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An Analysis on Safety Risk Judgment Patterns Towards Computer Vision Based Construction Safety Management

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Abstract

Due to dynamic and constantly changing nature of construction projects, the highest accident and fatality rate makes the industry infamous in mitigating hazardous safety risks and protecting workers at jobsites. Despite of enormous efforts and serious attention by government agencies and professional bodies, current safety management still relies on traditional manual approach by auditing and supervising safety rule compliance which are infrequent, inefficient and prone to error. With the advent of new emerging technologies such as BIM, VR/AR, AI, computer vision, and big data analytics, various tech-based solutions to help manage and reduce site risks has been introduced during the last decade. Computer vision technology, in particular, has been most attractive to site safety monitoring by academics and construction startups around the globe. However, literature review has revealed that the vision-based researches are limited to object detection such as workers' PPEs and machines to help subsidize the manual approach prototypically. The purpose of this study is to propose a wide-range applicability of computer vision technologies by investigating safety risk patterns. In doing so, entire safety rules and clauses described in the Korea Occupational Safety and Health Agency (KOSHA) regulations of construction sector is reviewed and analyzed with safety experts. Four main safety risk judgment patterns were found and grouped for various vision technology applications. The remaining clauses was classified into two different types. It is expected that the findings of this study would provide an insight to researchers and developers in construction safety domain.

Keywords: KOSHA Rules, Computer Vision, Safety rule compliance, safety risk correlation pattern, risk recognition, safety monitoring

1. Introduction

Safety in construction remains a major issue. Despite various efforts to reduce the number of accidents and fatality in construction sites, accidents are still happening daily in the workplace. According to 26,570 records in the year 2016 from KOSHA, 29.3% of accident occurrences were from the construction sector [1]. These accidents, fatalities, injuries and near misses are costly which can be avoided by taking safety measures. Implementation of industry best practices and safety rules is one way to deal with construction safety [2]. Unfortunately, enforcement of regulations and best practices still relies on conventional safety procedures. Checking rule and best practices compliance to identify the potential hazards is a crucial step to effectively prevent accidents on a construction site [3]. Considering the conventional safety supervision, the safety manager has to physically visit the job site and visually observe every activity for potential hazards which is impossible and prone to error [4]. Traditional safety management-based risk detection and analysis are not sufficient to protect workers in construction job sites [5].

Many researchers have addressed the construction safety management issue recently by applying new technologies. Among the recent trend of technological research to enhance safety monitoring, computer vision holds immense potential [5,6]. To deal with the high fatality rates confronting the construction industry, there has been an advancement in computer vision-based safety monitoring research recently. The computer vision-based monitoring approach has the advantage of being able to systematically identify unsafe behavior and unsafe environments without affecting the productivity of workers in the field, with little additional cost to expand separate devices after automated monitoring system algorithms are deployed. Recently, many researchers considered computer vision application as a vital measure to deal with the construction safety management issue. However, most of these researches have limited narrow scope and consider some specific tasks only [6–8]. Hence, to ensure a safe working environment, KOSHA insight is inevitable to propose a comprehensive framework and check if the current state of the art advancement in computer vision technologies can adopt these rules in the construction site.

In order to propose a comprehensive KOSHA classification based image recognition technology approach for safety monitoring that should be feasible in practical use, it is necessary to deeply examine the KOSHA regulations for the extraction of information about all the construction entities that could lead to possible accidents. The KOSHA rules which show the positive relationship between the construction entities were grouped under Type-1: positive relation between objects, whereas the rules dealing with an inverse relationship between the entities were kept in Type-2: negative relation between objects. The Type-3: numerical judgment, categories the rules which show the numerical measures information for the safe operating procedure of an entity. On the contrary, the rules related to the establishment of risk zones were clustered in Type-4: determination of risk zones. Apart from that, the rest of the rules were classified under the category of "others" which includes the rules which can be covered by sensing or other technologies and some subjective rules which comes under the jurisdiction of management and administration. The articles related to management and administration for safety required at construction sites were excluded from the scope of this study.

