Human-Centered Automation for Resilience in Acquiring Construction Field Information

by

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ABSTRACT

Resilient acquisition of timely, detailed job site information plays a pivotal role in maintaining the productivity and safety of construction projects that have busy schedules, dynamic workspaces, and unexpected events. In the field, construction information acquisition often involves three types of activities including sensor-based inspection, manual inspection, and communication. Human interventions play critical roles in these three types of field information acquisition activities. A resilient information acquisition system is needed for safer and more productive construction. The use of various automation technologies could help improve human performance by proactively providing the needed knowledge of using equipment, improve the situation awareness in multi-person collaborations, and reduce the mental workload of operators and inspectors.

Unfortunately, limited studies consider human factors in automation techniques for construction field information acquisition. Fully utilization of the automation techniques requires a systematical synthesis of the interactions between human, tasks, and construction workspace to reduce the complexity of information acquisition tasks so that human can finish these tasks with reliability. Overall, such a synthesis of human factors in field data collection and analysis is paving the path towards “Human-Centered Automation” (HCA) in construction management. HCA could form a computational framework that supports resilient field data collection considering human factors and unexpected events on dynamic job sites.

This dissertation presented an HCA framework for resilient construction field information acquisition and results of examining three HCA approaches that support

three use cases of construction field data collection and analysis. The first HCA approach is an automated data collection planning method that can assist 3D laser scan planning of construction inspectors to achieve comprehensive and efficient data collection. The second HCA approach is a Bayesian model-based approach that automatically aggregates the common sense of people from the internet to identify job site risks from a large number of job site pictures. The third HCA approach is an automatic communication protocol optimization approach that maximizes the team situation awareness of construction workers and leads to the early detection of workflow delays and critical path changes. Data collection and simulation experiments extensively validate these three HCA approaches.

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TABLE OF CONTENTS

CHAPTER Page

LIST OF TABLES

LIST OF FIGURES

Figure Page

CHAPTER 1 INTRODUCTION

Timely, detailed, and accurate field information for decision making will improve the safety, quality, and productivity in construction projects (Golparvar-Fard et al. 2009a; Zhang et al. 2009). The management team needs the actual or potential schedule delay or cost overrun within stipulated time for the early and effective response to those deficiencies (Golparvar-Fard et al. 2009a; Zhang et al. 2009). Early detection of defects in the construction processes will reduce the cost by 6-12% due to the waste of rework (Akinci et al. 2006). Furthermore, the key to maintaining construction safety is the time field information to identify the safety risks in the construction process (Garrett and Teizer 2009; Thevendran and Mawdesley 2004). Challenges that prevent the effective and efficient field inspection in construction projects include highly uncertain and frequently updated schedule due to contingencies (e.g., discoveries of hidden structural defects during field operations), multi-group coordination and communication, and highly uncertain human behaviors on construction sites (Le Blanc and Oxstrand 2012; Hameed et al. 2015; Hinze and Godfrey 2002; Muganyi and Mbohwa 2014; Obiajunwa 2012; Utne et al. 2012).

Construction information acquisition processes mainly involve three types of activities. The first type is sensor-based inspection, which requires the inspector to correctly handle the usage of sensors in data collection (Cheng et al. 2013; Dai et al. 2013; Montaser and Moselhi 2014). The second type is manual inspection, which requires the experience of inspectors in interpreting field data, records, and observations (Moore et al. 2001). The third type is communication, which means obtaining field information from other inspectors for collaborative operations or preparations for pending tasks (Alsehaimi et al. 2014; Gillard and Johansen 2004). Human interventions play important roles in all these three type of information acquisition activities (St. Germain et al. 2014; Oxstrand et al. 2014, 2015).

However, human behaviors can be unreliable in these information acquisition activities, especially in highly uncertain and dynamic job site environments. For sensor-based inspection, job site inspectors may collect missing or delayed job site data due to lacking the essential knowledge of using newly invented sensors and devices (Zhang and Tang 2015b). For manual inspection, uncertain and dynamic environments will challenge new generations of engineers or cause an overload for current inspectors in the coming decades with experienced construction inspection personnel retiring (Goldman et al. 2010). For communication in transmitting job site information, complicated social relationships and dynamic job sites also cause inefficient teamwork between management team, job site workers, and inspectors.

A resilient information acquisition system could help achieve safer and more productive construction by providing new techniques that improve the reliability of human behaviors in acquiring construction information. In such a context, various automation technologies, such as sensors and digital models of construction sites, can be critical for assisting new generations of engineers and workers in acquiring job site information by proactively providing the needed knowledge of using equipment, improve the situation awareness in multi-person collaborations, and reduce the mental workload of operators and inspectors. (Billings 1991, 1997; Goodrich and Boer 2000; Pyy et al. 1998).

Unfortunately, limited studies or commercial automation technologies consider human factors for construction field information acquisition. Human errors during field information acquisition are difficult to resolve using previous studies. The interaction between the dynamic job site and the tasks that are different for every project is exaggerating the unpredictability of human behaviors (Zhang et al. 2017). Therefore, achieving the reliable human behaviors in information acquisition needs systematically integration the interactions between human, tasks, and construction workspace to achieve more efficient and effective field data collection. Such synthesis is paving the path towards "Human-Centered Automation" (HCA) in construction management, which is a computational framework that defines the automation techniques that empower human performance in field operations through proper consideration of human factors. HCA concept grows up in other domains while gaining attention in the domain of construction automation in recent years (Billings 1991; Goodrich and Boer 2000; Su et al. 2015; Zhang et al. 2017). HCA consists of automation techniques that support the resilient field data collection considering human factors and unexpected events on dynamic construction job sites. Specifically, these automation techniques for field information acquisition help better guide the human behaviors in information acquisition activities by enhancing Situation Awareness (SA) and providing the needed technical knowledge while reducing Mental Workloads (MW).

The aim of this dissertation is to systematically incorporate human factors into the automated field information acquisition techniques. Specifically, this dissertation presented an HCA framework for resilient construction field information acquisition and results of examining three HCA approaches that support three use cases of construction field data collection and analysis. The first HCA approach is an automated data collection planning method that can assist 3D laser scan planning of construction inspectors to achieve comprehensive and efficient data collection. The second HCA approach is a Bayesian model-based approach that automatically aggregates the common sense of people from the internet to identify job site risks from a large number of job site pictures and can guide engineers in risk detection in new photos while reducing their mental workload in image interpretation. The third HCA approach is an automatic communication protocol optimization approach that maximizes the team situation awareness of construction workers through automatically assessing information needs of workers along workflows and generating protocols that best reduce the uncertainties of workers and streamline the team collaboration. The integrated application of the proposed approaches will shed light on achieving the resilient acquisition of information in dynamic and complex construction fields.

1.1 Motivating Case

This section describes the motivation of the proposed research using case studies.

Case 1: Sensor usage error in collection as-is geometric data

In construction environments, laser-scanning technologies can perform rapid spatial data collection tasks, such as streamlining field activities, monitoring construction progress, and controlling construction quality. However, even the most skilled of surveyors cannot guarantee comprehensive laser scanning data collection on a construction site due to its constantly changing environment, wherein many objects are subject to different data-quality requirements. The current practice of manually planned laser scanning often produces data of insufficient coverage, accuracy, and details. Whereas redundant data collection can improve data quality, this process can also be inefficient and time-consuming. There are many studies on automatic sensor planning methods for guided laser-scanning data collection in the literature. However, fewer studies exist on how to handle exponentially large search space of laser scan plans that consider data quality requirements, such as accuracy and levels of details (LOD).

The Level of Detail (LOD) is one of the data quality requirements of imagery data, which describe the smallest object recognizable from the imagery data. Specifically, LOD of a point cloud measures the data density within the neighborhood of each point goal in a point cloud. When collecting geometric point cloud data of a job site, different point goals require different LODs. For example, dense data may not be needed for simple geometries (e.g. flat walls). Instead, LOD may need to be increased for complex shapes, such as edges, openings, and decorations. Insufficient LOD causes missing details in data for further data processing and modeling, while excessively high LOD causes extra time and effort in data collection.

However, collecting laser scanning data with required LOD is difficult, even for professional surveyors. To show the difficulty of collecting laser scanning data with required LOD, I conducted a laser scanning experiment on a campus building following two plans generated by a 3D imaging researcher and a laser scanning professional who has been using laser scanners in more than ten large building projects. The experiment results shown in Section 2.5.2 indicate that it is difficult for manually generated laser scan plans to achieve 100% coverage of point goals with required LOD. The first difficulty is in choosing the right scanning resolution. The second difficulty is in estimating the area that one scan can cover with sufficient LODs. In the case study, the curved shape of the studied building caused additional challenges for a human to precisely choose the scanning positions so that areas with required LOD would connect without gaps.

Case 2: Inspection errors in identifying safety violations of the job site

Risk assessment based on imagery data is becoming popular in construction project management because cheap imaging devices can capture detailed as-is job site information with high efficiency. However, one challenge is that image-based safety risk identification heavily relies on the subjective image interpretation. Well-trained inspectors could be a limited resource that might not always be available to meet the safety inspection requirements on large and busy job sites.

Imagery has shown potentials for supporting risk management in construction and civil infrastructure management. In both China and the United States, civil infrastructure management agencies use imaging sensors for collecting detailed spatiotemporal information of bridges, dams, and other large structures for detailed condition assessment and risk analysis (Zhu and Brilakis 2010). Efficient and effective uses of imagery data for risk recognition is thus becoming increasingly important for establishing a data-driven risk management framework for civil engineering projects (Zhang and Tang 2015b).

Unfortunately, subjective safety inspection based on job site imagery manually conducted by inspectors brings uncertainties and biases in risk recognition results based on images. Even well-trained inspectors spend much time to achieve comprehensive and reliable risk recognition from images (Lagasse et al. 2009). In some cases, the uncertainties and biases within manual image interpretation processes can mislead the decisions about construction safety management and civil infrastructure maintenance (Moore et al. 2001). Liao et al. (Liao et al. 2016) presented the observation miss in a simulated safety inspection experiment of an elevator installation project. In the experiment, 40 job site photographs containing 30 risks taken at four typical locations (Hoistway, pit, Machine room, and Storeroom) from different job sites created a virtual environment of the elevator installation. Five inspectors from an elevator installation company with working age ranging from 1.5 to 25 years are then asked to identify the job site pictures with risks within 13 minutes. The experiment result shows that the inspectors can only identify 15-24% safety risks correctly. Also, only 62% of answers of identified risks are correct. This result shows that the complexity of the checklist, including having too many items to check and ambiguous in descriptions will increase the cognitive control load for the inspectors.

Civil engineers have been developing methods to increase the reliability of manual image interpretation in construction safety (Chang and Liao 2012; Lattanzi and Miller 2014; Papaelias et al. 2016). Some researchers examined image processing algorithms that can automatically extract certain features from images to assist engineers in identifying risks of construction (Chang and Liao 2012). However, engineers still need to decide how to setup and use such image processing algorithms so that the subjective factors still exist

(Moore et al. 2001). At present, interpretation of the images based on human intuition and experiences seems still unavoidable. Therefore, what the construction industry needs is an automation technique which can reduce the cognitive workload during the safety inspection.

Case 3: Communication error in collecting productivity and progress data

Nuclear power plant (NPP) outages involve a large number of maintenance and repair activities with a busy schedule and zero-tolerance for accidents. During an outage, more than 2,000 workers will be working around the NPP and finishing the maintenance work including more than 2,000 tasks within about 20 days, while the planning stage of a typical NPP outage is more than four months. Moreover, a one-day delay on the nuclear power plant outage project will cost $1.5 million loss. Therefore, these features of NPP outages call for a real-time, robust, effective workflow control to ensure the construction safety and productivity while reducing the wastes and resource consumption.

In NPP outages, one of the major practical problems is about how to control the efficiency and error rates of handoffs, which are the transitional stages between tasks. Handoffs involve highly uncertain activities, such as transports of resources and labors, inter-person and human-computer communications, field preparation, mobilization, and waiting. The transitional nature of handoffs causes time and resource wastes, incidents or accidents due to the involvement of multiple groups of workers and complex spatiotemporal interactions between space and resource needs of tasks, and decision difficulties under uncertainties.

Handoffs between tasks represent a large portion of overall activities in construction workflows (Cheng and Teizer 2013; Gouett et al. 2011; Hu et al. 2016), and can significantly influence the project efficiency. For example, the OCC needs to have 30-minute meetings up to every three hours to know the as-is status of the outage progress and performance. One major reason that aggravates the handoff time waste in NPP outages is the complicated organization of outage participants and processes (Petronas et al. 2016). The approval of each task involves multiple stakeholders to ensure safety. For example, an outage tasks should be confirmed by the following organizational units before the execution: 1) the outage control center, which determines whether the task is needed; 2) the schedulers, who arrange the schedules of interconnected tasks; 3) the maintenance shops, who arrange workforces for tasks; 4) the main control room staff, which configures the NPP according to the requirement of certain tasks; 5) the work execution center, which inspects the site preparation for safe execution of a given task. Complicated communications between all these organizational units are necessary for safety but will create long handoffs and possible time wastes.

Also, the communication activities in NPP outages are error-prone, and communication errors could introduce additional communications and delays. An example from Licensee Event Reports (LERs, a database documenting all the abnormal events which may compromise the safety and productivity of NPPs) shows the error-prone nature of handoffs. On May 8th, 2010, Palo Verde NPP Unit 1found that the containment building equipment hatch was found not capable of being fully closed for six days. If any accidents had occurred during this time, radioactive gas could be quickly released to the outside atmosphere within 2 hours. Two reasons that might cause this event: First, the hatch might be damaged during the maintenance on May 2nd, which could have caused by human errors or just a facility error. Second, the post-maintenance test procedures were not followed to ensure proper hatch motion, which is a communication error in the handoff involving the maintenance team, the post-maintenance test team, and the management team. In fact, for all the errors, incidents, and near misses documented in the LERs, about 50% of them are related to communication errors (Hobbins et al. 2016).

Furthermore, extremely busy schedules with a 10-minutes level of detail delays or mistakes due to communication could propagate to more tasks, which could compromise the productivity and safety of the entire workflow and even the whole outage. Therefore, precisely predicting and controlling the time wasted and information loss caused by human errors during handoffs can improve the productivity of NPP outages (Kim et al. 2010).

1.2 Problem Statement

The three motivating cases show that people could make mistakes in acquiring construction information in complex and dynamic environments of construction job sites. A resilient information acquisition should reduce human error rates by "*proactively and adequately adapt to perturbations and changes in the real world given finite resources and time*" (Madni and Jackson 2009). In this context, "resilient" information acquisition refers to the ability of proactive avoiding or quick recovery from errors, delays, interruptions, and changes in schedules to achieve as-planned project productivity and safety considering all the unexpected events in dynamic construction job site (Carayon et al. 2015; Madni and Jackson 2009).

Reducing the complexity of executing tasks by workers and engineers is the focus of resilience in acquiring construction field information. The high complexity of tasks is challenging human cognitive and physical capabilities and usually lead to reduced human and team performance in such tasks, which causes hardly predictable actions that lead to uncertain impacts on productivity and safety (Mitropoulos et al. n.d., 2005). Campbell (Campbell 1988) identified four types of source of task complexity: multiple potential ways, multiple desired outcomes to be attained; the presence of conflicting interdependence among paths to multiple desired outcomes; and the presence of uncertain or probabilistic linkages among paths and outcomes. Obviously, these source or complexity fulfills the tasks in construction projects, especially in information acquisition tasks. Such complexity poses challenges to ensuring "resilient" information acquisition, which requires an approach that should rapidly and proactively respond to delays, errors, or unexpected tasks added.

In the domain of construction management, researchers start analyzing the complexities of the field tasks based on the interaction between human behaviors and dynamic construction project. For example, studies exist about improving the productivity and safety of construction field workers by analyzing and categorizing activities in construction tasks (Awolusi and Marks 2016; Cheng et al. 2013; Gouett et al. 2011). However, approaches and theories are still in need on how automation could reduce the information-acquisition task complexity and improve the resilience of information acquisition for supporting proactive project control. Here, I summarize some of the practical causes of task complexity exceeding the capability of workers and engineers and thus result in reduced human and team performance.

The first cause of field workers' and engineers' unpredictable actions due to task complexity in construction information acquisition is the lack of knowledge about how to use the equipment. Experienced management personnel or surveyors are always the limited resources in a construction project, whereas novice management personnel or surveyor may not have the needed knowledge to acquire the job site information with required Level of Detail (LOD) and Level of Accuracy (LOA). For example, laser scanning technologies have many advantages that include high accuracy (mm level), faster data acquisition (up to hundreds of thousands of three-dimensional points per second), and more detailed spatial resolution (Boehler and Marbs 2003; Bosché et al. 2014; Huising and Gomes Pereira 1998; Turkan et al. 2013). The use of laser scanning in the construction field, however, comes with some challenges.

First, acquiring high quality 3D imagery data within the parameters of changing job sites and diverse projects is challenging even for experienced engineers, primarily because data quality, environmental conditions, scanning locations, and the technical parameters of laser scanners (e.g., data density options) all combine to create complex interactions (Akinci et al. 2006). Second, 3D imagery data collection is time-consuming, and in a fast changing construction environment, the data can become quickly outdated, which leads to misleading information for decision makers. Finally, when using sophisticated 3D imagery data collection, project managers must hire experienced surveyors who can properly operate laser scanners and achieve high-quality data collection, which can be costly (Dai et al. 2013; Eid et al. 2004).

The second and third causes of field workers' and engineers' unpredictable actions due to task complexity are the lack of Situation Awareness (SA) and the overload of mental workload (MW) of field personnel, which have a mutual interaction with each other. The performance of field information acquisition involves significant human interventions, which will be directly influenced by human factors SA and MW (O'Hara 2004). SA is "the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status shortly" (Endsley 1995). A human with good SA can properly assess the situation and take timely actions accordingly. Appropriate SA helps humans make a better decision according to the field conditions.

MW is a measurement of mental demands on a person (Hwang et al. 2008, 2009). All tasks require some variations of mental effort; however, the degree to which SA and MW are needed can vary significantly depending on the task. Moreover, a greater need for one will influence the other (Chen et al. 2016). Overall, having to maintain a high SA increases the mental workload of an operator which can negatively influence personnel task performance (Endsley 1995). For example, to achieve a comprehensive assessment of job site safety risks (i.e. achieve high SA on job site safety), the safety inspector need to inspect every corner on the construction job site and compare what he/she sees with the huge number of safety rules in the memory, which causes high mental workload.

Another example illustrating the relationship between SA and MW would be that several worker teams collaborate on a workflow in NPP outage project. The goal of the worker teams needs to minimize the duration of the entire workflow by reducing the handoff between tasks. Therefore, the leader of each worker team needs to communicate and collaborate with each other and get the information of the progress of other tasks from each other. The integrate knowledge of the progress of each task in the workflow is the “Team SA” (TSA) of these worker teams. Better TSA means more accurate information about the duration of each task so that the leader of each worker team can make a better decision about what to do next. However, better TSA requires a higher frequency of communication, which will interrupt the work each team is doing and causes a rise of the MW of each worker team leader.

The lack of SA and overload of MW are two important factor causing human errors in construction information acquisition. The best task performance will be achieved when the related personnel can adapt to the fluctuations of MW while maintaining an appropriate SA. Therefore, automation techniques that can reduce the task complexity can help reducing the MW of field personnel. Also, the optimization of the communication protocol between different workers according to the dynamic construction site and tasks can balance the TSA and MW of the workers and will achieve reliable human behavior in the communication activities in busy construction workflows.

