ICCEPM 2024 https://dx.doi.org/10.6106/ICCEPM.2024.0731
The 10th International Conference on Construction Engineering and Project Management
Jul. 29-Aug.1, 2024, Sapporo

Automated Data Collection and Intelligent Management System for Construction Site Disaster Prevention

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Abstract: The accident rate in the South Korean construction industry has increased by 50% over the past ten years, reaching seven times the average growth rate of the entire industry. However, the number of management personnel at construction sites is decreasing, making it increasingly difficult to establish a safety monitoring system through professional personnel. This study aims to develop an intelligent control system to address the problem of insufficient management personnel and support the establishment of a continuous safety monitoring system. This system consists of a mobile information collection robot (S-BOT) and an intelligent algorithm. The visual information collected by S-BOT can be analyzed in real-time using computer vision-based intelligent algorithms to detect unsafe situations. The results of this study will contribute to preventing unnecessary social and economic losses by maximizing safety management efficiency and supporting timely decision-making through the sharing of information provided by the intelligent control system.

Key words: construction safety, disaster prevention, computer vision, artificial intelligence, intelligent system

1. INTRODUCTION

1.1. Background

The production activities in the construction industry primarily take place outdoors. There is significant movement of resources (e.g., labor, equipment, etc.) depending on the worksite, and it is also characteristic of work being carried out simultaneously at multiple locations. Consequently, in contrast to the general manufacturing sector, the execution of safety management activities within construction sites presents significant challenges. Furthermore, the predominance of outdoor work processes subjects these operations to considerable influence from meteorological conditions, potentially exacerbating existing difficulties. In South Korea, the accident rate in the construction industry has risen by 50% over the past decade, and the sector accounts for 24.2% of all fatal accidents [1,2]. Accidents at construction sites are predominantly influenced by managerial factors, necessitating continuous management by site and safety managers to address unsafe behaviors of workers and poor working conditions [3]. However, the number of professionals available for management has decreased by 17.2% compared to a decade ago [4], making it increasingly challenging to establish a safety monitoring system through specialized personnel.

This study aims to develop an intelligent surveillance system specifically designed for construction site applications. The deployment of such an intelligent system represents a promising alternative to mitigate the issue of insufficient safety managers at construction sites. Additionally, it facilitates the establishment of an uninterrupted surveillance mechanism via real-time monitoring capabilities.

1.2. Scope and methodology

For the prevention of accidents at construction sites, the intelligent surveillance system has been designed to analyze metadata (i.e., video images and sensor data) obtained from an automated rail-running information collection robot (S-BOT) through artificial intelligence based on computer vision. The system is configured to support immediate action by sending a warning message to the manager (or worker) when AI operating on the construction site detects an unsafe situation. The S-BOT and server communication utilizes a closed network based on Ethernet wireless communication. The detectable hazard scenarios are defined as fire accidents and unsafe conditions that may arise during mobile scaffolding work.

2. SYSTEM DEVELOPMENT

2.1. Rail-driving robot (S-BOT) for information collection

2.1.1 Full-time power supply rail

The S-BOT incorporates several high-power-consuming devices, such as CCTV cameras, sensors, wireless communication modules, and propulsion motors. Sustaining an uninterrupted and stable power supply to these components via a mobile battery is challenged by technical constraints related to battery capacity and recharge duration. This study sought to overcome such limitations by applying a constant power supply technology. The methodology entails embedding a power supply line inside the S-BOT's rails. As the S-BOT traverses, its drive unit's power input terminals engage with this line, ensuring a consistent and stable electricity supply (Figure 1). This approach enables the establishment of an uninterrupted, real-time monitoring infrastructure.

