A Review of Data-Driven Accident Prevention Systems: Integrating Real-Time Safety Management in the Civil Infrastructure Context

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Abstract –

Statistical reports point to the fact that civil infrastructure projects remain hazardous working environments. Despite the implementation of various safety procedures, the frequency and cost of work-related injuries are significant. Improvements in sensor technologies, wireless communication and processing power of computers as well as advancements in machine learning and computer vision are now enabling data-driven systems as effective safety barriers for accident prevention. In recent years, many researchers have studied various methods of leveraging technology to improve safety in civil infrastructure projects. However, previous investigations have not produced a thorough analysis of the practicality of those approaches. While considerable progress has been made in developing methods to improve construction safety, few studies have focused on implementation of data-driven real-time accident prevention systems to effectively minimize risk in the event where other safety measures have failed or been absent. Motivated to facilitate the development of such method, this paper carries out thorough analysis of the field and its trends, identifies research gaps, provides a discussion of recent advancements, and highlights future research directions to help researchers gain an up-to-date overview of the state-of-the-art and navigate through this domain efficiently.

Keywords –

Automation; Behavior related accidents; Building information modeling (BIM); Infrastructure sector; Construction safety management; Information Technology; Machine learning; Neural networks; Object detection; Risk analysis and control; Sensors

1 Introduction

Around 15% of occupational fatal accidents have occurred on construction sites across Australia, where construction only accounts for 5% of the workforce [1]. In the same year, United States construction fatalities alone amounted to 991 lives lost [2]. In the past decades, research on safety climate and culture, worker-oriented safety, safety management programs, hazard recognition and risk assessment, and applications of information technology in construction safety has led to improvements in overall safety performance [3]. However, the number of fatal and non-fatal accident injuries still remain significantly high in the construction industry.

Recent advancements in machine learning, computer vision, and increased affordability and processing power of advanced technologies have prompted researchers to work towards the development of data-driven accident prevention systems, adding a technology-driven safety layer to construction sites.

Given that safety is an ongoing issue on the construction site, the development of continuous safety monitoring systems has great potential to improve safety risk management. As described by Australia's Work Health and Safety Act (WHS), the risk management process involves identification hazards, assessing risks, controlling risks, and reviewing control measures [4], [5].

This paper provides a review of recent developments of data-driven accident prevention systems designed to improve construction safety. It reveals the trend of technologies and approaches being used, and discusses their potential applications, and identifies future research directions. As such, it can be used as a guide for researchers interested in this particular domain to study an up-to-date account of state-of-the-art research.

2 Review methodology

A methodological approach is employed to conduct a comprehensive review. Scopus was selected as the database for the search, and the keywords such as construction safety management, machine learning, computer vision, sensors, information and communication technology, building information modeling and so on, were used for the initial search. The returned results are screened based on their title and abstract, and out of 982 documents, 118 were found to be relevant. To ensure a more comprehensive and thorough search, an explorative search was also carried out, leading to an additional 125 documents found, amounting to a database of 243 journal articles in total. Section 3 provides an overview of the selected articles, and critical review of the most relevant papers is carried out in section 4 of this study.

3 Analysis of the domain

The database of the selected papers cover articles published from 2006 to 2018. The number of relevant papers did not exceed 6 before the year 2012. In the past few years, however, the number of publications have risen significantly, due to increased interest in using sensor technologies and vision-based systems, wherein 2018 it nearly doubles to 78 publications. The analysis reveals that the United States, China, and South Korea are the top three countries contributing to the domain. Figure 1 shows the distribution of selected articles by year and country of affiliation.

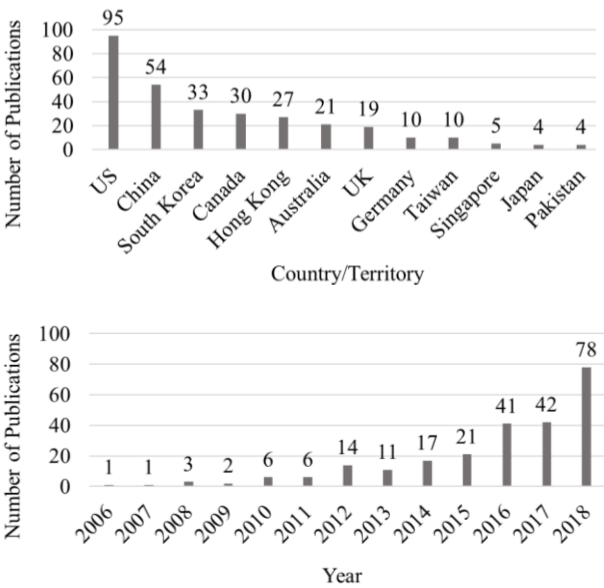

Figure 1. Distribution of articles by publication time, and country of affiliation