1.3 Vision

This research focuses on a systems approach with the goal of increasing system resilience and best-utilizing human and machine capabilities. Resilience engineering brings a new approach to safety management in a complex system. It focuses on how to help people handle complex situations (expected or unexpected) under pressure to achieve success (Hollnagel et al., 2006). Achieving a higher degree of automation in construction projects is a general trend (Goldman et al. 2010), but HCA techniques need to be developed in information acquisition. I define HCA for acquiring construction field information by synthesizing relevant automation techniques on three aspects of construction project control (Abdelhamid and Everett 2000):

- ***"Task"*** aspect involves the work that humans need to do according to certain standards, sequences, and time. For example, automatic scheduling is a typical automation technique for the task aspect.
- ***"Workspace"*** aspect focuses on managing non-human objects and spaces, i.e. facilities, materials, and building elements. Automation techniques on this aspect include automated workspace data collection, site layout design, and crane planning through various sensors such as laser scanners, etc.
- ***"Human"*** aspect refers to methods related to managing performance and behaviors of human individuals and organizations involved in the project, including workers, foremen, and management staff.

The motivating cases show that achieving reliable human behavior in information acquisition is critical but difficult due of the complex interaction between humans, workspace, and tasks. Furthermore, the knowledge of how to precisely model or describe such interactions is missing. In the laser scanning data collection example, acquiring high quality 3D imagery data considering the changing job sites and diverse projects is challenging even for experienced engineers. This challange is primarily because data quality, environmental conditions, scanning locations, and the technical parameters of laser scanners (e.g., data density options) all combine to create complex interactions

(Akinci et al. 2006). Also, 3D imagery data collection is time-consuming, and in a fast-changing construction environment, the data can become quickly outdated, which leads to misleading information for decision makers. The example of safety inspection also shows that the complicated interaction of human, tasks, and workspace can cause information acquisition defects. Usually, construction safety inspectors use the checklist as a comprehensive reference to reducing the chance of missing safety risks during the inspection. However, due to the complexity of the workspace, the number of items increases significantly. Such increase creates significant mental workloads for the inspectors. Inspectors can easily omit safety risks without an automation approach to guide the safety inspection according to a specific description of ongoing tasks and as-is job site environments.

Therefore, an HCA-based information acquisition improves the reliability of human behaviors of information acquisition tasks in construction fields considering the interactions between human, workspace, and tasks. Figure 1 visualizes the framework of HCA for efficiency and effectiveness of information acquisition in construction. The overall goal of this system is improving the safety, quality, and productivity of construction projects. This system will capture timely tasks, workspace, and human factor information to build an information model that contain sufficient information about site conditions, progress, and environments. Then the HCA techniques will achieve resilient information acquisition by reducing the task complexity in three aspects: 1) providing guidance to people according to the job site information when people lack the needed knowledge; 2) automating certain procedures of tasks to reduce the mental workload; 3) integrating the interaction between tasks, workspace, and human to evaluate the information needs of different people for achieving optimal TSA using minimum communication activities.

Currently, many automation technologies potentially useful for information acquisition are focusing on the of scheduling and resource allocation (Yang et al. 2015), visualization of construction processes (Cheng and Teizer 2013; Guo et al. 2017), and change detection between as-planned and as-is (Kundakci and Kulak 2016). However, only a few automation technologies focusing on human factors are invented and applied in the domain of construction information acquisition. More specifically, limited studies consider the human aspects of the practical problems described above – providing needed knowledge, improving SA, and reducing MW. Therefore, the human performance monitoring and robust design of information acquisition techniques that can effectively avoid or handle human errors becomes the bottleneck, which is the focus of the research studies in my dissertation.

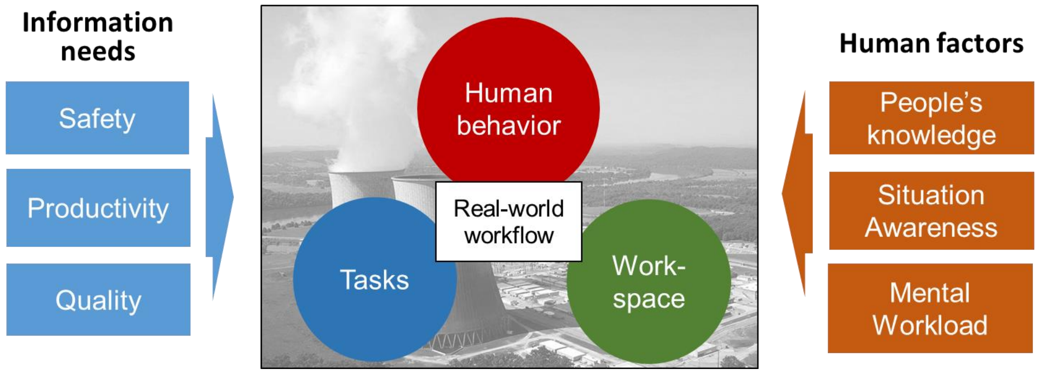


Figure 1. Challenges of Reducing Human Errors in Information Acquisition.

Figure 2 shows an IDEF0 model of HCA techniques for information acquisition. The input of an HCA technique is the needed information of the field related to the safety, quality, and productivity of the construction project. The constraints are: First, the information quality requirements. Second, the sensor model which people will use during the information acquisition. Third, the human behavior model related to their physical and mental conditions (e.g. human will walk at certain speed; people tend to underestimate the time they need to finish the task, etc.). Finally, the time, cost, and space limit of dynamic job site, which are decided by the as-is condition of the construction project job site. The major goal of this research is to reduce the human error during acquiring field information using HCA techniques by 1) helping the decision making, 2) Improving the SA (especially TSA), 3) reducing the MW. Thus, this research can improve the effectiveness and efficiency of the inspection in construction workflow.

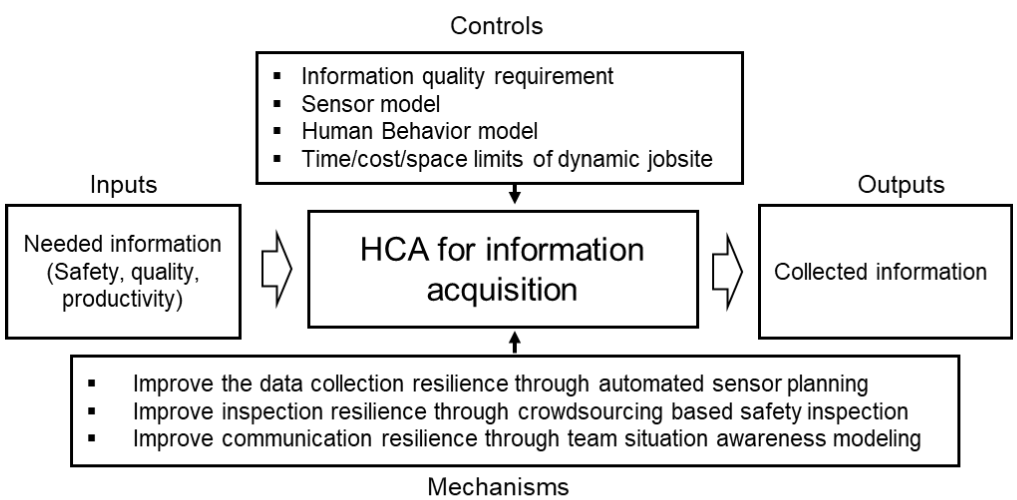


Figure 2. IDEF0 Model of HCA Techniques for Information Acquisition

1.4 Research Objectives

The objectives of the proposed research are as follows:

1. To provide technical knowledge to 3D laser scanning surveyors by developing an automated data collection planning method to achieve effective and efficient as-is information.
2. To reduce the MW of safety engineers by automatically integrating the common sense of people from the internet to identify job site risks from a large number of job site pictures.
3. To improve the TSA of construction workers by generating the optimal communication protocol according to the needs of the job site workflow to achieve effective and efficient information flow.

CHAPTER 2 RAPID DATA QUALITY ORIENTED LASER SCAN PLANNING FOR DYNAMIC CONSTRUCTION SITE

2.1 Introduction

Timely, detailed, and accurate geometrical information for decision making will improve the safety, quality, and productivity in construction projects (Golparvar-Fard et al. 2009a; Zhang et al. 2009). Reliable sensing methods and comprehensive data collection are, therefore, requisite and highly desirable in construction management environments. Compared with conventional data collection methods such as laser tapes and the Global Navigation Satellite System, laser scanning technologies have many advantages that include high accuracy (mm level), faster data acquisition (up to hundreds of thousands of three-dimensional points per second), and more detailed spatial resolution (Boehler and Marbs 2003; Bosché et al. 2014; Huising and Gomes Pereira 1998; Turkan et al. 2013). Researchers and project engineers, thus, have been actively exploring the uses of laser scanning technology in construction.

The use of laser scanning in the construction field, however, comes with its own set of challenges. First, acquiring high quality 3D imagery data within the parameters of changing job sites and diverse projects is challenging even for experienced engineers, primarily because data quality, environmental conditions, scanning locations, and the technical parameters of laser scanners (e.g., data density options) all combine to create complex interactions (Akinci et al. 2006). Second, 3D imagery data collection is time-consuming, and in a fast changing construction environment, the data can become quickly outdated, which leads to misleading information for decision makers. Finally, when using sophisticated 3D imagery data collection, project managers must hire experienced surveyors who can properly operate laser scanners and achieve high-quality data collection, which can be costly (Dai et al. 2013; Eid et al. 2004).

To overcome the above challenges, this paper describes the development of a new automatic laser scan planning method. For a given job site, the objective is to determine a laser scan plan by specifying a sequence of scanning positions and parameters at each position as a means to minimize the data collection time while optimizing the coverage and quality of the data. A fast and reliable laser scan planning method can thus save costs related to 1) poor decision-making due to low-quality data; 2) interruptions in construction processes caused by data collection activities, and 3) training and hiring laser scanning professionals for high-quality data collection.

This paper attempts to address three questions that have remained unresolved in previous studies about the laser scan planning problem in construction:

1) how to quantify and model the relationship between 3D imagery data quality and data collection parameters to develop a planning algorithm that uses the quantitative relationship for guiding the generation and assessment of laser scan plans (Tang and Alaswad 2012);
2) how to explore the extremely large search space of laser scan plans in the limited time of decision-making in the context of dynamic environments (Blaer and Allen 2009; Gordon et al. 2007);
3) how to achieve scalability of laser scan planning so that engineers can apply the same scan planning method to sites of different shapes and sizes (Song et al. 2014).

To address the first question, I developed a 3D-imaging sensor model that shows the mathematical relationship between 3D data collection parameters and spatial data quality. To explore the second question, I propose a “divide-and-conquer” planning method for achieving efficient optimization of laser scan plans. To ensure the scalability of this laser scan planning method (question 3), the divide-and-conquer method adaptively adjusts its parameters according to building size and shape to produce reliable laser scan plans.

The organization of this chapter is as follows: Section 2.2 introduces previous studies about laser scan planning while highlighting the contributions of this paper. Section 2.3 provides a problem statement and a discussion of the three research questions. Section 2.4 describes the laser scan planning method. Section 2.5 validates the developed laser scan planning method using case studies on real buildings. Sections 2.6 and seven present validation results, the conclusion, and future research plans.

2.2 Previous Research

Previous studies have stressed the importance of efficient and effective construction inspection using laser-scanning technologies. Akinci et al. (Akinci et al. 2006) and Gordon et al. (Gordon et al. 2007), for example, discuss how manual inspection could miss important site changes and defects, whereas the use of laser scanning could improve construction inspection through the delivery of timely and comprehensive as-built data. Turkan et al. (Turkan et al. 2013) emphasize the need for effective laser scan planning to achieve effective construction progress control. Park et al. (Park et al. 2013) illustrate the need for the best practices in collecting, searching and reusing defect information for construction quality control in the field.

Although construction industry practitioners acknowledge the importance of laser scanning, they are also confronted with the many obstacles that prevent both the effective and efficient use of laser scanning in construction (Nie et al. 2012; Park et al. 2007; Volk et al. 2014). One such obstacle is related to acquiring high-quality 3D imageries for field applications (Park et al. 2013). Since 3D image quality greatly influences as-built Building Information Model (BIM) quality (Klein et al. 2012; Tang et al. 2010; Xiong et al. 2013), examining quantitative relationships between data quality, scanning locations, and environmental factors become critical to the overall process (Anil et al. 2013; Bhatla et al. 2012; Granshaw 2014; Tang et al. 2009; Tang and Alaswad 2012; Weber et al. 2010). In this context, manually reviewing a large number of such relationships is a challenging task, even for experienced engineers. Also, manual data quality checks of numerous objects on job sites against data quality requirements are tedious and error-prone (Song et al. 2014). This second obstacle is the difficulty of optimizing data collection time while minimizing interferences from the data collection and productive activities (Akinci et al. 2006; Dadi et al. 2012; Gordon et al. 2007). It has been shown, for example, that a badly designed workflow may need up to 300% data collection time when compared to a standard workflow for the same laser scanning task (Dadi et al. 2012). Another obstacle relates to the high cost of training and hiring laser scanning professionals (Eid et al. 2004; Gordon and Akinci 2005). Eid et al. found that the cost of laser scanning for the evaluation of forest inventory is approximate twice the cost of using photogrammetry (Eid et al. 2004).

Effective laser scan planning methods are lacking in the literature to date. Many existing studies focus on occlusion and visibility analysis for capturing the entire surface of a targeted object, but these studies lack detailed analysis of data quality (Biswas et al. 2015; Fernández et al. 2008; Latimer et al. 2004; Lee et al. 2001; Pito 1996; Son et al. 2002). Most are marked by high computational complexities that result in long computation times when generating laser scan plans (Blaer and Allen 2009; Latimer et al. 2004; Nüchter et al. 2003). Finally, the current array of studies fails to use flexible scanning parameters for each scanning position, according to varying data quality requirements of different objects (Ahn and Wohn 2015; Blaer and Allen 2009; Pito 1996; Song et al. 2014). Lack of flexibility can potentially lead to unnecessary planning computation time as well as redundant data collection. In a recent study by Ahn et al. (Ahn and Wohn 2015), a semi-automatic scan planning method was used to decide the scanning position for achieving horizontal data quality requirements. However, it required manually selecting the same scanning resolution for all scans, thus failing to identify optimal plans that could have mixed use of scans with different resolutions. Also, the proposed semi-automatic method was not able to handle buildings with curve-shaped walls. The research methodology presented below will address this gap in order to improve the quality of field laser scanning significantly in dynamic construction environments.

2.3 Problem Statement

The goal of laser scan planning is to create a method that can automatically generate laser scan plans for the efficient collection of high-quality 3D imageries of a given job site. The generated laser scan plans should achieve the following:

- The laser scan plans should specify scanning positions and parameters at those positions so that an engineer with limited surveying experiences can rapidly collect comprehensive 3D imagery details of the job site with sufficient accuracy.
- Following the laser scan plan, the engineer should be able to achieve optimal data collection time to minimize the interferences between data collection and construction workflows.
- The time for generating a laser scan plan should be less than a few minutes to satisfy the dynamics of a construction job site.

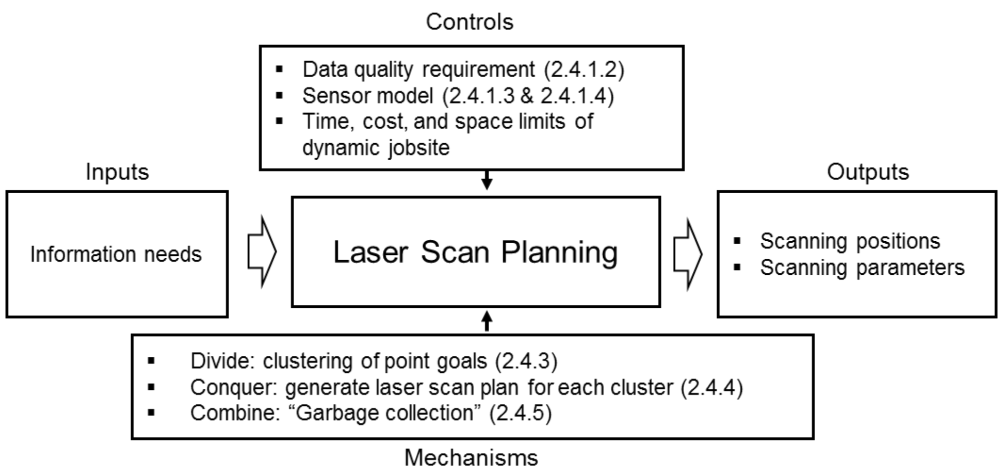


Figure 3. IDEF0 Process Model Describing the Laser Scan Planning Problem

Figure 3 shows an IDEF0 process model describing the laser scan planning problem. The inputs of the IDEF0 process model are point goals, which include objects of interest or geometric features. Section 2.4.1.1 details the representations of point goals. The outputs of the IDEF0 are scanning positions and parameters, such as angular scanning resolutions that determine the 3D data point intensities. The controls of the IDEF0 process model include:

1) Data quality requirements: For 3D imagery data, engineers require a certain level of accuracy (LOA, which indicates the measurement error) and level of detail (LOD, which measures the data density). The LOD requirement of laser scanning data is presented in Section 2.4.1.2.
2) Sensor model: An analytical sensor model describes the geometric principles of laser scanning, such as the relationship between laser scanning parameters and the point density of a laser scanning data. Given a sensor model, one can derive the scanning positions and the parameters at each position (e.g., angular resolution) to meet the data quality requirement (LOD). I use the concept of "feasible space" to visualize recommended data collection locations according to 3D data quality prediction based on a sensor model. Sections 2.4.1.3 to 2.4.1.4 present the sensor model developed in this research, and methods to utilize them for deriving feasible spaces of 3D data collection.
3) Schedule, budget, and space limits of a job site: These controls specify the spatiotemporal requirements of construction activities on a construction site, as well as cost information for quantifying the losses due to interferences between data collection and field activities.

Based on the IDEF0 model, I formulate here an optimization model of laser scan planning (Section 2.4.1.5). However, solving this optimization model is computationally expensive and challenging due to the exponentially large combinations of possible scanning locations and parameter values. For example, for a given a job site of 5,000 m^2, the optimization model consists of more than 1,500 constraints, 10,000 possible scanning positions, and 10^{60} calculations for solving this model with enumeration.

To shorten the calculation time, I propose a "divide-and-conquer" method to calculate the laser scan plan in a computationally efficient way. First, an algorithm is used to divide the overall construction site into several parts so that the large-scale optimization problem becomes smaller problems that require significantly fewer computations (Section 2.4.3). For each part of the construction site, the algorithm generates a laser scan plan and examines whether the correct execution of the plan could still result in any missing data (Section 2.4.4). Finally, the algorithm generates laser scan plans for addressing portions that are still missing (if there are any) in generated plans for parts of sites; it then combines the scan plans of all parts of the site together to form a complete laser scan plan for the entire site (Section 2.4.5).

2.4 Research Methodology

2.4.1 Technical concepts related to a laser scan planning problem

2.4.1.1 Point goals on construction sites

Inspection goals are targets of construction inspection for various purposes, such as progress monitoring, site analysis, and quality control (Gordon et al. 2007). This study uses "point type" inspection goals (termed "point goals" hereafter) as the inputs of the laser scan planning method. The term "point goal" can be defined as important points that represent geometric information, e.g., the corners of a wall. For instance, if an engineer acquires precise midpoint and endpoint positions (considered as point goals) of a beam using laser scanning data, he or she can easily derive the length and deformation of this beam from point goals. I plan to analyze how point goals influence other types of inspection goals in future studies.

The purpose of identifying point goals on a construction site is to achieve a computationally efficient analysis of a site for rapid scan planning. Blaer et al. (Blaer and Allen 2009) used $1m^3$ cubes termed as “voxels” to represent the 3D model of a large job site during laser scan planning. However, this study found that such representation would be computationally expensive because the number of voxels grew exponentially with the size of the job site. On the other hand, the number of point goals can be around 100-200 depending on the number of objects on site, much less than the number of voxels. Handling point goals thus will consume considerably less computational time than processing voxels.

