Automation in Construction 153 (2023) 104961

Contents lists available at ScienceDirect

Automation in Construction

journal homepage: www.elsevier.com/locate/autcon

Ontological inference process using AI-based object recognition for hazard awareness in construction sites

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ARTICLE INFO

Keywords:
Hazard awareness
Object relationship
Ontology
AI image recognition technology

ABSTRACT

Research on automating risk situation recognition using AI is being actively conducted. However, hazard situation recognition using AI has a limitation in securing a large amount of data for training of all hazard situations.

This study proposes an approach that combines the conventional AI image recognition technology and relation-based reasoning to overcome the limitations of the method of sufficiently training each image regarding various hazard situations. To validate the proposed process, we constructed ontology by defining the relations between construction site objects and working situations, safety situations required for each working situation, and hazard situations based on the case of the work using mobile scaffolding. This approach will enhance the efficiency of using AI by inferring the current working situation based on the relations between recognized objects and determining whether it is a safe situation based on the inference on the standard safety situation for the corresponding working situation.

1. Introduction

The construction industry in South Korea is accident-prone, exhibiting a higher death rate per 100,000 workers, three times or higher than that of other types of industrial accidents, and five to ten times or higher than that of other developed countries, such as the U.K. and Singapore. The number of accidental deaths was 828 in 2021, a decrease of 54 compared to 2020, with the construction industry accounting for 417, down 41 from the previous year, while nearly half the deaths from industrial accidents (50.4%) occurred at construction sites [1]. Meanwhile, in addition to the enactment of the 'Serious Accidents Punishment Act,' aimed to impose safety and health duties on business owners and managers, there have been various research and policy efforts for both preventing and responding to safety-related accidents at construction sites. The government, in alignment with these policy efforts, has mandated the installation of CCTV for apartment housing constructions over a certain size (such as 16 stories) from 2020 to monitor the wearing of personal protective equipment (PPE), while the Korea Land and Housing Corporation (LH) has promoted an intelligent CCTV installation pilot project for hazard situation awareness, allowing each construction and supervision office to monitor wearing of safety helmets and seat belts in real-time.

Even the installment of CCTVs is limited in practice by project representatives and supervisors having to continuously controlling the hazard situations of the site with the naked eye. To overcome this, there is active development of various technologies promoting prompt responses of managers at sites, including the implementation of AI image recognition technology to the video images obtained from CCTVs, when recognizing hazard situations, such as no wearing of PPE (helmets and safety belts) by construction site workers, failure in securing a safe distance between workers and heavy-duty vehicles, and intrusion into access control areas by workers, as well as sending alert notifications to managers via text message [2–12].

There is a need for a sufficient pre-training process regarding all hazard situations that arise from complex interactions among a large number of materials, machines, equipment, and workers to develop a hazard situation awareness model using conventional AI image recognition technology. However, this approach has difficulty in securing large amounts of training data.

Thus, this study proposes an approach that combines the conventional AI image recognition technology and relation-based reasoning to overcome the limitations of the method of sufficiently training each image in various hazard situations. The conventional method is to recognize hazard situations through prior training about hazard situations, while the proposed approach is to primarily determine whether a situation can be categorized as safe by inferring the current working

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https://doi.org/10.1016/j.autcon.2023.104961
Received 4 October 2022; Received in revised form 21 April 2023; Accepted 28 May 2023
Available online 7 June 2023

situation based on the relations between each recognized object, and then, a standard safety situation corresponding to the target working situation. It is difficult to predict all hazard situations because possible dangerous situations can occur due to various combinations of related objects. However, since the standard safety situation is limited in scope, it will be possible to solve the limitations of collecting a large amount of training data. This approach requires an ontology that defines the relations between various construction site objects, such as materials, machines, and workers. Protégé, an ontology editor, was utilized to construct a 'Construction Hazard Awareness Ontology' by defining the relations between construction site objects, working situations based the safety situation required for each working situation (safety standards, safety work rules), and the hazard situations on Description Logic (DL).

Chapter 2 is a literature review to identify the need to overcome the limitations of existing AI image recognition technology that requires large amounts of training dataset to be collected and the applicability of ontology for this purpose. Chapter 3 presents a process of recognizing the hazard situations of the construction site by using ontology. Chapter 4 defines the classes and attributes that constitute the ontology for recognizing hazard situations at construction sites. This study proposes a method of constructing and utilizing ontology to automatically recognize hazard situations that may occur at a construction site, then validates the proposed ontology, and the inference processes, through a case of utilizing mobile scaffolding among various works at construction sites. Chapter 5 discusses differentiation from existing studies, utilization and future research needed in terms of accuracy, sustainability, and usability to develop the proposed approach into a technology that can be used in practice in the field.

This study combines ontology technology with AI image recognition technology to propose a process of automatedly recognizing hazard situations from images, aiming to remove the real-world limitations of continuously controlling the hazard situations in monitoring the sites using CCTV, and securing a large amount of all types of training data required to learn various hazard situations. The application of this process will further enhance the efficiency of AI image recognition technology, reduce the possibility of various errors that may arise from the intervention of inaccurate judgment, and improve the efficiency of related work. Ultimately, this study will enhance the reliability and accuracy of hazard situation awareness processes at the construction site.

2. Literature review

According to similar domestic and overseas research trends, as shown in Table 1, related technologies include deep convolutional neural network (DCNN), with improved image interpretation ability compared to the conventional CNN model through artificial intelligence (AI) for situation awareness; Mask R-CNN, which recognizes multiple objects in one picture; the Bayesian method for tracking moving objects; Gaussian Mixture Model (GMM); and Background Modeling (BM). The situation awareness method using video training is basically preferred because it requires no additional technical applications along with a low difficulty of the training process.

As a result of analyzing the literature that recognized risk situations using the AI-based image recognition technology in Table 1, the accuracy of recognition increased, and the speed increased as the study progressed. However, image-based situation awareness using deep learning requires large training datasets for each of various situations. In most studies, a model that recognizes a very specific situation or object has been developed due to the difficulty of collecting a large amount of training dataset.

Since there are countless objects that need to be recognized at construction sites and risky situations that can arise from them, it is difficult to apply them to the field with a limited AI recognition model. To overcome this hurdle, research is underway to utilize various sensors and wearable devices, or studies are being conducted to semantically

Table 1
Research trends for Hazard Awareness at construction sites using image-based AI technology.

Authors	Purpose	Target	Methodology	Limitation
[2]	Presents a deep learning algorithm for detecting unsafe behaviors related to mobile scaffolding	Unsafe behavior in mobile scaffolding operations	Mask R-CNN	- Trained on a limited dataset for falls from height - Can fail in detecting unsafe behaviors depending on the angle at which the 2D image was captured - Cannot recognize structural errors in mobile scaffolding
[3]	Presents a vision-based safety rule inspection model by explicitly classifying the interaction of workers and safety equipment	Human–Object interaction (Ex: Workers who stand on scaffolding without wearing fall arrest equipment, or who are utilizing tools without wearing protective gear)	Faster R CNN	Requires a large amount of training data
[4]	Collects data for situational awareness by observing workers' work through computer vision-based motion capture technique	- 3D human skeleton - body joint positions	Tracking-based approach	Requires further studies to test the performance of the proposed model
[5]	Presents an algorithm to identify workers who do not wear hard hats at construction sites	Workers who do not wear hard hats	Faster R-CNN	Can identify workers, who are not wearing hard hats, while failing to identify related worker information
[6]	Presents a computer vision-based algorithm to monitor whether a worker working at a height is wearing a safety belt	- Worker - Safety belts	Faster R-CNN (worker) DCNN (safety belt)	- Can recognize work only at a height - Requires a large amount of training data
[7]	Presents a computer vision-based algorithm that detects workers crossing a fall hazard zone	- Worker - Relations between workers, and concrete and steel	Mask R-CNN	- Vulnerable to obstacles in identification - Requires a large amount of training data

(*continued on next page*)

Table 1 (*continued*)

Authors	Purpose	Target	Methodology	Limitation
[8]	Presents a computer vision-based algorithm for recognizing equipment used in civil engineering works.	Excavators and trucks	Multi-class support SVM classifier	- Requires improvement in datasets considering various variability, such as field conditions, and idle time detection - Requires model development for each equipment type
[9]	Presents a deep learning algorithm for real-time recognition of workers` compliance with PPE from the video	- PPE - Worker	VGG-16, ResNet-50, Xception	Requires a large amount of training data for expanding the recognition target of PPE.
[10]	Presents an integrated framework that can automatically and efficiently detect workers without PPE through computer vision technology from images captured at construction sites	Workers without wearing PPE	SVM	Requires a large amount of training data
[11]	Presents an algorithm that can determine whether the operation identified from the image is safe	Unsafe behavior of workers at a height	Convolutional-LSTM Network	- Requires development of an algorithm that can simultaneously recognize multiple units of equipment and workers - Requires improvement in motion capture algorithm to reduce the error detection time
[12]	Presents an algorithm that can accurately monitor the activity of workers.	Steel bending, walking, transporting	CNN that integrates RGB, optical flow, and gray stream CNNs	- Lack of a large-scale database - Real-time tracking of long sequences - Defining a time series of actions

recognize situations by applying ontology technology.