Table 1. Journals and the number of corresponding articles

Journal	Number of Appearances
Automation in Construction	93
Advanced Engineering Informatics	23
Journal of Computing in Civil Engineering	21
Journal Of Construction Engineering And Management	17
Safety Science	16
Visualization in Engineering	12
Sensors (Switzerland)	6
Engineering Construction And Architectural Management	4
Journal Of Management In Engineering	4

The selected studies include publications from more than 35 different journals. Table 1 lists the journals publishing more than four papers within the selected list of articles. Not surprisingly, Automation in Construction has contributed the most to this domain, with more than 38% of the papers being published in this journal. Other relevant journals include Advanced Engineering Informatics, Journal of Computing in Civil Engineering, Journal of Construction Engineering and Management, and Safety Sciences, each representing more than 15 papers in the selected database.

Based on the database of selected articles, co-publication of authors are analyzed using Gephi, an open source graph and network analysis software [6]. Figure 2 shows the network of the most prominent scholars, active in the domain.

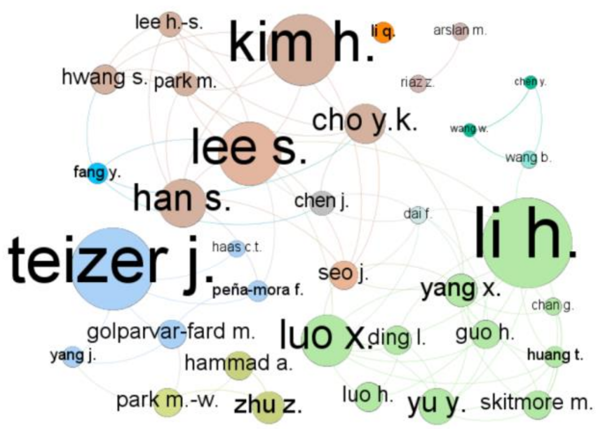

Figure 2. Network of the most influential scholars in the domain

4 Data-driven safety risk management

This section provides an overview of latest developments in data-driven accident prevention systems and discusses their relation to various steps of safety risk management as described by Australia's Work Health and Safety Act (WHS) [4], [7]. The following subsections cover the impact of such systems on identification of hazards, assessing risks, controlling risks and reviewing control measures.

4.1 Hazard identification

Hazard identification is the process of finding entities or situations that have the potential of causing harm. Developing data-driven systems for real-time hazard identification is a crucial step towards intelligent safety management. Three different approaches to hazard identification are discussed in this section. First, an indirect approach, which attempts to identify hazards by analyzing data from the construction site for anomalies that may be suggestive of an existing hazard. Second, identifying hazards as they directly relate to workers' behavior. And the last approach is to monitor the workplace for specific anticipated hazards.

4.1.1 Indirect hazard identification

Considering the dynamic nature of a construction site, regular safety inspections need to be carried out to ensure a hazard-free work environment. However, since inspections are often manually performed, it is not uncommon for newly appeared hazards to remain unidentified for a prolonged period of time, exposing workers of the site to risks of trip, fall, struck by falling objects, electrocution or other accidents. Continuous monitoring of the site can therefore immensely facilitate safety management. An innovative approach to automatically identify hazardous areas has been proposed by Kim et al. [8]. In this study, a real-time tracking system is used to identify potentially hazardous areas by comparing workers' actual path to their optimal routes. Location tracking is performed using an RFID-based Real-Time Location Tracking System (RTLS), where RFID tags are mounted on workers' hardhats. Upon testing the framework in a case study, it was found that 80% of the identified hazards by the system corresponded to real hazards such as material piles, openings, areas with inadequate electric wire protection, and areas with a lack of falling object protection.

Although RFID technology is used in various industries for tracking some entities, the rapidly changing nature of the construction sites and their complexity make effective use of RFID very challenging. RFID requires a direct line of sight for optimum accuracy, which is a condition hard to realize in construction. In addition, it requires installation of multiple tags and receivers which limit its practicality [9].

Ultra-wideband (UWB) is another radio frequency-based technology used for location tracking. UWB uses high-bandwidth radio pulses for communication, which makes it less susceptible to signal interferences. However, it still requires installation and maintenance of multiple tags and receivers [10].