Point goals contain two elements of information necessary for laser scan planning: 1) coordinates of points and 2) the normal vector of the surface where a point goal locates. The latter indicates the direction from which laser scanners can capture the point goal (Low and Lastra 2006; Oskouie et al. 2015; Scott et al. 2003). The proposed laser scan planning method will conduct visibility checks of point goals, requiring both locations and surface orientations of point goals, as detailed in Section 2.4.3.2.

2.4.1.2 Level of Detail (LOD) of a point cloud

Level of Accuracy (LOA) and Level of Detail (LOD) are data quality requirements of point clouds. LOA represents the tolerance of positioning and dimensional errors, while LOD measures the data density within the neighborhood of each point goal in a point cloud. In this paper, the focus is on laser scan planning based on LOD requirements; LOA aspects will be studied in the future. In practice, different point goals can have different LOD requirements. For example, dense data may not be needed for simple geometries (e.g. flat walls). Instead, LOD may need to be increased for complex shapes, such as edges, openings, and decorations. Insufficient LOD causes missing details in data for further data processing and modeling, while excessively high LOD causes extra time and effort in data collection. As a result, if engineers specify LOD requirement for each point goal, they can collect 3D imageries containing all required geometric information while avoiding unnecessary dense data, which contributes to wasted time in data collection and processing.

At present, there is no widely accepted definition of LOD for 3D point clouds. Researchers use two different methods to quantify LOD of point clouds. Dai et al. (Dai et al. 2013) use the number of points in a unit area (e.g., 1 square cm, 1 square meter, etc.) to define the data density. MacKinnon et al. (MacKinnon et al. 2009) assume that the laser source of a scanner rotates vertically to generate "scanning lines," such that the distance between two adjacent points along a vertical scanning line is a measurement of the data density along the vertical direction. In addition, the laser source also rotates horizontally to create scanning lines to form a 3D image. The distance between neighboring scanning lines defines the data density along the horizontal direction. This study defines LOD similar to MacKinnon et al. (MacKinnon et al. 2009). The vertical LOD (LOD_v) is the distance between a point and the next scanned point, and the angular resolution δ_v is the difference between the elevation angles of these two adjacent points on a vertical scanning line. Horizontal LOD (LOD_h) is the distance between two adjacent scanning lines, and the angular resolution δ_h is the difference between the azimuths of the two adjacent scanning lines. For normal laser scanners, $\delta_h = \delta_v \equiv \delta$.

2.4.1.3 3D feasible space

The laser scan planning algorithm needs to generate scanning parameters (scanning positions, angular resolutions at those positions) that can ensure acquiring 3D point cloud data with required LOD for all point goals. Therefore, it is essential to understand the geometric relationship between the data collection parameters and the densities of collected point clouds. In this paper, I define a “3D feasible space” as the set of scanning positions where a laser scanner can scan a point goal with required LOD using a defined angular resolution. Mathematically, a 3D feasible space S_i of point goal i, is the set of positions (x, y, z) in 3D space that satisfy:

$$S_i = \{(x, y, z) |\ s_h(x, y, z, \delta) < LOD_h,\ s_v(x, y, z, \delta) < LOD_v\} \tag{1}$$

where δ is the angular resolution of the laser scanner; s_v is vertical surface sampling distance along the scanning line (Tang and Alaswad 2012) and s_h is the horizontal surface sampling distance, which is the spacing between adjacent scanning lines. If the scanning position is within the 3D feasible space S_i of point goal i using angular resolution δ, the collected point cloud of point goal i will satisfy the horizontal LOD (LOD_h) and vertical LOD (LOD_v).

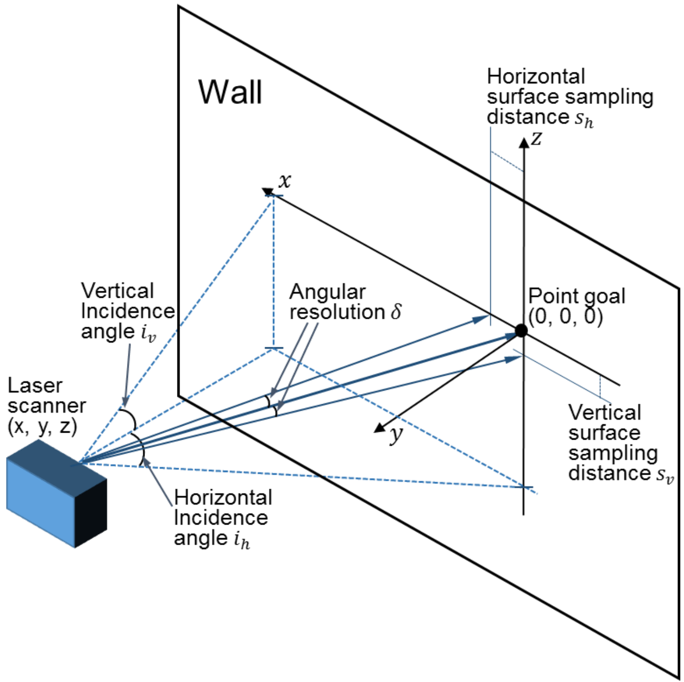


Figure 4. Geometric Representation of Surface Sampling Distance

Figure 4 shows the geometric principle of horizontal/vertical surface sampling distance of a laser scan. Without losing generality, I set the coordinate of the point goal as $(0,0,0)$, the normal vector of the surface as $(0,1,0)$, and the coordinate of the laser scanner as (x, y, z). In order to derive the mathematical representation of the 3D feasible space of the point goal at (0, 0, 0), I derive the mathematical representations of sampling distances along vertical and horizontal directions:

$$s_v = \frac{\delta D}{cos i_v} = \frac{\delta\sqrt{x^2+y^2+z^2}}{\frac{\sqrt{x^2+y^2}}{\sqrt{x^2+y^2+z^2}}} = \frac{\delta(x^2+y^2+z^2)}{\sqrt{x^2+y^2}}, s_h = \frac{\delta D}{cos i_h} = \frac{\delta(x^2+y^2+z^2)}{\sqrt{z^2+y^2}}$$

where D is the laser traveling distance; i_h and i_v are the horizontal and vertical incidence angle, respectively. The horizontal and vertical surface sampling distance in the point cloud around a point goal should satisfy the horizontal and vertical LOD requirement:

$$s_h \leq LOD_h, \qquad y > 0 \tag{2}$$

$$s_v \leq LOD_v, \qquad y > 0 \tag{3}$$

Figure 5(a) and (b) presents the space consisting of all scanning positions that enable Equation (2) and (3), respectively. In practice, the data within the neighborhood of a point goal should satisfy both vertical and horizontal LOD requirements. As a result, the 3D feasible space of a point goal should be the intersection of these two 3D feasible spaces, as shown in Equation (4) and visualized in Figure 5(c).

$$S_i = \left\{ (x, y, z) \middle| \begin{array}{c} \left(\sqrt{y^2 + z^2} - \frac{LOD_v}{2\delta}\right)^2 + x^2 \leq \left(\frac{LOD_v}{2\delta}\right)^2 \\ \left(\sqrt{x^2 + y^2} - \frac{LOD_h}{2\delta}\right)^2 + z^2 \leq \left(\frac{LOD_h}{2\delta}\right)^2 \\ y > 0 \end{array} \right\} \tag{4}$$

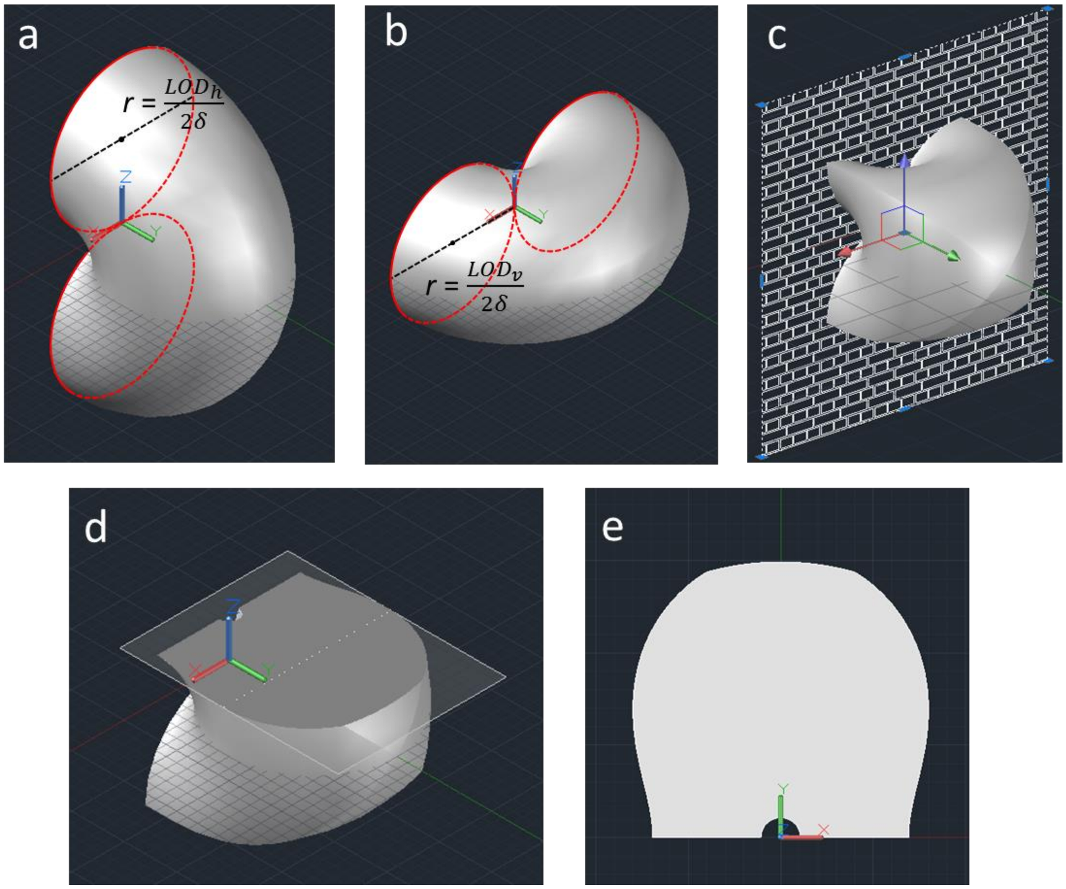


Figure 5. 3D Feasible Space and 2D Feasible Area. (a) shows 3D feasible space of horizontal LOD of a point goal; (b) shows the 3D feasible space of vertical LOD of a point goal; (c) shows the 3D feasible space of a point goal with the wall where the point goals is on, which is the intersection of (a) & (b); (d) shows the intersection of 3D feasible space and the horizontal plane passing laser source; (e) is the 2D feasible area generated by process (d)

2.4.1.4 2D feasible area

A 2D feasible area is the horizontal cutting area of a 3D feasible space at the height of the selected laser scanner. If a surveyor installs the laser scanner on the ground, then the 2D feasible area of point goal i (A_i) should show the scanning positions on the ground to scan the point goal i with LOD requirements, as shown in Figure 5(d) and described in the equation below:

$$A_i = \{(x, y) | s_h(x, y, \delta) < LOD_h,\ s_v(x, y, \delta) < LOD_v\}$$

where s_v is the vertical surface sampling distance; s_h is the horizontal sampling distance; δ is the angular resolution (see 3.2.3). Considering a case where all point goals are on the surface perpendicular to the ground, such as points on a vertical wall, I set up the laser scanner position as $(x, y, \Delta h)$, where Δh is the vertical distance between the point goal and the laser scanner. The mathematical representation of the 2D feasible area of a point goal is as Equation (5) below. Figure 5(e) visualize this 2D feasible space.

$$A_i = \left\{ (x, y) \left| \begin{array}{c} \dfrac{\delta(x^2 + y^2 + \Delta h^2)}{\sqrt{y^2 + \Delta h^2}} \leq LOD_h \\ \dfrac{\delta(x^2 + y^2 + \Delta h^2)}{\sqrt{x^2 + y^2}} \leq LOD_v \\ y > 0 \end{array} \right. \right\} \tag{5}$$

The set A_i in Equation (5) should not be an empty set; otherwise, no positions can achieve the required LOD for point goal i. To guarantee that A_i is non-empty, δ, Δh, LOD_h, and LOD_v should meet certain requirements described in Equation (6):

$$\begin{cases} \Delta h \cdot \delta_h \leq \dfrac{\delta(x^2 + y^2 + \Delta h^2)}{\sqrt{y^2 + \Delta h^2}} \leq LOD_h \\ 2\Delta h \cdot \delta_v \leq \dfrac{\delta(x^2 + y^2 + \Delta h^2)}{\sqrt{x^2 + y^2}} \leq LOD_v \end{cases} \Rightarrow \ \delta \leq min\left(\frac{LOD_v}{2\Delta h}, \frac{LOD_h}{\Delta h}\right) \tag{6}$$

The maximum value of δ that satisfies Equation (6) will be the sparsest resolution $\delta_{sparsest}$ qualified to capture a certain point goal with the required LOD. Otherwise, the feasible spaces of these points could have no intersections with the horizontal plane passing through the laser source, so that no positions on the ground could achieve the required LOD for the considered point goal.

2.4.1.5 Optimization model for the laser scan planning problem

This section uses an optimization model to show the computational complexity of solving the laser scan planning problem. The decision variables of this optimization model are:

1) The number of scans needed is k. When solving the optimization model, the optimal number of scans needed for the entire job site is unknown. As a result, I will try different iterations of k increasing from 1 to m, where m is the possible upper limit of the number of scans.
2) Angular resolution of the scanner $resolution_{j,k}$, which is the scanning angular resolution used at the scanning position j when the total number of scans is k.

The objective function of the optimization model is the scanning time T:

$$Min: T = \sum_{j=1}^{k} T(resolution_{j,k})\, , j \leq k, k \leq m \tag{7}$$

where $T(resolution_{j,k})$is the scanning time of the jth scan, a function of $resolution_{j,k}$.

The constraints of this optimization model (Equation 8) should be that at least one scan exists within the feasible area of every point goal. In these constraints, six parameters form the representation of a point goal: $[x_i,\ y_i,\ z_i, x_{oi}, y_{oi}, LOD_i]$. $(x_i,\ y_i,\ z_i)$ represents the coordinates of point goal i. The number of point goals is n. (x_{oi}, y_{oi}) represents the unit normal vector of the surface where point goal i locates. This is because this study assumes that all point goals are on flat surfaces perpendicular to the ground (i.e., vertical walls). LOD_i represents the level of detail requirements of i. h is the height of the laser scanner. In addition, $[x^*, y^*]$ is the horizontal coordinates of scanning position in the local point goal coordinate system, which has the origin at point goal i, y-axis is the normal vector of the surface where point goal i locates, and z-axis is the zenith direction. $[x_{j,k}, y_{j,k}]$ is the horizontal coordinate of the scanning position j in the global coordinate system. $s_i^{j,k}$ shows whether the scan at scanning position j covers point goal i. When $s_i^{j,k} = 1$, the scan at scanning position covers the point goal i with sufficient LOD with the angular resolution $\delta_{j,k}$ when the number of scans is k.

$$\begin{cases} s_i^{j,k} = \begin{cases} 1, & if \begin{cases} \dfrac{\left(x^{*2} + y^{*2} + (h - z_i)^2\right)\delta_{j.k}}{\sqrt{x^{*2} + y^{*2}}} \le LOD_i \\ \dfrac{\left(x^{*2} + y^{*2} + (h - z_i)^2\right)\delta_{j,k}}{\sqrt{y^{*2} + (h - z_i)^2}} \le LOD_i \\ \begin{bmatrix} x_{j,k} \\ y_{j,k} \end{bmatrix} = \begin{bmatrix} x_i \\ y_i \end{bmatrix} + \begin{bmatrix} y_{io} & -x_{io} \\ x_{io} & y_{io} \end{bmatrix} \begin{bmatrix} x^* \\ y^* \end{bmatrix} \end{cases} , i \in [1, n], j \in [1, k] \\ 0, & else \end{cases} \\ \sum_{j=1}^{k} s_i^{j,k} \ge 1, i \in [1, n] \\ resolution_{j,k} \in \left\{1, \frac{1}{2}, \frac{1}{4}, \frac{1}{5}, \frac{1}{8}, \frac{1}{10}, \frac{1}{16}, \frac{1}{20}, \frac{1}{32}\right\} \\ \delta_{j,k} = \dfrac{\pi}{20000 * resolution_{j,k}} \end{cases} \tag{8}$$

Assuming that 10,000 possible scanning positions and 200 point goals are in the whole job site. Also, the maximum number of scans necessary is 20. I need to solve $200 \times 3 \times \sum_{k=1}^{20} C_{10000}^{k} \times 9 = 2.182 * 10^{65}$ (“9” is the number of resolution options available from the laser scanner) inequalities and equations to find the solution using exhaustive searching, which is infeasible using any existing computing platform. I thus explore a new approach for solving such a large-scale optimization problem in a more efficient way, namely, the "divide-and-conquer" approach, as described in the following section.

2.4.2 Overview of the "divide-and-conquer" method

In order to reduce the computational complexity of the optimization problem described in the previous section, the laser scan planning algorithm developed in this study first divides the job site into parts. It generates a laser scan plan for each part of the job site and then combines the solutions of these job site parts into a comprehensive laser scan plan for the whole job site. I term this approach as the "divide-and-conquer" method of laser scan planning.

The inputs of this divide-and-conquer method are point goals. Field engineers can derive point goals from as-designed models of job sites, field photos, or sparse 3D imageries. Specifically, some studies generate point goals based on as-designed building information models (Akinci et al. 2006). Some image analysis methods can identify parts of the images where detailed spatial data is necessary, such as parts that have discontinuities of color and changes in curvatures (Zhang and Tang 2015b). Given point goals extracted from various data sources, the proposed algorithm can then automatically generate the laser scan plan through three steps, as shown in Figure 6:

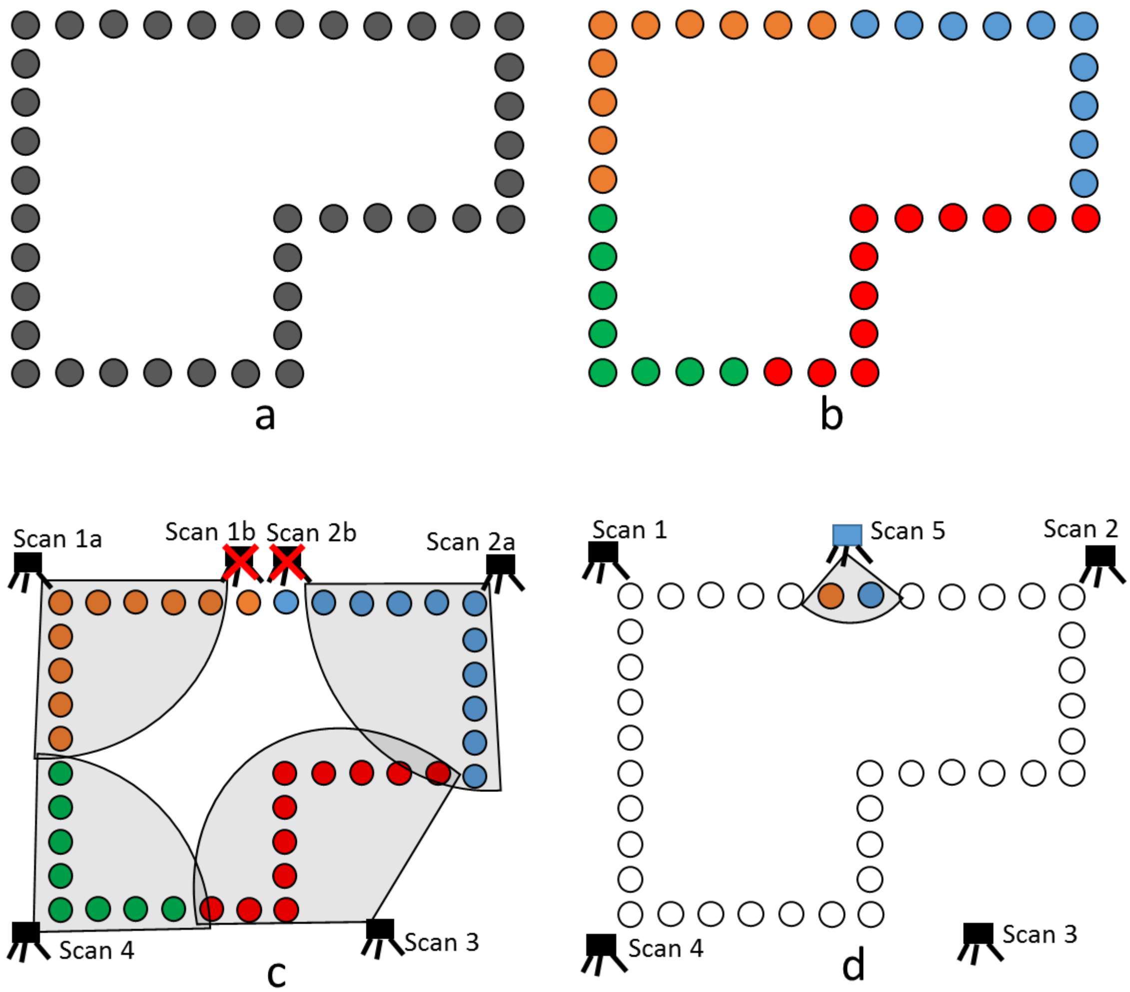


Figure 6. A Framework of the Divide-And-Conquer Method of Laser Scan Planning. (a) Top view of all point goals of a building. (b) Clustering the point goals into clusters. (c) Determine scanning positions in each cluster. Some scans may only cover a few point goals at the borders between clusters (e.g. scan 1b in the orange group and scan 2b in the blue group) so that adding them into the plan would cause redundancies. (d) Identify point goals that are at the borders between clusters and causing redundant scans as “garbage,” and determine scanning positions and resolutions for “garbage.”

