ICCEPM 2022
The 9th International Conference on Construction Engineering and Project Management
Jun. 20-23, 2022, Las Vegas, NV, USA

Automated Analysis of Scaffold Joint Installation Status of UAV-Acquired Images

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Abstract: In the construction industry, fatal accidents related to scaffolds frequently occur. To prevent such accidents, scaffolds should be carefully monitored for their safety status. However, manual observation of scaffolds is time-consuming and labor-intensive. This paper proposes a method that automatically analyzes the installation status of scaffold joints based on images acquired from a Unmanned Aerial Vehicle (UAV). Using a deep learning-based object detection algorithm (YOLOv5), scaffold joints and joint components are detected. Based on the detection result, a two-stage rule-based classifier is used to analyze the joint installation status. Experimental results show that joints can be classified as safe or unsafe with 98.2 % and 85.7 % F1-scores, respectively. These results indicate that the proposed method can effectively analyze the joint installation status in UAV-acquired scaffold images.

Key words: object detection, rule-based classifier, scaffold, scaffold joint, unmanned aerial vehicle

1. INTRODUCTION

According to the Korea Occupational Safety and Health Agency (KOSHA), 308 fatal accidents occurred in the construction industry in 2020; 135 of those occurred in temporary structures [1]. Safety inspection of temporary structures generally relies on manual observation [2], which is time-consuming and labor-intensive. To address this problem, technologies are being developed based on LiDAR [3, 4], strain gauge [5], accelerometer [6], and vision sensors [7, 8]. It is important to monitor scaffold joints because their installation status is a critical factor for scaffold safety. Scaffold joint monitoring is challenging because there are numerous joints to be monitored. To address this issue, this paper proposes a method for analyzing the installation status of scaffolds using UAV-acquired images. Thanks to UAVs, it is possible to monitor a large construction site in a safer and faster manner [8, 9, 10]. These previous studies motivatge the use of UAVs to acquire joint images of scaffolds.

The joint analysis process, as shown in Figure 1, is divided into four stages. In the first stage, scaffold image data are acquired from a UAV (Figure 1(a)). Second, joints are detected from UAV-acquired images (Figure 1(b)). Third, components of each joint are detected (Figure 1(c)). At last, a joint image is classified into either safe or unsafe status using a two-stage rule-based classifier (Figure 1(d)). The proposed method can accurately check the scaffold joint installation status in a short time.

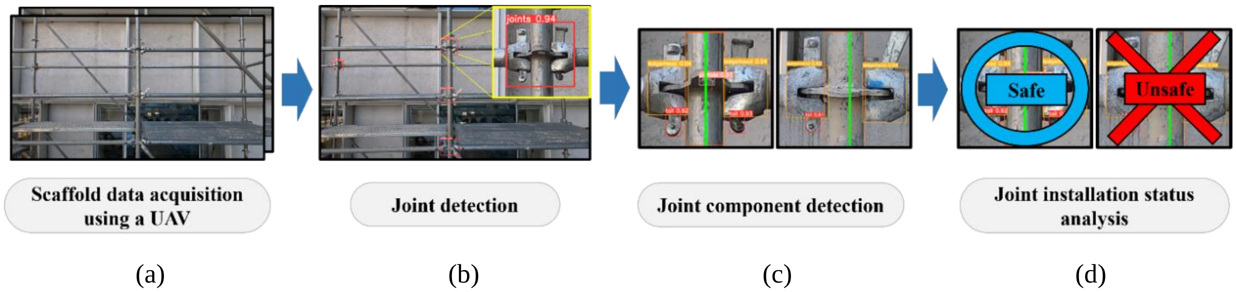


Figure 1. Research framework; (a) scaffold data acquisition using a UAV (b) joint detection, (c) joint component detection, (d) joint installation status analysis

