Ontology-Based Semantic Modeling of Knowledge in Construction: Classification and Identification of Hazards Implied in Images

Botao Zhong[1]; Heng Li[2]; Hanbin Luo[3]; Jingyang Zhou[4]; Weili Fang[5]; and Xuejiao Xing[6]

Abstract: Identifying potential hazards of construction project is a data-intensive process that involves various types of information such as site data, specifications, and engineering documents. How to effectively convert the information into a machine processable format for safety management is a challenging task. To address this problem, in this paper, combining the HowNet and specific taxonomies from the relevant construction specifications, a semantic modeling approach is developed for the proactive construction hazard identification from images. A semantic scoring system is then introduced for quantifying the similarities between images, via comparing their annotations with the construction hazard specification. Furthermore, an image processing framework is developed to semantically annotate site images and further automatically classify the images into the categories. In this way, the potential hazards implied in the images can be identified automatically. Examples are developed to demonstrate the feasibility of the approach. The outcomes of this study have offered an alternative method to enhance site safety management on site. **DOI:** 10.1061/(ASCE)CO.1943-7862.0001767. *© 2020 American Society of Civil Engineers.*

Author keywords: Safety; Hazards identification; Ontology; Image retrieval; Image.

Introduction

Safety management is a crucial part of construction project management. Identifying potential hazards is a prerequisite to ensure that preventative safety measures can be adopted. Construction projects are usually data-intensive which may involve site data, specifications, and engineering documents, etc., especially for megaprojects such as tunnels, bridges, railways, and ports. Existing data acquisition is largely a manual process that is both time-consuming and tedious. Moreover, how to transform these manually collected data into a machine-readable format for computer processing remains a challenging task (Goh and Chua 2010; Fang et al. 2018a, b, 2019, 2020).

There are various safety guidelines and specifications available to workers to protect them against potential site hazards, such as unified specification for safety technology in construction (GB50870-2013) and Quality and Safety Inspection Guide of Urban Rail Transit Engineering. These guidelines specify what hazard objects need to be monitored and how associated hazard events may occur. However, relying on self-specifications and complying with guidelines cannot eliminate all site accidents because of workers' own limitations and dynamic site situations.

Digital imaging technologies have recently been extensively used in construction projects and construction images have become an essential part of project documentation (Brilakis et al. 2011; Kim et al. 2016, 2018; Ding et al. 2018; Fang et al. 2018a, b; Konstantinou et al. 2019; Fang et al. 2019). How to analyze these site images to automatically identify potential site hazards is becoming an important but still to be conquered research challenge. Technological developments aided by computer vision and deep learning have been identified as an effective approach to automatically extract knowledge from images for various applications, such as unsafe behavior recognition (Yu et al. 2017; Fang et al. 2018b), activity identification (Luo et al. 2018), and object detection (Kim et al. 2016; Fang et al. 2018a). For example, Kim et al. (2016) developed a data-driven scene parsing method to recognize various objects from images in construction. Despite their success on scene understanding, there exists a semantic gap between the low-level features extracted from the images by computer vision algorithms and the high-level semantic meaning that people can recognize on the image (Bottou 2014; Russakovsky et al. 2015), which has not considered ontological and semantic relationships of objects identified in the images. For example, the relevance between crane and hoist is highly related to certain hazards and this relationship should be considered in hazard identification.

To fill this research gap, this paper develops a HowNet-based semantic modeling approach to automatically identify construction hazards from images. In our approach, a HowNet-based semantic knowledge modeling approach is adopted to classify ontological

[1]Associate Professor, Dept. of Construction Management, School of Civil Engineering and Mechanics, Huazhong Univ. of Science and Technology, Wuhan, Hubei 430074, China. Email: dadizhong@hust.edu.cn

[2]Professor, Dept. of Building and Real Estate, Hong Kong Polytechnic Univ., Hong Kong, China. Email: heng.li@polyu.edu.hk

[3]Professor, Dept. of Construction Management, School of Civil Engineering and Mechanics, Huazhong Univ. of Science and Technology, Wuhan, Hubei 430074, China. Email: luohbcem@hust.edu.cn

[4]Research Fellow, School of Civil and Mechanical Engineering, Curtin Univ., Perth, WA 6845, Australia. Email: j.zhou@curtin.edu.au

[5]Research Fellow, Dept. of Construction Management, School of Civil Engineering and Mechanics, Huazhong Univ. of Science and Technology, Wuhan, Hubei 430074, China; Research Fellow, School of Civil and Mechanical Engineering, Curtin Univ., Perth, WA 6845, Australia (corresponding author). Email: weili_f@hust.edu.cn

[6]Ph.D. Candidate, Dept. of Construction Management, School of Civil Engineering and Mechanics, Huazhong Univ. of Science and Technology, Wuhan, Hubei 430074, China. Email: xing021493@163.com

Note. This manuscript was submitted on August 9, 2018; approved on July 15, 2019; published online on January 20, 2020. Discussion period open until June 20, 2020; separate discussions must be submitted for individual papers. This paper is part of the ***Journal of Construction Engineering and Management***, © ASCE, ISSN 0733-9364.

and semantic relationships of objects from site images. Then, a knowledge database including construction hazard images and semantic annotation is presented based on the semantic knowledge modeling model. Finally, a retrieval and classification mechanism is developed such that new images can be categorized and potential hazards within the new image can be identified using a semantic scoring system between the new image and categorized images in the database. In this way, site hazards can be automatically identified, and proactive measures can be taken to enhance site safety. The main contribution of this paper lays the development of modeling a HowNet-based semantic approach, considering ontological and semantic relationships of objects identified in the images, to automatically identify construction hazards from images, an approach that does not currently exist. Benefits stemming from our approach lie in the ability to automatically classify the images into the standard categories based on the semantic model and similarity calculation, and further enable automatic hazard identification. We commence our research with a review of the extant ontologies-based risk management, and then we introduce the new semantic modeling approach, which is subsequently tested and validated using an experiment.

Research Background

Managing Construction Risks Using Ontology

An *ontology* is an information model that can explicitly represent a domain by defining the concepts and the various relationships among the concepts. Because of its computer-oriented and logic-based features, ontology engineering has been widely adopted for information modeling and analysis such as semantic integration of heterogeneous databases and information retrieval and management. Representative studies applying ontology-based approaches to manage construction risks are summarized within (Tserng et al. 2009; Wang and Boukamp 2011; Jiang et al. 2013; Lin et al. 2012; Lu et al. 2015; Zhong and Li 2015; Ding et al. 2016; Guo and Goh 2017). Specifically, Jiang et al. (2013) utilized a semantic retrieval system based on the ontology of construction risks to support effective risk assessment. Ding et al. (2016) initiated an ontology-based framework to automatically derive relationships between risk factors, causes, and preventative measures. Similarly, Zhong and Li (2015) combined construction process knowledge reuse methodology with ontology and semantics for risk knowledge formalization and reasoning. Guo and Goh (2017) developed an ontology to formalize the knowledge of active fall protection system (AFPS-Onto) design. The AFPS-Onto is probably the first attempt to develop a global ontology for construction safety hazard management. These studies demonstrate the potential benefits of ontology in risk management.

Semantic-Based Image Retrieval

A plethora of studies have been carried out to explore semantic based image retrieval technologies that have been used in various applications, such as museum artifact retrieval (Sharma and Siddiqui 2016), plant identification (Gonçalves and Guilherme 2017), and mapping diseases with medicines (Burdescu et al. 2013; Kurtz et al. 2014; Kumar et al. 2016). In these studies, information is extracted from images and semantically represented in ontology (Magesh and Thangaraj 2011). For example, Sharma and Siddiqui (2016) developed an ontology-based conceptual framework for image retrieval of digitized museum artifacts. Likewise, Burdescu et al. (2013) presented a system in the medical domain for image annotation, semantic based image retrieval, and content-based image retrieval. Chen et al. (2016) presented an intelligent annotation-based image retrieval system on resource description framework (RDF) descriptions. To the best of authors' knowledge, how to semantically classify construction site images remains a research challenge.

An image retrieval approach depends on calculation of similarity of the annotation sets of images. Several different computation methods have been developed for evaluating the similarity (Chen 2006; Mehmood et al. 2018). For example, Chen (2006) proposed a semantic similarity method considering the hierarchical relationships and relatedness between concepts to calculate the semantic similarity of the concepts. The calculation of similarity in their work consists of two parts: (1) semantic concept similarity; and (2) information item similarity. In our research, we followed Chen (2006) to calculate the similarity of two concepts. Here, semantic concept similarity is obtained by following three steps:

- *Calculation of semantic concept initial similarity.*
- *Calculation of semantic concept relatedness.*
- *Calculation of semantic concept actual similarity.*

Semantic Concept Similarity

Initial Similarity of Concepts. The initial similarity can be obtained by calculating the semantic distance between two different concepts (C_1 and C_2, $C_1 \neq C_2$) which are of the same hierarchy. The initial similarity can be calculated by Eqs. (1) and (2) as follows:

If C_1 and C_2 are synonymous

$$I_{\text{sim}}(C_1, C_2) = 1 \tag{1}$$

If C_1 and C_2 are not synonymous

$$I_{sim}(C_1, C_2) = \frac{a \times [dl(C_1) + dl(C_2)]}{[dist(C_1, C_2) + a] \times 2 \times \max dl \times [dl(C_1) - dl(C_2)]} \tag{2}$$

where, $dl(C_1)$ and $dl(C_2)$ = semantic level of concepts; $dist(C_1, C_2)$ = minimum distance between C_1 and C_2 in the hierarchy, $\max dl$ = maximum number of hierarchy conceptual structure to normalized process, and a = adjustable parameter that is the semantic distance of similarity to 1.

Semantic Relevancy of Concepts. Based on the initial similarity, the semantic relevancy of concepts aims to calculate the similarity of nonhyponym relations, which is marked as $Sim_{fuss}(C_1, C_2)$ ($C_1 \neq C_2$). Then, the relational concepts of C_1 and C_2 should be defined, which are shown in Table 1.

As shown in Eq. (3), the Cartesian product can be calculated through the relational concept sets $C_{r1'}$ and $C_{r2'}$, which were marked as $C_r(C_{1'}, C_{2'})$. Then, the $Sim_{fuss}(C_1, C_2)$ can be calculated by Eq. (4).