Ontology can be defined as Formal, an explicit specification of a shared conceptualization [13]. A shared concept refers to an abstract model for expressing concepts related to phenomena occurring in the conceptualized world for a specific purpose, implying that conceptualization is based on the knowledge agreed upon by members of the corresponding domain, as well as computers. In this respect, ontology can be understood as a metamodel capable of reusing knowledge in a specific form that can be processed by a computer. The ontology concept can be used to define the relations between objects based the description logic provided in the web ontology language (OWL), which enables a computer to perform inference on relations, and infer hidden relations other than explicitly defined ones.

According to R&D trends using ontology for risk identification, 1) provide a logical basis for inferring undiscovered knowledge in the current AEC area. In particular, in relation to risk identification, studies have defined safety rules defined in official documents as ontologies to automate the process of judging risks through information extracted from the Building Information Modeling (BIM) [14–17], 2) attempt to semantically recognize situations by utilizing both image recognition technology and ontology [18,19,21].

According to the studies using both image recognition technology and ontology in detail, H. Wu et al. [18] proposed a process of inferring activity based on ontology by recognizing the presence and location of building elements, labor, and resources via image recognition technology, as well as possible hazard situations arising from the activity; however, their proposed process showed limitations in recognizing the relations between objects. W. Fang et al. [19] proposed a technique for extracting geometric and spatial features of an object through image recognition technology, calculating the relation for each object as one of 'within, overlap, and away' based on the intersection over union (IoU) formula, and inferring the situation of an image and identifying risk factors through the ontology defined based on a checklist of risky behaviors related to falls from height (FFH). However, this technique is limited by the relation for each object being designated to the only one of the tree categories (within, overlap, and away). R. Xiong et al. [20] extracts the scene graph representing the relations between objects via image recognition technology and infers potential risk factors through safety rules defined based on the ontology. Although the same study represents the relations between objects in various manners, such as geometry (e.g., beneath), possession (e.g., has), and actions (e.g., hold), which is limited in that this technique requires training of a large amount data because it extracts these relations only through image recognition technology.

The commonality of the studies is that object information is obtained through image recognition technology, and the situation is inferred semantically based on the ontology using this information. However, even in these studies, since the relationship between objects is recognized by image recognition technology, the limitations of collecting large amounts of training data have not been resolved, so only limited relationships are targeted.

3. The process of hazard awareness using ontology and AI

3.1. Overview of hazard awareness using ontology and AI

This study proposes a convergence model of machine learning and relation-based reasoning, as shown in Fig. 1, to remove the practical limitations of the approach, in which a large amount of training data is collected and sufficiently trained for each hazard situation. The convergence model proposed in this study is primarily aimed at recognizing individual objects, such as material-machine/equipment-worker present at construction sites, through AI image recognition technology, while refraining from training the incalculable hazard situation images. Second, it intends to concurrently infer the current working situations by recognizing the relations between objects based on individual object information, such as recognized material-machine/equipment-worker, and a predefined ontology, as well as the standard safety situations of the corresponding working situations.

The method utilizing the conventional image recognition technology determines whether a situation is hazardous by training images representing hazard situations. In contrast, the proposed technology uses the following steps: 1) It individually recognizes construction site objects via image recognition technology, as well as the relations between objects,

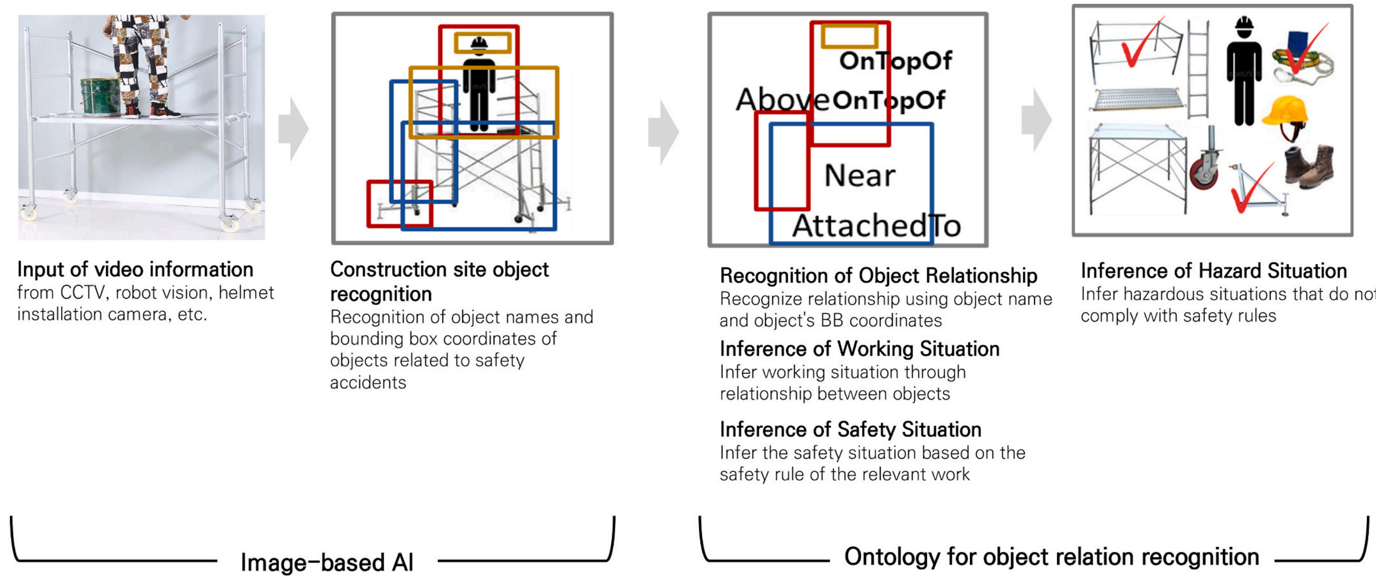

Fig. 1. The convergence model of ontology and AI.

by utilizing ontology; 2) it determines what type of work is currently underway based on the determined relations; 3) it determines whether the situation is a safety situation according to predefined reasoning rules based on the safety rules of the corresponding work; and 4) it finally determines cases that do not match a safety situation as hazard situations.

3.2. Process of hazard awareness based on ontology

This study proposes an approach that converges AI image recognition technology and relation-based reasoning, and validates its applicability. Thus, the scope of this study is to present a process for recognizing the relations between objects, as well as safety situations by utilizing ontology technology as a process following the recognition of object information via AI image recognition technology, and define the ontology in this respect.

The approach proposed in this study consists of the following three steps (see, Fig. 2). Using the results of individually recognizing construction site objects with image recognition technology, 1) after determining what kind of work the current work is (Working Situation) 2) Determining whether it is a safety situation according to predefined inference rules based on the safety rules of the work (Safety Situation). 3) Finally, if the safety rule is not met, it is judged as a hazard situation (Hazard Situation). The safe situation of the work is defined as when both safe condition and safe behavior are satisfied, and all other situations are inferred as unsafe.