1. Clustering the point goals into different clusters according to contradicting visibility relationship analysis (Section 2.4.3, Figure 6b):

   Different areas on a job site may require different LODs, leading to different angular resolution requirements. If the algorithm configures scanning resolution for each point goal, the computational complexity of the algorithm will be high. On the other hand, if the algorithm configures the angular resolution for all point goals as a whole, the imaging plan will always satisfy the most LOD-demanding point goals, and thus waste time on generating unnecessary dense data for point goals that require lower LODs. Instead of using the above two inefficient planning strategies, the divide-and-conquer method will first cluster point goals that have similar LOD requirements and locate close to each other and then determine laser scanning positions and resolution for each cluster.

Overall, the algorithm automatically detects whether a single scan can capture two point goals with sufficient data quality, termed as the "contradicting visibility relationship" between two goals. Then the algorithm groups all point goals that have no contradicting visibility relationship with each other into one cluster, so that the number of clusters is the minimum number of necessary scans to satisfy the data quality requirements of all point goals.

2. Determining scanning positions and resolutions for clusters of point goals to satisfy the data quality requirements (Section 2.4.4, Figure 6c):

   Within each cluster, the algorithm first derives the feasible area (discussed in Section 2.4.1.4) for every point goal. The algorithm then determines the minimum scanning positions according to the feasible areas, ensuring the coverage of all point goals in the current cluster. Some scans may only cover a few point goals at the borders between clusters (e.g., scan 1b in the orange group and scan 2b in the blue group in Figure 6c) so that adding them into the plan would cause redundancies. The algorithm thus ignores any scans that only cover a small portion of total point goals in order to address most point goals with least number of scans to improve scanning efficiency. In the next step, the planning algorithm will address those missed point goals through a "garbage collection" step.

3. Addressing point goals not covered by the laser scan plan through "garbage collection" (Section 2.4.5, Figure 6d)

   After determining scanning positions and the angular resolution for each cluster of point goals, the algorithm identifies point goals at the borders between clusters and assigns redundant scans as "garbage." The algorithm then combines these point goals into a new cluster, thereby determining the angular resolution and positions of this new cluster. This particular algorithm is named as "garbage collection" in this paper. Finally, the algorithm combines all scanning positions and their respective angular resolutions to form the laser scan plan based on plans that address clusters of point goals.

2.4.3 Divide: clustering of point goals

The proposed laser scan planning method uses two levels of simplification to reduce the computational complexity. The first level of simplification generates point goals to represent critical information requirements across the whole job site. The second level of simplification clusters point goals to decompose the job site into parts and generates laser scan plans for each cluster of point goals, which are parts of the job site. The objective of point goal clustering is to divide them into the minimum number of clusters so that the planning method would consider fewer clusters while having as many possible point goals within one cluster that are visible to a single scanning position. This two-level simplification enables the algorithm to choose the optimal scanning position and resolution for the point goals in each cluster. Therefore, the method strives to minimize the number of scans for covering all point goals, thereby improving the overall computational efficiency.

Figure 7 shows that the clustering algorithm uses several rules to assess whether every pair of point goal is visible at certain scanning positions, hereby termed as "contradicting visibility relationship." For example, if two point goals are on two sides of a wall, the visibility of these two points contradicts with each other. Another example of contradicting visibility relationship is two point goals that are too far away from each other. The rules assessing the contradicting visibility relationship of point goals (Section 2.4.3.2) involve three variables: 1) the angle between the surface orientation at two point goals, 2) the distance between two point goals, and 3) "featured length" of the job site determined by the elevation and LOD of all point goals (Section 2.4.3.1). Knowing the contradicting visibility relationship of any pair of point goals, the clustering algorithm is able to cluster point goals without contradicting visibility relationship into the same cluster, in order to obtain the minimum number of clusters. Section 2.4.3.3 presents the algorithm of clustering point goals according to the visibility-contradict assessment rules.

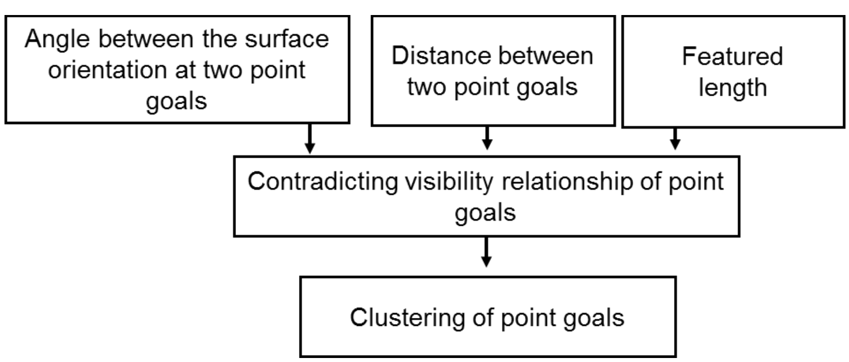


Figure 7. Overview of the Point Goals Clustering Algorithm

2.4.3.1 Featured length

Generally, the clustering algorithm will cluster all the point goals that one single scan can cover. The clustering algorithm thus needs to determine the likelihood of capturing certain point goals in one scan. The “featured length” of a building facade is the horizontal range that one single scan will cover using the sparsest angular resolution that can secure all goals on the façade with the required LOD, which is equal to the width of the 3D feasible space of the point goal requiring the densest scanning resolution. If the distance between two point goals is longer than the featured length, a sparse scan will not capture both goals, and increasing the data density will cause a significant increase in scanning time.

Figure 8 demonstrates the geometric concept of featured length. The distance between point goals A and B in Figure 8 (a) is 15 m, while the distance between point goals A’ and B’ in Figure 8 (b) is 25 m. A and B are 4 m above the height of the laser scanner, while A’ and B’ are 24 m above the scanner. The LOD requirements of all four goals (A, B, A’, B’) are 0.025 m. Among all the point goals in the building shown in Figure 8 (a), A and B require the densest scanning resolution to meet the LOD requirement because of their elevation. According to Equation (6) in Section 2.4.1.4, engineers need to choose the scanning angular resolution of 2.51×10^{-3} rad to scan the wall that AB is on in order to satisfy the LOD requirements. In the point cloud of the wall, the horizontal range with required LOD is equal to the width of the 3D feasible space of the point goal A or B, which is around 4.97 m. I identify this length as the featured length of the building in

Figure 8 (a). Similarly, the featured length of building (b) is *l'* = 39.78 m because engineers need to use a much denser angular resolution of 3.14×10^{-4} rad to scan A' and B'. Therefore, *AB* > *3l* while *A'B'* < *l'*, which means that it is efficient to scan point A' and B' in a single sparse scan in (b), while it is not necessary to cover A and B in one scan in (a) because that needs denser scanning that significantly increases the data collection time. Section 2.4.3.2 will show more details about how featured length will help the grouping of point goals.

The first step of deriving the featured length is to determine the sparsest angular resolution that can cover any point goal on all facades of the building on the job site with required LOD,$\delta_{jobsite}$, which relates to the elevation and LOD of each point goal:

$$\delta_{jobsite} = \min(\delta_{sparsest,i}), i = 1,2,3 \dots n$$

where

$$\delta_{sparsest,i} \leq \frac{LOD_i}{2\Delta h_i}$$

where n is the number of point goals at the job site, and *i* refers to any point goals at the job site. $\delta_{sparsest,i}$ is the sparsest resolution applicable for point goal *i*, and Δh_i is the vertical distance between point goal *i* and the laser scanner (Section 2.4.1.4).

The second step in deriving the featured length l is determining the range that one single scan can cover based on $\delta_{jobsite}$ and the LOD of the point goals that need to be scanned with $\delta_{jobsite}$:

$$l = \max(LOD_j/(2\delta_{sparsest,j})), j \in \left(j \middle| \delta_{sparsest,j} = \delta_{jobsite}\right)$$

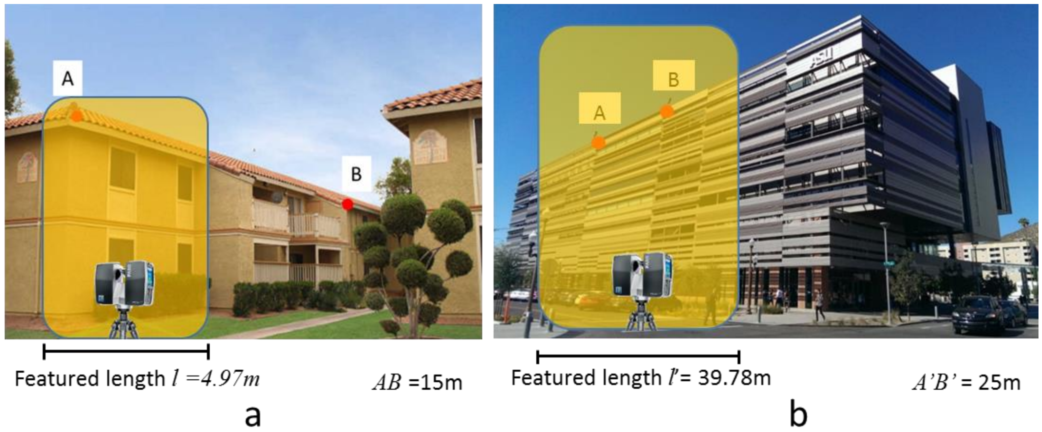


Figure 8. Comparison Between Point Goals of Buildings with Different Feasible Lengths. *Yellow shades* indicate the approximate range one laser scan can cover with required LOD using an adequate angular resolution.

2.4.3.2 Contradicting visibility relationship analysis using featured length and orientations

Contradicting visibility relationship analysis determines the likelihood of having one scan cover two point goals with required LOD. This also means the possibility of having the 3D feasible spaces of two point goals intersect. Instead of calculating the 3D feasible spaces of all point goals and then checking for overlaps, which is time-consuming, this approach will instead calculate the contradicting visibility relationship using a fast and approximate approach. The inputs of the contradicting-visibility-relationship analyzing algorithm include the distances between pairs of point goals, angles between the surface orientations at pairs of point goals, and the featured length of the job site. In the clustering stage, the algorithm assumes the angular resolution used as $\delta_{jobsite}$ (defined in 4.3.1). This algorithm utilizes an extensive library that contains a number of visibility-contradict analysis rules generated from geometric relationships of 2D feasible areas of point goals and experimental results. The following rules are some examples selected from this library:

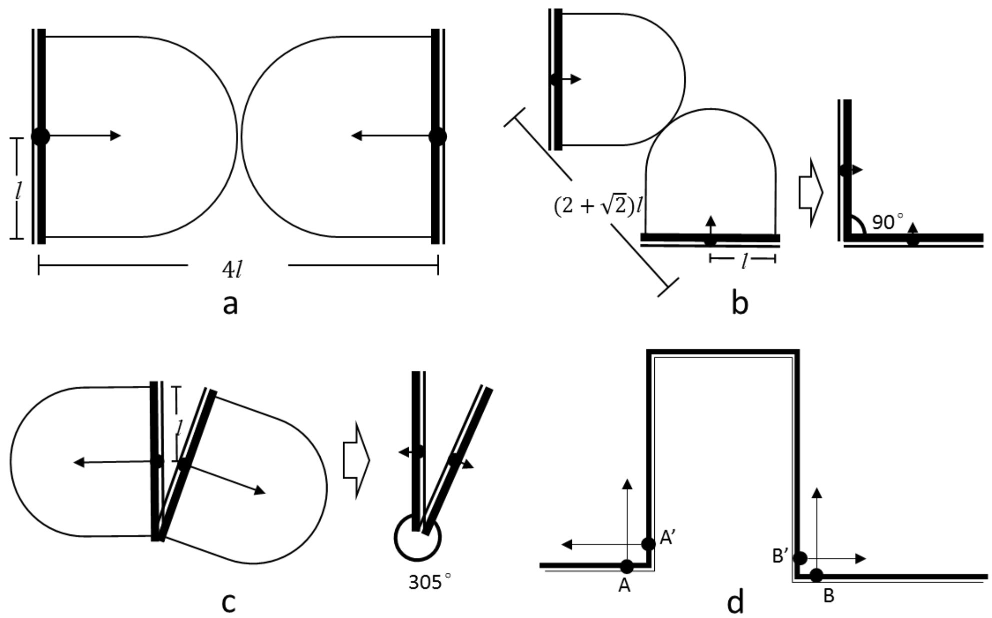


Figure 9. Examples of Rules for Contradicting Visibility Relationship Analysis.

1. Figure 9 (a) shows two point goals, A and B, and the possible outer boundaries of their feasible areas, which are the projections on the x-y plane of the 3D feasible spaces of these two point goals. Figure 9 (a) shows that if the distance between A and B is larger than four times of the featured length *l*, then the two point goals contradict in visibility. Hence, it is not efficient to use unnecessarily high scan resolution to cover distance goals, A and B, in the same scan, because other areas covered in this scan will be over sampled. No matter what the orientations of point goal A and B are, it is impossible for the feasible spaces to intersect with each other if the distance between A and B is larger than four times the featured length.

2. Figure 9 (b) shows two point goals that have the surfaces between them form a 90-degree angle. According to the geometric relationship of two feasible areas of point goals shown in Figure 9 (b), if the distance between A and B is larger than $(2 + \sqrt{2})$ times of the featured length *l*, and the angle between the surfaces at A and B varies from 90 to 180 degrees, then the two point goals have contradicting visibility relationship. If the distance increases or the angle decreases, then it is impossible for the two feasible spaces to intersect with each other.
3. Figure 9 (c) shows two surfaces with 305-degree angles and close to each other. If the angle between the surfaces at A and B was between 305 and 360 degrees, then the two point goals have contradicting visibility relationship. One example is that two point goals are on two sides of a wall. In this case, the orientation angle of two point goals is 180 degrees. If two point goals are close enough, their feasible area may intersect. However, this case is very rare on actual job sites. Therefore, two point goals are in contradicting visibility relationship as long as the angle of the surface is larger than 305 degrees.
4. Figure 9 (d) shows that two point goals A and B are occluded by an object, which has point goals A' and B' on its two sides. In practice, A is often occluded by the object when B is visible, and vice versa. Therefore, A and B have a contradicting visibility relationship due to the occlusion of the object between A and B. Furthermore, such an object between A and B often contains point goals with contradicting visibility relationships, shown in rule 3 (A' and B' in Figure 9d). As a result, this rule means that A and B have a contradicting visibility relationship if: 1) two point goals (A and B) are "close" to another pair of point goals (A' and B')

with contradicting visibility relationship described in (3); and 2) the distance AB is greater than A'B'. Here, "close" is defined as "the length of AA' (or BB') in x-y plane is less than 10% of the featured length."

2.4.3.3 Clustering of point goals

The clustering algorithm will group all point goals that satisfy two conditions. The first condition is that the point goals without contradicting visibility relationships are in the same clusters while ensuring the least possible number of clusters. The second condition is that the point goals in the same cluster should be close to the geometric center of the cluster.

The first clustering condition uses the following statement: n vertices are in a graph to represent *n* point goals; an edge connects two vertices if they are contradicting in visibility. The algorithm will label two connected vertices as different colors to indicate that they belong to different clusters. So the least number of colors needed to color the whole graph, called the 'chromatic number' of the graph (Berge 1973), is the smallest positive integer *k* that allows the algorithm to partition the set of point goals into *k* parts containing point goals not contradicting with each other. Vertices coloring is a heavily discussed topic in modern graph theory and there are multiple coloring algorithms available in the literature (Caramia and Dell'Olmo 2008; Elghazel et al. 1918; Kučera 1991). The clustering algorithm uses the greedy coloring algorithm, which considers the vertices of the graph in sequence and assigns each vertex its first color without contradiction (Kučera 1991). The "divide" algorithm will run greedy coloring algorithm repeatedly and choose a clustering result with the minimum number of clusters as the starting point for further optimization of the clustering result. Figure 10 (a and b) shows the clustering of point goals according to the first clustering condition.

The result of the coloring of graph nodes using a greedy algorithm is not unique (Kučera 1991). There could be multiple clustering results achieving the same minimum number of clusters. Therefore, the "divide" algorithm will further improve the clustering results according to the second clustering condition. Without losing generality, a clustering result has k clusters, and a cluster i has n_i point goals. In one cluster, the performance index of clustering results is the sum of the square distance between point goals and the geometric center of clusters:

$$C = \sum_{i=1}^{k} \sum_{j=1}^{n} \left[\left(x_{ji} - x_{ci}\right)^2 + \left(y_{ji} - y_{ci}\right)^2 \right] \tag{9}$$

where x_{ji} and y_{ji} are the (x, y) coordinates of the jth point goal in cluster i, respectively. x_{ci} and y_{ci} are the (x, y) coordinates of the center point of cluster i, respectively. Based on the clustering result that satisfies the first clustering condition (Figure 10b), the divide algorithm will iteratively improve the result by moving the point goals between clusters to minimize C defined in Equation (9), keeping the point goals having contradicting relationship in different clusters (the first clustering condition). Figure 10 (b and c) shows the algorithm for improving the performance of the clustering result. The result shown in Figure 10c is different from the starting point (Figure 10b), because of moving point goals between clusters to minimize C.