Table 1. Relational concepts of C_1 and C_2

Concept	C_1	C_2
Relational concepts	$C_{\text{r1}} = \{C_{\text{r11}}, C_{\text{r21}}, C_{\text{r31}} \ldots C_{\text{rp1}}\}$	$C_{\text{r2}} = \{C_{\text{r12}}, C_{\text{r22}}, C_{\text{r32}} \ldots C_{\text{rq2}}\}$
Relational concepts set	$C_{\text{r1}'} = \{C_1, C_{\text{r11}}, C_{\text{r21}}, C_{\text{r31}} \ldots C_{\text{rp1}}\}$	$C_{\text{r2}'} = \{C_2, C_{\text{r12}}, C_{\text{r22}}, C_{\text{r32}} \ldots C_{\text{rq2}}\}$

$$C_r(C_{1'}, C_{2'}) = \begin{cases} \langle A_1, B_1\rangle, \langle A_1, B_1\rangle, \cdots \ \langle A_1, B_1\rangle | A_k \in C_{r1'}, B_k \in C_{r2'}, \\ k = \min(n, m), \ \forall \ h = 1, 2, \ \ldots, k, \ \text{and } A_h \neq A_g, B_h \neq B_g, \ \forall \ g, s \neq h \end{cases} \tag{3}$$

$$Sim_{fuss}(C_1, C_2) = \frac{\max\limits_{S\in C_r(C_1,C_2)} [\sum_{(A,B\in S)} Isim(A, B)]}{\max[\max(n, m), 1]} \tag{4}$$

Semantic Similarity of Concepts. The semantic similarity between two different concepts can be obtained by calculating the weighted sum of the initial similarity and the sematic relevancy, as shown in Eq. (5)

$$Sim(C_1, C_2) = \beta Sim(C1, C2) + \gamma Sim_{\text{fuss}}(C_1, C_2)(\beta + \gamma = 1) \tag{5}$$

where, $\beta \in [0, 1]$ and $\gamma \in [0, 1]$ are weighting parameters for the initial similarity and the relatedness respectively.

Information Item Similarity

Each annotation sentence is treated as an information item that consists of a set of annotation concepts. Let, $T_{1i}(i = 1, 2, \ \ldots, m)$ be the m semantic concepts of the queried text, $T_{2j}(j = 1, 2, \ \ldots, \ n)$ be the n semantic concepts of the standard specification and $S_{T_{1m}T_{2n}}$ denote the similarity between T_{1m} and T_{2n}. Then the queried text matrix K_1, the standard specification matrix K_2, and the similarity matrix K_{12} can be defined by Eq. (6)

$$\begin{gathered} K_1 = \{T_{11}, T_{12}, T_{13} \ldots T_{1m}\} \\ K_2 = \{T_{21}, T_{22}, T_{23} \ldots T_{2n}\} \\ K_{12} = K_1 * K_2^T = \begin{bmatrix} S_{T_{11}T_{21}} & S_{T_{12}T_{21}} & \ldots & S_{T_{1m}T_{21}} \\ S_{T_{11}T_{22}} & S_{T_{12}T_{22}} & \ldots & S_{T_{1m}T_{22}} \\ \ldots & & & \\ S_{T_{11}T_{2n}} & S_{T_{12}T_{2n}} & \ldots & S_{T_{1m}T_{2n}} \end{bmatrix} \end{gathered} \tag{6}$$

The similarity of the information items can be calculated by Eq. (7)

$$Sim(S_1, S_2) = \frac{1}{k}\sum_{i=1}^{k} Sim(\max s_i) \tag{7}$$

where $\max s_i$ is the maximum similarity of the phrase for the ith search and k is the semantic concept collection that is the minimum quantity.

State of the Art and Knowledge Gaps

To mitigate safety risks in construction both manual inspections and video surveillance have been used to monitor workers' activities and operation. As a result, images are recorded and used for the purpose of monitoring safety. Guo et al. (2016), for example, developed a big data-based platform to classify, collect and store the data of workers' unsafe behavior derived from construction project. In their work, vector space model (VSM) was applied to match the collected images with safety rules that can be used to determine unsafe behavior. despite their success on identification of unsafe behavior, the objects implied in images are manually annotated (Guo et al. 2016).

With the development of deep learning and computer vision, a plethora of deep learning-based computer vision approaches have been applied and developed to automatically annotate objects, identify hazards, and monitor workers' activities in construction (Ding et al. 2018; Fang et al. 2018a, b; Luo et al. 2018; Fang et al. 2019). For example, Ding et al. (2018) proposed a hybrid deep learning model to automatically recognize workers' unsafe actions. Fang et al. (2019) applied a computer vision approach with Mask R-CNN to identify workers traversing on structural support. Likewise, Fang et al. (2018a) developed a hybrid computer vision approach to identify workers not wearing a safety harness working in height. In this work, a Faster R-CNN was used to detect workers from images. These researches were dedicated to automating the semantic annotation of the construction images, however using a computer to process the images based on sentences without semantic loss still remains a difficult task. In fact, up to now, only very limited types of construction hazards can be detected from images.

Ontology, having intelligent inference capability, can be used to improve the effectiveness and accuracy of semantic information retrieval (Manzoor et al. 2015). HowNet is an information database that reveals the inter-conceptual and inter-attribute relations of concepts of the Chinese and English languages (Dong and Dong 2003, 2006). The foundation of the HowNet framework was initially developed based on the general common-sense knowledge that can be further extended to dedicated domain through the creation of a specialized database. As an information database, the structure of HowNet is represented using graphs rather than tree topologies, which enables it to be able to depict the relations between concepts from both the same and different categories (Dun et al. 2009; Li and Yang 2016; Fu et al. 2017).

With this in mind, a HowNet framework is adopted as the fundamental knowledge representation structure for modeling the information of potential construction hazards. The goal of our research is how to effectively manage construction images for automatic classification and identification of hazards. Taxonomies are developed based on the Chinese specification Quality and Safety Inspection Guide of Urban Rail Transit Engineering. Based on these taxonomies, the fundamental structure of HowNet is further extended, and then applied into the ontological model for the construction hazard analysis. Using a pilot research project, a construction image management framework is developed based on the proposed semantic model. The images are semantically annotated based on the potential hazard events. A semantic scoring system is developed for classification and retrieval of the construction images.

HowNet-Based Ontological Modeling for Construction Hazard

In the HowNet framework, seven categories of information are defined, i.e., thing, part, attribute, time, space, event, and attribute-value. *Event* is the core concept and can be further classified as static and dynamic types. The static event concept consists of two information elements, i.e., relation and state. The dynamic event concept denotes the changes to the relation and state of the static event. In construction engineering, a potential hazard refers to an unsafe condition (situation) or unsafe behavior and can change in particular time and space. More specifically, the potential construction hazard can be described as: risk resource causes (leads to) potential risk (potential safety hazard) in specific time and space, under (triggered by) specific actions (situation), which is inconsistent with the definition of the event given in HowNet.

An effective hazard analysis of a construction project requires accurate interpretations of the potential hazardous events. Goh and Chua (2010) pointed out that the core concepts of the construction hazard information include activity, object, resource, location, material, and other variables. This classification is derived based on the linguistic structure: Action(s) executed on object(s)-worked-on using resource(s) at location(s) with nearby object(s) and nearby action(s) (Goh and Chua 2010). To describe the safety situation of a construction site, Wang and Boukamp (2011) categorized all the contextual concepts into three primary classes: component, activity, and resource. In general, a potential hazard event can be defined as in a given time and space, the entities (with specific attributes) undergo certain activities. Thus, the hazard event mainly consists of five aspects of semantic information, i.e., hazard entity, activity, attribute, time, and location (Fig. 1).

In this research, using a metro construction project as a pilot study, we focus on analyzing the potential hazards that are related to construction procedures. A detailed description of the semantic concept is provided in Table 2 which provides a fundamental understanding of the core semantics of potential construction hazards. These concepts can be incorporated into the HowNet framework as an extension for hazard analysis of the metro construction domain. Some classes of the five top-level concepts, such as hazard entity, may contain multiple concepts to be further classified that require the taxonomies to be developed.

Taxonomy Development

In this research, taxonomy is developed based on the Chinese specification Quality and Safety Inspection Guide of Urban Rail Transit Engineering (China Building Industry Press 2016), which is commonly used as a reference to examine the hazard events of the construction procedures in China. In this specification, the potential hazards relating to construction tasks and techniques of metro projects can be classified into 21 inspection categories, such as safety management, civilization construction, fastener type scaffolding, full-style scaffolding, foundation pit support engineering, template engineering, and hoisting. By manually excluding the specification clauses that are irrelevant to metro construction site, a total of 694 potential hazards have been identified under the 21 inspection categories. Each hazard is then assigned an identification code. The obtained hazard list can be used as a checklist of the construction hazard inspection.

Table 3 shows the potential hazards relating to the hoisting work on a metro construction site. According to different construction activities, the hazards can be classified into seven subcategories, i.e., location condition, operation and control, process management, walking with objects, working at heights, a stack of components, and security alert. Each subcategory contains a number of specific hazard items (Table 3). The core concepts identified in Table 3 are analyzed and classified in Table 4, which can serve as an extension to the taxonomy. Thus, the HowNet framework and the extended taxonomy can be used to derive the ontology model of the hazard events.

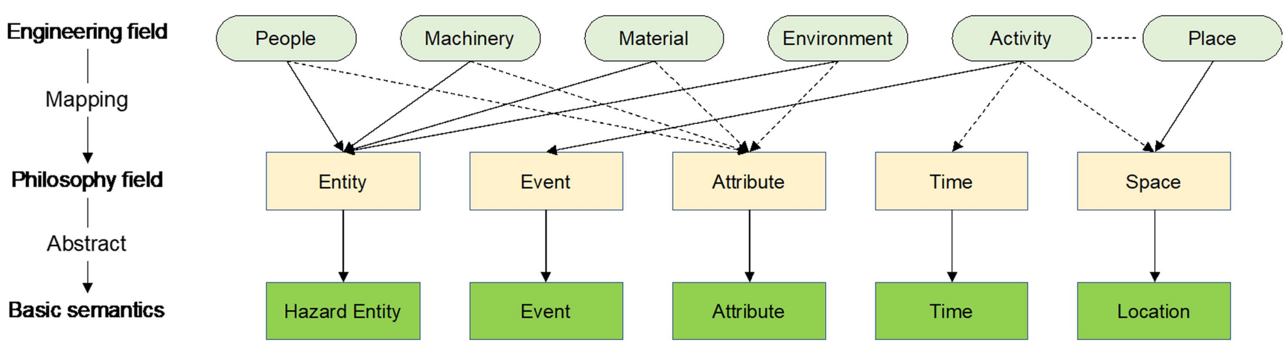

Fig. 1. Semantic framework of the construction hazard information.