This study describes the proposed model through the case of a mobile scaffolding work for understanding. There are 15 safety rules for work

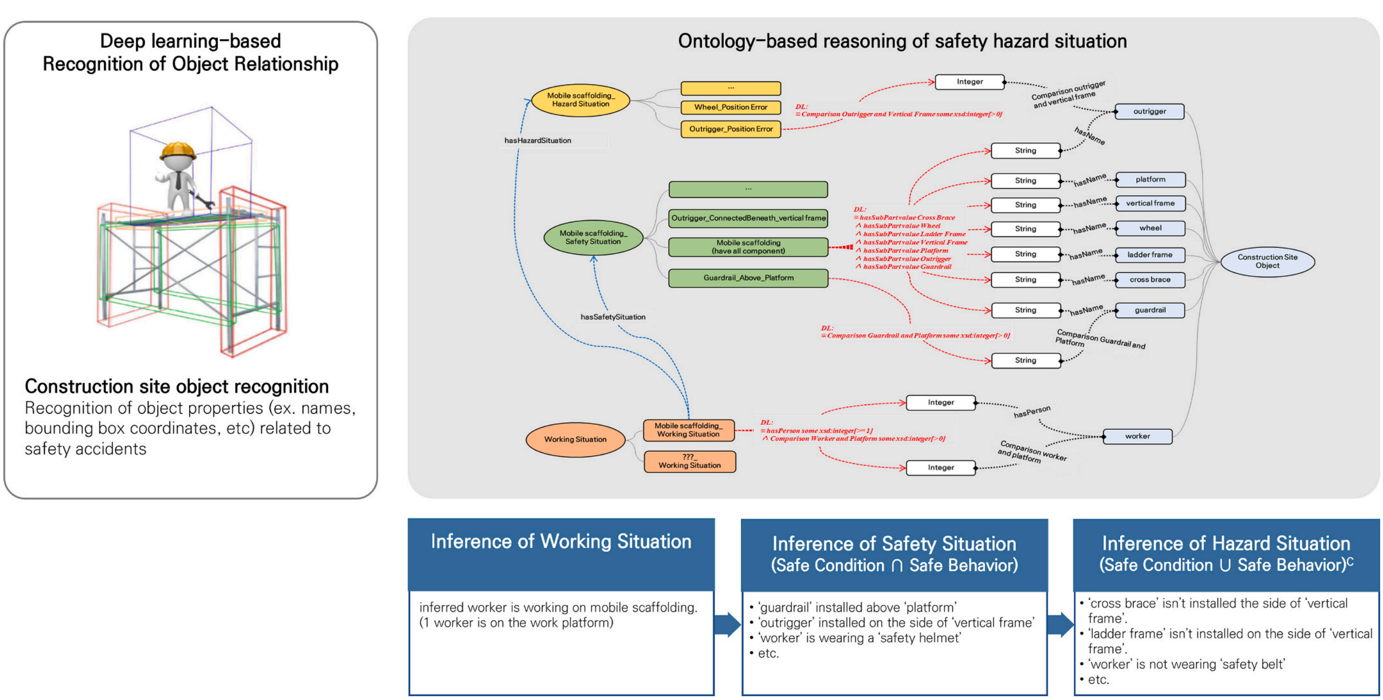

Fig. 2. Hazard awareness process using the proposed technology.

using mobile scaffolding selected as examples in this study. The 15 safety rules refer to the safety rules presented in the 'Standard Safety Guidelines for Temporary Construction' provided by the Ministry of Employment and Labor in Korea [21]. There are 10 objects to be recognized that appear in the 15 safety rules. The detail of each step is described below.

3.2.1. Recognition of object relationship

This phase is related to recognizing the relations between objects by the names of the objects at the sites, as well as the distance between the object and the object coordinates. The names of individual objects, and the coordinate information between individual objects, are extracted by using deep learning technology.

There is a need for predefining the relations between the related objects, to recognize the relations between objects, as well as criteria for the coordinate comparison value that can most accurately represent the relations between the objects. In this manner, this study is based on quantitative values, such as the bounding box coordinate value, in recognizing the relations between objects. It also applies the optimal values for the bounding box coordinate comparison, which can be utilized to most accurately infer the locations of sub-elements by their relation because these values are not fixed.

Among the image recognition technologies available for recognition of object information, the bounding box information extracted through YOLO, consists of five estimated values (location coordinates (x, y), magnitude (w, h), and confidence value), which represents the IOU value between the ground truth box and the estimated box. Furthermore, each grid cell estimates a probability value for an object class, calculating a conditional probability according to the proportion of a specific object. Fig. 3 shows an example of defining the relations with the coordinate values that can be obtained through image recognition technology.

For example, if to determine whether there is work on mobile scaffolding it is necessary to determine whether a worker is on a platform, object detection using image recognition technology is performed to obtain the object names, 'Worker' and 'Platform' and the coordinate values of each Bounding Box. Subsequently, the object name is recognized as an instance of the class 'worker,' and the coordinate comparison values of 'Worker' and 'Platform' (ex.$y_c^{Worker} - y_c^{Platform}$) is recognized as the data attribute value of Worker (ex. Comparison_Worker_and_Platform '1'). This property information of object becomes input for inference of working situation, safety situation, and hazard situation.

3.2.2. Inference of working situation

This phase infers what type of work a worker is currently engaged in based on the relations between the worker and the object. The definition of the 'reasoning rule for working situations at construction sites' is required to infer this working situation by first defining the relations between construction site objects that can describe the characteristics of each working situation. For example, the rule for determining whether there is work on mobile scaffolding can be that a worker is on the platform, which can be represented by a formula, $y_c^{Worker} - y_c^{Platform} > 0$. If the object attribute of the 'Worker' instance is inferred as 'OnTopOf Platform' in Phase 1, then the recognized 'Worker' is inferred as an instance of the 'Mobile scaffolding_Working Situation' class in the same phase.

The reason why the work situation is first inferred is not to focus only on unsafe behavior, but because the safety rules provided are defined on a work unit basis. When applied to the field in the future, the location where people are located, that is, the working situation can be judged first. After inferring the work situation, the safe situation of the work is defined as when both Safe Condition and Safe Behavior are satisfied, and all other situations are inferred as unsafe.

3.2.3. Inference of safety situation

This phase infers whether the inferred work is safe based on the relations between objects when the work in which a worker is engaged was inferred in the previous phase. To this end, the definition of the 'safety situation reasoning rule' is required for each work activity, and this reasoning rule formulates the relations between construction site objects based on the experience of experts, or officially published safety standards and safety work rules. The safety situations for work using mobile scaffolding in this reasoning rule are largely divided into 1) whether all the components that should be present (=in place) and 2) whether the location of components are in the correct (=in the correct position). For example, as one of the safety rules for mobile scaffolding, a rule for determining whether a Guardrail is installed above a platform can be defined as '$x_c^{Guardrail} - x_c^{Platform} > 0$'. Then it is inferred as an instance of 'Guardrail_Above_Platform,' a subclass of 'Mobile scaffolding_Safety Situation' in this phase.

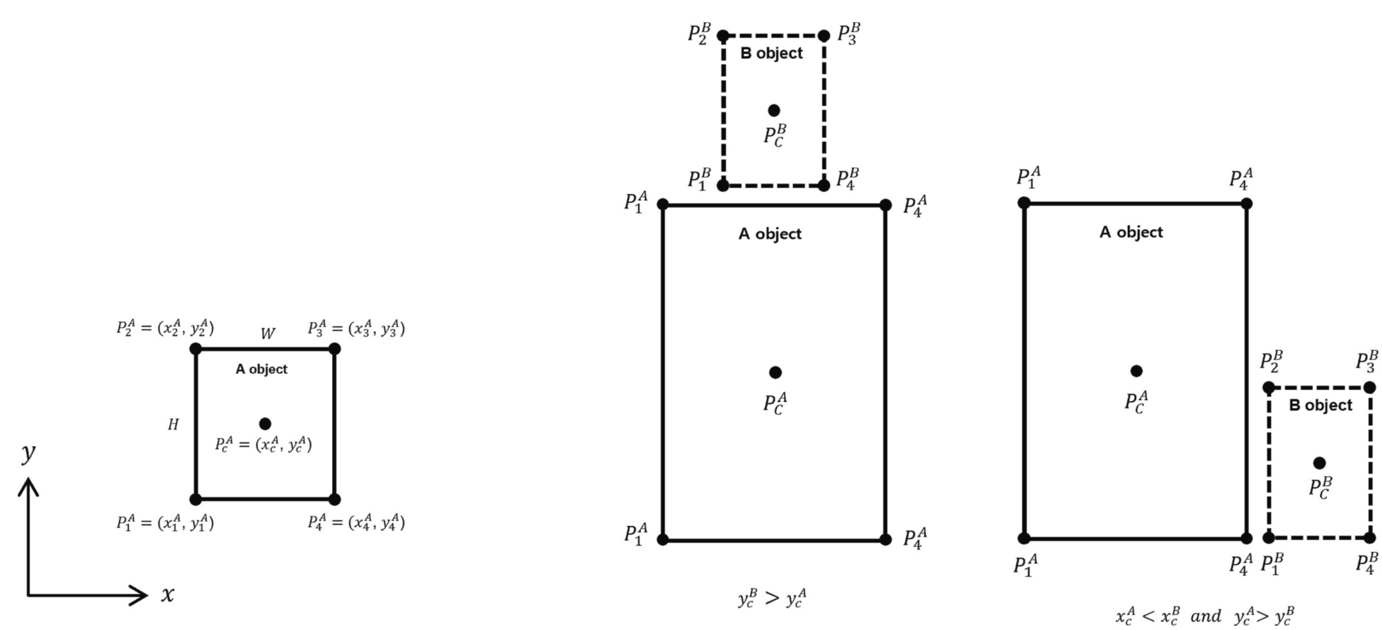

Fig. 3. The example for recognizing object using AI.