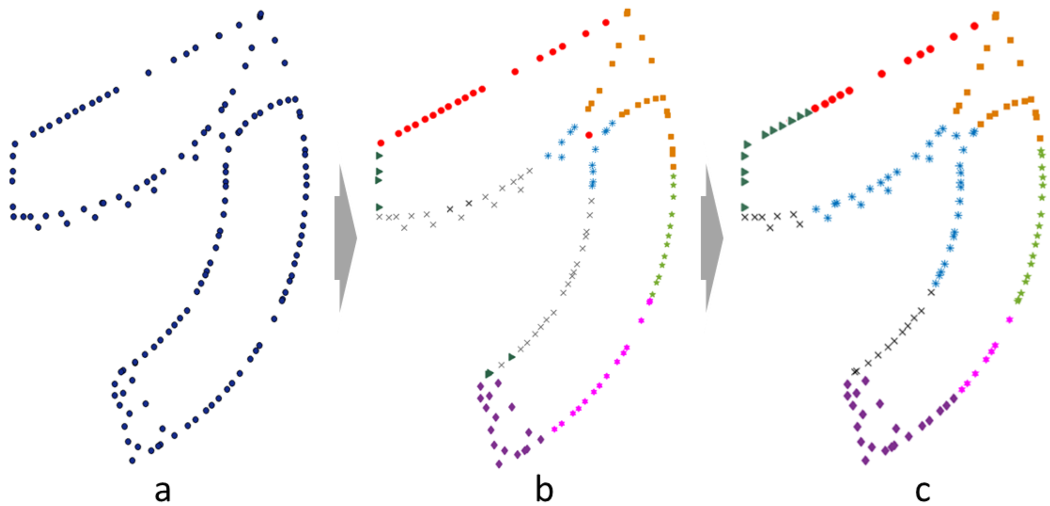


Figure 10. Point Goal Clustering Algorithm. (a) Top view of all point goals in a job site. (b) one clustering result shown by color and shape of points. This result involves the first rule of point goal clustering (visibility contradict). The number of clusters is the minimum, but the points in the same cluster are more sparsely distributed. (c) Optimized point goal clustering result. This clustering result has a minimum number of clusters, and point goals in the same cluster are close to the geometric center of the cluster.

2.4.4 Conquer: generating laser scan plans for clusters of point goals

After clustering point goals, the algorithm will generate a laser scan plan for each cluster called the "conquer" algorithm. These laser scan plans for clusters are thus parts of a complete laser scan plan that covers the whole job site. The pseudo code of the conquer algorithm below shows the process of scanning position detection and resolution configuration in each cluster.

This algorithm of generating "local" plans includes four steps: first, the "conquer" algorithm will set a sparse angular resolution value for initializing the generations of feasible spaces of point goals within a cluster. Second, the "conquer" algorithm will generate scanning positions according to the feasible areas, called "next-best-view" algorithm (Connolly 1985; Song et al. 2014; Zhang and Tang 2015a). Third, the algorithm will progressively densify the angular resolutions and repeat step 2, and then compare the total scanning time of the plans generated based on different angular resolution values. In this way, the “conquer” algorithm will find the most time-efficient combination of scanning resolution and positions for this cluster of point goals. In the fourth step, the algorithm will identify the point goals that were ignored by the “next-best-view” algorithm, for the algorithm ignores a percentage of total point goals when scanning those single goals can significantly increase the data collection time. Parameter “*a*” is the function of the number of clusters, the highest resolution used in all clusters, and the resolution determined in the current cluster. For example, in one of the case studies, the algorithm ignored two point goals in one cluster, which is less than 1% of total point goals. If the algorithm planned a scan for the ignored point goals, the total scanning time would have increased by about 10%.

The outputs of this algorithm of generating laser scan plans for clusters of point goals include the scanning positions and the corresponding angular resolutions, as well as “garbage” - point goals that remain un-scanned in the current cluster. Section 2.4.5 presents a garbage collection algorithm that addresses these remaining point goals.

Pseudo code of the “Conquer” algorithm

1:	Input: point goal information in one cluster
2:	Output: Scanning positions in the cluster; scanning resolution; point goals un-scanned
3:	resolution ← sparsest_resolution_in_current_cluster // set initial value of scanning resolution

```
[scanning_position] ← next_best_view(pointgoals, resolution) // Use next-best-view algorithm to generate the scanning positions according to initial scanning resolution
scan_time_previous ← scan_time_initial
scan_time_current ← scan_time_initial
while scan_time_current <=  scan_time_previous do // find the optimal scanning resolution
scan_time_previous ← scan_time_current
[scanning_position, scan_time_current, un-scanned_point_goals] ← next_best_view(pointgoals, resolution)
resolution ← higher_resolution (resolution)
end while
return scan_position, scan_time_current, un-scanned_point_goals
```

2.4.5 Combine: "garbage collection" and finalizing scan configurations

The "conquer" algorithm only requires the scans to cover most of the point goals in one cluster and ignore some difficult point goals that significantly increase the data collection time.

For each cluster, the algorithm will collect point goals that remain un-scanned after determining the local laser scan plans. These un-scanned point goals from all clusters form a new cluster, and the algorithm will carry out the laser scan planning for this new cluster using the same process described in the previous section. I name this algorithm as "garbage collection". The pseudo code of "garbage collection" algorithm below shows the detailed information of this step.

Pseudo code of the "Garbage collection" algorithm

```
Input: all point goals remain un-scanned from all clusters, scanning positions from other clusters
Output: Scanning position(s) and scanning resolution for "garbage" cluster
if  scanning positions from other clusters cover any un-scanned_pointgoals do
delete current un-scanned_ pointgoals
end if // Because the scans for Cluster A may cover the "garbage" point goals in Cluster B, the algorithm examines whether previous scans have already covered any of the point goals from other clusters. If so, delete these point goals from the "garbage" cluster.
[scanning_position, scanning_resolution, pointgoals_covered_in_each_scan] ← "Conquer" algorithm(un-scanned_pointgoals)
for each scanning_position
if pointgoals_covered_in_each_scan < a% * total_number_of_ pointgoals do
delete current scan_position
end if
end for // If a scan will only cover a% of the total number of point goals, I consider it inefficient and discard this scan. This is a trade-off between data quality and scanning efficiency. In addition, doing this improves the robustness to outlier point goals due to inaccurate data or model.
return scanning_positions,  angular_resolutions
```

2.5 Validation

2.5.1 Runtime analysis of the laser scan planning algorithm

In this study, I conducted big-O analysis (Latimer et al. 2004) to show the upper bound on the runtime of the laser scan planning method. The inputs of the planning method are point goals, so the big-O analysis examines how the computational time increases with the number of point goals *n*. The runtime of "divide" algorithm is $O(n^2)$ because the algorithm needs to check the contradicting visibility relationship between all goals. The runtime of “conquer” and “combine” is also $O(n^2)$ because the algorithm needs to calculate the feasible area for each point goal. As a result, the computational complexity of the laser scan planning method developed in this study is $O(n^2)$.

In order to validate the big-O analysis, I executed the developed laser scan planning algorithm for multiple sites with different numbers of point goals and buildings of various shapes. I developed the laser scan planning algorithm using Matlab R2014b, and tested the algorithm on a computer with 3.60 GHz CPU and 32 GB RAM. Figure 11 shows that the square root of the running time of this algorithm increases linearly with respect to the number of point goals, and so does the square root of the number of contradicting visibility relationships between point goals. This reveals a computational complexity of $O(n^2)$. Looking into these results, I found that in one case study, the number of a large campus building with a gross area of 13,015 m^2 had 258 point goals. The runtime of the algorithm for this building was 381.6 s, about 6.36 minutes. This shows the potential of achieving real-time laser scan planning on construction sites that require timely and detailed spatiotemporal information for proactive project control.

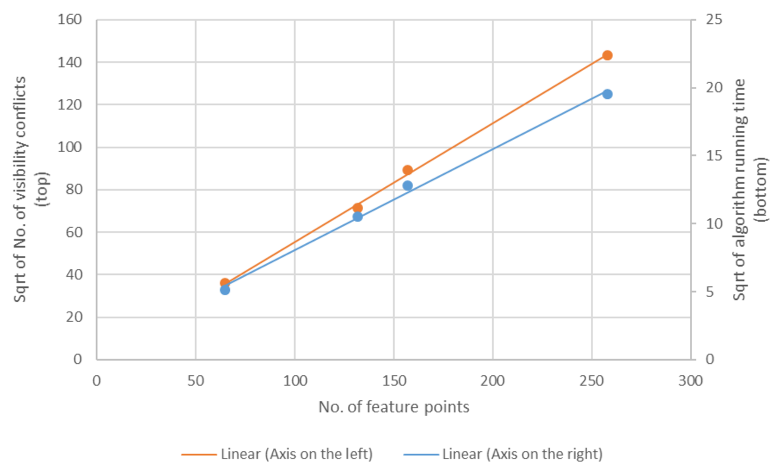
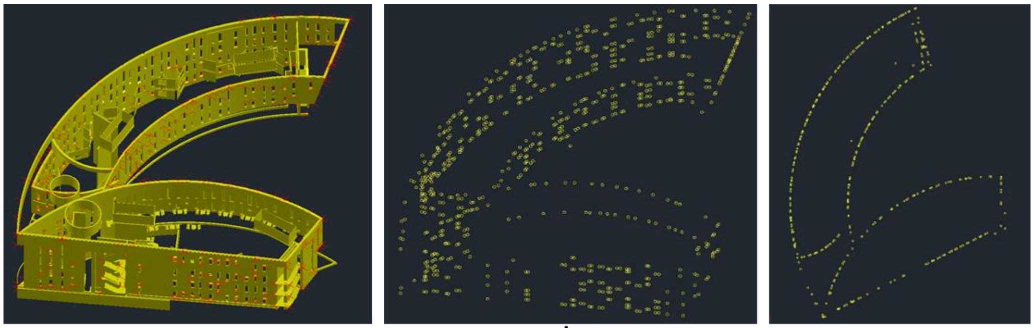


Figure 11. Relationship between Number of Point Goals, Number of Contradicting Visibility Relationships and Program Running Time

2.5.2 Case study: a campus building of complex shape

To validate the proposed laser scan planning method, I conducted laser scanning on a campus building based on the optimal plan automatically identified by the algorithm and several plans generated by a 3D imaging researcher and a laser scanning professional who has been using laser scanners in more than ten large building projects. Figure 10a shows the as-designed model of this campus building at Arizona State University (ASU). All the automatic and manual laser scan plans use 258 point goals specified by an engineer on the as-designed model (Figure 10b-c) of the building, according to the General Services Administration (GSA) manual of laser scanning for building facades (U.S. General Services Administration 2009). The point goals include the corners of windows, points along the edges of walls, and the corners of walls. In addition, I set the LOD requirement of each goal as 25mm (one inch), which is GSA Level 2, a commonly adopted standard for building exterior design and renovation (U.S. General Services Administration 2009).



a b c

Figure 12. A Campus Building in Arizona State University (ASU): (a) As-designed model with point goals (red crosses). (b) Elevation view of all the point goals. (c) Top view of all the point goals.

2.5.2.1 Overview of performance evaluation

In the study of the campus building, I compared the performance of three laser scan plans. Plan A: a plan automatically generated by the developed laser scan planning algorithm; Plan B: a plan manually created by a 3D imaging researcher, and Plan C: a plan manually created by a laser scanning professional from a general contractor who built this studied building.

This study uses two metrics to measure the performances of laser scan plans: 1) data collection time, and 2) data quality. The data collection time consists of scanning time, time for moving scanners between stations, and time for setting up at each station. The data quality assessment focuses on the level of detail (LOD) captured in the collected data. The metric of data quality is the percentage of point goals captured with their required LODs (P).

The evaluation of a laser scan plan has three phases: Phase 1, collecting laser scanning data of the building according to the developed plan; Phase 2, calculating the percentage of point goals captured with their required LODs; Phase 3, performing additional scans for addressing point goals that were missing or lacking details. Overall, I compared laser scan plans in terms of: (1) *Percentage of point goals captured with the required LODs (P)*; (2) time for completing the scans in phase 1; (3) time for completing the scans in phase 1 plus additional time required to perform scans in phase 3.

2.5.2.2 Generating laser scan plans

Given the point goals as the inputs for manual laser scan planning, the developed algorithm generated the automated scanning plan (Plan A). The researcher and the laser scanning professional generated plans B and C, respectively, by following the Building Information Model Guide for Laser Scanning of the United States General Services Administration (GSA BIM Guide) (U.S. General Services Administration 2009). GSA BIM Guide specifies that the distances between adjacent scanning locations should be between 20 m to 40 m to capture high-quality data. The yellow stars in Figure 11(a) (b) and (c) show the scanning positions of the three laser scan plans. In these plans, the numbers next to the scanning positions (e.g. 1/5, 1/4, etc.) are the scanning resolutions used at those scanning positions. The noise level of laser scanning data was kept at constant for all scans, which is the other parameter influencing the laser scanning time. The corresponding angular resolution of 1/5, for example, equals to $\delta_{1/5} = \frac{\pi}{20000*(\frac{1}{5})} = 7.85\times10^{-4}$ rad (*Faro ® Laser Scanner Focus 3D Manual* 2010).

2.5.2.3 Comparison of manually planned and automatically generated data collections

The data quality of the 3D laser scanning point clouds of the studied campus building was evaluated using the software “CloudCompare”(Girardeau-Montaut 2013). Figure 14 visualizes all points where the LOD requirements were satisfied in the point clouds collected through the three compared plans. The red circles in these figures highlight areas where the point cloud does not satisfy the GSA Level 2 LOD requirements due to poorly designed scanning positions and resolutions.

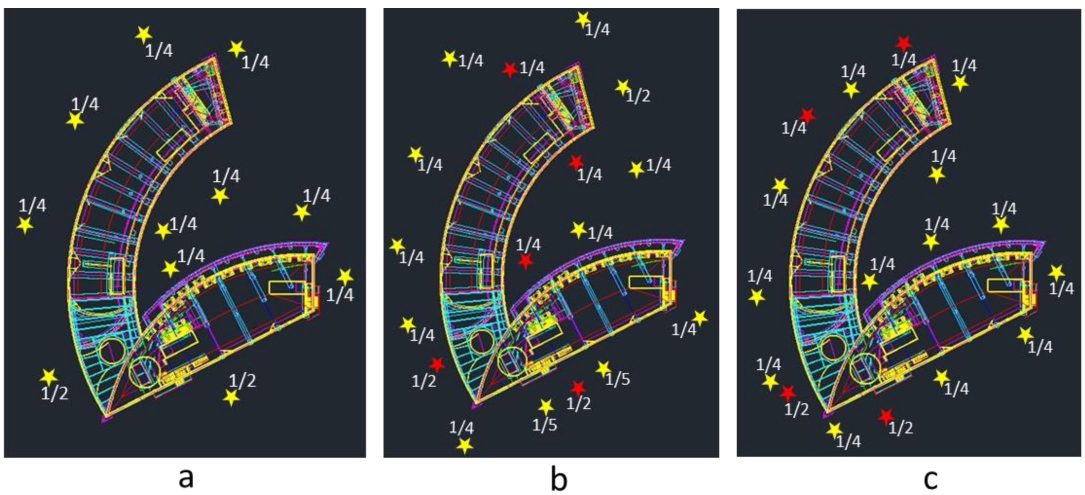


Figure 13. Laser Scan Plan Comparison: (a) a plan automatically-generated by the proposed method (b) a plan manually created by an experienced 3D imaging researcher, and (c) a plan manually created by a laser scanning professional. Note: Yellow stars show the scanning positions of the above laser scan plans in Phase 1. Red stars show the additional scanning positions for the point goals that were missed during the previous scans according to each laser scan plan in Phase 3. Numbers beside the stars are the respective scanning resolution.

Figure 14a shows that the data collected according to the automatically generated plan cover more areas with sufficient LODs compared with the data collected according to manually generated plans. In the results of automatic laser scanning planning (Figure

14a), all 258 point goals were with the required GSA Level 2 LOD (denser than 25 mm along both vertical and horizontal directions). However, only 151 out of 258 point goals have the required GSA Level 2 LOD in data collected through manual planning by the experienced laser scanning researcher (Figure 14b). Only 195 out of 258 point goals meet LOD requirement in data collected according to the plan manually created by a laser scanning professional (Figure 14c).

In order to address point goals missed by manual planning, I conducted five additional scans for Plan B, and four additional scans for plan C. Red stars and corresponding numbers in Figure 13(b) and (c) shows the locations and resolutions of these extra scans. Table 1 shows a detailed comparison of the performances of manual and automatic laser scan planning.

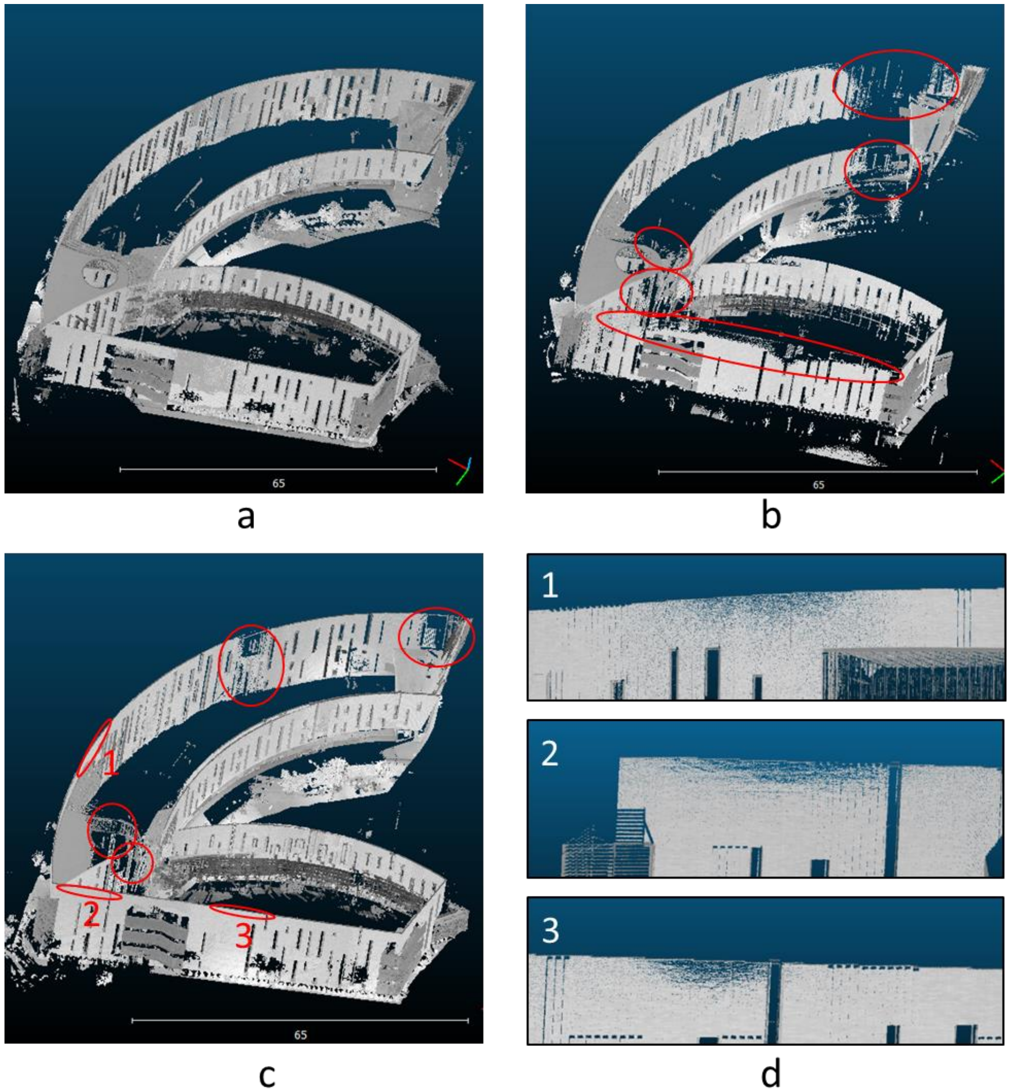


Figure 14. Data Quality Comparison of Point Clouds Collected According to Three Different Plans: (a) a plan automatically-generated by the proposed method (b) a plan manually created by an experienced laser scanning researcher, and (c) a plan manually created by a laser scanning professional. Red circles highlight the areas with low data quality. Fig (d) shows details of three areas marked as having insufficient LOD in (c).