Table 2. The basic structure of the potential construction hazard information item

No.	Semantic concept	Implication
1	Hazard entity	Refer to the entities that are the objective existence and can be distinguished in metro construction potential safety hazard events. The entities contain the specific concepts such as specific persons and materials, also can be the abstract definitions such as specifications and measures
2	Activity	Refer to changes caused by the hazard entities, such as the attributes, states, and relations
3	Location	Refer to the specific locations and the interface concepts involved with metro construction potential safety hazard events
4	Time	Refer to the specific time involved with metro construction potential safety hazard events
5	Attribute	Refer to the specific description of the substance properties

Table 3. Checklist of potential hazard items in hoisting work

First code	Large class of hazard	Second code	Small class of hazard	Third code	Potential point of hazard
16	Hoisting	16-01	Equipment position	16-01-01	Unfit ground bedding
				16-01-02	Unfit position of landing leg
		16-02	Operation control	16-02-01	Uniform lifting speed or sudden movement
				16-02-02	Uneven rotation
				16-02-03	Landing arm or making two movements under full load condition
				16-02-04	Using main and vice hook of the crane at the same time
		16-03	Process management	16-03-01	Insufficient lighting on site
				16-03-02	Hoisting the objects of unknown weight
				16-03-03	Overload operation
				16-03-04	Person stands on the construction machinery when hoisting construction machinery
				16-03-05	The hoisted object has the floating object
				16-03-06	Not use the special hanging basket when hoisting air bottles
		16-04	Moving with weight	16-04-01	Machine moving with overweight
				16-04-02	500 mm Uneven road, the height is greater than 500 mm
				16-04-03	Persons push the hoisted object directly without haulage cable
		16-05	Work at height	16-05-01	Not set working platform for high-place operation
				16-05-02	Unfit working platform setting
				16-05-03	Unfit hanging point of safety belt
		16-06	Loading	16-06-01	Loading weight of objects goes beyond the bearing capacity of working face
				16-06-02	Loading height of objects goes beyond the formulary requirement
				16-06-03	No steady measures for large weight
		16-07	Safety warning	16-07-01	Small things without reliable bearing container
				16-07-02	No warning signs while hoisting
				16-07-03	Workers entering warning areas

Table 4. Concept identification of hazard information in hoisting engineering

Hazard information (in sentence)	Semantic keyword: Hazard entity	Activity type	Location	Attribute
Insufficient lighting on site	On site			Lighting
Hoisting the objects of unknown weight	Material		Hoisting	Weight
Overload operation by hoisting machine	Hoisting machine	Overload		
Person stands on the construction machinery when hoisting construction machinery	Material person	Existence hoisting		
The hoisted object has the floating object	Material	Hoisting existence setting		
Not use the special hanging basket when hoisting air bottles	Air bottle hanging basket	Hoisting		Special
Persons push the hoisted object directly without haulage cable	Person material haulage cable	Push set hoisting without		
Not set aerial work platform	Aerial work platform	Set not		
Loading weight of objects goes beyond the bearing capacity of working face	Object	Load beyond	Working face	Bearing capacity
Loading height of objects goes beyond the formulary requirement	Object formulary requirement	Load beyond		Height
Small things without reliable bearing container	Material container	Without bearing		
No warning signs while hoisting	Warning sign	Hoisting no		

Classes

Potential Hazard Entity

The potential hazard entity can be expanded by adjusting the primary and secondary semantic structures based on the domain knowledge and the classifications defined in the HowNet framework. In the HowNet system, material and spirit coexist. Material refers to the physical objects, such as humans, tools, and land; while spirit refers to the abstract existences, such as emotion, methods, and ideas. Thus, the potential hazard entities can be classified into two categories, i.e., objective entity and spiritual entity. According to unified specification for safety technology in construction (GB50870-2013) and specification for quality management of engineering construction enterprises (GB-T50430-2007), the objective entity of the potential hazards includes people, material, equipment, and environment; spiritual entity contains specifications,

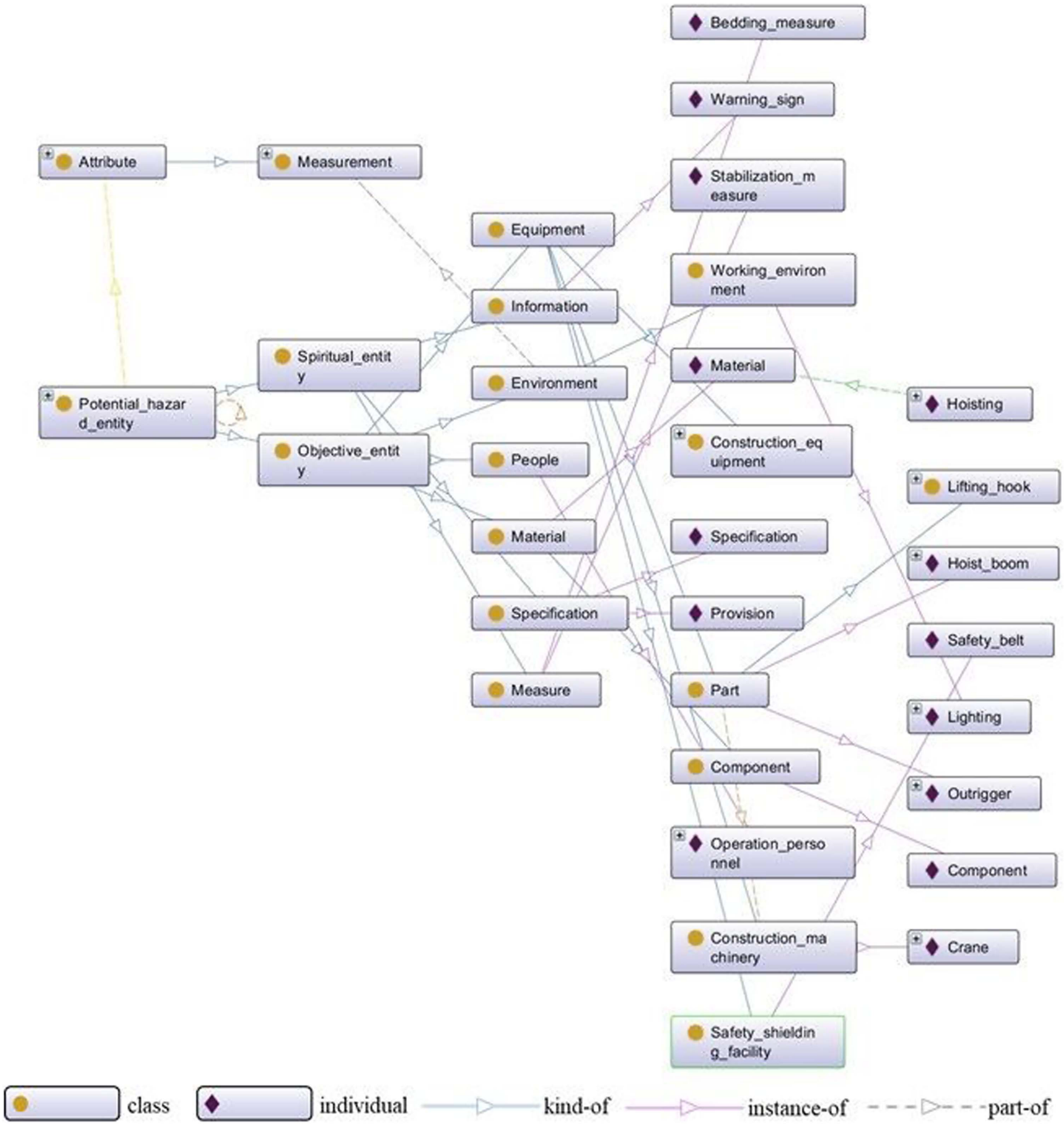

Fig. 2. Classification of the potential hazards.

information, and measures, etc. A detailed classification can be found in Fig. 2.

Activity

The potential hazard refers to the unsafe condition (situation) or behavior that can vary in the given time and space. The changes of the condition/state can be defined as activity that can be further divided into static and dynamic subclasses. Static activity denotes the relations and states of the entities, such as existence, comparison, and time-space relationship. For example, in the sentence "An entrance door does not exist in the entrance of the construction site." "does not exist" represents the static existence. Dynamic activity indicates the changes to the relations or states of the entities. For instance, in the sentence "The special hanging basket is used, when hoisting air bottles." "hoisting" represents the change of state. Fig. 3 illustrates a detailed information structure of the activity types.

Location

In the open geospatial consortium (OGC) spatial model, three basic special data types are supported, i.e., point, line, and surface that can be described using direction, metric, and topological relations. The spatial model and relations can be adapted to indicate the location of the potential hazards. In this study, the location of a potential hazard event can be categorized into three types, namely, working place, area, and direction (Fig. 4). Working place