2. Computer vision application in construction safety

Computer vision is an integrative field that deals with acquiring and processing digital images or videos to automate those tasks what the human visual system cannot perform. To automate the construction processes, several researchers have focused on computer vision technology for performance measurement, productivity analysis and safety monitoring [9]. In construction, many machine learning aided vision-based system has been developed to detect and track the construction entities (i.e. people, machinery and material), and recognize their unsafe behavior [6]. Despite the recent attraction and efforts of many researchers towards computer vision in construction safety, research being done in this domain is still premature to be applied practically. Concerning the KOSHA safety rules classification for effective implementation of image recognition technology in the real site, this paper reviews the concepts, techniques, and applications been done so far in construction safety and health.

3. Detection of unsafe acts based on correlation, numeric and risk area information

3.1. Positive correlation detection

The positive correlation could be the absence of a hard hat, failure to wear a safety harness while working on heights (person have a positive relationship with a hard hat and safety harness). To detect unsafe behaviour of a worker, Fang (2018) applied Faster-R-CNN to determine whether to wear or not, a protective helmet for job site workers [5]. To overcome fall accidents, another study from the same authors detects the safety harness and person while working at hights [6]. The previous efforts show the specific examples of recognizing construction entities and the positive relation between the entities. However, more insight is required to understand the comprehensive correlation structure among the construction entities advised in safety regulation by KOSHA.

3.2. Negative correlation detection

The negative correlation could be the risky actions having inverse relation with other construction entities (object/s) such as traversing structural members to take shortcuts, unsafe posture of humans to the ladder or scaffolding, the relation between electric wire and water, person and toxic material, etc. It was intended to identify the negative correlation of a worker to the given activity (leaning on handrails, dumping from height, climbing ladder) and determine if they have a hazard by depending on the body joints as parameters [10]. Likewise, to automatically recognize workers' unsafe behavior while using the ladder, Ding (2018) proposed a method of combining a convolution neural network (CNN) and long short-term memory (LSTM) to create a new hybrid deep learning model. Moreover, computer vision-based Mask-Region based Convolution Neural Network (Mask-RCNN) has been developed for detecting unsafe behaviour (the negative correlation between the person traversing and structural member) of individuals traversing the structural member in job site [7].

3.3. Object's numeric information extraction and detection

Visual monitoring of construction job sites needs numeric information (e.g. diameter, dimension checking, angle measurement, and weight) of the object for assessing several activities and ensure safe best practices. Many computer scientists focused on this domain considering some particular objects, yet, studies in this domain are still premature to be adopted practically in a construction site. In the manufacturing sector, a non-contact online approach was used to efficiently inspect, and measure the train wheel set's geometry based on optoelectronic measuring techniques employing a charged couple device camera[11]. Another study proposed multiple view images-based segmentation techniques with utilizing density formula to calculate steel bars weights [12]. To reduce the human input of manual measurement and automate the concrete workability test process, a 3D depth sensor (Kinect) based slump processing algorithm approach was proposed [13]. Considering the above example in the literature, the possibility of practical adoption of these techniques for the numerical measures to ensure safe operation of any tool or equipment in the real construction site is immense. To comprehend computer to detect unsafe behaviour based on the objects dimensions and specific numeric measure advised for safe operation, recognition of objects with additional spatial information (an object with numeric info) is requisite. The determine numeric information (angle of the ladder, dimensional information of object for calculating allowable weight for equipment or scaffolding, etc.) are then compared with specification and regulations to check the rule compliance and unsafe conditions.

3.4. Surrounding risk area recognition

This type of risk assessment recognizes sets of the risk zone and checks whether workers enter or leave the determined zone. As many construction worker's fatalities are related to struck-by events, for instance, workers on foot being in proximity to geo-referenced hazards or close to heavy equipment. To tackle these kinds of unsafe acts and conditions, one of the key considerations is to track the position of the resources [9]. Many previous studies attempted to automatically locate the real-time position of the construction entities using sensors technologies and computer vision techniques. However, computer vision-based tracking is getting popularity due to the advent of artificial intelligence aided vision technologies over sensor technologies such as non-contact, less cost and efforts. Vision-based tracking can generate a report of the temporal trajectory by assigning the consistent labels to the detected object [14]. Visual data were acquired from the readily available cameras in the heavy machinery and 3D position coordinates using a monocular camera to prevent the possible collision of workers and heavy equipment [15]. An Unmanned Aerial Vehicle (UAV) supported visual monitoring approach was proposed to tackle that struck-by hazards using YoloV3 and image rectification [16]. Similarly, a proactive construction hazard avoidance system that delivers hazards information through an augmented reality device is developed. The distance between the objects is calculated based on the spatial relation and the processed information that is safety level and distance are displayed using a wearable device (AR) [17]. The previous efforts depict significant contributions contemplating recent advancement in object tracking, however, due to the complex and dynamic environment of construction, object tracking is still challenging. One of the key limitations of the previous efforts is the limited application and narrow scope (i.e. human and specific equipment). To broaden the scope of computer vision-based tracking and risk recognition systems considering the risks and limited access zones, a deep analysis of regulations is needed.