Table 1 Statistics comparing manual and automatic laser scan planning

Laser scan plans	No. of scans in Phase 1	Scanning time in Phase 1	Index of data quality (P)	No. of scans in Phase 3	Scanning time in Phase 3	Total scanning time
Automatic	11	8495s	100%	0	0s	8,495s
Manual plan by the laser scanning researcher	12	6788s	58.5%	5	5201s	11,989s
Manual plan by the laser scanning professional	13	7017s	75.6%	4	4652s	11,669s

The above results indicate that it is difficult for manually generated laser scan plans to achieve 100% coverage of point goals with required LOD. The first difficulty is in choosing the right scanning resolution. For example, for these areas shown in Figure 14d, only scanning with the resolution of 1/2 can ensure the LOD because the elevation of these areas is high above the ground. The second difficulty is in estimating the area that one scan can cover with sufficient LODs. In the case study, the curved shape of the studied building caused additional challenges for a human to precisely choose the scanning positions so that areas with required LOD would connect without gaps.

The case study of this campus building shows that the coverage of automatically planned laser scanning is better than that of manually planned laser scanning (100% point goals in automatic planning versus 58.3% (researcher) and 75.6% (surveying professional) point goals in manual planning satisfy the required LOD), although the data collection time of automatically generated laser scan plan is longer than that of the manually generated plan. This is because the laser scan planning method uses data quality requirements as the priority. When both automatic and manual planning generates high-quality 3D imageries, automatic laser scan planning is time-efficient (8495s versus 11989s and 11669s) because the laser scan planning method will optimize the data collection time while ensuring that data quality requirements are satisfied.

2.6 Discussions

The developed new laser scan planning method in this study comes with some limitations as detailed next, which serve as objectives for future research.

1. The generation of point goals for the laser scan planning algorithm is manual. In future research, I plan to explore methods that can automatically identify point goals based on patterns in collected imageries (images, videos, etc.) that will help guide the divide-and-conquer method, particularly if the as-designed model of the building is not available. In a separate publication, I have explored the use of pictures and the "structure from motion" method (Westoby et al. 2012) to generate sparse 3D point clouds of a building, and then identify areas that are visually complex in the point cloud as point goals for guiding scan planning (Zhang and Tang 2015b). In addition, I will extend the job site presentation from point goals to goals of different geometric elements, including lines, planes, cylinder surfaces, and spheres. The analytical solution of scanning goals of different geometric elements could simplify the scan planning process.
2. Different construction environments and tasks have different LOD requirements. Currently, the developed approach still requires engineers to specify LOD requirements

of point goals based on GSA requirements and the experiences of experts. Future studies will focus on automatically deriving the LOD of every point goal to fully reflect the dynamic properties and visual information requirements (e.g., shapes and colors) for comprehensive monitoring of different kinds of building features and structures.

3. In the proposed method, contradicting visibility relationship analysis is able to help identify the scanning locations where no point goal blocks the visibility of any other point goal. However, objects that do not have a point goal (e.g., vegetation) may block the visibility of other point goals during laser scanning, thus causing occlusion problems in the collected point data. Therefore, utilizing previously collected sparse 3D imagery data, future studies will develop a time-efficient visibility checking process to reduce the influence of the unknown environment on data quality.
4. This study does not cover how the laser scanning positions and parameters influence the accuracies of 3D measurements, and how to coordinate multiple scanning stations to achieve accurate and detailed imageries. In surveying science, there is a theory about arranging surveying positions for maximum accuracy by ensuring the "strength of figure" of the network consisting of all surveying positions (Brinker and Minnick 1995), which I believe could be applied to the laser scan planning method. In the future, I plan to enable the scan planning algorithm to cover all given point goals with sufficient LOD and LOA by maximizing the strength of figure of the automatically generated scan plans.
5. In addition, I will try to integrate the laser scan planning method with construction scheduling. I expect that the optimization of construction workflows for inspection

activities will realize real-time and proactive construction quality control while minimizing interferences between data collection activities and construction workflows.

2.7 Conclusion

This paper describes the development of a rapid laser scan planning method that generates scanning positions and recommends angular resolutions for different positions in order to achieve efficient and effective laser scanning data collection. Compared with previously developed sensor planning methods, this new approach not only guarantees the density of collected 3D data but also optimizes the data collection time. Moreover, the new laser scan planning method is able to achieve a computational complexity of $O(n^2)$, which is more efficient than previously developed algorithms. Evaluation results on different buildings show the effectiveness of the proposed method. Laser scan plans generated by the new method will benefit high quality data collection without wasting time and resources. In future research, I will focus on the automation of point goal generation in order to achieve an automatic data-driven workflow of 3D data collection on dynamic job sites.

CHAPTER 3 IMAGERY-BASED RISK ASSESSMENT USING CROWDSOURCING TECHNOLOGY IN COMPLEX WORKSPACES

3.1 Introduction

Imagery has shown potentials for supporting risk management in construction and civil infrastructure management. In both China and the United States, civil infrastructure management agencies use imaging sensors for collecting detailed spatiotemporal information of bridges, dams, and other large structures for detailed condition assessment and risk analysis (Zhu and Brilakis 2010). Efficient and effective uses of imagery data for risk recognition is thus becoming increasingly important for establishing a data-driven risk management framework for civil engineering projects (Zhang and Tang 2015b). Unfortunately, subjective image interpretation manually conducted by inspectors brings uncertainties and biases in risk recognition results based on images. Even well-trained inspectors spend much time for achieving comprehensive and reliable risk recognition from images (Lagasse et al. 2009). In some cases, the uncertainties and biases within manual image interpretation processes can mislead the decisions about construction safety management and civil infrastructure maintenance (Moore et al. 2001). Civil engineers have been developing methods to increase the reliability of manual image interpretation in construction safety (Chang and Liao 2012; Lattanzi and Miller 2014; Papaelias et al. 2016). Some researchers examined image processing algorithms that can automatically extract certain features from images to assist engineers in identifying risks of construction (Chang and Liao 2012). However, engineers still need to decide how to setup and use such image processing algorithms so that the subjective factors still exist

(Moore et al. 2001). At present, interpretation of the images based on human intuition and experiences seems still unavoidable.

Recently, crowdsourcing is becoming a promising tool for reducing the training costs of professional inspectors while maintaining or even improving the reliability of inspection (Brabham 2008; Kittur et al. 2008). A "crowdsourcing" approach collects risk recognition results through online image interpretation games, and aggregates answers from game players into hopefully more comprehensive and reliable risk recognition results (Brabham 2008; Poetz and Schreier 2012). Crowdsourcing integrates the recognition power of human individuals into formal reasoning and pattern classification algorithms for solving image analysis tasks that are challenging state-of-the-art computer vision methods. Examples of such tasks include image segmentation, object recognition, and scene understanding (Brabham 2008; Poetz and Schreier 2012; Ranard et al. 2014).

Unfortunately, while applying such methods to risk assessment based on images, unreliable answers from some game players who lack professional inspection training can cause biases in the aggregated results. As a result, taking the answer of the majority as the risk assessment result could be wrong (Burnap et al. 2015). New theories are thus necessary to overcome the limitation of majority-based approach to alleviate the distortions caused by biased or unprofessional answers.

This research presents a study showing that without knowing the actual risks on construction sites, human-image interaction behavior analyses of anonymous online image interpreters can overcome the limitation of the majority-based approach and acquire reliable risk detection from job site imageries. I conducted this study with the following steps: 1) train anonymous interpreters in a few minutes on limited safety rules and then have them assess a few images to identify violated safety rules, and 2) automatically aggregate the risk assessments of trained interpreters using a Bayesian network model into results. I validate this method using an online image-based risk assessment experiment in elevator installation projects. The risk assessment results of the experiment show that the proposed method can achieve reliable results compared with the result following the majority's vote.

3.2 Motivating Case

The overall goal of this research is to test the hypothesis that without knowing the actual risks on construction sites, the crowdsourcing-based risk assessment method can automatically aggregate risk assessments of anonymous people who just took simple training about construction safety rules into reliable risk evaluations. Figure 15 visualizes such a bias of groups of anonymous online image interpreters the majority of who provide a wrong answer about the risk captured in an image. Specifically, Figure 15(A) shows a crowd-sourced risk assessment result of a job site picture that contains a violation of a construction safety rule. In the assessment result, the majority (65.5%) of the online anonymous image interpreters correctly identified the violated construction safety rule after observing the picture. Figure 15(B) shows the result of a job site picture that contains no violation, wherein the blue region shows the number of correct answers, which is "no violation." Unfortunately, in this case, the majority of the answers about the type of safety rule violated in that picture mistakenly identified that the scene captured in the picture violated a particular safety rule due to the lack of knowledge about that particular rule (green region). Figure 1(B) also shows that the second largest portion of the game players chose “no violation,” which is quite close to 23.8%, the majority, and other answers are not very far behind. Such diverse answers reflected confusions and disagreements among people about the image contents, and slight biases can easily cause a switch of the “majority answer.”

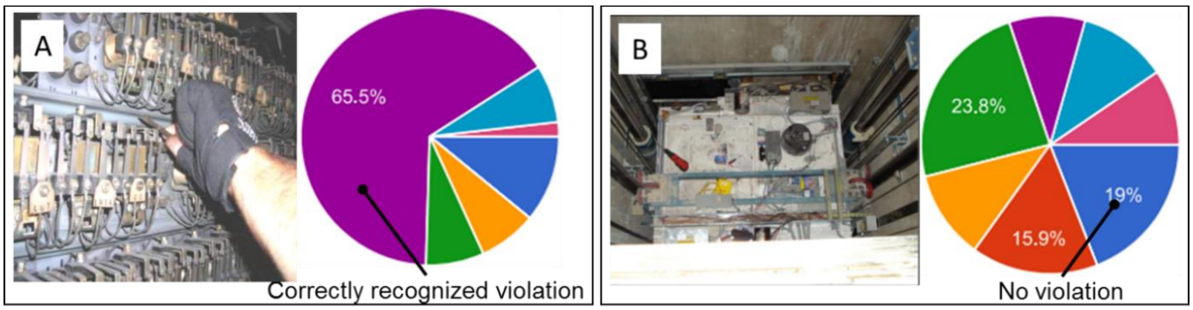


Figure 15. Crowdsourced Risk Assessment Result of Different Job Site Pictures. A: picture with a violation of “wearing or holding metallic objects around live equipment”; B: a picture with no violation.

3.3 Previous Research

3.3.1 Construction safety inspection

Construction is one of the most hazardous industries with high fatality and injury rate, because the uniqueness, dynamic, and complexity of construction sites increases not only workers' exposure to hazards, but also the difficulty in identifying these hazards(Chen et al. 2016; Cheng and Teizer 2013; Fang et al. 2004; Seo et al. 2015). Researchers and industry propose many techniques to maintain safety before and during construction projects. These techniques include: 1) designing safety, which is the consideration of the safety of construction workers in the design of a project (Gambatese et al. 2005); 2) safety training (Ho and Dzeng 2010; Su et al. 2015); measuring and improving the safety climate (Flin et al.

2000; Hallowell et al. 2013; Hinze et al. 2013; Liao et al. 2013), and 4) safety planning which identifies of all potential hazards along with the corresponding safety responses (Zhang et al. 2015). A frequently used technique to prevent safety hazards in construction projects is safety inspection during the construction process (Lu et al. 2015; Reese and Eidson 2006). Job site inspection works as the final line of defense against the accidents when safety training, safety planning, and other front-end techniques occasionally fail.

However, the manual job hazard analysis is time-consuming, and even error-prone (Liao et al. 2016; Seo et al. 2015). Currently, construction safety inspection mainly relies on manual works. Inspection personnel needs to go to the job site frequently to identify and resolve the potential hazard related to the job site environment, worker behavior, and facility usage (Seo et al. 2015). Manual safety inspections are costly, time-consuming, and error prone because they require manual observations and documentations by experienced supervisors or safety personnel (Awolusi and Marks 2016; Levitt and Samelson 1993; Wang and Boukamp 2011). Liao et al. (Liao et al. 2016) presented the observation miss in a simulated safety inspection experiment of an elevator installation project. In the experiment, 40 job site photographs containing 30 risks taken at four typical locations (hoist way, pit, machine room, and storeroom) from different job sites created a virtual environment of the elevator installation. Five inspectors from an elevator installation company with working age ranging from 1.5 to 25 years are then asked to identify the job site pictures with risks within 13 minutes. The experiment result shows that the inspectors can only identify 15-24% safety risks correctly. Also, only 62% of answers of identified risks are correct. This result shows that the complexity of the checklist, including having too many items to check and ambiguous descriptions increase the cognitive control load for the inspectors. Therefore, new technology is needed to reduce the workload and improve the effectiveness of safety inspection work.

Researchers are trying to achieve automatic safety inspection on the job site using computer vision. For example, Rubaiyat et al. (Rubaiyat et al. 2016) automatically detect the users of construction helmets from the construction surveillance images. Han and Lee (Han and Lee 2013) propose a framework of vision-based unsafe action detection in a construction site. This research uses job site videos to reconstruct 3D human skeleton models containing motion information, which is used to detect predefined unsafe action in the data. However, current computer vision for construction safety can only focus on one aspect (e.g. worker behavior.), and the interaction between worker, facility, and job site environment make the computer-vision based hazard identification very difficult. Seo et al. (Seo et al. 2015) review the previous attempts of using computer vision technologies for safety and health monitoring. In this research, I identify the following technical and practical issues that commonly arise when applying diverse computer vision techniques for safety and health monitoring at real construction sites: 1) the lack of task-specific and quantitative metrics for evaluating unsafe conditions and acts; 2) dynamic conditions on construction sites create obstacles such as occlusions, selections of appropriate camera positions, and needs for comprehensive image datasets with diverse viewpoints; and 3) privacy issues due to continuous monitoring at construction sites. Therefore, the integration of human and automation technology is a possible solution to resolve all these issues of pure manual or automatic approach for construction safety inspection.

3.3.2 Crowdsourcing

To overcome the current limitations of construction safety inspection, crowdsourcing technology can utilize the intelligence of non-expert to identify the potential job site risks. Crowdsourcing, which is a human-automation integration technology can effectively achieve reliable job site safety inspection while avoiding the drawbacks of computer vision techniques. Crowdsourcing is defined as decision making based on aggregating the opinions of agents for higher quality than based on the opinions of single individuals (Bachrach et al. 2012; Howe 2006). For example, Ranard et al. reviewed the application of crowdsourcing in the health domain. This research identified many successful cases although the use of crowdsourcing in health research is at an early stage, such as solving protein structure problems, improving the alignment of promoter sequences, tracking H1N1 influenza outbreaks, classifying colonic polyps, etc. A few applications of crowdsourcing have been applied in civil engineering and construction domain. Liu and Golparvar-Fard (Liu and Golparvar-Fard 2015) proposes crowdsourcing the task of workforce assessment from job site video streams to overcome the limitations of labor intensiveness and erroneous results.

However, challenges exist in the application of crowdsourcing techniques. Some crowdsourcing research focuses on the optimization problems that have a clear performance function to evaluate the performance of each answer (Ren et al. 2016). The research questions for which the correct or best answer is unknown results in challenges to aggregate the answer from the crowd-sourcing participants and derive the correct answer. Furthermore, the performance of crowdsourcing will be greatly compromised when most the participants' answers are wrong (Radanovic et al. 2016; Zhao and Zhu 2014). Drapeau et al. (Drapeau et al. 2016) mentioned many techniques for dealing with cases in which the majority may be wrong. The most commonly used approach is to add questions with known answers to the crowdsourcing question pool to evaluate the intellectual capability and identify gaming of the participants. Tournament voting (Sun and Dance 2011) allows the crowdsourcing participants to evaluate other answers and vote to delete the most unreliable answers. Bayesian Truth Serum (Prelec 2004; Witkowski and Parkes 2012) asks the participants to predict the distribution of the answers. Then this method "assigns high scores not to the most common answers but to the answers that are more common than collectively predicted, with predictions drawn from the same population" (Prelec 2004). MicroTalk (Drapeau et al. 2016) allows the participant's chat and debate when answering the crowd-sourcing questions to seek a consensus solution. However, all these methods cannot guarantee the identification of job site risk considering the complex and dynamic nature of the job site. Furthermore, these methods have a common limitation: they bring extra work to the participants, which is a big problem considering the huge amount of job site images and the timely needs of safety inspection results of job sites. Also, extra tasks will increase the cost of crowdsourcing risk analysis, which makes it less competitive to the traditional manual work.

To fully utilize the advantage of the integration of human and automation, crowdsourcing-based job site risk analysis needs to solve the problem caused by the cases in which the majority is wrong in an effective way while minimizing the workload of the participants.

3.4 Methodology

3.4.1 Overall problem description and methodology overview

Figure 16 shows the IDEF0 model of the proposed crowd-based assessment method. Its inputs consist of three parts: 1) pre-defined safety rules of the construction activities; 2) job site pictures that may contain cases that violating safety rules; 3) the common sense of safety from anonymous participants on the internet. The output is the probability of the event that the assessed job site picture violates each safety rule in the predefined list of rules. The constraints are the Bayesian's rule and the training data set. The mechanisms of this crowdsourcing-based risk assessment involve the training process of anonymous image interpreters, the testing process for collecting risk assessments of these interpreters, and the decision-making process that determines the probabilities of the image certain rule violations.

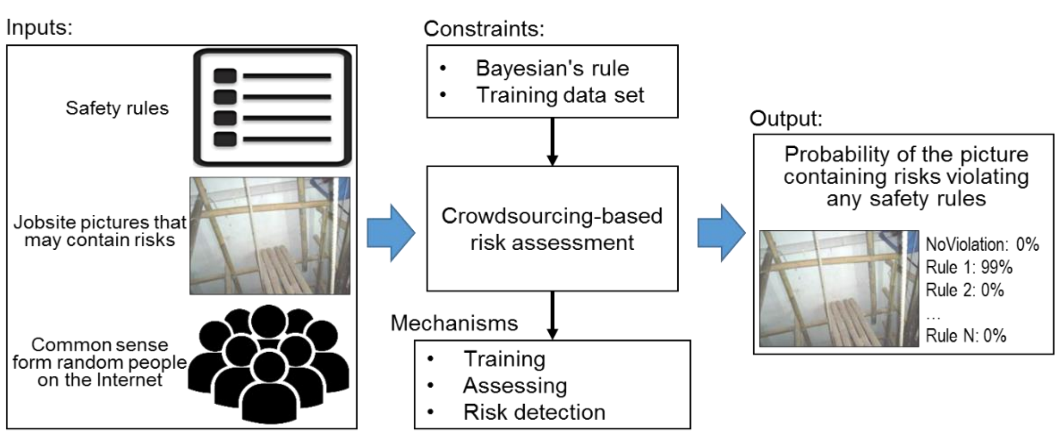


Figure 16. IDEF0 Model of Crowdsourcing-Based Risk Assessment

The assumptions I made in this research are as follows:

- Assessors are independent, i.e., the assessment of one design from one assessor will not be affected by the assessment of other assessors.
- The probability of each rule is violated in a given image is independent of each other, which is obviously not true in the real job site. I will explore the correlation that different rules are violated in one job site picture in future research.
- Each job site picture may contain at most one violation.

I also made the assumptions about the participants' common sense which the participants need to use in the crowdsourcing system:

- They can recognize the objects used on a construction job site in the pictures if they know the shape of the objects.
- They can understand the spatial logic between objects by looking at the pictures (e.g. object A is under object B).
- They have the basic knowledge about how people can be hurt (e.g. people fall from high elevation will be injured or killed; people touching objects with the electric current will be injured or killed).

3.4.2 Crowd-sourcing system design

Figure 17 shows the process of the crowdsourcing-based risk assessment. Job site pictures that may contain violations will be uploaded to the online crowdsourcing platform. Then the platform will set up a violation assessment game played by anonymous participants to identify the violations of safety rules based on images collected on the job site. The game consists of three steps: the training process, the assessing process, and the risk-detection process. In the training process, the participants are divided into groups and then asked to learn about a section of safety rules using the training materials. In the testing process, these participants will become “risk assessors” and identify potential violations of each safety rule they have learned in the training process. Finally, the decision-making process will aggregate the answers from the assessors and then uses the Bayesian network to determine whether a job site picture contains the violation against any safety rules. Among answers from different groups of assessors, the safety-rule violation that received the highest probability in the picture is considered as the actual violation captured in the picture.