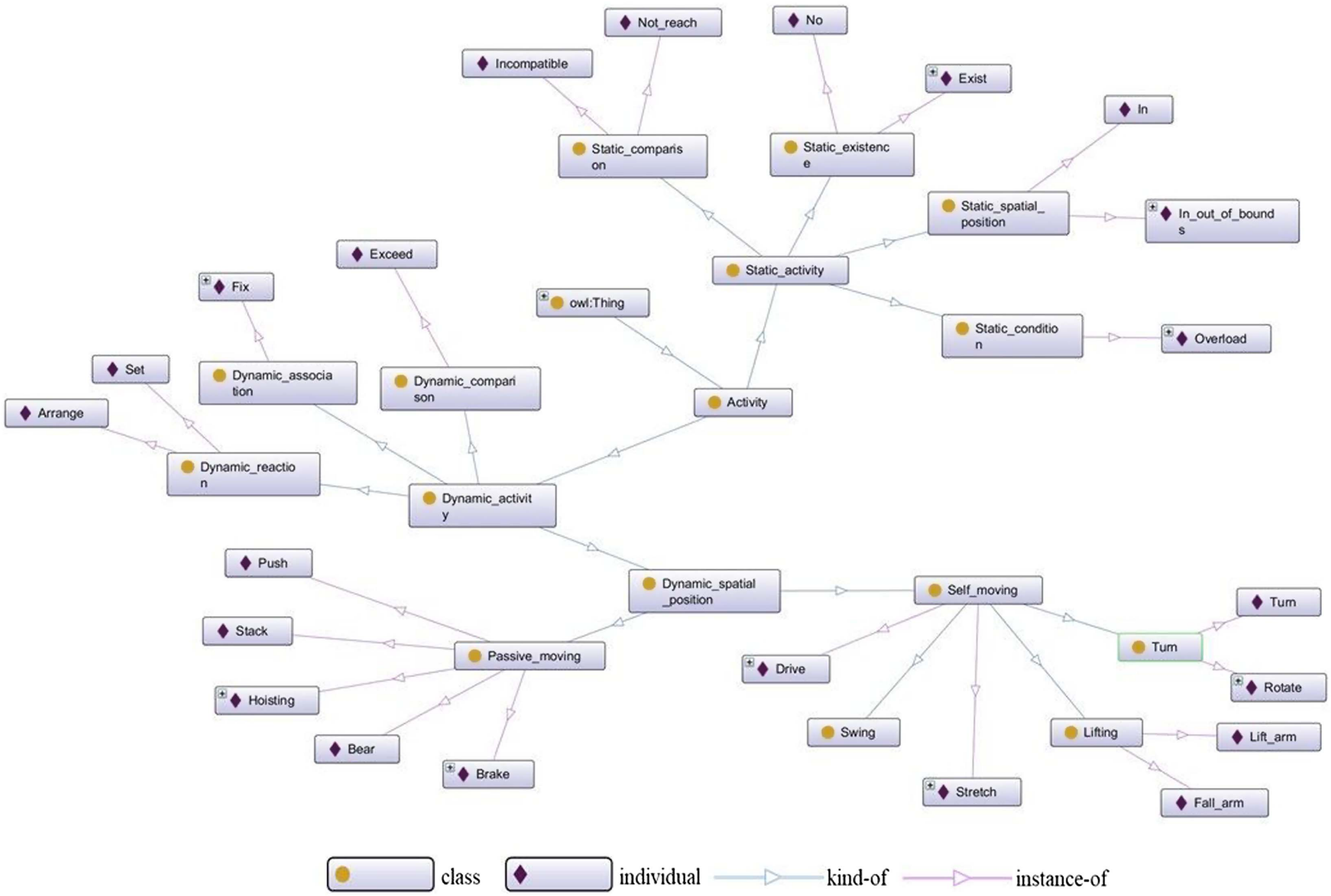

Fig. 3. Semantic structure of activity.

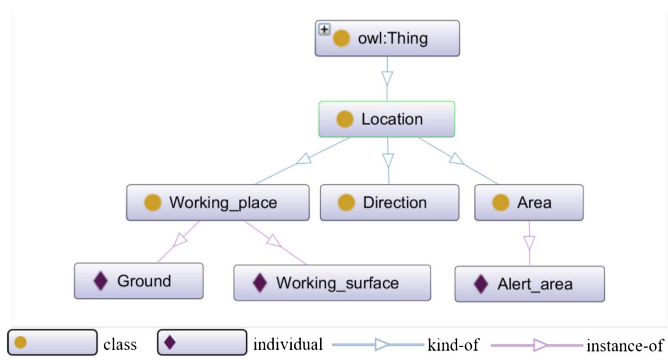

Fig. 4. Semantic structure of location.

represents specific location, such as "on the ground," "in the height," etc. Area defines the zoning of the construction site such as a warning zone. Direction is used to indicate specific direction, such as right, left, front, and back, etc.

Time

Two types of time models are employed to indicate the event on the timeline, i.e., point and span. Time point indicates a specific event time that can be accurate to hour, minute, or second according to the precision requirement. Time span is used to show the duration of the event on the timeline.

Attribute

Attributes reflect the specific characteristics of an entity. In the HowNet system, attributes can be classified into four types, i.e., appearance, measurement, feature, and state (Fig. 5). Appearance is used to describe the external image of an entity when a hazard event occurs. Measurement is adopted to indicate the changes to the nonobservable values of the hazard entity. Feature is used to show the performance and functionality while state indicates the condition and availability of the hazard entity.

Semantic Relations

Semantic relations can be defined as meaningful associations between two or more concepts, entities, or sets of entities (Khoo and Na 2006). Based on the semantic relations in the HowNet framework, the internal and external semantic relations of the taxonomies are analyzed and identified. Table 5 illustrates the semantic relations for the hazard information of metro construction project. The relations are modeled and implemented using Protégé 5.1 (Fig. 6), which is a free and open-source ontology editor.

Construction Image Processing Framework for Construction Hazard Analysis

How to make construction images machine-understandable to identify the potential hazard events (e.g., unsafe behavior) has received widespread attention in the literature. In this research, an image

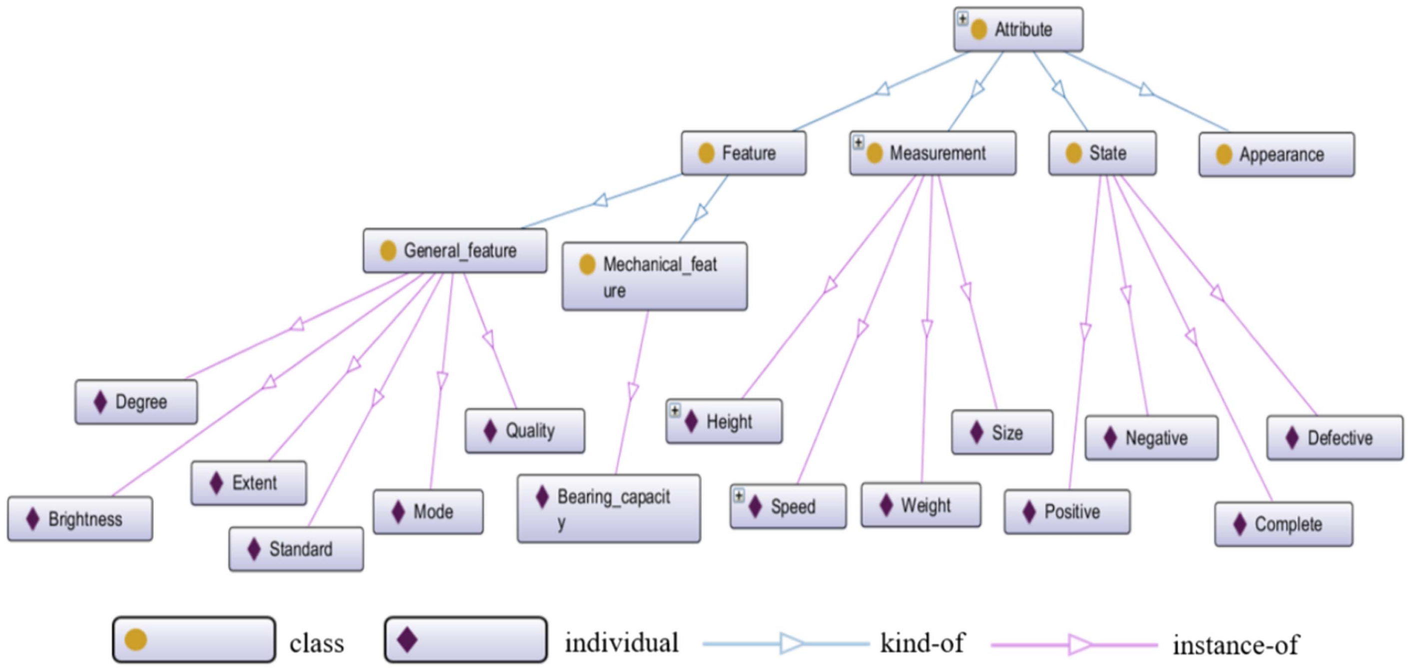

Fig. 5. Classification of attributes.

Table 5. Metro construction potential safety hazard knowledge relations

Semantic type	Relation type	Relation name
Hazard entity	Hierarchical relation	Subclass of, kind of, part of, restrictive
	Modified relation	Attribute
	Dynamic relation	Agent, patient, content, partner, contrast, relevant, existent
Activity	Hierarchical relation	Subclass of
		Before, during, overlaps, accompaniment
		Condition
	Modified relation	Attribute
Location	Hierarchical relation	Subclass of
	Dynamic relation	Departure, destination, located
Time	Hierarchical relation	Subclass of
	Dynamic relation	Temporal
Attribute	Hierarchical relation	Subclass of
	Attribute value	Attribute value

processing framework containing image retrieval and classification is developed for construction hazard analysis based on the semantic model. Images would be semantically annotated according to the potential construction hazards, and a semantic scoring system is then developed based on the annotations of the images to quantify the similarity of these hazards. Thus, the potential risks can be effectively identified and classified from images for enhancing construction safety. The structure of the developed framework is shown in Fig. 7.

Description and Semantic Annotation of Construction Images

Image annotation can be achieved by assigning a set of semantic words to the target images. These words are derived from controlled vocabulary or by annotators. In this paper, a sentence-based method is adapted to annotate construction images. First, engineering professionals are employed to annotate the construction images using easily understandable natural language sentences that contain the critical hazard information to be identified. Then, the natural language processing (NLP) technique is applied to extract the keywords from the sentences such that they can be semantically matched with the concepts in the ontology. Once matched, the keywords can be used as the indications of the potential hazard information of the corresponding images. Then, synonyms of these keywords are identified based on the synonym dictionary that has been developed. The semantics of the annotation can be extended by introducing relevant semantic concepts of the ontology as additional keywords. In such a way, the matched keywords and their synonyms and the extended semantic concepts form the core data of the annotation of the target images.

In our research, PanGu Segment (Eaglet), a software application that can segment Chinese words from the sentence, is adopted to process the queried text. To ensure the accuracy of word segmentation, PanGu enables users to configure and customize the inbuilt dictionaries such as thesaurus extension, synonym establishment, and stop words configuration. In this paper, a synonym list is established based on Tongyici Cilin (Mei 1983) and Synonym Text of PanGu (Eaglet). According to the proposed semantic concepts of the information model, 130 synonym concepts related to hoisting works are incorporated into the dictionary.

To illustrate the annotation process, an example sentence "Small pieces have no reliable bearing container." is adopted and analyzed. After word segmentation and synonym identification, the output word set can be obtained where {materials, no, bearing, container} are four core semantic concepts. The extensions of the corresponding semantic concepts can be identified based on the ontology, which is listed below.