2. METHODOLOGY

2.1. Joint detection & Joint component detection

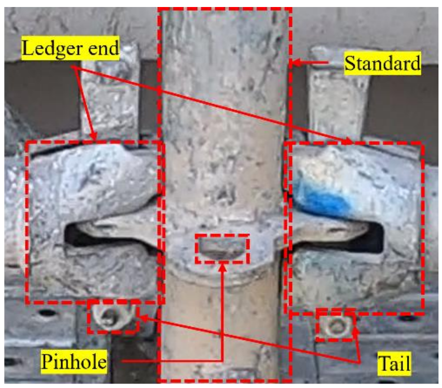


Figure 2. Joint components of the ringlock scaffold

For the real-time ringlock scaffold joint detection and joint component detection from UAV-acquired images, the proposed method used an object detection algorithm, YOLOv5 [11]. The joint components of interest are tail, pinhole, standard, and ledger end as shown in Figure 2. The presence of a ledger end and standard indicates that the horizontal member of the scaffold is connected to the standard, and the presence of a pinhole means the joint image is vertically angled. Because the existence of the tail depends on the installation status of the joint, it can be an indicator for determining the safety of the joint.

2.2. Joint installation status analysis

It is not appropriate to use all joint images acquired by a UAV. The position and angle of the UAV may generate joint images of which quality is not fit for the safety analysis because the tail can be occluded by other objects. To use only desired image and analyze the installation status of the joint, a rule-based classifier is used. For example, if a pinhole is detected in the image (Figure 3(a)), the tail is likely to be occluded by the pinhole and the ledger end. If the bounding boxes of standard and ledger end overlaps with more than a certain ratio as shown in Figure 3(b), the tail may be blocked by the standard. In contrast, if both tail and ledger end are detected, the joint is considered safe.

(a) (b)

Figure 3. Examples of poor quality joint images; (a) vertically angled, (b) horizontally angled

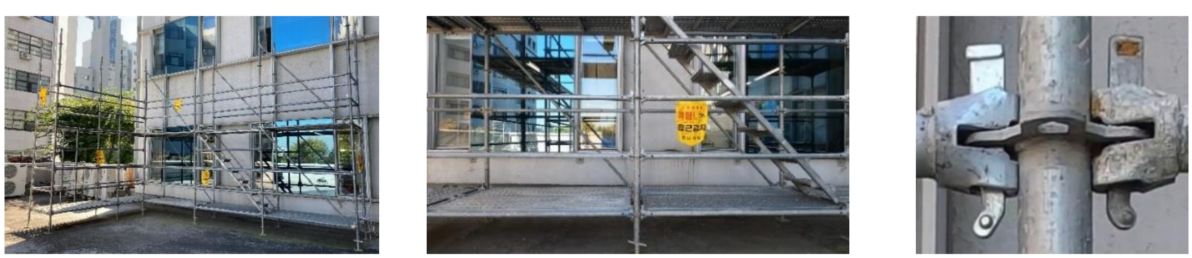
3. EXPERIMENTS AND RESULTS

3.1. Datasets and implementation

Two image datasets (Site A (Figure 4) and Site B (Figure 5)) were used in this research. 300 images from Site A and 60 images acquired from Site B were used for training and testing the joint detection model, respectively. Joint images were automatically cropped and used to train and test the component detection model. 693 joint images from Site A and 118 images from Site B were used to train and test the model, respectively. The data from Site A were used to determine the parameter values, while the data from Site B were used to test the rule-based classifier; a total of 1,716 joint images from Site B were used.

(a) (b) (c)

Figure 4. Site A; (a) the scaffold, (b) UAV-acquired image, (c) joint image



(a) (b) (c)

Figure 5. Site B; (a) the scaffold, (b) UAV-acquired image, (c) joint image

Two different detection models were trained using the YOLOv5 algorithm. For both models, the weights pre-trained with the COCO [12] dataset were used. Batch size, epochs, and learning rate were set to 1, 150, and 0.01, respectively to train the joint detection model. To train the joint component detection model, batch size was set to 4, epoch value to 50, and learning rate to 0.01.

3.2. Results

As shown in Table 1, the scaffold joint detection model achieved an 89.6% F1-score. Table 2 shows that the joint component detection model achieved 98.0% to 99.3% F1-scores for detecting tail, standard, and ledger end; but a 56.5% F1-score was recorded for detecting pinholes. Examples of detection results are shown in Figure 6. As shown in Table 3, the classifier identified safe joints and unsafe joints with 98.2% and 85.7% F1-scores, respectively.