3.2.4. Inference of hazard situation

The last phase is to infer the converse of the safety situation as a hazard situation. The 'hazard situation reasoning rule' is defined as the opposite of the 'safety situation reasoning rule' (ex. $x_c^{Outrigger} - x_c^{VericalFrame} > 0$). In this reasoning process, similar to inference on safety situations, if the 'outrigger,' which has been recognized via image recognition technology is inferred as 'NotConnectedBeneath Vertical Frame,' an object attribute representing the object relation with 'Vertical Frame' in Phase 1, then it is further inferred as an instance of 'Outrigger_ Position Error,' a subclass of 'Mobile scaffolding_Hazard Situation' in this phase.

4. Ontology for hazard awareness

4.1. Definition of class and property

This study intends to construct working situation, which is defined as a relation between construction site object and worker; safety situation, which is defined as a relation between worker and object, or between objects; and hazard situation as an ontology to verify whether hazard situation awareness may be available by inferring the relations between individual objects. For this purpose, the 'Construction Hazard Awareness Ontology,' and related reasoning rules were defined by employing mobile scaffolding as an example among the works occurring at construction sites, and Protégé v5.5 was used as a construction tool.

4.1.1. Definition of class

Super-classes consist of the major concepts of hazard situation awareness at construction sites: 1) construction site object, 2) working situation, 3) safety situation, and 4) hazard situation.

First, the class of 'Construction Site Object' is a class that includes objects necessary for judgment in safety standards, and safety work rules as sub-classes. The corresponding class is recognized as one instance according to the name of the object recognized via AI image recognition technology. The recognized instance has the object name and has the Bounding Box coordinate comparison values with the surrounding objects as data property. For example, in the case of mobile scaffolding, as the elements mentioned in the safety standards and safety work rules to follow when working using mobile scaffolding, Cross Brace, Wheel, Ladder Frame, Guardrail, Vertical Frame, Platform, Outrigger, Worker (these constitute the mobile scaffolding class) are allocated as subclasses.

Second, the class of 'Working Situation' is a superclass with subclasses of works occurring at the site, which is defined with the rules that can determine that each work is underway. For example, in the case of mobile scaffolding, work using mobile scaffolding can be defined as when at least one worker is on the platform. If this rule is satisfied, the instance recognized as the 'worker' class, which is a subclass of the Construction Site Object class, is further inferred as an instance of the working situation class.

Third, the class of 'Safety Situation' is a superclass having safety situations as subclasses, defined by the rules that can determine a safe situation based on safety standards and safety work rules. For example, the subclasses of the Mobile scaffolding_Safety Situation class include 'Mobile scaffolding,' which determines whether all elements are in place, and 'Outrigger_ConnectedBeneath_Vertical Frame,' which determines whether the outrigger is in the correct position. If the rules defining each class are satisfied, each instance recognized in the subclass of the Construction Site Object class is inferred as an instance of the related safety situation class.

Fourth, the class of 'Hazard Situation' is a superclass that has hazard situations as subclasses. In this case, because the applicable rules are defined as a converse of the rules that determine the safety situation, if the safety situation rule is not satisfied, then each instance recognized in the subclasses of the Construction Site Object class is inferred as an instance of the related hazardous situation class.

Table 2 presents the classes and their detailed definitions described in the ontology of this study. The subclasses of safety situation and hazard situation can be added or modified according to safety standards.

4.1.2. Definition of property

Object property connects an instance of one class with an instance belonging to another class. In this case, the relation between classes can be defined by designating the range of the class in an RDF triplet structure represented by object 1 (domain), property (relationship), and object 2 (range), which enables a relation to connect different instances.

Data property connects specific values of data possessed by a class or instance. Object property is used to represent the relations between objects, which have been discovered through comparison of numerical values during the inference process, while data property is mostly utilized to represent the property information for construction site object. Because this study is focused on determining the possibility of recognizing hazard situations from the information that can be extracted via image recognition technology using ontology, the research proceeds by assuming the bounding box coordinate comparison values.

For the safety rules of mobile scaffolding presented here, only examples of the distance are expressed because the important issue was whether there was an object to be there and, if so, whether it was in the correct position. However, depending on the work, not only the relationship between objects but also the property information of objects can be used to define safety rules, and such information can be defined by adding it as a data property of the object class.

This study has defined the object property and data property for inferring the hazard awareness of work using mobile scaffolding as examples, presented in Table 3.

Table 2
The definition of class.

Class	Definition	Example of Subclass name (Example of mobile scaffolding)
Construction Site Object	Objects and workers required for judgment according to work safety standards and safety work rules	Cross brace, Wheel, Ladder frame, Guardrail, Vertical frame, Platform, Outrigger, Worker
Working Situation	Work that occurs at the construction site	Mobile scaffolding_Working Situation
Safety Situation	Work safety standards and safety work rules	Mobile scaffolding_Safety Situation: - Mobile scaffolding (has all sub part) - Outrigger_ConnectedBeneath _Vertical frame - Platform_Across_Vertical frame - Ladder frame_AttachedTo_Vertical frame - Cross brace_SideConnectTo_Vertical frame - Wheel_Under_Vertical frame - Guardrail_Above_Plaform
Hazard Situation	Opposite of safety situation	Mobile scaffolding_Hazard Situation: Outrigger_Position Error, CrossBrace_Position Error, Guardrail_Position Error, Platform_Position Error, Ladder frame_Position Error, Wheel_Position Error, Guardrail_ None, Platform_ None, Ladder frame_ None, Cross brace_ None, Wheel_ None

Table 3
The definitions of object property and data property.

Type	Relation	Domain	Range
Object Property	hasSubPart	Mobile scaffolding	Construction Site Object
	hasSafetySituation	Working Situation	Safety Situation
	hasHazardSituation	Working Situation	Hazaed Situation
Data Property	hasName	Construction Site Object	xsd:string
	hasPerson	Worker	xsd:integer
	Comparison_Worker_and_Platform	Worker	xsd:integer
	Comparison_Guardrail_and_Platform	Guardrail	xsd:integer
	Comparison_Outrigger_and_Vertical frame	Outrigger	xsd:integer
	Comparison_Wheel_and_Vertical frame	Wheel	xsd:integer
	Comparison_Ladder frame_and_Vertical frame	Ladder frame	xsd:integer
	Comparison_Cross brace_and_Vertical frame	Cross brace	xsd:integer
	Comparison_Platform_and_Vertical frame	Platform	xsd:integer

4.2. Definition of DL for inferring hazard situations

This study, based on the previously defined class and property, set the reasoning rules to infer the hazard situations at construction sites by utilizing the DL. In the Class tab of protégé, the DL for Class can be defined by using the phrases shown in Table 4 in Equivalent To(≡) and SubClassOf(⊑). The rules defined in this manner can be utilized to create complex rules by combining them with and (Intersection; ∧), or (Disjunction; ∨), and not (negation; ¬).

Cross Brace, Wheel, Ladder Frame, Guardrail, Vertical Frame, Platform, Outrigger, and Worker information, which have been recognized via image recognition technology, are factors mentioned in the safety standards and safety work rules to be followed when working using mobile scaffolding. These are also recognized as each instance in the corresponding subclass of the Construction Site Object class. The recognized instance has the data attribute values of the object related to the working situation and safety standards, such as 'object name,' 'coordinate comparison value with related object.' In the instance of worker, the number of workers is defined as the data property called 'hasPerson' (ex. hasPerson 1), and the coordinate distance value between the worker and the platform is defined as the data property 'Comparison_Worker_and_Platform' (ex. Comparison_Worker_and_Platform 1). These recognized instances are defined as object properties by inferring their relations with instances of other classes according to the predefined inference rules.

Hazard situation recognition based on this object relationship consists of three steps: 1) working situation 2) safety situation 3) hazard situation. An example of DL for hazard situation inference related to mobile scaffolding is provided as follows (see Table 5), and the reasoning process is presented in Fig. 4. The example safety rules refer to 'Standard Safety Guidelines for Temporary Construction' provided by the Ministry of Employment and Labor in Korea [21].

Table 4
The example of DL for hazard awareness in construction sites.