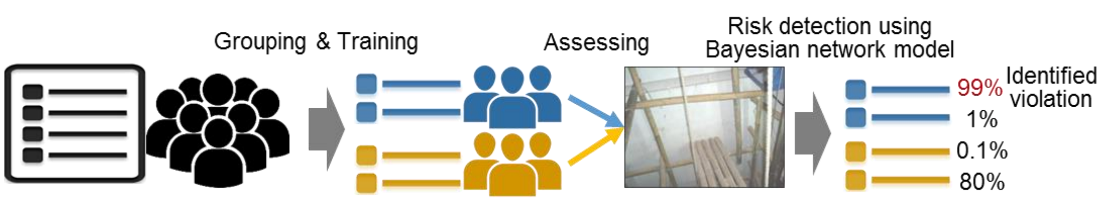


Figure 17. The Process of the Crowdsourcing-Based Risk Assessment

3.4.2.1 The training process on the crowdsourcing platform

The purpose of the training process was to provide the anonymous participants basic understanding about the safety rules in a short period. The training process should be informative and easy to understand for normal people. In the training process of the crowdsourcing platform, all the safety rules were divided into sections and learned by a different group of assessors to reduce the cognitive workload of the assessors. The training material of each safety rule showed the dangerous and safe scenes. This training module used word description combined with pictures to enhance both the heuristic and analytical ability of job site risk analysis. Figure 18 shows the training material of an exemplary safety rule.

3.4.2.2 The assessing process

The risk detection process consisted of the assessing process and the decision-making process. The assessing process collected the assessments of job site pictures. Then the assessors assessed whether each picture violated any safety rules they had just learned in the training process. The test pictures might have violations of the safety rules that the assessors had not learned in the training process, in which case the assessors were asked to select "no violation" to avoid ambiguity.

Then the decision-making process used a Bayesian network model to calculate the probability of each safety rule was violated using the answers from the assessing process. Section 3.4.3 will introduce the Bayesian network model in detail.

Figure 18. Training Materials of a Safety Rule "Improper Working Platforms on Scaffold Structure."

3.4.3 A Bayesian network model for crowdsourcing risk detection

The Bayesian network model aims at determining the probability that a violation of a rule exists in a job site picture, given all the assessments from one group of assessors who learned one section of safety rule and then assessed that image on the crowdsourcing platform. Without losing the generality, the whole crowdsourced risk assessment platform involves *I* job site pictures, *N* anonymous online image assessors, and *K* safety rules. The input of the Bayesian network, which is the assessment of picture *i* from *N* assessors, is:

$$A_i = \{a_{i0}, a_{i1}, \dots\ a_{ik}, \dots\ a_{iK}\}, \sum_{k=0}^{K} a_{ik} = N$$

where *k* denotes a certain safety rule. Notice that the assessors can also choose "no violation" in the picture, noted as $k = 0$. Therefore, a_{i0} denotes the number of people that think the picture *i* contains no violation against the rules they have learned in the training process, while a_{ik} $(k \neq 0)$ denotes the number of people that think the picture *i* contains violations against safety rule *k*.

I define r_{nik} as the assessment of picture *i* from the assessor *n* for rule *k*. $r_{nik} = 1$ means that the assessor *n* thinks picture *i* is violating rule *k*, while $r_{nik} = 0$ means no violation. The ground truth of picture *i* capturing a violation *k* or no violation is defined as $\Phi_i = 0,1,2, \dots, K$. I assume that the probability of choosing the wrong options in this image assessment game are the same. The assessment r_{nik} is modeled as a random variable following a categorical distribution, as detailed by Eq. (10):

$$P(r_{ni}) = f(r_{ni} = k \mid \boldsymbol{p}) = p_k = \begin{cases} p_{tp}, & when\ k = \Phi_i \neq 0 \\ \dfrac{1 - p_{tp}}{K}, & when\ k \neq \Phi_i\ an\&d\ \Phi_i \neq 0 \\ p_{tn}, & when\ k = \Phi_i = 0 \\ \dfrac{1 - p_{tn}}{K}, & when\ \ k \neq \Phi_i = 0 \end{cases} \tag{10}$$

where $\boldsymbol{p} = (p_{1,}p_{2,\ldots,}p_K)$. p_{tp} is true-positive rate of an assessment r_{nik}, which is the probability of an assessor correctly identifying the violation of a safety rule in the job site picture. Similarly, p_{tn} is the true-negative rate, which is the probability of an assessor correctly answering that there is no violation in the job site picture. I assume that the categorical distribution parameter $\boldsymbol{p}$ is the same for any *n*, *i*, *k*. p_{tp} and p_{tn} can be estimated using maximum likelihood estimation through training data set.

Now I would like to know the probability of the event "the picture contains a violation of rule *k"* when M out of N assessors chose rule *k* as the potential violation in picture *i*. I denote this probability as $P(\mathrm{A} \mid B)$:

$$P(A \mid B) = \ P(B|A\ ) \cdot P(A)/P(B) \tag{11}$$

Where event A is that the option *k* represents the truth in picture *i*; and event B is that M out of N assessors chose the option *k* for picture *i*. I will discuss how to calculate the probability of violating the certain rule (k≠0) or no violation (k=0) based on (11) in the following subsections.

3.4.3.1 The probability of a certain rule being violated in a job site picture

In (11), $P(B|\mathrm{A}) = f(N, M, p_{tp})$ is the probability that M out of N people are choosing the rule k is violated when k≠0. $P(A)$ is the probability that rule k is violated in a job site picture which is provided by the historical safety assessment data. $P(B)$ is the overall probability that M out of N people are choosing rule k no matter rule k is violated or not, which includes three circumstances: 1) rule k is violated in the picture (event A, $k = \Phi_i$); 2) any other rule is violated in the picture, represented by the event A' ($k \neq \Phi_i, \Phi_i \neq 0$); 3) no violation in the picture, represented by A''($k \neq \Phi_i = 0$). I use $P(B|A') = f(N, M, p_{tp})$ and $P(B|A'') = f(N, M, p_{tn})$ to denote the probabilities that the assessors mistakenly chose rule k when the truth is "other rule is violated" and "no violations", respectively. As a result, $P(B)$ can be calculated by:

$$P(B) = P(B|A) \cdot P(A) + P(B|A') \cdot P(A') + P(B|A'') \cdot P(A'')$$

where $P(A')$ and $P(A'')$ are the probability of "other rules are violated" and "no violations", respectively, which are obtainable from historical risk assessment database.

3.4.3.2 The probability of "no violation" in a job site picture

In (11), $P(B|\mathrm{A}) = f(N, M, p_{tn})$ is the probability that M out of N people are choosing "no violation" when correct. $P(A)$ is the probability that the picture contains no violation. $P(B)$ is the probability that M out of N people are choosing rule k (k =0 means choosing "no violation") in both circumstances: 1) no violation in the picture ($k = \Phi_i = 0$); 2) violation exists in the picture, noted as event A' ($k = 0 \neq \Phi_i$). $P(B)$ can be represented with the help of $P(B|A') = f(N, M, p_{tp})$:

$$P(B) = P(B|A) \cdot P(A) + P(B|A') \cdot P(A')$$

where $P(A')$ is the probability of violating any rules. In sum, $P(A|B)$ can be calculated using $P(B|\text{A})$, $P(A)$, and $P(B)$:

$$P(A|B) = f(k, M, N, p_{tp}, p_{tn})$$

3.5 Validation

3.5.1 Experiment Setup and Performance Measures

I designed the experiment to validate the proposed crowdsourcing safety inspection system using the safety rules of the elevator installation. The elevator company has 91 rules for the safety inspection of the elevator installation. In this experiment, I picked 12 rules that have the biggest influence on the elevator influence safety and created the training material using related pictures. The crowdsourcing participants need to assess the potential violation of the 12 safety rules in 6 job site pictures, shown in Disqualification percentage.

3.5.2 Risk assessment results under different training workload

The 12 safety rules are divided into six rules/section* 2 sections and three rules/section*4 sections in the experiment set 1 and 2, respectively to test how cognitive workload will influence the assessment performance. The assessing process collected answers from 389 anonymous participants using the crowdsourcing platform Amazon Mechanical Turk ("Amazon Mechanical Turk" n.d.).

Table 2 12 rules with the biggest influence on the elevator safety. The risk of each picture is defined as Disqualification Percentage (DP) * Influence Rating (IR)

Rule No.	Description	DP	IR	Risk (DP*IR)
1	Improper working platforms on scaffold structure	6.26%	4.33	0.271
2	Improper door blocking device	4.84%	3.33	0.161
3	Failure to provide overhead protection while working in the hoist way	3.88%	4.06	0.157
4	Failure to use Ground Fault Circuit Interrupters or equivalent protective devices	4.07%	3.36	0.137
5	Inadequate electrical protection in proximity of work activity	2.67%	3.24	0.086
6	Slings not protected against sharp edges	1.50%	4.12	0.062
7	Improper Guardrail System	1.48%	3.83	0.057
8	Working near unguarded drive or diverter sheaves or other rotating equipment	1.19%	3.38	0.040
9	Employees working in wet pit with power on	0.91%	3.83	0.035
10	Jewelry and other metallic objects worn around live equipment	0.48%	3.50	0.017
11	Unsafe oxygen-acetylene or compressed gases welding, cutting, heating equipment or procedures	0.31%	3.92	0.012
12	Storage of job site materials creating an unsafe mechanical energy source	3.56%		

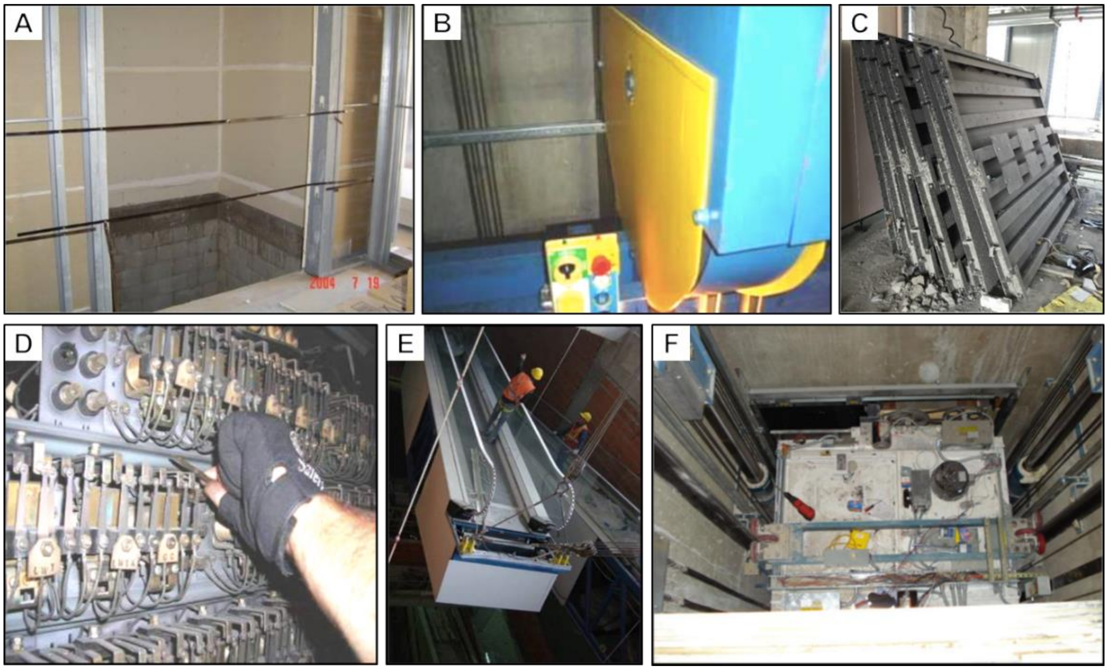


Figure 19. Six Job Site Pictures That May Contain Violations of Safety Rules.

Table 3 compares the true-positive rate p_{tp} and true-negative rate p_{tn} between two experiment sets. The true positive rates between two experimental sets are close. The difference between the true-negative rate may because the number of choice in Set 2 are significantly fewer than that of Set 1. This result supports the hypothesis that: if the assessors are confident when they identify a violation in the picture; the assessors are less confident when they didn't find any violations in the pictures. This pattern enables the crowdsourcing method to identify the job site pictures containing violations of safety rules.

Table 3 Parameters of 2 experiment sets

Parameters	True-positive rate	True-negative rate
Set 1, 6*2	0.7152	0.3517
Set 2, 3*4	0.7884	0.5353

Table 4 shows the crowdsourcing-based risk assessment results of six job site pictures. The Bayesian network-based crowdsourcing assessment result is correct for all six texting job site pictures in both experiment sets. On the other hand, the majority voting result made two and one false-positive mistakes in the experiment set 1 and 2, respectively.

Table 4 Risk assessment results

Picture Number			A	B	C	D	E	F
Violating which safety rule ("0" means no violation)	Ground truth (pre-defined by experienced professionals)		7	0	12	10	0	0
	Set 1, 6*2	Bayesian network	7	0	12	10	0	0
		Majority vote	7	0	12	10	1	3
	Set 2, 3*4	Bayesian network	7	0	12	10	0	0
		Majority vote	7	0	12	10	7	0

3.5.3 Impact of data set size to the assessing result

I examine how a different number of participants will influence the performance of crowdsourcing-based risk assessment in construction projects. For any given crowd size answering each question from 10 to 55, I randomly select the answers from 100 subsets of participants of that size.

Figure 20 compares the overall correct rate concerning different crowd size. Figure 20A shows the result of experiment Set A, where the participants are divided into two groups and each group learns about six safety rules, while Figure 20B shows the result of Set B, where the participants are divided into four groups and each group learn three rules. The result shows that, for both Set A and Set B, the risk assessing the performance of using the Bayesian network is better than that of using majority vote. In addition, the correct crowdsourcing rate with the crowd size of 10 using the proposed Bayesian network is more than 80%. This result shows that the Bayesian network-based crowdsourcing can achieve good performance with small crowd size.

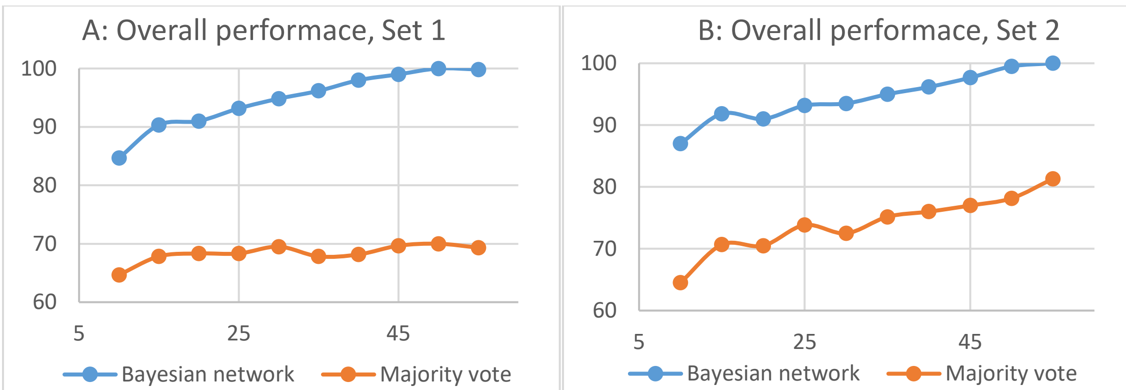


Figure 20. The Overall Correct Rates with Respect to Different Crowd Sizes

Figure 21 compares the true positive rate of the crowdsourcing risk assessment result of job site picture A, C, and D, which means the crowd correctly identify the safety violation in a job site picture. In both Set A and B, the true positive rate is higher than 75% for both Bayesian network and majority vote. The result shows that the training module can effectively improve the capability of identifying the

Figure 22 compares the true negative rate of the crowdsourcing risk assessment result of job site picture B, E, and F, which is the rate that the crowd correctly determine the picture with no violation. In both Set A and B, the true negative rate using Bayesian network model achieves 100% at the crowd size larger than 50, while the majority vote can only achieve 40% or 70% true negative rate in Set A and B, respectively. Also, the true negative rate of the result using the Bayesian network is higher than 80% even at the crowd size of 10 people, while the counterpart using majority vote is about 40%-50%. This result shows that the Bayesian network model can effectively improve the true-negative rate of job site risk analysis against majority vote with only a small number of participants.

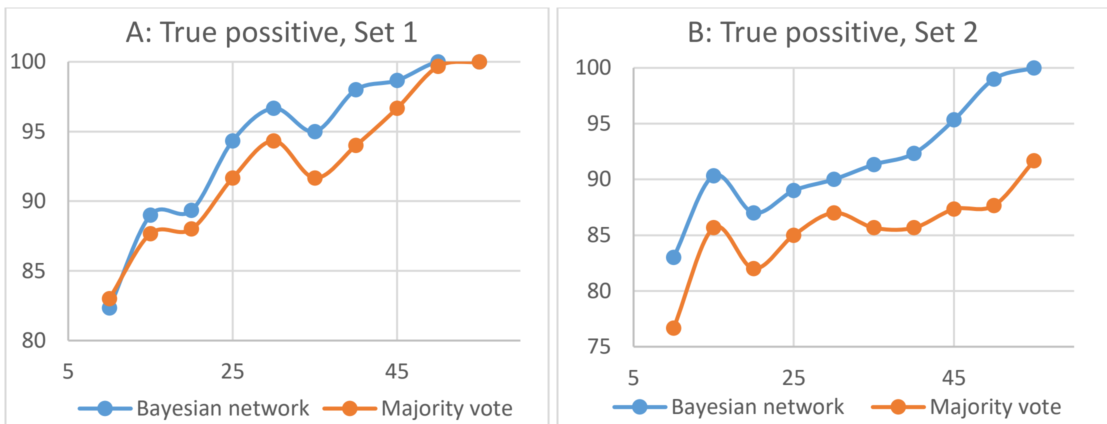


Figure 21. The True Positive Rate of The Result of Job Site Picture A, C, and D

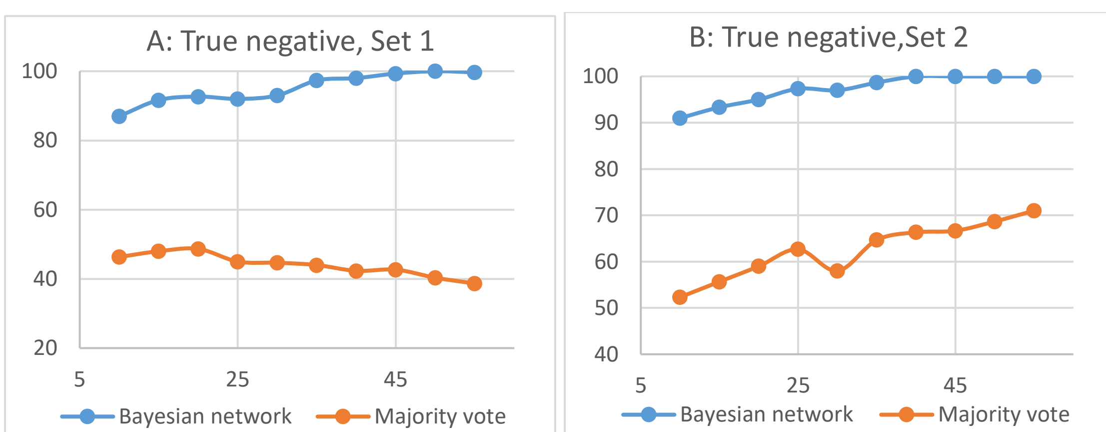


Figure 22. The True Negative Rate of the Result of Job Site Picture B, E, and F

3.6 Discussion

3.6.1 Limitation of current research

One limitation reflected in this research is that the crowdsourcing performance will be compromised when two safety rules are similar. A common mistake that the crowdsourcing assessment made at different crowd size is that picture D is assessed as violating safety rule 5 while the designed ground truth of picture D is a violation of rule 10. If image interpreters look at Picture D shown in Figure 23 and then compare rule 5 (inadequate electrical protection in the proximity of work activity) and rule 10 (wearing or holding metallic objects around living equipment), I can see the ambiguity of this safety rule. In the experiments, these two rules are divided into different groups. Therefore, reducing the ambiguity of this safety rules using more comprehensive training material can potentially improve the correct rate of the system. In addition, such mistake may also be a way to reveal ambiguity in rules so that they can be better written or defined.