(a) (b)

Figure 6. Examples of detection results; (a) joint detection, (b) joint component detection

Table 1. Scaffold joint detection performance

	Precision	Recall	F1 score
Joint	92.7%	86.7%	89.6%

Table 2. Scaffold joint component detection performance

	Precision	Recall	F1 score
Tail	98.7%	97.9%	98.3%
Pinhole	74.5%	45.5%	56.5%
Standard	98.7%	100.0%	99.3%
Ledger end	99.0%	97.1%	98.0%

Table 3. Scaffold joint installation status analysis performance

	Precision	Recall	F1 score
Safe joint	99.4%	97.0%	98.2%
Unsafe joint	78.3%	94.7%	85.7%

4. CONCLUSION

This research proposed a new methodology for automatically analyzing the scaffold joint installation status. Joints and joint components were detected through the deep learning-based object detection algorithm, YOLOv5, from UAV-acquired images. The two-stage rule-based classifier was designed to choose the only desired images and analyze the installation status of scaffold joints based on the information on the detected joint components. Using this rule-based classifier, it was possible to analyze the installation status of scaffold joints with an 98.2% F1-score for safe joints and an 85.7% F1-score for unsafe joints, respectively. Future studies are required to improve the proposed method. Data augmentation and rule refinement are expected to enable the usage of more image data of scaffold joints.

ACKNOWLEGEMENTS

This work was supported by the National Research Foundation of Korea (NRF) grant funded by the Ministry of Science and ICT (No. 2021R1A2C2004308) and the Ministry of Education (No. 2018R1A6A1A08025348).

REFERENCES

[1] KOSHA (Korea Occupational Safety and Health Agency). Industrial Accident Analysis for 2020.
Online:
https://www.kosha.or.kr/kosha/data/industrialAccidentStatus.do?mode=view&articleNo=427416&article.offset=0&articleLimit=10 Accessed: 08/02/2022.

[2] MOLIT (Ministry of Land, Infrastructure and Transport). Guidelines for Safety Management of Construction Work.
Online:
https://www.law.go.kr/LSW//admRulLsInfoP.do?chrClsCd=010202&admRulSeq=2100000204526 Accessed: 10/02/2022.

[3] Wang, Qian. "Automatic checks from 3D point cloud data for safety regulation compliance for scaffold work platforms." Automation in Construction 104 (2019): 38-51.

[4] Kim, Juhyeon, et al. "Deep learning-based 3D reconstruction of scaffolds using a robot dog." Automation in Construction 134 (2022): 104092.

[5] Cho, Chunhee, et al. "Machine learning for assessing real-time safety conditions of scaffolds." ISARC. Proceedings of the International Symposium on Automation and Robotics in Construction. Vol. 35. IAARC Publications, 2018.

[6] Yuan, Xiao, and Chimay J. Anumba. "Cyber-Physical Systems for Temporary Structures Monitoring." Cyber-Physical Systems in the Built Environment. Springer, Cham, 2020. 107-138.

[7] Chi, Hung-Lin, et al. "Scaffold progress monitoring of LNG plant maintenance project using BIM and image processing technologies." 2017 International Conference on Research and Innovation in Information Systems (ICRIIS). IEEE, 2017

[8] Jun, Byong-Hee, et al. "Safety management of steel pipe scaffold using UAV." Journal of Korean Society of Disaster and Security 12.3 (2019): 59-67.

[9] Bang, Seongdeok, and Hyoungkwan Kim. "Context-based information generation for managing UAV-acquired data using image captioning." Automation in Construction 112 (2020): 103116.

[10] Bang, Seongdeok, Yeji Hong, and Hyoungkwan Kim. "Proactive proximity monitoring with instance segmentation and unmanned aerial vehicle-acquired video-frame prediction." Computer-Aided Civil and Infrastructure Engineering 36.6 (2021): 800-816.

[11] Jocher, Glenn, et al. "yolov5." Code repository https://github. com/ultralytics/yolov5 (2020).

[12] Lin, Tsung-Yi, et al. "Microsoft coco: Common objects in context." European conference on computer vision. Springer, Cham, 2014.