Global Positioning System (GPS) has also been widely used to track workers' trajectories in construction sites in order to improve safety. For instance, Arslan et al. [11] demonstrated a prototype of a GPS-based system for identifying stay points, the intersection of multiple trajectories, and classifying the trajectory into running or walking. Such semantic enrichment of data using various data mining and machine learning techniques helps improve the decision-making process by providing insight on workers' behavior.

Vision-based systems as an alternative to other methods for tracking various entities on construction sites has recently attracted researchers' attention. Although still in early stages of development, vision-based systems have the advantage of not requiring installation of multiple tags, have lower costs, and are easier to maintain.

Park et al. [12] propose a vision-based method that uses videos obtained from ordinary 2D cameras, and employs detection and tracking algorithms in a hybrid system for tracking entities. However, the method is limited to tracking workers across video frames, and is unable to produce trajectories with respect to the workplace.

In another study, Konstantinou et al. [13] developed a framework for obtaining 3D trajectories using multiple camera views. The proposed method uses three sequentially activated matching techniques. The output of a 2D tracking method is first checked using a motion matching technique, followed by a geometry matching, and finally a template matching technique. In any step if a match is found, further checking is terminated, therefore significantly reducing the required computational power.

In a comparative study, Xiao et al. [14] evaluated the performance of a number of 2D vision-based tracking methods employed in the context of construction. Their study showed that although vision-based systems have promising potentials, many challenges such as occlusion, clutter, illumination, and scale variation need to be tackled for practical deployment of such systems.

Another innovative approach for identifying potential hazards based on real-time information obtained from construction site was proposed by Yang et al. [15]. They propose using wearable Inertial Measurement Unit sensors to analyze workers' gait abnormalities to identify potential fall hazards. In their experiment, subjects were asked to walk across a steel beam in a controlled environment. There were two hazards placed along the beam, a slippery surface, and an obstacle. Upon analysis of data obtained from multiple subjects, it was found that the correlation between collective gait abnormality and presence of a hazard is significant. However, this study was limited to one dimension only. The extension of such method to two or three dimensions by taking advantage of location tracking methods as discussed above would provide valuable information that could be used for effective real-time hazard identification. Moreover, such spatio-temporal data enriched with information about gait pattern, activity, etc. can be used for further analysis.

4.1.2 Behavior-related accident precursors

Construction accidents are often directly related to the worker's behavior. In an investigation of identifying the root causes of accidents, Abdelhamid et al. [16] explained that accidents occur either due to the failure of workers in identifying hazards, workers deciding to proceed despite identification of hazardous condition or workers deciding to act unsafely regardless of work condition.

Real-time safety monitoring systems have great potential to be used as supplementary tools for safety supervision. Workers' disregard of hazards often manifests itself in lack of adequate personal protective equipment usage. Recent advancements in computer vision and machine learning provide powerful tools for object detection using images. For instance, Park et al. [17] used Histogram of Oriented Gradients along with Support Vector Machines to detect human bodies and hardhats, and by matching geometric and spatial relationship of the two, identify cases where the person is not using a hardhat.

Fang et al. [18] developed a method for monitoring appropriate usage of harness, anchoring and hardhats by steeplejacks. In the proposed method, cameras are installed inside the rooms and facing the windows where steeplejacks are to perform the aerial work on exterior walls. They use the Single Shot MultiBox Detector (SSD) algorithm, which uses Convolutional Neural Networks (CNNs), and reported precision and recall rates of higher than 90%.

In a similar study, Fang et al. [19] used Faster R-CNN, and a deep CNN model to identify workers not wearing a safety harness when working at height. Using automated safety inspections, safety managers can be notified of unsafe behaviors, and take appropriate action to mitigate the risks in a timely manner.

A different approach of identifying unsafe behaviors was proposed by Guo et al. [20] whereby they used depth cameras to identify various postures related to unsafe behavior. Various body angles obtained from the skeleton-based posture information are compared to an unsafe behavior database in order to identify postures that are suggestive of unsafe actions, such as jumping over a guardrail or dumping construction waste from higher levels.

Other forms of unsafe behavior leading to hazardous conditions include working under the influence of drugs or alcohol, working under a high level of fatigue or attempting a hazardous task with low relevant skill level. One example is the loss of balance possibly induced by the aforementioned factors. To address this issue, Umer et al. [21] developed a balance monitoring tool that uses wearable Inertia Measurement Units (IMUs) and fuzzy set theory to determine workers' balance performance by taking 20-second tests at different times of the day.

Monitoring physiological condition of workers using Physiological Status Monitors (PSMs) has also been explored [22]. Using these methods, metrics such as heart rate and breathing rate can be monitored, providing valuable information for identifying unsafe working conditions as they arise.