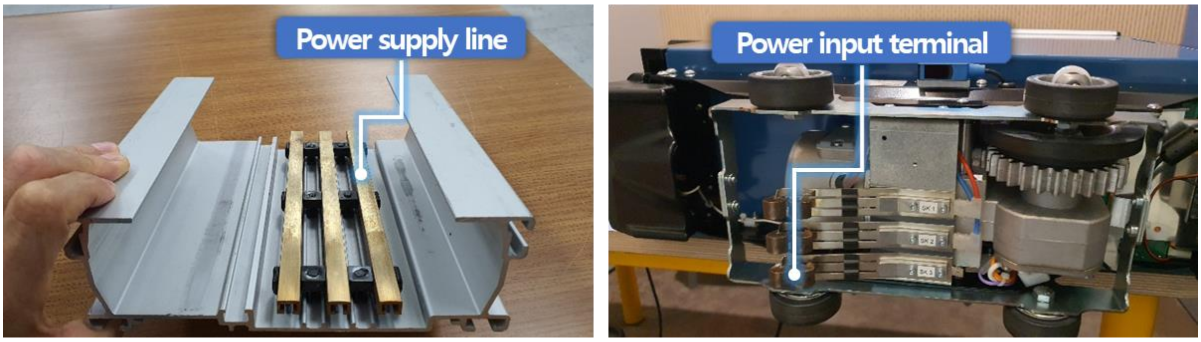
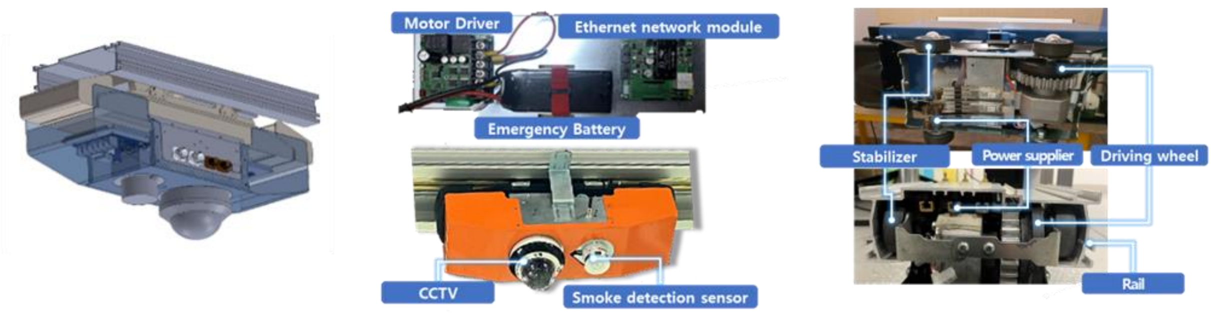


Figure 1. Full-time power supply rail and power input terminal of the S-BOT

2.1.2 S-BOT

The S-BOT's main body has been constructed with a steel frame to ensure the durability of the device and designed to provide sufficient driving force (30kg) for stable operation. It is equipped with a CCTV module capable of collecting video information and transmitting it to the server via an Ethernet wireless closed network (Figure 2).



(a) **3D modeling** **(b) Component of sensors and controller** **(c) Driving module**

Figure 2. S-BOT Prototype

2.1.3 Turnaround device (Turn table)

Typically, information collection robots (rail-bots) that travel on rails are installed within linear structures such as tunnels or underground utility tunnels, characterized by their ability to only move forwards or backward along the structure. The S-BOT developed in this research incorporates a rotating mechanism (turn table) within the rail, allowing direction changes within a 360-degree range. This feature enables the S-BOT to not only navigate linear structures but also facilities with broad flat areas, allowing for rapid movement via the shortest possible route. When the S-BOT utilizes the rotating mechanism (turn table) to navigate through intersections, the algorithm (i.e., S-BOT Approach detection → Adjusting the crossway direction → Forwarding entry command → Confirming the entry completion → Turnaround command → Forwarding driving command) operates in sequence. This process secures the S-BOT's entry path at intersections and is implemented to prevent collisions with other S-BOTs.

