual unsafe joints. Therefore, a total of three unsafe joints were manually created by cropping and removing the scaffold joint pins from the point cloud data acquired from site C.

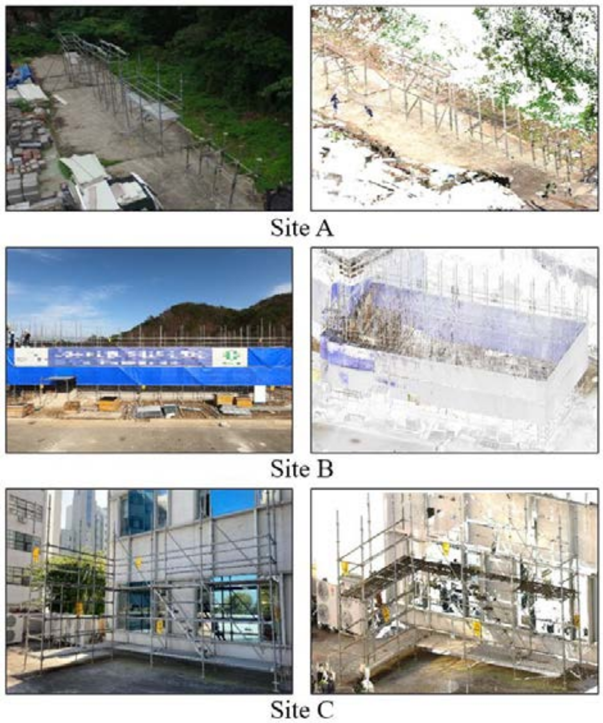

Figure 7. Image (left) and acquired point clouds (right) of data acquisition sites.

3.2 Results

Applying the methodology of [5] to the site C data yields 3D segmentation results that are divided by scaffold entities (results of former research in Figure 1). The segmented point cloud data of site C were fed into the Point-to-Image algorithm, producing 114 images from 78 joints (42 parallel joints and 36 corner joints) in 12m 53s. Object detection, joint safety analysis, and localization performed on the generated images took 1.74 seconds in total. Our methodology resulted in a per image accuracy of 74.6% and a per joint accuracy of 82.1% for site C. The results are summarized in Table 1.

Table 1. Joint safety analysis results

	Accuracy (%)
Per Image (114 images)	74.6
Per Joint (78 joints)	82.1

As explained in Section 2.3, unsafe joints can be automatically localized on the point cloud map. In order to visually display the locations, we created a

(a) (b)

Figure 8. Localization & visualization of unsafe joints; (a) Prediction (red box), (b) Ground truth (blue box).

visualization algorithm that generates a red box around the unsafe joint. Figure 8(a) is the localization result of predicted unsafe joints.

3.3 Discussion

As shown in Figure 9, the proposed method successfully inspected a total of 78 joints in site C with a per joint accuracy of 82.1%. The 14 joints that were incorrectly predicted include one case that predicted an unsafe joint as “no joint” and two cases that predicted a safe joint as unsafe. These 14 misclassifications were mainly divided into two reasons; when the joint is occluded by obstacles such as work platforms or work ropes (Figure 10(a)), and when the object detection model fails to detect the joint (Figure 10(b)).

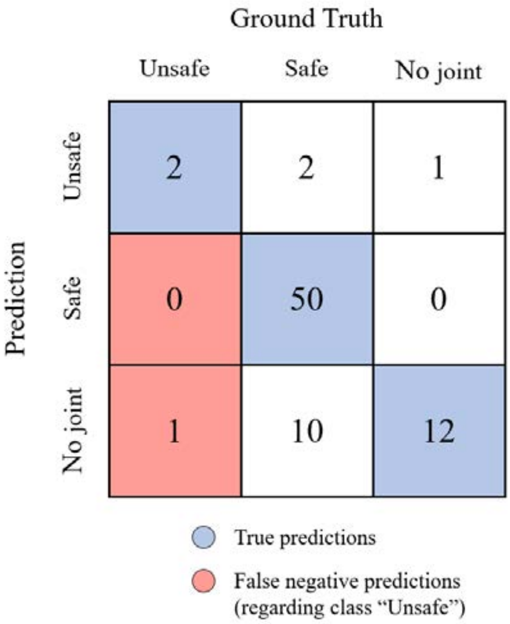

Figure 9. Confusion matrix of the safety analysis results. Numbers represent the number of joints.

Safety analysis is a field that requires perfect predictions. False negative predictions are particularly important to avoid; an unsafe object predicted to be safe is vulnerable to accidents. Our model had one false negative error (red box in Figure 9), which occurred when the joint was occluded by a work rope.

4 Conclusion

This study presented a methodology for automating scaffold joint safety analysis by generating 2D image data from 3D point cloud data; thereby combining the advantages of both data types. The framework of this study is divided into three parts including Point-to-Image transformation, object detection, and rule-based joint safety analysis and localization. An accuracy of 82.1% was obtained for the joint safety status of a ringlock scaffold on a construction site. In contrast to previous image-based studies, the proposed method was able to easily localize the identified unsafe joints.

In future studies, the limitations mentioned in section 3.3 should be addressed. The scanning method should be optimized to minimize occlusion of data. The training dataset of the detection model should be supplemented to increase the accuracy of the detection model. Additionally, the joint analysis method should be developed and tested to be applicable to various sizes and types of scaffolds.

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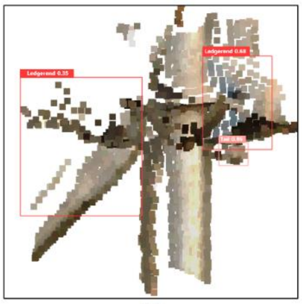
(a)



(b)

Figure 10. Misclassified image example; (a) occlusion by work rope, (b) detection failure of YOLOv5.

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