4. Need for a safety rules classification structure

To enhance the construction safety management tasks, various technologies such as BIM-based safety planning, sensor and location tracking are being developed. However, the sensor, location-based technology applied to prior studies must be equipped with relevant devices in the worker's body or helmet, thereby reducing the efficiency of the work [17]. Also, devices are installed on a per-target basis, additional work is done to manage various components, and overspending is inevitable as the scope of control increases. On the contrary, the computer vision is getting popularity due to cost efficiency, does not need any attachments to the worker body and many efforts. Even though, currently, many researchers proposed very few computer vision-based systems with limited scope, as mentioned in the literature. To broaden the scope and develop a comprehensive computer vision-based risk recognition system, understanding of the safety monitoring expert knowledge such as industry best practices, accident cases, and safety regulations are mandatory. However, this study only focuses on the KOSHA regulations, specifically related to South Korea. This study aims to expand the scope of visual technology application for automatic safety rule checking during physical execution by exploring and classifying KOSHA rules. Therefore, this research developed a pattern-oriented classification of KOSHA rules that can employ a large scale of safety hazard recognition.

5. KOSHA legal analysis and classification

In 1953, labor standard law led the foundation for industrial safety and health policy in Korea. Thereafter in 1987, Korea Occupational Safety and Health Agency (KOSHA) was established with regards to the rapid development of industries in 1970 to 180. This research work used a logic-based mapping to interpret the safety rules from a human language such as KOSHA database to enhance technology advancement in machine learning. The name, type, and other properties were analysed and extracted from the rule. The rules were then classified into different groups based on the image recognition technology adoption nature. Rule translation typically has two aspects: (a) the condition or context where the rule applies and (b) the properties upon which the rule applies. The first step was identifying the target activity or object, for example, an activity such as foundation concrete work or a building element such as a rooftop. the second step was then checking whether the KOSHA rule related to this specific activity or element can adopt the state of art image recognition technologies or not.

Table 8 Analysis of KOSHA Regulations

Classification		Sub-level clause	Percentage
Application of Image Recognition Technology	Type-1: Positive relation between objects	214	25.9
	Type-2: Negative relation between objects	91	11
	Type-3: Numerical judgment	119	14.4
	Type-4: Determination of risk zones	52	6.3
Subtotal		476	57.6
Other	Rules covered by other technologies	106	12.8
	Clauses related to managerial and administrative issues	245	29.6
Total		827	100

The rules of KOSHA consist of 671 articles in 13 chapters, of which 277 are related to the construction industry. The 277 articles have then been categorized and broken down to the sub-category detail level. These 277 standards further contained 827 clauses that were thoroughly investigated and classified within this study. Articles that can adopt the visual judgment and measurement tools were then analyzed to classify statutes deemed necessary for the application of image recognition technology as shown in Table 2.

As a result, the KOSHA rules that were being considered applicable to the image recognition technology were noticed approximately 57% of the total articles, as depicted in Table 1. In addition, 29.6 percent of articles were not able to cope with the technologies. Among them, 12.8 percent were expected to be covered with other information and communication technologies (ICT). Thus, the remaining 43% of the rules that were unable to be adopted by IRT were categorized as “other” and were excluded from this research.

5.1. Type-1: Positive relation between objects

The positive relationship refers to two targets that must be presented together and are considered a hazard if one of them exist without the other one. Mainly, the positive relationship refers to determining whether a safe facility is installed and whether the protective gear is equipped or not. For example, in the site, while attempting welding activities fire extinguisher must exist near the welding area to prevent any hazard actions from occurring. For illustration, figure 1 shows some example of extracted rules from KOSHA for positive relation between the objects: (a) outriggers having positive relation with mobile scaffolding, (b) guardrails with mobile scaffolding, (c) stabilization base plate for scaffolding and (d) fire prevention shield while working with wielding.