High levels of stress induced by schedule pressure or other factors may cause workers to act unsafely in certain conditions. Therefore, it is essential to provide a work environment, which is free of stress-producing conditions.

4.1.3 Workplace-related accident precursors

Certain hazards can be identified by monitoring the workplace for specific accident precursors. One example is site congestion. Congested working areas are more prone to accidents. Location tracking systems as discussed in section 4.1.1 can enable workplace analysis in terms of congestion. Zhang et al. [23] used GPS sensors attached to workers' hardhats to track their activity while working on cast-in-place concrete columns. The workspaces were then visualized in a BIM platform to identify conflicts among other work-zones or material handling paths.

Environmental factors of the site such as temperature, noise level, and pollutants are important workplace hazards that require constant monitoring. For instance, Riaz et al. [24] have proposed using wireless sensor networks for monitoring workplace temperature conditions, and integrating the system with a BIM platform for enhanced work and safety management.

Temporary structures on construction sites are another aspect requiring a thorough inspection to ensure all safety requirements are met. Safety inspection of scaffolds, for instance, is performed visually by the inspector and is a labor-intensive process. Cho et al. [25] proposed a system for real-time safety monitoring of the structure using strain sensors mounted on the scaffolds. With the aid of Finite Element Method (FEM) analysis, they develop a machine learning model to classify various states of the scaffolds such as over-loading, uneven settlement, and over-turning based on the data obtained from the strain sensors.

Vision-based systems also have the potential to be used as an effective monitoring method to ensure worksite safety. Kolar et al. [26] explored using transfer learning and CNN-based models for detecting guardrails in images. Furthermore, an improved version of Faster R-CNN can be used for detecting workers and equipment in images of civil infrastructure projects [27].

Often in construction sites, workers are required to perform their task alongside heavy equipment in a shared working area and therefore are exposed to high risk of struck-by accidents. Developing proactive real-time alarm systems are another active area of research. In a recent study, Soltani et al. [28] developed a method, fusing computer vision based systems with real-time location systems to estimate the poses of excavators in three dimensions, using surveillance cameras installed on the construction sites as stereo-cameras.

Understanding task-specific accident precursors, and defining quantitative metrics for evaluation of unsafe behaviors or conditions will facilitate the development of effective real-time monitoring systems.

4.2 Risk Assessment

Assessing risks associated with the identified hazards requires consideration of how severe the consequences are if someone is exposed to the hazard, and how likely it is to occur. Data-driven systems facilitate the process of risk assessment and reduce the bias caused by the subjectivity of the analysis.

The context in which hazards appear and the co-occurrence of various hazards determine the severity and likelihood of risks. For instance, in the case of struck-by accidents, heavy equipment approaching a worker in a congested working area is more likely to cause an accident than one approaching worker spacious area. Similarly, the close proximity of a worker and equipment is more indicative of high risk if the worker is standing in the blind spot of the equipment. Seo et al. [29] developed a method to monitor struck-by accidents using computer vision. They propose using fuzzy inference for determining the safety level, based on risk factors such as congestion and proximity.

Evaluating safety and health risks associated with a given task is another important part of safety management. A number of studies have focused on methods of performing ergonomic analysis in a minimally intrusive way. The rapidly changing and complex nature of construction make reliable ergonomic assessment challenging. To address this issue, researchers have developed data-driven systems to quantitatively perform ergonomic risk analysis [30]. The outcome of such systems can be used to improve safety training, planning, and task design.

For instance, insole pressure sensors have been used to detect and classify awkward working postures. In a study, Nath et al. [31], using accelerometer and gyroscope sensors built-in in smartphones, and machine learning algorithms estimated duration and frequency of various activities. And by doing so evaluated the overexertion risk level associated with the task.

Vision-based systems have also been used to perform ergonomic risk assessment using posture analysis based on body angles. Golabchi et al. [32] proposed a framework for data collection, analysis, and visualization to facilitate ergonomic analysis. Vision-based techniques that utilize CNNs, to estimate 3D skeleton of the subject from 2D images for ergonomic assessment have also been reported.

Risk assessment is a crucial step in safety risk management. Therefore, development of effective automated safety monitoring systems requires the integration of data-driven risk assessment systems into the frameworks.

4.3 Control risks

Controlling risks, once identified and assessed, can be categorized into three levels based on their effectiveness. The most effective level of control is elimination [33]. Real-time safety monitoring systems facilitate elimination control by identifying newly appeared or unidentified hazards and informing safety managers or site supervisors, which will then take the necessary steps to eliminate the risks if applicable.