Keyword	Example	Intuitive Meaning
some (Existential Restriction;∃)	hasSafetyCondition some Mobile scaffolding_Safety Situation	Things that have a Safety Condition that is a Mobile scaffolding_Safety Situation Individuals that are instances of this class expression have a relationship along the hasSafetyCondition property to an individual that is an instance of class Mobile scaffolding_Safety Situation.
value (Has Value restriction; ∀)	OnTopOf value Plaform	Things that have a OnTopOf that is Plaform. Plaform is a specific individual.
min (Min cardinality restriction; ≥)	hasOutrigger min 4	Things that have at least four Outrigger
max (Max cardinality restriction; ≤)	hasPerson max 1	Things that have at most one worker.

Inference rules for situation awareness at each stage are as follows. First, according to the inference rule that working using mobile scaffolding is underway if there is at least one worker is on the platform, the following necessary and sufficient conditions of the Mobile scaffolding_Working Situation class are defined as: (Comparison_Worker_and_Platform some xsd:integer[$>$ 0]) and (hasPerson some xsd:integer [$\geq$ 1]). Then, the corresponding instance is inferred as an instance belonging to the 'Mobile scaffolding_Working Situation' class.

The necessary condition of 'Mobile scaffolding_Working Situation' is defined as 'Mobile scaffolding_Safety Situation', which is defined as the safety situation of mobile scaffolding work with an object property called hasSafetySituation. If working using mobile scaffolding is determined to be underway, then it is connected to the result of safety situation recognition belonging to 'Mobile scaffolding_Safety Situation.'

Second, safety situation reasoning is performed according to the relations between the inferred objects as in the working situation reasoning. As previously described, the safety situations are largely divided into 1) whether all the required objects are present, and 2) whether the objects are in the correct positions.

According to the reasoning rules for determining whether all objects constituting mobile scaffolding are present, when the necessary and sufficient conditions of 'Mobile scaffolding' class are defined as (hasSubPart value Cross Brace), (hasSubPart value Wheel), (hasSubPart value Ladder Frame), (hasSubPart value Vertical Frame), (hasSubPart value Platform), (hasSubPart value Outrigger), and (hasSubPart value Guardrail) among subclasses of 'Mobile scaffolding_Safety Situation', if all construction site objects constituting mobile scaffolding are recognized as instances. It is inferred to have all the components as the object property of the instance recognized in the 'mobile scaffolding'. The determination on whether the objects constituting the following mobile scaffolding are in the correct position proceeds as follows. The object name of the outrigger instance is defined with the data property of 'hasName' (ex. hasName 'Guarderail'), while the coordinate distance value between the guarderail and platform (ex. Comparison_Guarderail_and_Platform 1) is defined with the data property of 'Comparison_Guarderail_and_Platform'. According to the reasoning rule for determining whether an guardrail is installed above platform (one of the safety rules for mobile scaffolding) when the necessary and sufficient condition of the 'Guardrail_Above_Platform' corresponding to the relation between guardrail and platform among the subclasses of the 'Mobile scaffolding_Safety Situation' are defined as Comparison_Outrigger_and_Vertical Frame some xsd:integer[$<$ 0]. Then the corresponding instance is inferred as an instance belonging to the 'Guardrail_Above_Platform' with respect to the location of the outrigger among the subclasses of the 'Mobile scaffolding_Safety Situation'.

Finally, any situation that does not meet the previously defined conditions for safety situation is recognized as a hazard situation. As a converse of the previously defined rules, when the necessary and sufficient conditions of 'Outrigger_Position Error,' which corresponds to the

Table 5
Inference Rule for hazard awareness inference related to mobile scaffolding.

Inference Rule		Example (Work using Mobile scaffolding)
Working Situation		Working Situation using Mobile scaffolding - Necessary & Sufficient (Equivalent To) *(Comparison_Worker_and_Platform some xsd:integer[> 0]) and* *(hasPerson some xsd:integer[≥ 1])* - Necessary (SubClass of) *hasSafetySituation some Mobile scaffolding_Safety Situation* *hasHazardSituation some Mobile scaffolding_Hazard Situation*
Safety Situation	In place	Mobile scaffolding≡ - Necessary & Sufficient (Equivalent To) *(hasSubPart value Cross Brace) and (hasSubPart value Wheel) and (hasSubPart value Ladder Frame) and (hasSubPart value Vertical Frame) and (hasSubPart value Platform) and (hasSubPart value Outrigger) and (hasSubPart value Guardrail)*
	In the correct position	Guardrail_Above_Platform ≡ - Necessary & Sufficient (Equivalent To) *Comparison_Guardrail_and_Platform some xsd:integer[> 0]*
Hazard Situation		Outrigger_Position Error ≡ - Necessary & Sufficient (Equivalent To) *Comparison_Outrigger_and_VerticalFrame some xsd:integer[> 0]*

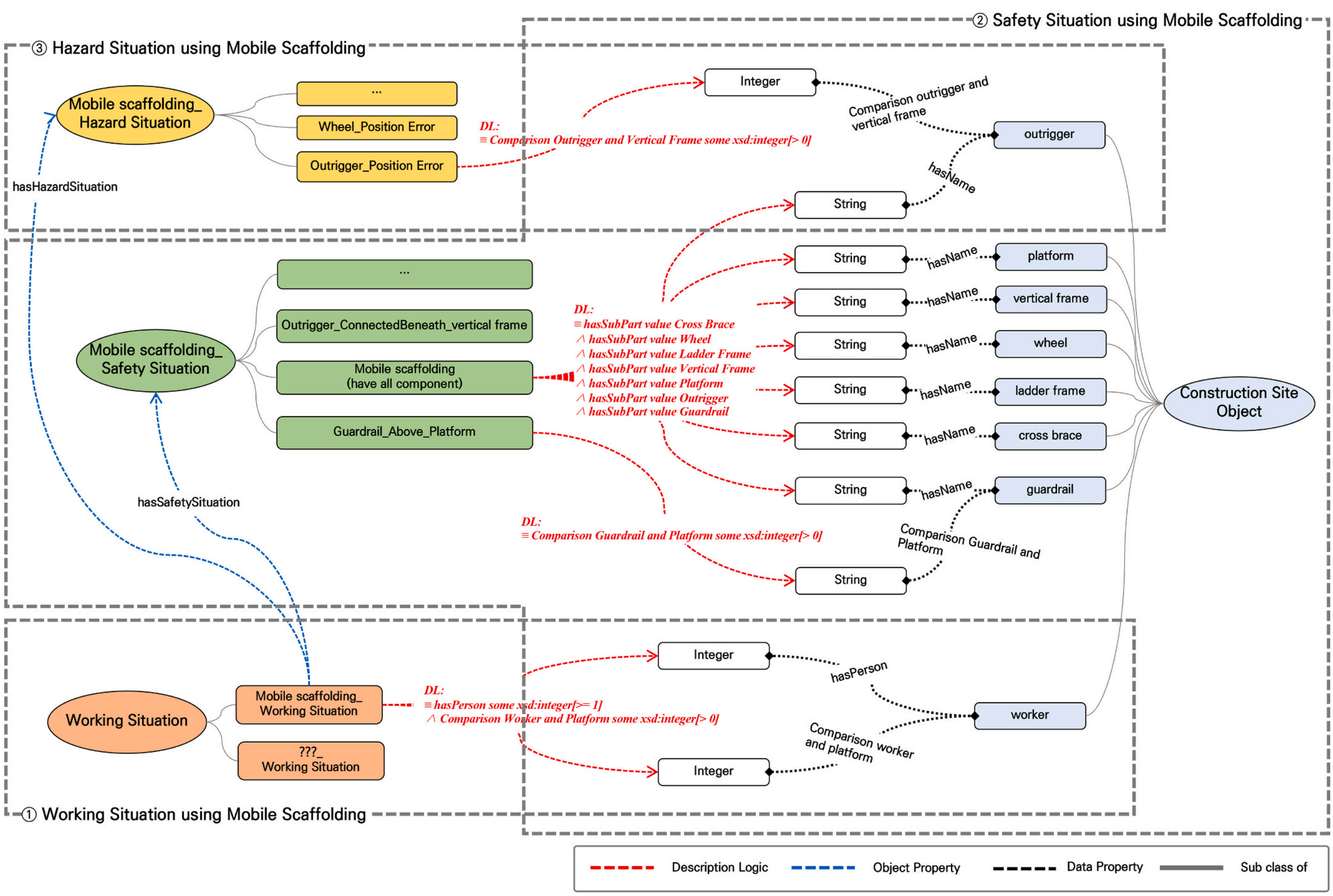

Fig. 4. The reasoning process for hazard awareness related to mobile scaffolding.

relation between outrigger and vertical frame among the subclasses of the 'Mobile scaffolding_Hazard Situation', are defined as Comparison_Outrigger_and_Vertical Frame some xsd:integer[> 0]. Then, the corresponding instance is inferred as an instance belonging to the 'Outrigger_Position Error' with respect to the outrigger position among the subclasses of the 'Mobile scaffolding_Hazard Situation'.