Figure 13 Example of positive relation between the objects: (a) outriggers with mobile scaffolding, (b) guardrails with mobile scaffolding, (c) stabilization base plate for scaffolding (d) fire prevention shield with weilding machine

According to article 32 of KOSHA, the worker should wear protective gear in the following situations: 1. protection helmet; work in which there is a risk of falling or flying objects or falling workers. 2. Fall-protection built; working in a place at the likelihood of falling more than two meters in height or depth. 3. protection shoes; falling and landing on heavy objects, equipment or shocked by electric charges. 4. Googles; operations that may cause objects to fly. 5. Fire extinguisher; work where there is a possibility of sparks or objects flying during welding. 6. Electric shock preventing gloves; activities at a chance of electric shocks. 7. Heatproof clothing; operations that may cause burns due to high heat. 8. Dustproof mask; in the dusty weather or activities required putting on a dustproof mask as illustrated in Table 2.

Table 9 Example of a positive relationship between two objects

Location/activity/condition	Object A	Object B
In the job site	Worker	Helmet
Depth or height more than 2m	Worker	Hock (fall-protection belt)
In the job site	Worker	Shoes
Holding equipment	Worker	Googles
Risk of sparks or flying objects	Welding	Extinguisher
Cables or electric work	Wire, circuit box	Protection gloves
Welding	Fire, sparkling objects	Heatproof clothing
Dusty weather	Worker	Dustproof mask

5.2. Type-2: Negative relation between objects

In this case, two target objects should not be compatible with one another, and they are supposed to be a hazard and be determined as a direct risk factor, if present together. For instance, Type-2 focuses on electric shocks of electric machinery and appliances as mentioned in Article 302 of KOSHA (Ground of Electric Machinery and Instrument), Article 303 (Equipment of Electrical Machinery), Article 304 (short circuit breaker of Electrical Equipment). Figure 2 exemplified negative correlation between objects: (a) water with electric wire having negative relation, (b) explosive gas container having inverse relation with electric wires,

(c) ladder should not be used aerial lift platforms (d) awkward climbing action on scaffolding also shows unsafe behavior based negative correlation.

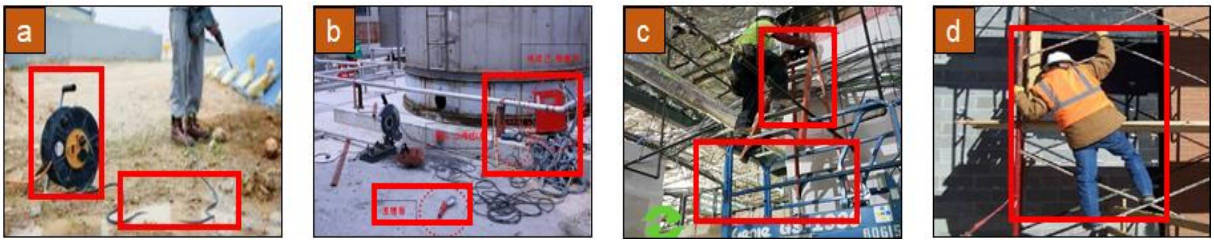

Figure 14 Example of negative relation between objects: (a) Water having negative relation with electric wire, (b) Explosive gas container having inverse relation with electric wires, (c) Ladder on aerial lift platform (d) Awkward climbing action on scaffolding

In the job site, liquids and water that can transmit electricity have a high danger factor when existing near or meet the electric installments. Therefore, electrical machines and appliances used in wet places are at risk of electric shock. It's advised to take preventive actions such as installing an electric leakage breaker. As a result, electricity transmitting liquids and machinery working on batteries or electric source appliances have a negative relationship with each other, and If the two targets coexist, they are perceived as a hazard as shown in Table 3.

Table 10 Example of negative relation between objects

Location/activity/condition	Object A	Object B
Near	Electric equipment	Inflammable substance
Near	Welding sparkles	Anti-falling net
Close to	Flammable liquid	Fire source
Under	Aerial lift platform	Ladder
Climbing action	Worker	Scaffolding/Ladder

The ladders using mobile scaffolding in the site is also considered an example of negative relationality. The article 68 (mobile scaffolding) of KOSHA restricts people from working with support or ladder on the work bed supported by mobile scaffolding. In the case of having a moving scaffolding recognizing a ladder installed above a moving scaffolding, it has a negative relationship and considered a hazard.