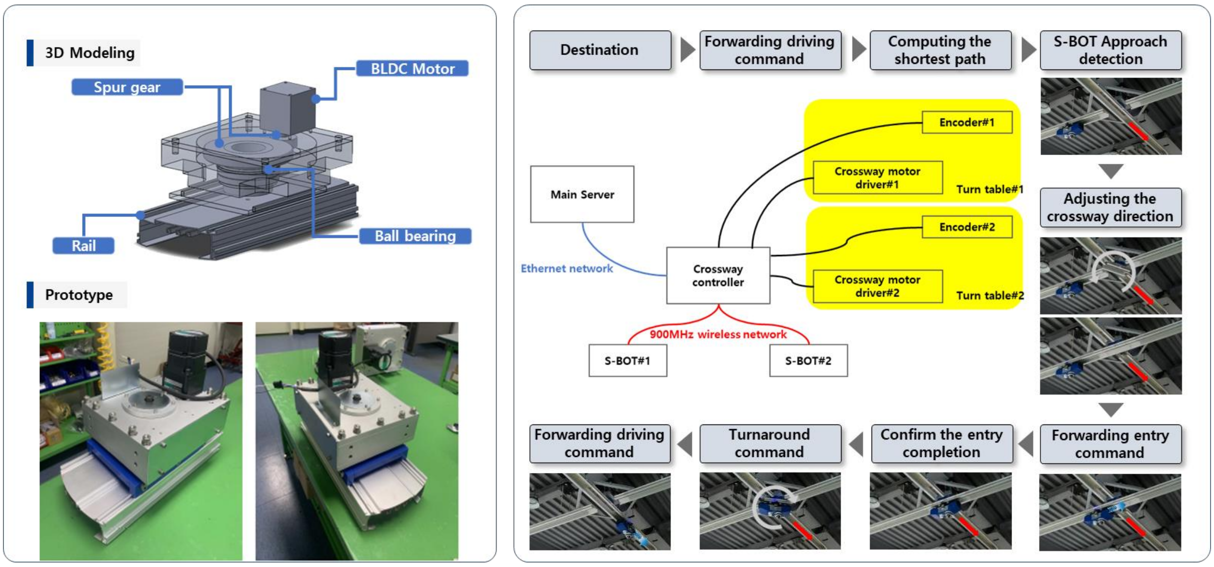


Figure 3. Turn table prototype and the control algorithm

2.2. Intelligent algorithms

2.2.1 Unsafe action detection of mobile scaffolding work

To identify unsafe conditions in activities involving mobile scaffolding, this study employed the Human Object Interaction (HOI) methodology, which analyzes the relative spatial layout between objects and workers to discern states (Figure 4). The adoption of the HOI approach offers a significant advantage in the model development process, obviating the need to compile a situational image dataset for training purposes. The initial steps in HOI involve detecting various objects within the visual field. Deep learning techniques such as R-CNN [5], FAST R-CNN [6], and YOLO [7] are renowned for their capability to identify multiple objects within a single image. Of these, the YOLO algorithm, notable for its rapid detection capabilities, was chosen to formulate an algorithm tailored for multi-object detection. YOLO's effectiveness is particularly pronounced in construction environments, where the dynamic nature of worker and object positions demands robust, simultaneous object detection capabilities.