4.3. Validation

The purpose of this study is to improve the learning efficiency of the image recognition model by reducing the amount of learning data required to recognize hazard situations only with AI image recognition technology. The approach of this study is to define the safety situation as an ontology so that the situation that does not match the image recognition situation is recognized as a dangerous situation. To validate the proposed approach, we confirmed that does not have logical errors and is well inferred according to the intention through HermiT Reasoner 1.4.3.456 version, included in Protege v5.5 and compared the amount of training data required for the existing AI-based hazard situation awareness model and the proposed AI-Ontology based hazard situation awareness model.

First, HermiT Reasoner 1.4.3.456 version, included in Protege v5.5, was utilized for the validation check and reasoning of the ontology. It was found that ontology was defined consistently without logical errors, and that inferences regarding the relations between instances, safety situations, and hazard situations proceeded properly according to the intent of construction (The yellow shaded area in Figs. 5-8 indicates the inference result). The results showed the work using Mobile scaffolding was recognized to be underway according to the relations between objects (See Fig. 5), further indicating whether Mobile scaffolding has all components (See Fig. 6), whether the guardrail is installed above the platform (See Fig. 7), and whether it can be classified as a Hazard Situation unless outrigger is attached on the side of the vertical frame (See Fig. 8). That is, if construction site object information that can determine the class of ontology is input, it means that it is recognized as a work situation, a safety situation, and a hazard situation through an inference process.

Second, the existing AI-based risk situation recognition model and the proposed model was compared (See, Table 6). Hazard situations that can occur are very diverse, but for comparison, we compare them based on the officially defined Safety Guidelines. The 'Standard Safety Guidelines for Temporary Construction' [21] provided by The Ministry of Employment and Labor defines 15 safety rules to be followed when working with mobile scaffolding defined in this study. And there are 10 objects to be recognized that appear in the 15 safety rules. A hazard situation is a situation in which even one of the 15 safety rules is not followed, and the number of possible unsafe situations can be calculated as a combination of 15 unsafe conditions and unsafe behaviors, that is, $2^{15} = 32{,}768$. If 1000 images are trained for each situation to implement an AI model capable of recognizing one type of hazard situation, a total of 32,768,000 images are required to learn all hazard situations. In contrast, in the case where AI and ontology are combined to recognize individual objects and determine a hazard situation based on the relations between the recognized objects, this technology can be implemented with a total of 10,000 training data, assuming that ten types of objects are trained with 1000 training data for individual objects. Thus, this technology will significantly enhance the applicability of AI to the real world.

5. Conclusion

5.1. Distinction from existing studies

Comparison with AI image recognition technology; There are limitations in monitoring hazard situations on-site through CCTV, in that the manager must continuously control the operation, and a large amount of data for situation-specific training is required to train various hazard situations.

The purpose is not to replace AI technology with ontology technology, but to improve the efficiency of training compared to recognizing hazards only with AI image recognition technology. This study proposed a process of automatedly recognizing hazard situations from the images by combining the AI image recognition technology with the ontology technology to remove these practical limitations. The proposed approach infers the current working situation based on the relations between recognized objects, as well as safety situation or hazard situation according to the rules defined by the standard safety situation of the working situation. The final product of this study is an ontology for situation inference. Therefore, although there are assumptions, we compared the amount of training data required for the existing technology and the proposed technology (see Table 6).

In addition, not only recognition accuracy but also fast recognition in

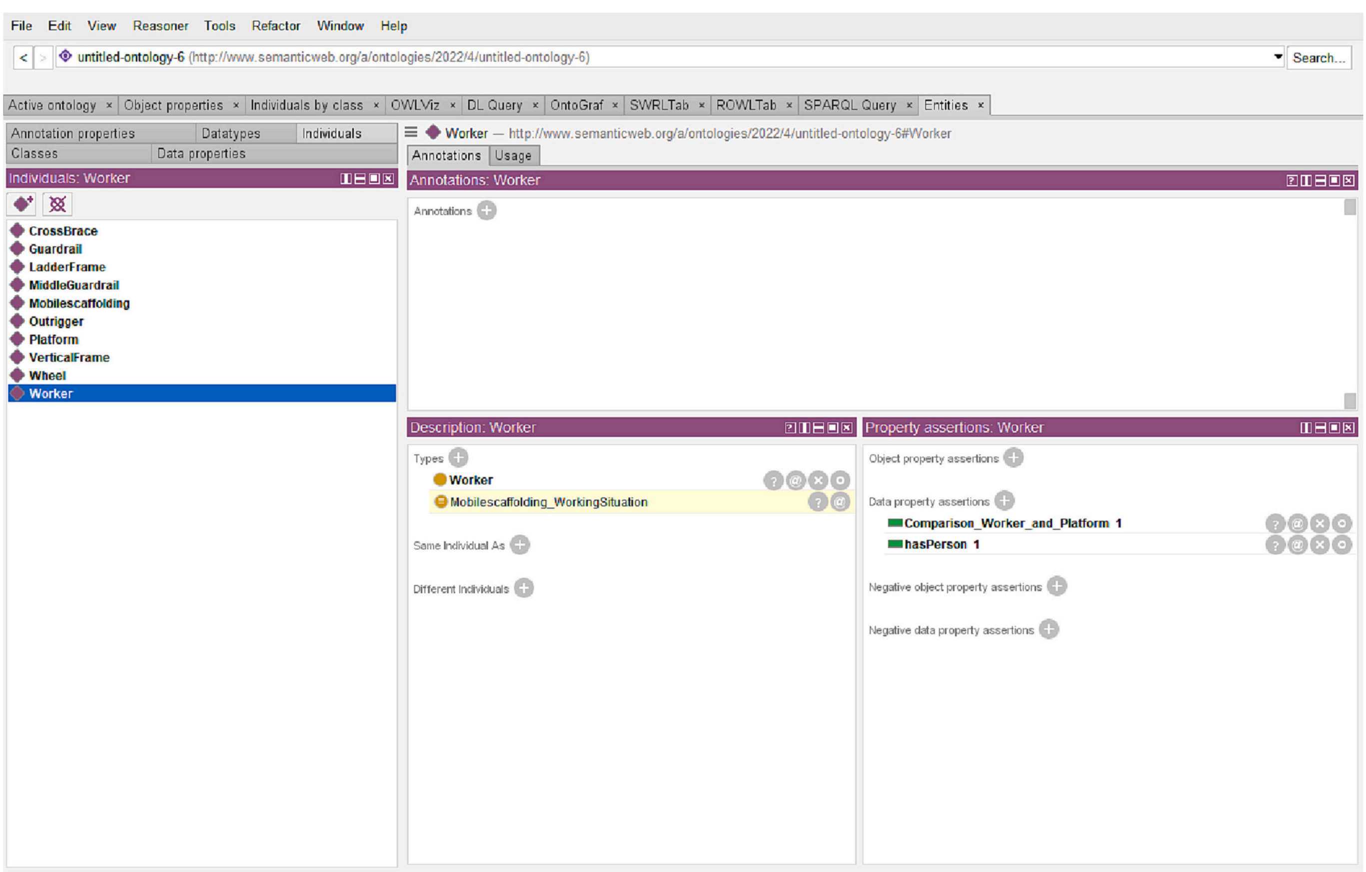

Fig. 5. The result of working situation reasoning (work using mobile scaffolding).