5.3. Type-3: Numerical judgment

Type-3 determines numeric information of a target, such as a length, spacing, and angle of the target object advised by the industry best practices and safety rules for the safe operation of the required tools and equipment. Failure to fulfil the required conformity, the system should raise alarm when measurements are outside the acceptable threshold. First, an example of installation intervals is a guard rail installed to prevent the falling risk. The temporary rail consists of rail handler, middle railing, and columns, which shall be installed at least 90 centimetres from the floor surface, and in case the rail handler height is more than 120-centimeter, then mid-bar should be installed. The gap between the rail handler and the floor surface should not exceed 60 cm in the cases illustrated above as shown in Figure 3. Next, scaffolding installation main bars should be horizontal/vertical, as mentioned in article 70 of KOSHA as shown in Figure 3. Other minor measurement standards related to scaffolding and machinery in different scenarios can be analysed and integrated within Type-3 as illustrated in Figure 3.

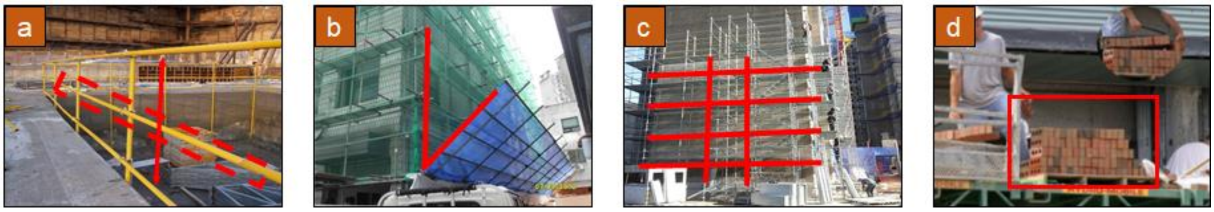

Figure 15 Example of Numerical judgment (Type-3): (a) Guardrails dimensions and specification for safe operation (b) Angle of safety net (c) horizontal and vertical distance and level checking (d) Load calculation of bricks on the scaffolding

5.4. Type-4: Determination of risk zones

As many construction worker's fatalities are related to struck-by events, Thus KOSHA advise many rules to make sure the safe working environment for construction worker. This type of risk assessment requires real time information to recognizes the controlled zone and checks whether workers enter to the determined zone. To tackle these kinds of unsafe acts and conditions, one of the key considerations is to track the position of the resources. For instance, lifting work using cranes where the load passing over the worker's head is prohibited, and the trace path of the cargo is considered controlled danger zone for workers, as shown in the Figure 4. Apart, it further includes prohibiting the workers from entering the loading area to prevent struck or collision with the unloading machines such as a forklift, etc, as illustrated in Figure 4.

Figure 16 Determination of risk zones:(a) worker entering to the proximity zone (b) risk zone under lifted material by crane (c) controlled zone around the opening in floor (d) controlled zone for the scaffolding work.

6. Discussion and conclusion

The purpose of this study is to propose a wide-range applicability of computer vision technologies by investigating safety risk patterns. In doing so, entire safety rules and clauses described in the Korea Occupational Safety and Health Agency (KOSHA) regulations of construction sector is thoroughly reviewed and analyzed with safety experts. Four main safety risk judgment patterns were found and grouped for various vision technology applications: Type-1: positive relation between objects, Type-2: negative relation between objects, Type-3: numerical judgment, and Type-4: determination of risk zones. The rest of the remaining clauses was classified into two different types - 'Clauses related to managerial and administrative issues' and 'Others'. Each safety risk pattern is matched with applicable computer vision technologies such as deep learning-based image recognition and processing algorithms. These findings of this study would provide an insight to researchers and developers in construction safety domain, though it is quite difficult and challenging to be realized at construction sites. The computer vision technology has a potential to greatly change current manual safety monitoring practices nonetheless and would help step towards global tech-based site management with other traditional management issues such as progress measurement, defect prevention, and so on.

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