A = {person, hoisting, fix, container, bearing, push, beyond, weight},

B = {load, stabilization measure, aerial work platform, existence, warning sign, container},

C = {hanging basket, container, material, move, degree, air bottle, drop arm},

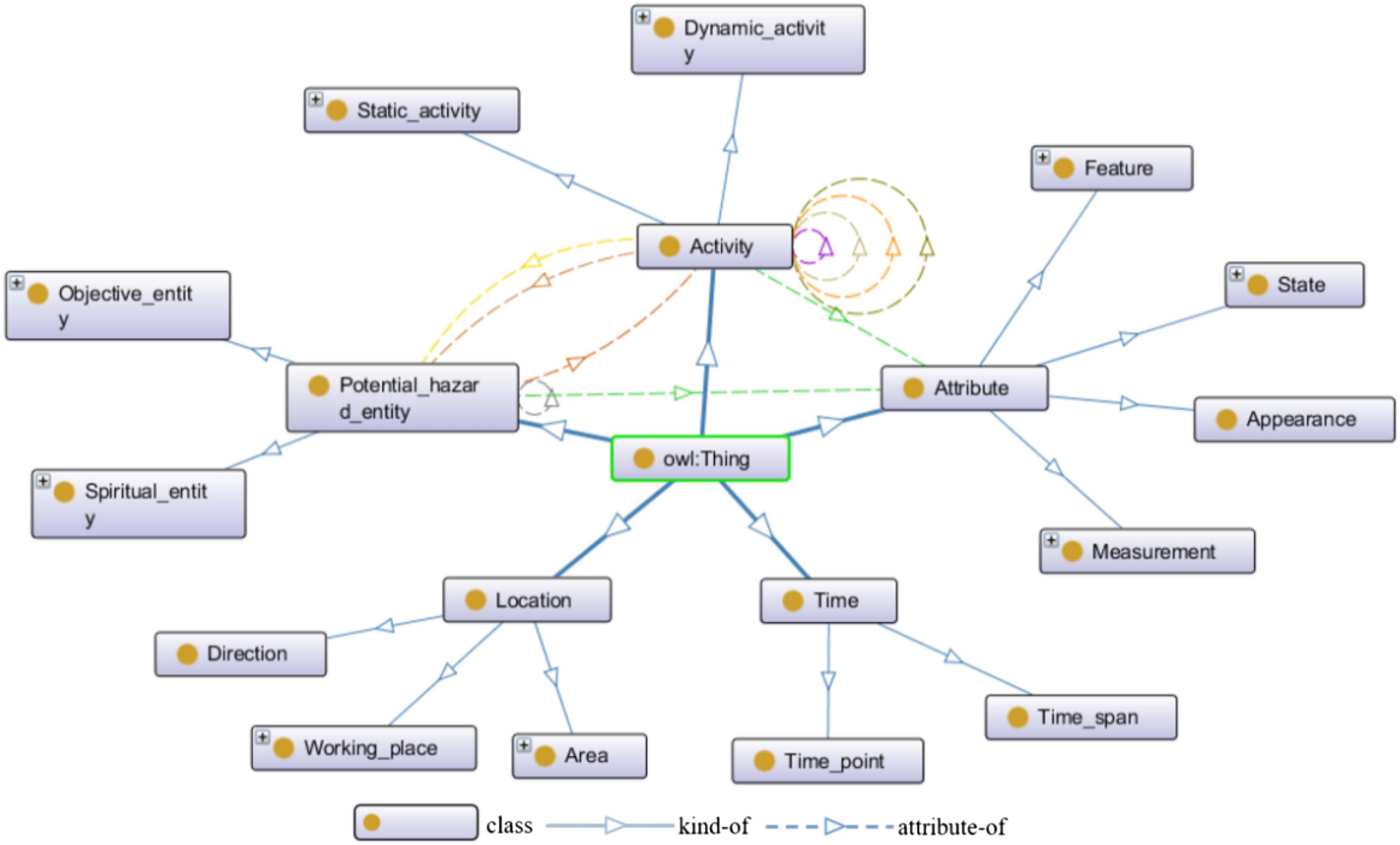

Fig. 6. Hazard information model by Protégé.

D = {construction equipment, quality, material, bearing, no}
Thus, the following semantic annotation set can be obtained {materials, no, bearing, container, A, B, C, D}

Semantic Similarity between Images

By using the annotations, the semantic concepts can be treated as the queried information and compared with the standard specifications such that the similarity between the images can be identified. The construction images can then be categorized by evaluating the similarity of their semantic annotation sets.

The semantic similarity method mentioned previously, proposed by Chen (2006), is adopted in this paper to calculate the semantic similarity of the concepts. Two steps are adopted to evaluate the similarity between the annotation sets: (1) semantic concept similarity; and (2) information item similarity. In this paper, a is equal to 0.5 through a large number of experiments β is 0.5, which aims to detect the concept similiraty in terms of the weight of semantic distance and semantic relevancy.

Validation and Results

Examples: Identification of Construction Hazard Implied in Images

To illustrate the process and effectiveness of our proposed framework, an urban metro project under construction in Wuhan, China, was selected. The web-based urban metro hazard management system is developed to facilitate inspections by the safety engineers and track construction hazards. In this system, a large amount of construction information, such as, images of construction hazards, construction tasks, construction location, construction hazards, and risk levels are recorded. In addition, images were analyzed and the potential hazards were identified and annotated manually with sentence describing the potential hazards, as shown in Fig. 8. For example, a construction image with an annotation "person is standing on the construction machine when hoisting" is chosen and analyzed. It can be seen that this image belongs to the category of "person stands on the hoisted object."

In this research, the hoisting work is selected as the case to validate the feasibility and effectiveness of our approach, therefore, only terms about hoisting work are used to enrich the dictionary of PanGu. For other types of construction work, more domain-specific terms should be added into the dictionary. Moreover, some other online resources, such as the Occupational Safety and Health Administration (OSHA) web site containing a large number of valuable keywords, can be used to supplement the dictionary.

A stop word list, which can be used to refine the word segmenting process, is established based on stop words developed in PanGu. There are mainly three kinds of word segment methods, i.e., unigrams, bigrams, and trigrams, specific multi-grams (TSMG). In PanGu, unigrams and bigrams are used respectively for cutting the text into a bag of one-word or two-words. TSMG means that an annotation text is cut into a bag of multiwords, including one-word and two-words. For TSMG, when a chunk in the text can be cut into several small-scale phrases and also can be cut into larger scale phrases, the latter is selected. In this paper, the TSMG method is selected to improve the efficiency of word recognition and segmentation because many domain-specific terms are composed of more than two words and their synonyms are also added into the dictionary.

After word segmentation and synonym extension, the analysis output of "hoisting workers stand on the machine" can be obtained.

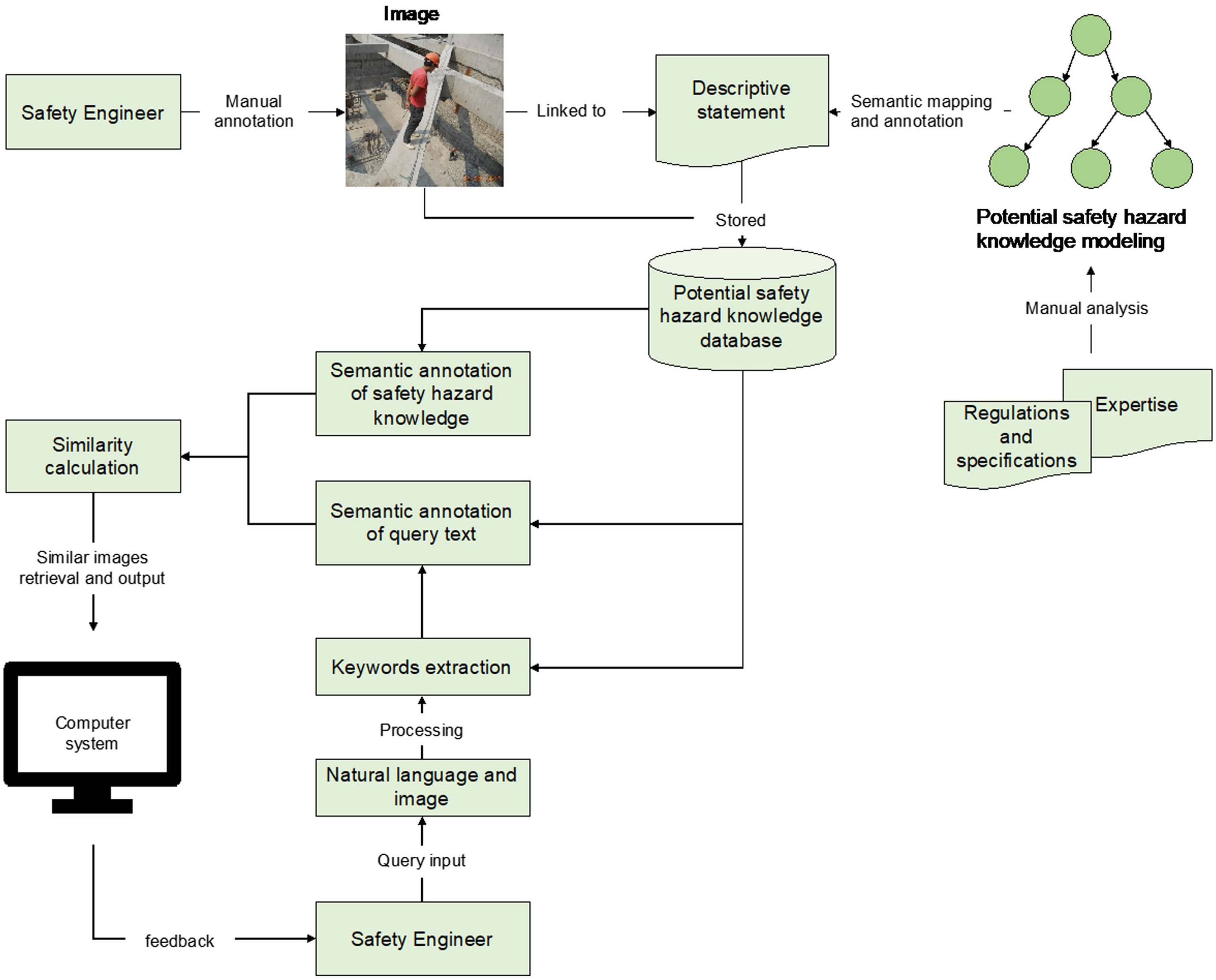

Fig. 7. Image processing framework for the construction hazard analysis. (Image by Weili Fang.)