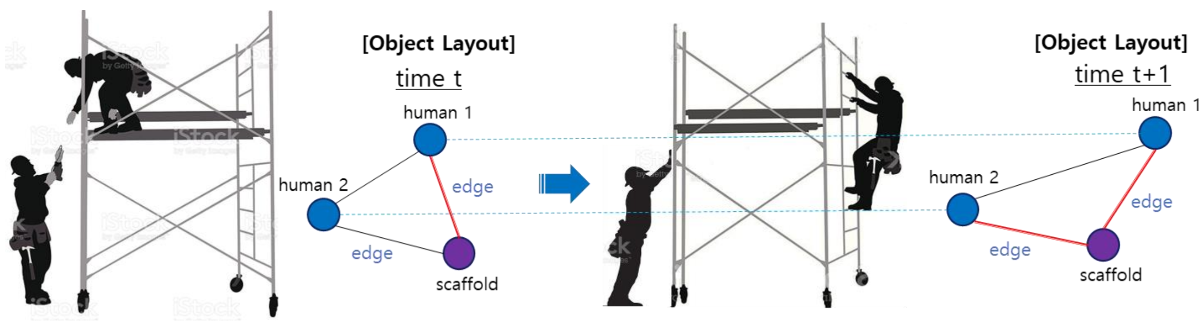


Figure 4. Analysis of the layout of detected objects in HOI methodology

In this research, the unsafe situations targeted for detection include: (1) a worker stepping onto a platform (pedal) placed on top of a mobile scaffold, and (2) when Worker #1 is positioned on top of the mobile scaffold and Worker #2 moves the scaffold (Table 1). For situation (2), recognizing the movement of detected objects necessitates object tracking technology. Hence, the DeepSORT [8] algorithm was employed. To mitigate the potential for false detections arising from the characteristics of HOI, which performs analysis in a two-dimensional plane, the algorithm for 'situation (2)' was designed such that an unsafe condition is identified when if Worker #1, the mobile scaffold, and Worker #2 are moving at the same speed and in the same direction, as determined by the DeepSORT algorithm.

Table 1. Unsafe action detection conditions of mobile scaffolding works

Cases		**Detection algorithms**
Case ①	Situation Definition	Case: A worker steps onto a platform (pedal) placed on top of a mobile scaffold
	Object Detection	Detection Method: YOLO version 5 (for detecting the worker, platform, and mobile scaffold)
	Situation Discrimination	Human Object Interaction
	Discrimination Criteria	'A pedal is on the scaffold.' AND 'A worker is on the pedal.'
		 
Case ②	Situation Definition	Case: Worker#1 is positioned on top of the mobile scaffold while Worker#2 moves the scaffold
	Object Detection	Detection Method: YOLO version 5 (for detecting Worker #1, Worker#2, and the mobile scaffold)
	Object Tracking	Tracking Method: DeepSORT algorithm (for tracking the direction and speed of object movement)
	Situation Discrimination	Human Object Interaction
	Discrimination Criteria	'Worker#1 is on the scaffold' AND 'Worker#2 is close to scaffold' AND 'Scaffold is moving' AND 'The moving direction and speed of the worker#1, worker#2, and scaffold are the same'
		 

2.2.2 Fire detection and location estimation

The fire detection AI system incorporated the YOLO algorithm, initially applied for object detection within the AI framework designed to identify unsafe conditions on mobile scaffolds. This system underwent a methodical enhancement of its performance through a triphasic training regimen, as detailed in Table 2. The YOLOv5x model, known for its intricate configuration and extensive training duration, was selected for its comparatively superior detection efficacy. By expanding the dataset, the system achieved a notable performance increase of 21.5% (improving from an mAP of 0.65 to 0.79) relative to the baseline training model. The dataset distribution for training, testing, and validation phases adhered to an 8:1:1 ratio, utilizing an auto-split function for efficient segmentation.

Table 2. Training results of fire detection AI

Training	Training Model	Dataset Size (EA)	Improvement Activities	Training Results (mAP)
First Stage	YOLOv5l	900	-	0.65
Second Stage	YOLOv5l	900	Optimizing Parameters	0.75
Third Stage	YOLOv5x	1400	Adding dataset Changing training model	0.79

Misinterpretation of ephemeral sparks produced during work activities as fires can significantly impede workflow by generating unwarranted alarms. To mitigate this issue, an algorithm was developed to classify fire events into two distinct stages: 'Suspected Fire' and 'Confirmed Fire Outbreak.' This classification is determined by the persistency of the condition, quantified by the frequency of occurrences, thereby reducing the likelihood of false alerts and minimizing operational disruptions.