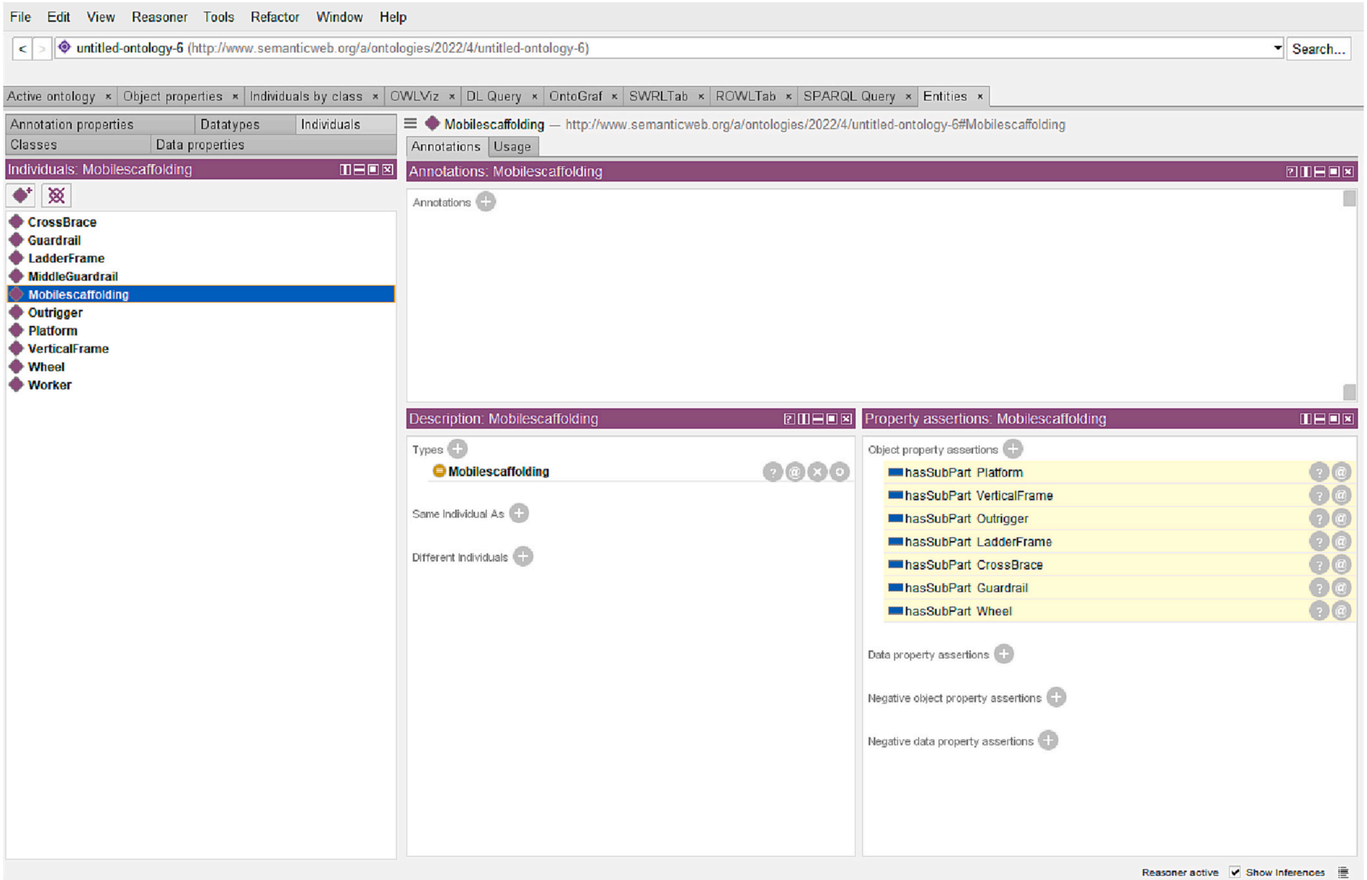

Fig. 6. The result of safety situation reasoning (mobile scaffolding has all components).

real time is an important factor in the actual field. In this study, the priority of recognition was defined to be able to recognize the dangerous situation first for the place where people are, that is, the working situation. In addition, all unsafe conditions and unsafe behaviors that do not meet the safety standards related to the work were recognized.

Work using mobile scaffolding during construction site work was employed as an example to validate the process proposed in this study. In this respect, the 'situation ontology on construction site' was defined through the definitions of the relations between the construction site object and the working situation, the safety situation required for each working situation, and the hazard situation. Ontology validity was checked using HermiT Reasoner (version 1.4.3.456), included in Protege v5.5, revealing that it was consistently defined without logical errors. Moreover, this study validated whether the information in the instance recognized via the image recognition technology was properly inferred according to the intent of construction.

Comparison with Ontology for Situational Awareness; The ontology that defines the object relations has typically been defined based on the relations between vocabulary (including inclusion relation, instance relation), whereas that proposed in this study uniquely recognize situations at the sites by defining relations through quantitative values, such as the ontology proposed in this study is not only the name, size, and number of the objects, as well as the distance values for the bounding box coordinates.

5.2. Utilization of the proposed methodology

Improves the efficiency of using AI image recognition technology: When it is necessary to recognize a hazard situation via the conventional AI image recognition technology, a large amount of training data, including the hazard situation, is required. However, the approach presented in this study will enhance the efficiency of utilizing AI image recognition technology for situation awareness by defining the safety situation with the ontology, and by allowing any situation that does not match the situation recognized by the image to be recognized as a hazard situation.

Enables accurate follow-up through recognition of specific hazard situations: Because the safety situation and the hazard situation are defined by the relations between individual objects, this approach enables managers to communicate precisely what follow-up actions are needed to ensure safety by understanding whether there is a hazard situation, what factors cause recognition as a hazard situation, and what type of problem is arising.

Provides the foundation for automation of construction site safety control and safety management plan: Safety situation ontology and hazard situation reasoning model can be utilized as key element technology for automating construction site safety management. This approach enables the client who lacks expertise to execute the safety plan of the facility without significant effort or training. Moreover, this approach can reduce the possibility of various errors that may arise from the intervention of inaccurate judgment, and enhance the efficiency of related work. As a result, this approach will improve the reliability and accuracy of the hazard situation recognition processes at construction sites.

Establishes a systematic and consistent basis for accumulating knowledge regarding safety-related accidents at construction sites: This approach enables an integrated management of the databases regarding construction safety-related accidents, including the Korea Occupational Safety and Health Agency, and the Korea Authority of Land and Infrastructure Safety, through analysis of semantic relations between construction site objects, and safety-related accident ontology. This is also applicable to development of the semantic retrieval function of the 'Construction Safety Management Integrated Information.' Ultimately, this approach