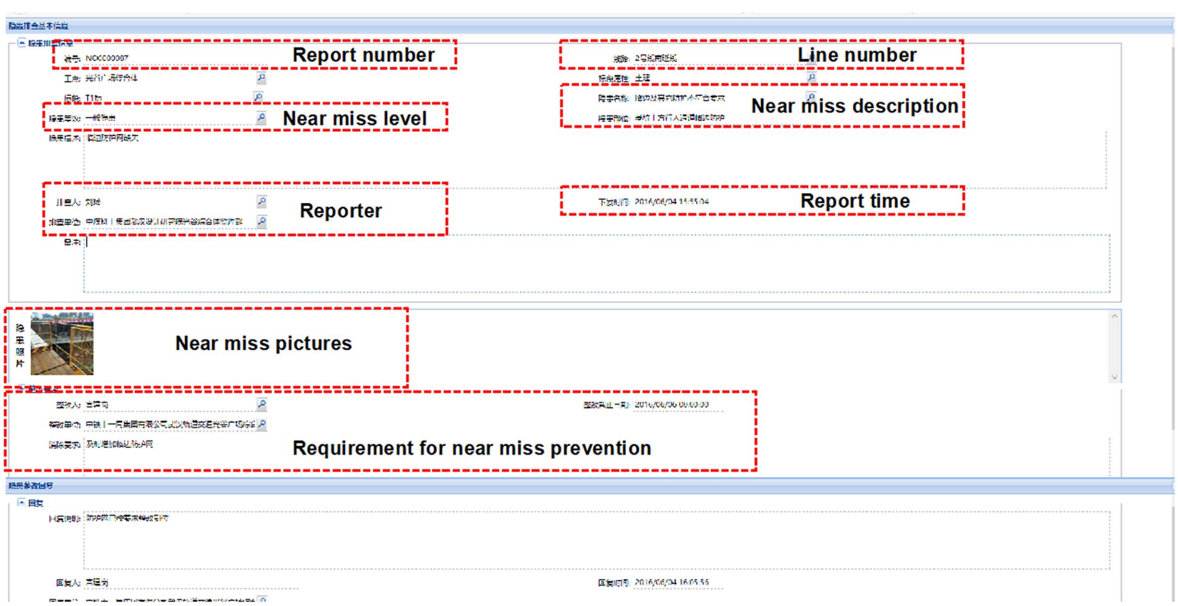

Fig. 8. Screen shot of the web-based urban metro hazard management system.

Table 6. Relevant semantic concept extension

Concept	Relevant semantic concept extension set
Existence	Exist, surface, ground
Material	Hazard entity, object, person, hoisting, setting, container, bearing, push, beyond
Construction machine	Construction machines and components
On	Space, person

"Hoisting," "construction machine," "person" and "on" are identified as the core concepts by matching the result with the ontology. Then these words are annotated using the corresponding semantic concepts such as "hoisting," "construction machine," "person" and "on." The corresponding semantic concepts of the standard specification are "hoisting," "object," "person," and "on." The relevant semantic concept extension is shown in Table 6, and the relevant semantic concept extension is shown in Fig. 9.

Then, the semantic similarity between the queried sentence and the standard specification can be calculated based on the annotation set. The semantic similarity between two different concepts can be obtained by calculating the weighted sum of the initial similarity and the semantic relevance.

The first step is to calculate the initial similarity $I_{sim}(C_1, C_2)$ which can be obtained by Eqs. (1) and (2).

For example, as shown in Table 6, the I_{sim} (existence, construction machine), I_{sim} (existence, on), I_{sim} (material, construction machine), and I_{sim} (material, on) were calculated through the following parameters: [*dl*(existence) = 4, *dl*(material) = 3, *dl*(construction machine) = 4, *dl*(on) = 4, mas*dl* = 4, *dist*(existence, construction machine) = 9, *dist*(existence, on) = 4, *dist*(material, construction machine) = 3, *dist*(existence, on) = 7]. The $dl(C_1)$ was decided by the semantic level in the developed semantic model.

Based on the initial similarity, the semantic relevancy of concepts can be defined through Eqs. (3) and (4). Finally, the semantic similarity between two different concepts can be obtained by calculating the weighted sum of the initial similarity and the sematic relevancy, as shown in Eq. (5). The similarity calculation process is shown in Tables 7–12.

Based on the semantic similarity of concepts, the information similarity is calculated by Eq. (5) as follows:

$$K_{12} = K_1 * K_2^T = \begin{bmatrix} 0.049, & 0.063, & & \\ 0.115, & 0.292, & & \\ & & 1 & \\ & & & 1 \end{bmatrix}$$

$$Sim(s_1, s_2) = \frac{1}{k}\sum_{i=1}^{k} Sim(\max s_i) = \frac{1+1+0.292+0.049}{4} = 0.586$$

We suggest that our proposed approach can be easily used for on-site safety managers. The construction safety engineers firstly manually annotate the images with sentences or phrases, which are treated as the query sentence and proceeded with the NLP. Based on our approach, the similar standard specification is recommended in the order of similarity. Then, the safety engineer can select the most similar one as the standard annotation, thereby identifying construction hazards implied in images. In this way, we suggest that our proposed approach has several potential advantages in practical applications. First. it provides a template and standard to help workers and safety engineers annotate the hazards implied in

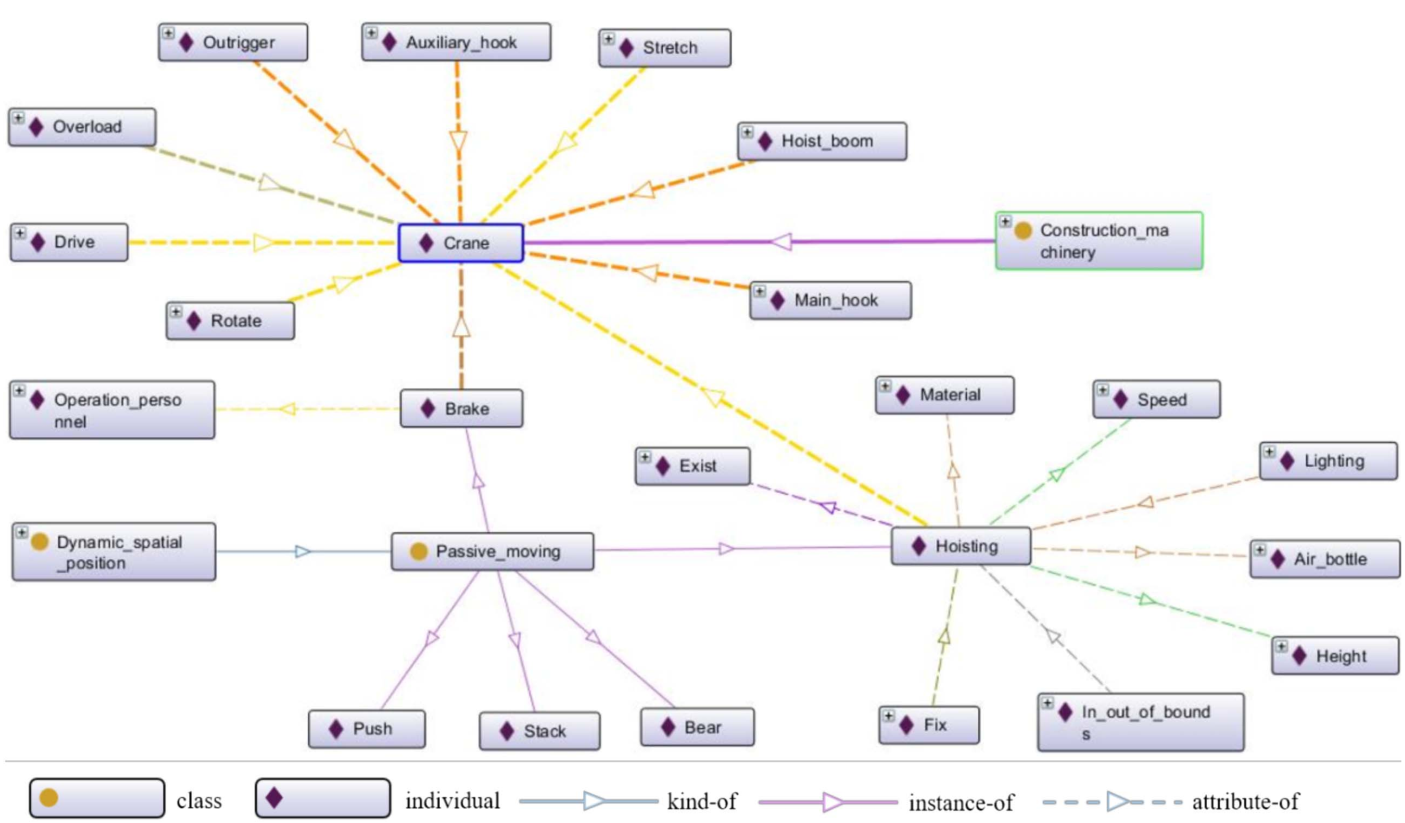

Fig. 9. The relevant semantic concept extension.

Table 7. Semantic concept initial similarity

Initial similarity ($Isim(C_1, C_2)$)		C_2 Construction machine	On
C_1	Existence	0.053	0.074
	Material	0.146	0.058

Note: $I_{\text{sim}}\{\text{hoisting, hoisting}\} = 1$; and $I_{\text{sim}}\{\text{person, person}\} = 1$.

Table 8. Semantic concept relatedness (1)

		Existence		
Semantic similarity ($sim(C_1, C_2)$)		Exist	Surface	Ground
Construction machinery	Construction machines	0.038	0.038	0.038
	Components	0.045	0.023	0.045

Note: $I_{\text{sim}}\{\text{exist, construction machinery}\} = 0.045$.

Table 9. Semantic concept relatedness (2)

Semantic similarity		Existence		
($sim(C_1, C_2)$)		Exist	Surface	Ground
On	Space	0.075	0.028	0.029
	Person	0.029	0.014	0.029

Note: $I_{\text{sim}}\{\text{existence, on}\} = 0.051$.

Table 10. Semantic concept relatedness (3)

Semantic similarity		Equipment	
($sim(C_1, C_2)$)		Construction machines	Components
Material	Hazard entity	0.139	0.083
	Object	0.083	0.095
	Person	0.083	0.095
	Hoisting	0.020	0.044
	Setting	0.039	0.044
	Container	0.020	0.044
	Bearing	0.020	0.044
	Push	0.020	0.044
	Beyond	0.039	0.044

Note: $I_{\text{sim}}\{\text{material, construction material}\} = 0.083$.