The second level of control includes substitution of the hazard with a safer alternative, isolating the hazard from people, or reducing the risks through engineering controls [34]. Safety will be enhanced by timely identification of hazards, and notification of the people in charge to take appropriate actions. In addition, real-time safety alarm systems that will notify the workers or equipment operators of danger can be considered as another form of engineering control, driven by data-driven monitoring systems.

The last level of control is aimed at reducing exposure to hazards. This level includes methods such as Personal Protective Equipment (PPE) and administrative controls. Proper usage of PPE is often overlooked on construction sites. Real-time monitoring systems provide a promising solution to continuous supervision of their appropriate utilization. The data obtained from real-time systems can also be used for trend analysis and evaluating safety culture at different work zones or various stages of the project. Thus, facilitating targeted administrative controls, and enhancing safety training quality.

4.4 Safety Control Measures

The last step in the safety risk management process refers to performing hazard identification, risk assessment and controlling risks repeatedly to ensure appropriate control measures are taken at all times. Data-driven monitoring systems facilitate automation of the process. By continuously monitoring the workplace and workers' conditions, the automated safety risk management systems supplement human supervision to effectively prevent accidents at the construction site.

5 Discussion of Research Gaps

In this study, we have reviewed various aspects of safety risk management that can be improved using data-driven systems. This section identifies a number of research gaps and suggests future research directions.

1. At the current stage, most studies have focused on the development of monitoring systems that collect and process certain types of information from various entities at construction sites (e.g. workers' gait pattern, physiological state, workers' activity, workspace congestion, temperature, etc.). A desirable feature would be a framework for combining information obtained using various methods into an integrated system. The added dimensionality to the data can provide managers with valuable information. For example, a system that is able to detect safety violations can be extended to include more information such as where the violation has occurred, information about the subcontractor, environmental factors at that time (e.g. temperature), and information about the physiological conditions of the workers.
2. Near-miss events are important safety-leading indicators that are often left unreported and undocumented. Although frameworks, which facilitate the process of reporting near-misses and visualizing them through BIM have been proposed [35], the possibility of using real-time monitoring systems to identify and document near-misses automatically has not yet been fully explored.
3. Real-time monitoring systems create enormous amounts of data. Further domain specific studies, including Big Data Engineering and Data Analytics, are required to extract valuable information from data obtained from real-time monitoring systems, and explore their applications to construction safety [36][37].
4. Visualization of information obtained via real-time monitoring systems through BIM platforms can improve analysis, facilitate accessibility, and enhance communication and training. While some studies have explored the integration of wireless sensor networks with BIM [38], solutions that combine vision-based monitoring systems with BIM platforms have not been sufficiently explored.
5. Rapid advancements in the field of computer vision, and an abundance of cameras on construction sites create an exceptional opportunity for vision-based techniques to be used as effective monitoring systems in the industry. However, the majority of vision-based studies have evaluated their proposed algorithms on datasets that are proprietary to that project and are often small in size. Lack of publicly available large datasets for construction safety monitoring that can be used as benchmarks makes performance comparison of various algorithms difficult.
6. Further research in the identification of critical accident precursors as they relate to fall, struck-by, caught in or between, and electrocution, and detailed breakdown of each accident precursor by defining quantitative parameters to be monitored can accelerate the development of automated monitoring systems.

6 Conclusion

Developing sensor-based systems for improving construction safety has recently gained a considerable amount of attention. In particular, vision-based monitoring systems have become an active topic of research in construction. This study has provided an overview of recent advancements in the domain as they relate to safety risk management and mapped the area for future work.

Safety risk management as described by Safe Work Australia {4} includes four steps, identifying hazards, assessing risks, controlling risks, and reviewing control measures. The impact of data-driven systems on each aspect of the process, along with examples of various methods employed by researchers have been discussed. The reviewed studies cover a range of technologies and approaches being used. These include but are not limited to utilization of wireless sensor networks, RFID, UWB, IMUs (accelerometers and gyroscopes), and vision-based techniques for location tracking, gait analysis, object detection, activity recognition, ergonomic assessment, and so on for the development of data-driven accident prevention systems.

Data-driven systems can be used for automated continuous monitoring of construction sites. They can be used to proactively prevent accidents by notifying workers or equipment operators of an incoming hazard. Further, such systems can be used to notify safety managers or site supervisors of unidentified, or newly appeared hazards. As a result, necessary actions can be taken in a timely manner to prevent accidents.

The overview provided in this study can be used as a guide for researchers pursuing research on intelligent accident prevention systems. It is acknowledged that this review study is only limited to construction industry.

Future research effort should examine state-of-the-art techniques and technologies used in other sectors and consider their applicability to tackling construction safety challenges.

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