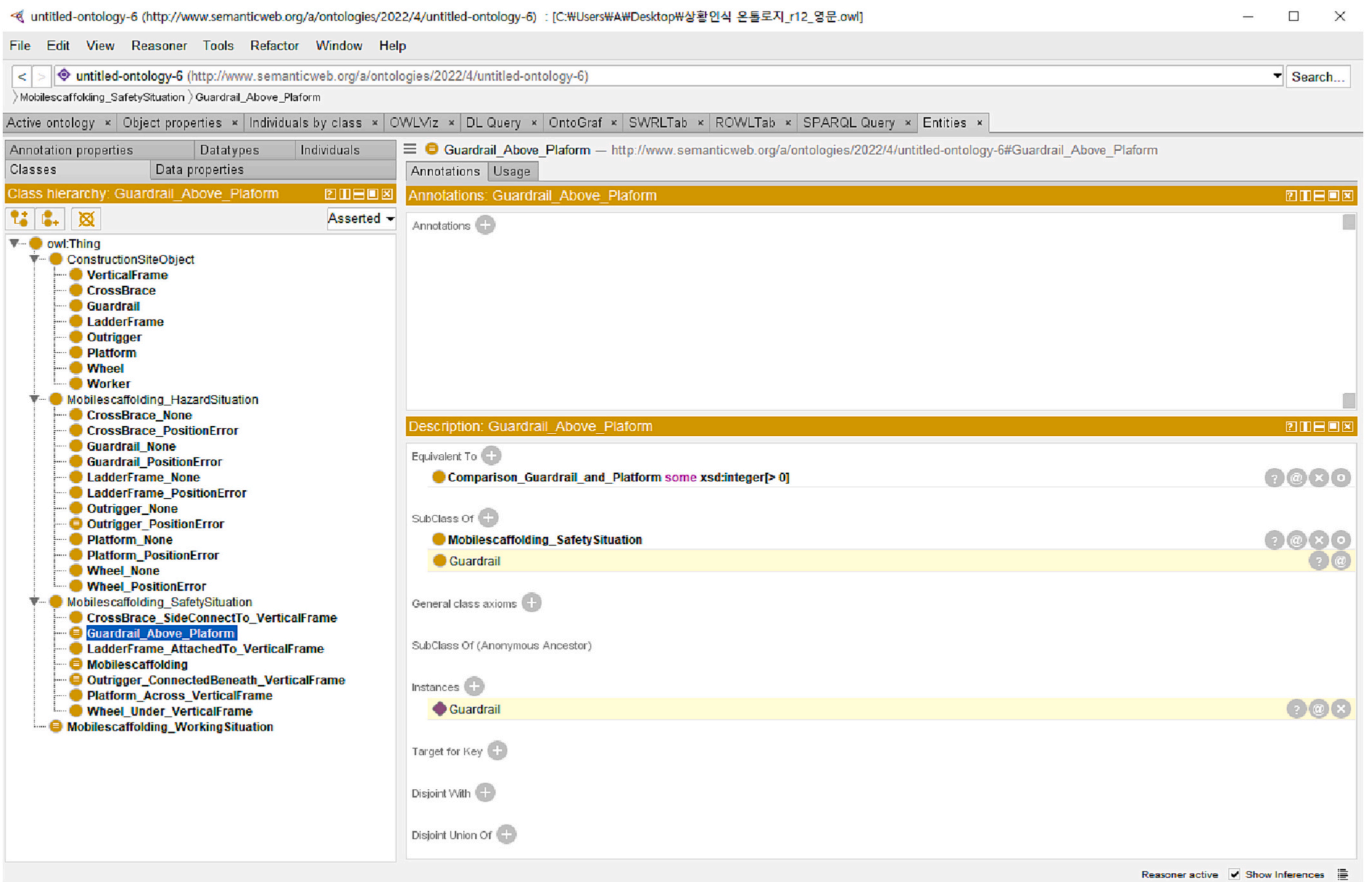

Fig. 7. The result of safety situation reasoning (Guardrail position).

can contribute to the accumulation of knowledge related to safety-related accidents.

5.3. Limitation and future research

The purpose of this study is to propose an approach that combines AI image recognition technology and relationship-based reasoning technology to solve the inefficiency of the method of training each image of various hazard situations. Possible hazard situations are difficult to predict because they can be defined by various combinations of related objects, but safety situations that must be observed are fixed. It is expected to solve the limitations of collecting large amounts of training data. Since this study is a study to confirm the possibility of convergence of existing AI image recognition technology and relationship inference technology, future research is needed to secure the accuracy, sustainability, and usability of the proposed technology for practical use.

Accuracy: To validate the proposed approach, this study defined the ontology as an example of mobile scaffolding among the safety guidelines for work suggested by the Ministry of Employment and Labor in Korea. There are 15 safety rules for work using mobile scaffolding and there are 10 objects to be recognized that appear in the 15 safety rules. For the safety rules of mobile scaffolding presented here, only examples of the distance are expressed because the important issue was whether there was an object to be there and, if so, whether it was in the correct position. However, judging whether an object is in the correct position may also require other factors besides distance, and since the criteria for judging the relationship may vary depending on each situation, many tests are needed to present the most appropriate factors and criteria. Since recognizing certain object relationships at once can be more accurate than recognizing and defining them individually, a test is also needed to define criteria for classifying objects to be recognized by image recognition technology.

Sustainability: This study presents a hazard situation awareness process using ontology with a focus on the example of mobile scaffolding. Future studies are required to categorize various work occurring at construction sites to provide and extend a standard guide for developing an ontology for inferring the working situation and safety situation for each work. Thus, it is important to secure the sustainability of the ontology that defines the safety situation for each work situation. Otherwise, if hazard situations are recognized using only AI image recognition technology, the effect of resolving inefficiencies caused by large-scale image collection may be reduced. Therefore, future research is needed to automatically extract objects and relational data required for constructing an ontology from the existing safety guideline by utilizing web-crawling and natural language processing (NLP).

Usability: to fully automate the hazard situation recognition process using ontology, there is a need for developing an information extraction and data format conversion module, as well as a semantic reasoning module. In addition, research on the development of an interface that provides workers or safety managers with the inference results to increase the usability of the technology presented in this study in actual construction sites. Then, for the actual application of the proposed technology, as pointed out by the reviewers, a test is needed to compare accuracy when using only the AI image technology and when using the technology proposed in this study.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Seul-Ki Lee and Jung-Ho Yu have patent Method and Apparatus for Determining a Dangerous Situation in Work Sites pending to

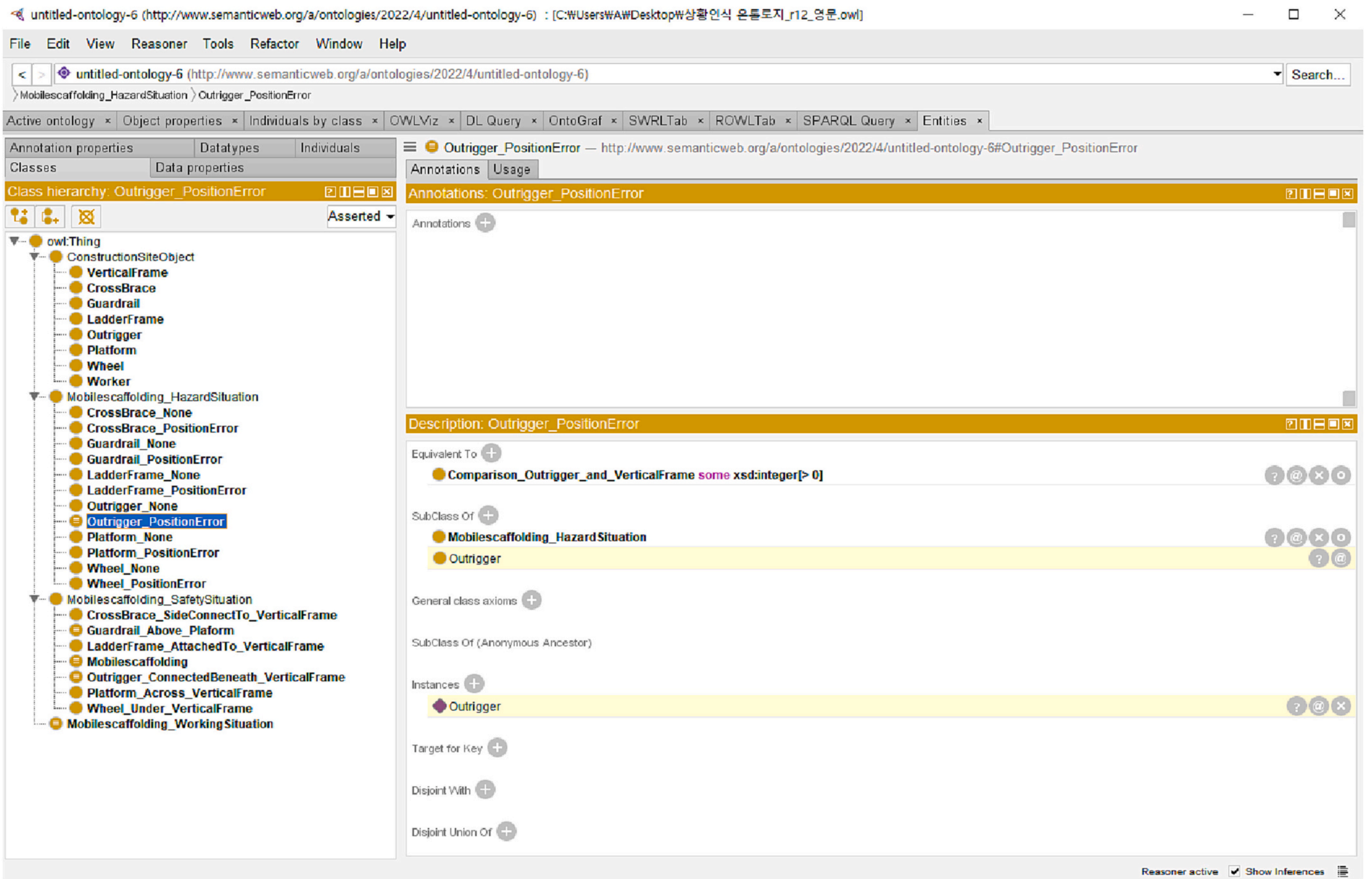

Fig. 8. The result of hazard situation reasoning (Outrigger position error).

Table 6
The distinction between the proposed technology and the existing technology.

Division	AI-based Hazard Situation Awareness	AI-Ontology based Hazard Situation Awareness (Proposed Approach)
Awareness Method	Image training	Image training + Relationship inference
Awareness Target	Unsafe situation Unsafe situation that does not follow safety standards and work rules	Individual object 10 Types of construction site objects used in Mobile scaffolding works
Awareness criteria	Unsafe situation Image training for all possible unsafe situations due to non-compliance with 15 rules	Safe Situation 'Working situation' and 'Standard safety situation for each task' defined based on the relationship between 10 recognized individual objects
Required Training Data	32,768,000	10,000

Kwangwoon University.

Data availability

No data was used for the research described in the article.

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