Table 11. Semantic concept relatedness (4)

		On	
Semantic similarity ($sim(C_1, C_2)$)		Space	Person
Material	Hazard entity	0.038	0.050
	Object	0.031	0.074
	Person	0.022	1
	Hoisting	0.026	0.039
	Setting	0.053	0.039
	Container	0.020	0.039
	Bearing	0.026	0.039
	Push	0.026	0.039
	Beyond	0.053	0.039

Note: $I_{\text{sim}}\{\text{material, on}\} = 0.526$.

images in the annotation sentence. This facilitates the process of image annotation and helps standardize the annotation style by using the recommended most similar regulatory text from the standard specification as the annotation to reduce the subject in the event that different safety engineers annotate the same images with different annotation sentences.

Table 12. Semantic concept actual similarity

Semantic similarity ($sim(C_1, C_2)$)		C_2 Construction machinery	On
C_1	Existence	0.049	0.063
	Material	0.115	0.292

Note: $I_{\text{sim}}\{\text{hoisting, hoisting}\} = 1$; and $I_{\text{sim}}\{\text{person, person}\} = 1$.

Second, our approach can be used to identify construction hazards (i.e., specific hazard categories) by classifying images according to standard specifications. Through automatic classification and comparison of incoming site images with semantically annotated images in the database, the specific hazard categories of the incoming site images can be determined and the corresponding necessary preventions can be arranged. Thereby, it offers an alternative method to enhance site safety management.

Performance Evaluation

Effectiveness of the Approach

To evaluate the performance of the proposed approach, seven categories of potential construction hazard information that are related to the hoisting works are selected and tested. The corresponding semantic concepts for each category are given in Table 13. Three different construction images that have been annotated with textual information are tested to illustrate the approach. The query texts are listed in Table 14. First, we calculate the similarity score between each query text with each category to evaluate the accuracy of the proposed method. The similarity scores are listed in Table 15.

The results of the queries can be examined according to the similarity of the semantic concepts as well as the similarity of the information items. For Query 1, the sentence contains three semantic concepts, i.e., "person", "construction machine," and "hoisting." It can be seen that two concepts, "person" and "hoisting" appear in both specification Clauses 1 and 3. Clauses 2, 4, 5, 6, and 7 each contain one concept while no concept can be identified in Clause 8. The similarity of the query and the specification increases when more common concepts are shared between them. Thus, Specification Clauses 1 and 3 are more likely to be associated with Query 1. A further examination reveals that Query 1 depicts the locations of person and construction machinery in hoisting tasks that is also presented in Specification Clause 3. However, Specification Clause 1 addresses the subject–object relation. Thus, Query 1 is more closely related to Clause 3. The similarity between Query 1 and Specification 2 is increased by the relation of person and hoisting contained in Specification 2 because the person is highly about workers. Clauses 4–7 describe the relations between hoisting tasks and the objects involved. According to the semantic information structure, similarity between Query 1 and the individual specification clause can be determined based on the distance of the corresponding semantic concepts.

Similarly, Query 2 contains the semantic concepts "hoisting," "person," and "alert area," among which "hoisting" is more closely related to "person." It can be seen that all the three concepts can be identified in Specification Clause 1 which indicates that it is highly related to Query 2. Moreover, as "worker" is similar to "person," Clause 2 possesses higher similarity to Query 2 than Clause 3.

Query 3 describes the unsafe location of the workers during hoisting tasks. Thus, specification clauses that regulate workers' behavior, hoisting operation, and alert area are more related to

Table 13. Categories of potential safety hazard knowledge of hoisting

No.	Potential safety hazard specification	Semantic concepts
1	Hoisting the objects of unknown weight	Hoisting, weight, object
2	Overload operation	Overload
3	The hoisted object has the floating object	Hoisting, object, setting, existence
4	Person enters the alert area when hoisting	Hoisting, person, on, alert area
5	Persons push the hoisted object directly without haulage cable	Set, haulage cable, person, push, object, hoisting
6	Not use the special hanging basket when hoisting air bottles	Hoisting, air bottles, special, hanging basket
7	No warning signs while hoisting	Hoisting, no, warning sign

Table 14. Query texts and the corresponding category

No.	Query text	Corresponding category
1	Person stands on the construction machinery when hoisting construction machinery	Person stands on the hoisted object
2	Persons enter the danger area in the hoisting process	Person enters the alert area when hoisting
3	Person is standing under the cargo boom when hoisting operation	Person enters the alert area when hoisting

Table 15. Similarity score between each query text with each category

		Semantic similarity					
		Query 1		Query 2		Query 3	
No.	Standard specification	Score	Rank ordering	Score	Rank ordering	Score	Rank ordering
1	Person enters the alert area when hoisting	0.534	2	0.623	1	0.585	1
2	Persons push the hoisted object directly without haulage cable	0.469	3	0.526	2	0.391	3
3	Person stands on the hoisted object	0.586	1	0.484	3	0.577	2
4	Hoisting the object of unknown weight	0.373	7	0.401	4	0.349	7
5	Not use the special hanging basket when hoisting air bottles	0.420	4	0.394	5	0.377	4
6	Person hoists objects without alert signs	0.383	6	0.373	6	0.373	5
7	The hoisted object has the floating object	0.384	5	0.329	7	0.364	6
8	Overload operation	0.108	8	0.109	8	0.288	8

Query 3. With this criterion, Clauses 1, 2 and 3 are ranked higher than 5, 6, and 7, while Clauses 4 and 8 have the lowest scores. It can be seen from Table 15 that using the ranking scores, the three images can be classified correctly.

Comparison with TF-IDF Method

To demonstrate the effectiveness of the proposed approach, the computation results are compared with those obtained by Term Frequency–Inverse Document Frequency (TF–IDF) method. TF–IDF is the most fundamental form of document representation and has the longest history. It is based on the bag-of-word scheme in which a document can be represented by a collection of words used in the document. TF–IDF also assumes that if a word is important for a document, it should repeatedly appear in that document whereas it should rarely appear in other documents. Most of retrieval is based on the keywords, to be more specific, TF–IDF is widely used for keyword-based retrieval. Albitar et al. (2014) has applied TF–IDF to calculate semantic similarity and demonstrate the effectiveness of it for text classification. Therefore, the comparison with TF–IDF in this paper can further prove the function of the proposed method. The similarity score obtained by the TF–IDF scheme is shown in Table 16.

From the results, Query 1 and Query 2 can be classified correctly. Query 3 is categorized into Specification 7, which should belong to Specification 4. In general, the actual similarity of the proposed method in this paper can more accurately reflect the relevance between knowledge items.

Limitations

It should be acknowledged that there still exist some limitations in this research. First, the identification of a construction potential hazard is based on the similarity calculation that is decided by the developed ontology model. Therefore, in the semantic modeling progress, it needs the domain experts (safety engineers) and the domain knowledge engineer to work together closely. Since the language computation lie heavily on the competency of the ontology and the taxonomy, the whole safety guidelines clauses should be analyzed, and the taxonomies should be prepared carefully to cover the domain concepts. However, the development of domain ontology is time-consuming. Considerable initial work needs to be done, which may hinder its applications. In the near future, the development of these ontologies can also serve as the starting point for further research.

Second, only the images about the hoisting work are collected for the illustration and validation. In the future, the other types of images should be collected for further validation of the approach and framework.

Third, we also note that in this paper we mainly focus on the potential hazards that are implied in the construction images.

Table 16. Similarity of TF–IDF scheme

No.	Standard specification	Similarity of TF-IDF scheme					
		Query 1		Query 2		Query 3	
		Score	Rank order	Score	Rank order	Score	Rank order
1	Person enters the alert area when hoisting	0.331	7	0.863	1	0.777	2
2	Persons push the hoisted object directly without haulage cable	0.549	5	0.547	3	0.488	4
3	Person stands on the hoisted object	0.904	1	0.272	7	0.308	6
4	Hoisting the object of unknown weight	0.331	8	0.662	2	0.155	8
5	Not use the special hanging basket when hoisting air bottles	0.621	4	0.342	6	0.387	5
6	Person hoists objects without alert signs	0.879	2	0.442	4	0.500	3
7	The hoisted object has the floating object	0.827	3	0.389	5	0.983	1
8	Overload operation	0.331	6	0.168	8	0.168	7

In fact, the construction risk identification also needs other information, not only the hazard implied in images. At the current stage, the annotation of construction imagery is done manually, which is time-consuming. The recent development of computer vision techniques enables automatic information extraction from digital images to be possible. These issues should be addressed in future studies.

Conclusion and Future Works

The paper introduced a novel ontological approach/model to represent the construction potential hazard implied in construction images. The Chinese specification Quality and Safety Inspection Guide of Urban Rail Transit Engineering is used for developing the taxonomies. The structure of HowNet is introduced and extended by incorporating specific taxonomies for the construction potential hazard analysis. Based on the semantic model, a framework is developed for processing construction images using semantic annotation and similarity calculation. This paper outlines the process of construction potential hazard identification using the ontology-driven semantic approach to facilitate classifying the construction images into the right categories automatically.

To validate the effectiveness and feasibility of our HowNet-based semantic approach, we undertake examples that derived from a rail project. The results demonstrated that our proposed approach was able to accurately classify and retrieve images. In this case, construction hazards are automatically identified. Examples are developed to illustrate the risk identification of the construction image about the hoisting work to demonstrate the feasibility of the approach that we proposed.

Benefits stemming from our approach and framework lie in the ability to automatically classify the images into the standard categories basing on the semantic model and similarity calculation, and further enable the automatic risk identification. Based on the framework, the potential safety hazard implied in the construction images collected in the database can be automatically identified via calculating the semantic similarity between the images.

Considering the accuracy of our proposed approach, we believe that there is considerable potential to automatically recognize construction hazards. Being able to identify construction hazards from images, which can be used for managers and site inspectors to improve intervention by management.

It also should be acknowledged that the method proposed in our research is still in the initial stages of development. This paper describes an initial effort on integrating the HowNet structure and ontology-based semantic similarity to implement automated classification of construction images. The results represented in this paper only provide an initial step toward developing a new construction safety management capability by annotating and automatically classifying hazards from images.

To enact the hazards identification system on-site for the improvement of safety performance requires further research, which would require a combination of computer vision and ontology. We suggest that computer vision can automatically provide information (i.e., object types, attributes) that is observed on-site, and ontological reasoning delivers the output necessary to perform complex hazards recognition.

Data Availability Statement

Data generated or analyzed during the study are available from the corresponding author by request.

Acknowledgments

This research is partly supported by "National Natural Science Foundation of China" (Nos. 51878311, 71732001, 71821001, 51978302, and 51678265) and China Scholarship Council (CSC).