IF fire detection count > 10 THEN 'Suspected Fire'

IF fire detection count > 60 THEN 'Confirmed Fire Outbreak'

In fire detection AI systems, pinpointing the precise location of a fire outbreak is of paramount importance. The resultant data is a critical input for response mechanisms, such as firefighting robots and evacuation systems, in the immediate aftermath of detection. This research has developed an algorithm for fire source location estimation employing a Kalman filter approach. This method capitalizes on the intensity of flame wavelengths captured by dual UV sensors to infer the fire's origin. By implementing a sliding window technique, the algorithm procures a 5-second snapshot of electrical signal data (ranging from 0-5V) from both sensors, from which it derives statistical attributes, including the mean, standard deviation, kurtosis, and skewness. These statistical parameters, alongside distance measurements configured as relative vectors, facilitate the estimation of the distance from each UV sensor to the fire source utilizing a pre-trained model. Incorporating these distances into the cosine rule enables the calculation of precise relative coordinates to the fire origin, enhancing the efficiency and effectiveness of subsequent fire response actions.

3. INTELLIGENT SURVEILLANCE SYSTEM

A User Interface (UI) was developed to facilitate the visualization of data generated during the operation of the S-BOT, effectively integrating the device's hardware with sophisticated intelligent algorithms. This integration was pivotal in creating a coherent framework that supports real-time monitoring and control functionalities. Subsequently, to rigorously evaluate the detection capabilities of the Intelligent Management System against two specific hazards (i.e., fire incidents and precarious conditions associated with mobile scaffolding), a comprehensive performance assessment was conducted within a laboratory environment, as depicted in Figure 5. This evaluation aimed to validate the system's efficacy and reliability in hazard detection.

The assessment was conducted by artificially generating each of the two identified hazard scenarios ten times to evaluate the effectiveness of the system's real-time situation discrimination and detection capabilities. In the case of fire events, the evaluation extended to include the accuracy of the fire source distance estimation results. The analysis revealed an outstanding 100% detection accuracy for the hazard scenarios, and the fire source distance estimation algorithm exhibited a high accuracy rate of 98.3%.

(a) Fire detection and location estimation AI (b) Unsafe action detection AI

Figure 5. Intelligent surveillance system and performance test

These results provide a robust foundation for imparting critical information to the anticipated fire response mechanisms (including firefighting robots and evacuation protocols) that are the focus of planned future research (Table 3).

Table 3. Performance test results

Category		Measurement										
		1	2	3	4	5	6	7	8	9	10	Accuracy (%)
Fire Detection		S	S	S	S	S	S	S	S	S	S	100
Fire Source Distance Estimation	SensorA (3.478)	3.39	3.32	3.46	3.40	3.34	3.31	3.36	3.45	3.36	3.33	96.9
	SensorB (2.934)	2.96	2.86	2.87	2.94	2.90	2.98	2.88	2.99	2.98	2.92	99.7
Mobile Scaffolding	Case①	S	S	S	S	S	S	S	S	S	S	100
	Case②	S	S	S	S	S	S	S	S	S	S	100

* Note: S (Detection success), F (Detection failure)

4. CONCLUSION

The achievements of this study support the establishment of an uninterrupted real-time management and supervision system, which not only enables the prevention of potential disasters on-site but also contributes to minimizing the workforce required for management and supervision. The continuous operation of information collection robots and the control system will maximize the efficiency of safety management and support rapid decision-making by sharing information provided by the control system. Consequently, this can contribute to preventing unnecessary social and economic losses.

ACKNOWLEGEMENTS

This work was supported by the National Research Foundation of Korea (NRF) grant funded by the Korea government (MSIT) (No. NRF-2018R1A5A1025137), by Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Education (RS-2023-00249407), by the Korea Agency for Infrastructure Technology Advancement (KAIA) grant funded by the Ministry of Land, Infrastructure and Transport (Grant RS-2023-00251002), and by Korea Innovation Foundation through the Ministry of Science and ICT (2023-DG-RD-0022).

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