References

Albitar, S., S. Fournier, and B. Espinasse. 2014. "An effective TF/IDF-based text-to-text semantic similarity measure for text classification." In *Web information systems engineering—WISE 2014*, edited by B. Benatallah, A. Bestavros, Y. Manolopoulos, A. Vakali, and Y. Zhang. New York: Springer.

Bottou, L. 2014. "From machine learning to machine reasoning: An essay." *Mach Learn* 94 (2): 133–149.

Brilakis, I., M. W. Park, and G. Jog. 2011. "Automated vision tracking of project related entities." *Adv. Eng. Inf.* 25 (4): 713–724. https://doi.org/10.1016/j.aei.2011.01.003.

Burdescu, D. D., C. G. Mihai, L. Stanescu, and M. Brezovan. 2013. "Automatic image annotation and semantic based image retrieval for medical domain." *Neurocomputing* 109 (8): 33–48. https://doi.org/10.1016/j.neucom.2012.07.030.

Chen, H., A. Trouve, K. J. Murakami, and A. Fukuda. 2016. "An intelligent annotation-based image retrieval system based on RDF descriptions." *Comput. Electr. Eng.* 58 (Feb): 537–550. https://doi.org/10.1016/j.compeleceng.2016.09.031.

Chen, J. 2006. "Concept similarity computation for domain ontology." *Comput. Eng. Appl.* 33 (42): 163–166.

China Building Industry Press. 2016. *Quality and safety inspection guide of Urban Rail Transit Engineering*. Beijing: China Building Industry Press.

Ding, L., W. Fang, H. Luo, P. E. D. Love, B. Zhong, and X. Ouyang. 2018. "A deep hybrid learning model to detect unsafe behavior: Integrating convolution neural networks and long short-term memory." *Autom. Constr.* 86 (Feb): 118–124. https://doi.org/10.1016/j.autcon.2017.11.002.

Ding, L., B. T. Zhong, S. Wu, and H. B. Luo. 2016. "Construction risk knowledge management in BIM using ontology and semantic web technology." *Saf. Sci.* 87 (Aug): 202–213. https://doi.org/10.1016/j.ssci.2016.04.008.

Dong, Z., and Q. Dong. 2003. "HowNet: A hybrid language and knowledge resource." In *Proc., Int. Conf. on Natural Language Processing and Knowledge Engineering Proc.*, 820–824. New York: IEEE.

Dong, Z., and Q. Dong. 2006. *HowNet and the computation of meaning*. Singapore: World Scientific Publishing.

Dun, L. I., M. A. Yong-Tao, and J. L. Guo. 2009. "Words semantic orientation classification based on HowNet." *J. China Univ. Posts Telecommun.* 16 (1): 106–110. https://doi.org/10.1016/S1005-8885(08)60188-0.

Fang, W., L. Ding, H. Luo, and P. E. D. Love. 2018a. "Falls from heights: A computer vision-based approach for safety harness detection." *Autom. Constr.* 91 (Jul): 53–61. https://doi.org/10.1016/j.autcon.2018.02.018.

Fang, W., L. Ding, B. Zhong, P. E. D. Love, and H. Luo. 2018b. "Automated detection of workers and heavy equipment on construction sites: A convolutional neural network approach." *Adv. Eng. Inf.* 37 (Aug): 139–149. https://doi.org/10.1016/j.aei.2018.05.003.

Fang, W., P. E. D. Love, H. Luo, and L. Ding. 2020. "Computer vision for behaviour-based safety in construction: A review and future directions." *Adv. Eng. Inf.* 43 (Jan): 100980. https://doi.org/10.1016/j.aei.2019.100980.

Fang, W., B. Zhong, N. Zhao, P. E. D. Love, H. Luo, J. Xue, and S. Xu. 2019. "A deep learning-based approach for mitigating falls from height with computer vision: Convolutional neural network." *Adv. Eng. Inf.* 39 (Jan): 170–177. https://doi.org/10.1016/j.aei.2018.12.005.

Fu, X., W. Liu, Y. Xu, and L. Cui. 2017. "Combine HowNet lexicon to train phrase recursive autoencoder for sentence-level sentiment analysis." *Neurocomputing* 241 (Jun): 18–27. https://doi.org/10.1016/j.neucom.2017.01.079.

Goh, Y. M., and D. K. H. Chua. 2010. "Case-based reasoning approach to construction safety hazard identification: Adaptation and utilization." *J. Constr. Eng. Manage.* 136 (2): 170–178. https://doi.org/10.1061/(ASCE)CO.1943-7862.0000116.

Gonçalves, F. M. F., and I. R. Guilherme. 2017. "Semantic guided interactive image retrieval for plant identification." *Expert Syst. Appl.* 91 (Jan): 138–153.

Guo, B. H. W., and Y. M. Goh. 2017. "Ontology for design of active fall protection systems." *Autom. Constr.* 82 (SC): 138–153. https://doi.org/10.1016/j.autcon.2017.02.009.

Guo, S., L. Ding, H. Luo, and X. Jiang. 2016. "A big-data-based platform of workers' behavior: Observations from the field." *Accid. Anal. Prev.* 93 (Aug): 299–309. https://doi.org/10.1016/j.aap.2015.09.024.

Jiang, S., J. Zhang, and H. Zhang. 2013. "Ontology-based semantic retrieval for risk management of construction project." *J. Netw.* 8 (5): 1212–1220.

Khoo, C. S. G., and J. C. Na. 2006. "Semantic relations in information science." *Ann. Rev. Inf. Sci. Technol.* 1 (40): 157–228.

Kim, H., K. Kim, and H. Kim. 2016. "Vision-based object-centric safety assessment using fuzzy inference: Monitoring struck-by accidents with moving objects." *J. Comput. Civ. Eng.* 30 (4): 04015075. https://doi.org/10.1061/(ASCE)CP.1943-5487.0000562.

Kim, J., S. Chi, and J. Seo. 2018. "Interaction analysis for vision-based activity identification of earthmoving excavators and dump trucks." *Autom. Constr.* 87 (Mar): 297–308. https://doi.org/10.1016/j.autcon.2017.12.016.

Konstantinou, E., J. Lasenby, and I. Brilakis. 2019. "Adaptive computer vision-based 2D tracking of workers in complex environments." *Autom. Constr.* 103 (Jul): 168–184. https://doi.org/10.1016/j.autcon.2019.01.018.

Kumar, A., S. Dyer, J. Kim, C. Li, P. H. W. Leong, M. Fulham, and D. Feng. 2016. "Adapting content-based image retrieval techniques for the semantic annotation of medical images." *Computerized Med. Imaging Graphics* 49 (Apr): 37. https://doi.org/10.1016/j.compmedimag.2016.01.001.

Kurtz, C., A. Depeursinge, S. Napel, C. F. Beaulieu, and D. L. Rubin. 2014. "On combining image-based and ontological semantic dissimilarities for medical image retrieval applications." *Med. Image Anal.* 18 (7): 1082–1100. https://doi.org/10.1016/j.media.2014.06.009.

Li, W., and C. Yang. 2016. "Combining channel theory, HowNet and extension model to analyze big data." *Procedia Comput. Sci.* 91: 452–459. https://doi.org/10.1016/j.procs.2016.07.118.

Lin, K. Y., and S. H. Hsieh. 2012. "Extracting construction safety domain ontology from job hazard analysis databases and construction safety standards." In *Proc., 14th Int. Conf. on Computing in Civil and Building Engineering*, edited by V. Telichenko, A. Volkov, and I. Bilchuk. Reston, VA: ASCE.

Lu, Y., Q. Li, Z. Zhou, and Y. Deng. 2015. "Ontology-based knowledge modeling for automated construction safety checking." *Saf. Sci.* 79 (Nov): 11–18. https://doi.org/10.1016/j.ssci.2015.05.008.

Luo, H., C. Xiong, W. Fang, P. E. D. Love, B. Zhang, and X. Ouyang. 2018. "Convolutional neural networks: Computer vision-based workforce activity assessment in construction." *Autom. Constr.* 94 (Oct): 281–289. https://doi.org/10.1016/j.autcon.2018.06.007.

Magesh, N., and P. Thangaraj. 2011. "Semantic image retrieval based on ontology and SPARQL query." In *Int. Conf. on Advanced Computer Technology.* New York: International Journal of Computer Applications.

Manzoor, U., A. Mohammed, B. Zafar, H. Umar, and M. Shoaib. 2015. "Semantic image retrieval: An ontology based approach." *Int. J. Adv. Res. Artif. Int.* 4 (4). https://doi.org/10.14569/ijarai.2015.040401.

Mehmood, Z., T. Mahmood, and M. A. Javid. 2018. "Content-based image retrieval and semantic automatic image annotation based on the weighted average of triangular histograms using support vector machine." *Appl. Intell.* 48 (1): 166–181. https://doi.org/10.1007/s10489-017-0957-5.

Mei, J., M. Zhu, Y. Gao, and H. Yin. 1983. *Tongyici cilin (Chinese Synonym Forest)*, edited by S. L. P. House. Shanghai, China: Shanghai Press of Lexicon and Books.

Russakovsky, O. et al. 2015. "ImageNet large scale visual recognition challenge." *Int. J. Comput. Vis.* 115 (3): 211–252.

Sharma, M. K., and T. J. Siddiqui. 2016. "An ontology based framework for retrieval of museum artifacts." *Procedia Comput. Sci.* 84: 169–176. https://doi.org/10.1016/j.procs.2016.04.083.

Tserng, H. P., S. Y. L. Yin, R. J. Dzeng, B. Wou, M. D. Tsai, and W. Y. Chen. 2009. "A study of ontology-based risk management framework of construction projects through project life cycle." *Autom. Constr.* 18 (7): 994–1008. https://doi.org/10.1016/j.autcon.2009.05.005.

Wang, H., and F. Boukamp. 2011. "Ontology-based representation and reasoning framework for supporting job hazard analysis." *J. Comput. Civ. Eng.* 25 (6): 442–456. https://doi.org/10.1061/(ASCE)CP.1943-5487.0000125.

Yu, Y., Y. Guo, Q. Ding, H. Li, and M. Skimore. 2017. "An experimental study of real-time identification of construction workers' unsafe behaviors." *Autom. Constr.* 82 (Oct): 193–206. https://doi.org/10.1016/j.autcon.2017.05.002.

Zhong, B., and Y. Li. 2015. "An ontological and semantic approach for the construction risk inferring and application." *J Intell. Rob. Syst.* 79 (3–4): 449–463. https://doi.org/10.1007/s10846-014-0107-9.