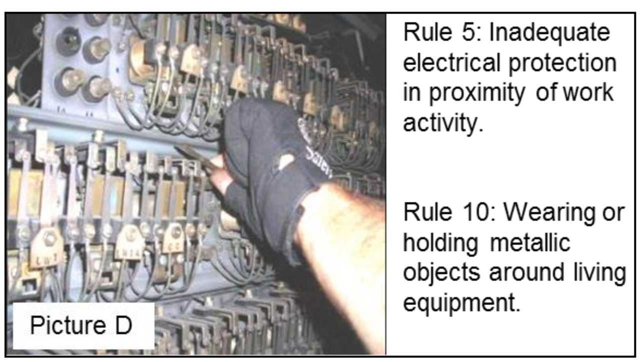


Figure 23. Comparing Rule 5 and Rule 10 Given Picture D

3.6.2 Analyzing the possible cognitive process of crowdsourcing participants in job site risk assessment.

To further address the crowdsourcing challenge that the majority of participants might agree to a wrong answer, the crowdsourcing platform needs to consider the decision-making process of the participants during the job site risk assessment. Naturalistic Decision Making (NDM) describes "how people make decisions in real-world settings" (Klein 2008). Specifically, NDM studies the decision-making problem with time pressure, vague problem description, missing information in familiar and meaningful environments (Canellas and Feigh 2016; Lipshitz and Strauss 1997). Such decision-making problems match the issues in crowdsourced job site risk assessment. Participants are usually not construction safety experts so that they are not familiar with the safety rules directly. However, they can identify job site risks using their experience in daily life, such as falling from high elevation may cause injury or death. Finally, participants have time pressure when doing the tasks because they want to answer as many questions to make more profit.

Recognition Primed Decision (RPD) is the most accepted cognitive model of the decision-making process of NDM (Klein 1993). RPD argues that the following features of NDM allow the decision makers can use their experience to avoid painstaking deliberations (Canellas and Feigh 2016; Klein 1993; Lipshitz and Strauss 1997):

- Experience enables a person to understand a situation regarding plausible goals, relevant cues, expectancies, and typical actions.

- Decision makers can evaluate a single course of action through mental simulation. They do not have to compare several options. Recognitional decision strategies are more appropriate under time pressure and ambiguity; analytical strategies are more appropriate for abstract data and pressure to justify decisions. In a variety of operational settings, recognitional decision strategies are used more frequently than analytical strategies, even for difficult cases.
- Experienced decision makers usually try to find a satisfactory course of action, not the best one. Experienced decision makers can usually identify an acceptable course of action as the first one they consider, and rarely should generate another course of action.

From the drop-down list below, please select which safety rule is violated in the above picture, or there is no violation in the picture. *

Mark only one oval.

- ◯ (No violation)
- ◯ Improper working platforms on scaffold structure
- ◯ Improper door blocking device
- ◯ Failure to provide overhead protection while working in the hoistway
- ◯ Failure to use Ground Fault Circuit Interrupters or equivalent protective devices
- ◯ Inadequate electrical protection in proximity of work activity
- ◯ Slings not protected against sharp edges

Figure 24. An Example Question of Crowdsourcing Risk Assessment

Figure 24 shows an example question of crowdsourcing risk assessment. According to the NDM and RPD theory, the most likely decision-making process of a crowdsourcing risk interpreter is as follows: After the interpreter see the job site image that may contain violations of safety rules, he or she will first match this picture with his/her personal experience and try to identify familiar objects and spatial, and logical relation of objects. Instead of using logic to comprehensively understand all of the safety rules and rank the possibility of this picture violating each listed safety rule, the integrator might scan the safety rules one by one and try to find one safety rule that may be violated by the picture as the correct answer. The interpreter will choose “no violation” only when he/she is very confident that no safety rule is possibly violated by the scenario shown in the job site image. Such cognitive process explains why the participants tend to choose diverse answers instead of choosing "No violation" when the picture shows no violation. The limited information provided in the job site picture, the lack of professional safety knowledge, and the lack of logic training may cause the interpreters use experience and even imagination to heuristically assess which rule is violated in the job site image, which has a bias. Therefore, the interpreter tends to mistakenly choose one of the non-violated safety rules as “violated” instead of correctly choose “no violation” as the correct answer after rejecting all the non-violated rules.

To improve the accuracy of job site risk analysis using the crowdsourcing technique, this proposed crowdsourcing system needs to have the following features based on the RPD model to resolve the decision-making bias stated above: First, the system needs to provide essential knowledge to improve the capability of job site risk analysis of the non-professional interpreters. Second, the assessing process needs to guide the cognitive process in order to reduce the influence of the aforementioned cognitive bias. Third, the crowdsourcing system should model the cognitive bias and designed a filter to integrate the answers to resolve such bias.

3.7 Conclusion

This research shows the capability of using crowdsourcing-based assessment method to identify violations of safety rules based on images collected in complex construction workspaces. Compared with the results of majority votes, the Bayesian network-based crowdsourcing risk assessment is reliable in eliminating the job site pictures which contain no violation of any safety rules while identifying the pictures capturing violations. The experiment result also validates the hypothesis that the assessors are confident when they identify a violation in the picture; the assessors are less confident when they do not find any violations in the pictures. The high true-positive and true-negative rate of the proposing risk assessment method show the potential of applying such risk assessment method in real-world project management to reduce the cost and improve the performance of safety control. The safety inspection outcomes can help the management team to process on-site risk identification effectively and cost-efficiently.

CHAPTER 4 PROACTIVE PROGRESS MONITORING FOR EARLY DETECTION OF DELAYS AND CRITICAL PATH CHANGES IN NUCLEAR POWER PLANT OUTAGES

4.1 Introduction

Nuclear power plant (NPP) outages are among the most challenging projects that involve a large number of maintenance and repair activities with a busy schedule and zero-tolerance for accidents. During an outage, more than 2,000 workers will be working around the NPP and finishing the maintenance work including more than 2,000 tasks within about 20 days, while the planning stage of a typical NPP outage is more than four months. Moreover, a one-day delay in an NPP outage could cost $1.5 million. These features of NPP outages call for a real-time, robust, effective workflow progress monitoring to identify and resolve delays or critical path changes.

However, early detection of workflow delays or critical path changes is challenging in busy NPP outage workflows. The first challenge is the large number of tasks in NPP workflows. Outage management team needs to spend much labor and resource on monitoring the progress of all the tasks on critical paths. Also, sometimes outage management team also needs to monitor the progress of the non-critical-path tasks, because the accumulation of delays of non-critical-path tasks may cause critical path change and delay the entire workflow. Therefore, the lack of progress monitoring personnel and resource often exists in NPP outage projects.

Another challenge is the long communication chain caused by the complicated organization of outage participants and processes (Petronas et al. 2016; Tang et al. 2016;

Zhang et al. 2016). When a worker finishes a task in an outage, he or she needs to "… update the task status to his or her supervisor, who often updates an outage maintenance coordinator who then updates the Outage Control Center (OCC) outage maintenance manager who then updates the paper copy of the schedule" (St. Germain et al. 2014). The delays in this reporting chain prevent the real-time updating of the overall outage schedule using the scheduling software directly to coordinate work because the tasks are completed long before their statuses are updated as complete in the scheduling software.

Furthermore, changing the used communication technology already in daily use and modifying the organizational structures are difficult. NPPs cannot afford the risks of trying new communication technologies without carefully evaluating the gain of changing the current communication technology. Similarly, current organizational structure and the "report chain" are designed for the sake of safety, which cannot be simplified. Considering the limited personnel and resource for progress monitoring, a viable way of improving the progress monitoring efficiency in NPP outage workflows is to identify the value of progress monitoring activities by calculating the risk of each task is delaying the workflow or causing critical path change. Then the value of monitoring different tasks at different times could guide the proactive progress monitoring activities.

In the domain of construction management, limited explorations focus on the theory of proactively identifying the probability of each task is delaying the workflow or causing critical path changes. To build such a theory, I borrowed the concept of Team Situation Awareness (TSA) from cognitive science domain, which describes the states of a team knowing what happened and what will happen. In the context of progress-monitoring, the

TSA of the people working on a workflow is the status of the management personnel being aware of the risks of workflow delay or critical path change caused by the potential delay of each task. This link between TSA theory and progress monitoring sheds lights on the early detection and resolve of workflow delays and critical path change. However, previous studies related to TSA have limited focus on quantitatively modeling and optimizing the information transmission processes in complex workflows. This research is trying to bridge the gap between the TSA theory and the need for evaluating the progress monitoring activities by quantitatively determining the risk of each task delaying the workflow or causing critical path change. Then the management team can acquire the the timely answers of "which task to monitor" and "when to monitor" in busy, complex NPP outage workflows.

4.2 Background Research

4.2.1 Construction progress monitoring

Early detection of actual or potential delays in field construction activities is pivotal to project management (Golparvar-Fard et al. 2009b). Current construction progress monitoring research studies mostly focus on using automatically acquire progress information. For example, Golparvar-Fard and his research team proposed a series of new imagery-based construction progress monitoring and visualization method using 4D Building Information Models (BIM) and 3D point cloud models generated from site photo logs for monitoring construction progress deviations at the operational-level (Golparvar-Fard et al. 2009b; a; Han and Golparvar-Fard 2015). Cheng and Chen developed an automated schedule monitoring system by tracking the erection of prefabricated structural components based on the integration of barcode and Geographical Information System (GIS) (Cheng and Chen 2002). However, such approaches cannot solve the progress-monitoring problem in NPP outages for several reasons. First, many NPP outage tasks do not have a visible construction component, such as removing the valve insulation, shutting down the electricity supply of a motor, etc. These tasks are difficult to be monitored by the mentioned above computer vision technologies. Second, the main obstacle of the progress monitoring in NPP outages is to transport the timely progress information of tasks from the workers to the needed personnel in management teams through the long reporting chain caused by the complex organizational structure of NPP outage team (St. Germain et al. 2014). Therefore, I need to identify new approaches to improve the communication to achieve effective and efficient progress monitoring in NPP outage workflows.

4.2.2 Communication in NPP outage

One of the most important factors influencing the productivity and safety of NPP outage workflow is the complicated organization of outage participants and processes (Petronas et al. 2016). The approval of each task involves multiple stakeholders to ensure safety. For example, an outage task should be confirmed by the following organizational units before the execution: 1) the outage control center, which determines whether the task is needed; 2) schedulers, who arrange the timing and relationship between tasks; 3) maintenance shops, who coordinate workforces for tasks; 4) the main control room staff, which configures the NPP according to tasks' requirements; 5) the work execution center, which inspects the site preparation for safe execution of tasks. Complex communications across all these organizational units are necessary for safety but will create long handoffs and possible time wastes (Gorman et al. 2006).

4.2.3 TSA theory

NPP outages are a command, control, communications, computers, and intelligence (C4i) systems (Salmon et al. 2006). Currently, there are limited mature theories of monitoring, commanding, and controlling such a system because of the informational complexity and ongoing technological evolution embedded in such a system (Salmon et al. 2014; Walker et al. 2006). Therefore, the theory of how to effectively and efficiently monitor the task progress in such dynamic NPP outage projects is missing. In such context, the theory of TSA can be potentially helpful in guiding the progress monitoring activities because TSA focuses on identifying “knowing what is going on” (Endsley 1995) in such dynamic environment involving multiple people and even autonomous systems. This section introduces how to generate the quantitative TSA model for progress monitoring based on the existing approach of TSA.

Situation awareness (SA) describes the ability of humans or automatic systems to become and remain informed to the changing environment to react to possible uncertainties (Stanton et al. 2017). The most accepted definition of SA is “the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status shortly.” (Endsley 1995). Endsley proposes a three-level model of SA (Endsley 1995):

- Level 1 SA: Perception of the Elements in the Environment.
- Level 2 SA: Comprehension of the Current Situation
- Level 3 SA: Projection of Future Status

SA usually describes the information about the dynamic environment held by an individual. In a teamwork scenario, two or more individuals (or automatic systems) share the common environment, timely understanding of the situation of the environment, and another person's interaction with the cooperative task. To have a good understanding of the "what is going on" in the cooperative task the core of achieving good TSA is to make sure each team member knows what he/she needed to know at the correct time.

Achieving TSA means the team acquires needed information to achieve the trajectory of value in a dynamic environment through information exchange at the right time with the right person (Salas et al. 1992). Because the team has one main goal instead of multiple goals, the TSA represents the team's needed information, which is the three-level SA information for the team goal. Therefore, the team SA is the information perception and information exchange to achieve the three levels of SA for the team goal. TSA not only requires the information held in each team member's mind, but it also requires the mechanism of ensuring to acquire the information for the team goal by different team members. Such mechanism of information acquisition and exchange can be derived from the relationship between the sub goal of each team member and the overall team goal and the social network between team members.

I extend the concept from SA to TSA by identifying how to acquire this information, and how to exchange this information to acquire three-level of SA information in a team, which is shown in Figure 25:

- Identify the overall team goal of the progress monitoring activities.
- Identify the relationship between the sub-goals of each team member and overall team goal.
- Each team member perceives his or her situation information (Level 1 SA)
- Each team member gets needed information at a time when this piece of information is needed.
- TSA information interpretation (Level 2 and 3 SA)

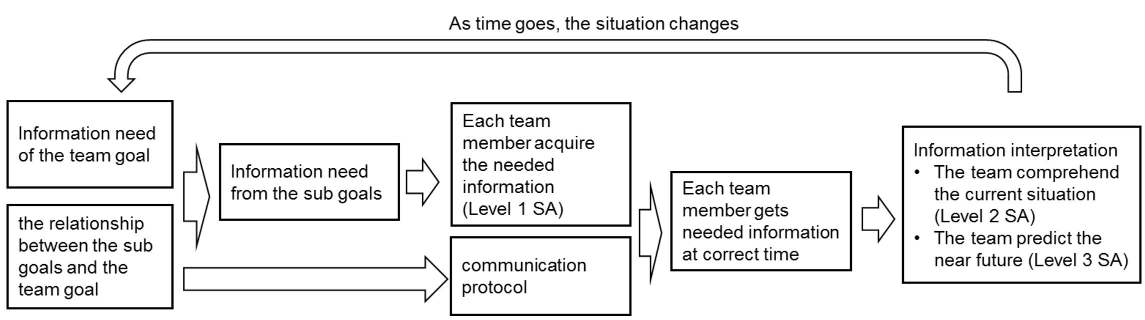


Figure 25. Framework of Achieving TSA in a Dynamic Environment

4.3 Methodology

This section will first describe the example progress monitoring problem for demonstrating the methodology, and then introduce the analogy between existing TSA theory and the progress monitoring activities, and finally, derive the quantitative model of TSA in progress monitoring. Figure 26 shows the IDEF0 model of the proposed proactive progress monitoring method. The input of the proactive workflow progress monitoring method is the as planned workflow schedule, the maximum/minimum duration of each task, and the previous progress monitoring information. The constraints are the spatial, temporal, and cost constraints of NPP outage projects as well as the Interactive Team Cognition (ITC) theory (Cooke et al. 2013) that describes the TSA of the people working on the workflow. The output is the proactive progress monitoring plan: which task to monitor, when to monitor, and who should talk to whom to monitor the progress of tasks.

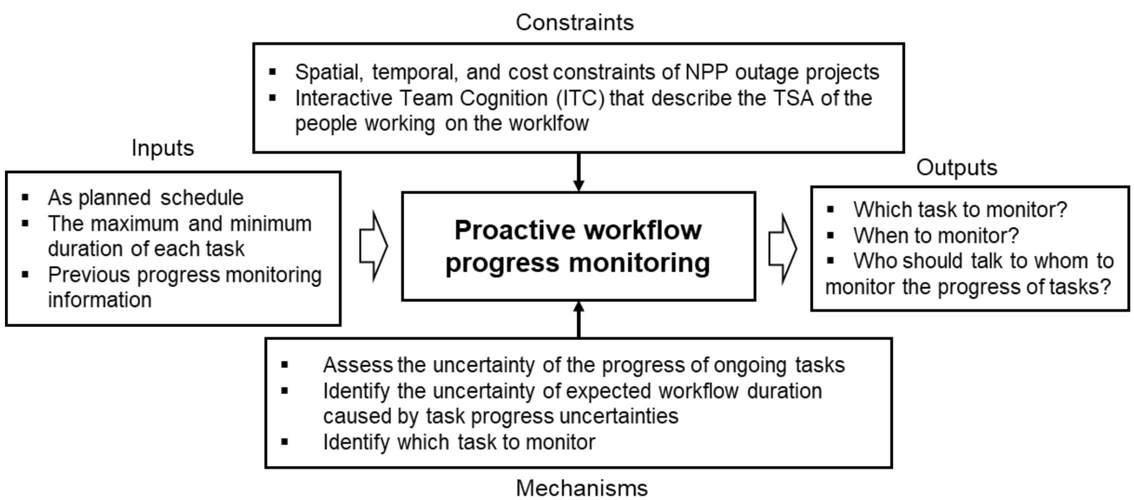


Figure 26. IDEF0 Model of Resilient Workflow Progress Monitoring

The organization of the rest of this section is as follows: in Section 4.3.1 introduces a simple workflow as the example problem for demonstrating this methodology. Section 4.3.2 discusses how to model the TSA in a workflow consisting of multiple tasks and how the TSA model can guide the progress monitoring activities using the example workflow. Section 4.3.3 shows the quantitative process of identifying the optimized answer of “when to monitor,” “which task to monitor” and “who should talk to whom to monitor the progress of tasks.”

4.3.1 Example problem for demonstrating the developed progress monitoring methodology

This research is trying to identify the quantitative method to guide the progress monitoring activities in NPP outage workflows. Although NPP outage workflows could consist of hundreds of thousands of tasks, I first use a simple workflow as an example to illustrate the methodology in this section. In this workflow model, I assume that the relationship between the progress and the working time of each task is linear. Figure 27 shows the as-is task duration. The detailed as-planned workflow information is shown in Table 5.

I then model the progress monitoring activities. I assume that each worker knows the precise progress of the task on which he/she is working. However, the supervisor of the team who needs to know the progress of the workflow cannot go to each task and watch the progress. Therefore, the supervisor needs to communicate to monitor the progress of each task and thus monitor the progress of the entire workflow. Frequently monitoring the progress of every task is not practical because the productivity of the workers will be compromised and the supervisor is too busy to communicate with the workers all the time. Therefore, this research is trying to generate a method to define how the management team communicates with the people working in the workflow to acquire the precise progress information with a minimum number of communications. Specifically, two questions need to be answered:

- When to monitor?
- Which task to monitor, i.e. which worker to communicate?

Table 5 Detailed workflow information

Task name	Worker	Expected duration (min)	Min. duration (min)	Max. duration (min)
Task 1	1	500	400	600
Task 2	2	300	200	400
Task 3	1	400	300	500
Task 4	3	600	400	800
Task 5	2	200	150	250

To answer these questions, I need to find the indicator to quantify the need for monitoring under different conditions, say, the workflow is part of the critical path or not. Such an indicator of progress monitoring need can help people decide what progress monitoring to use analytically instead of purely based on human experience. Then I need to find a way to quantitatively evaluate the information collected by the progress monitoring activities to determine whether the need of monitoring is satisfied.

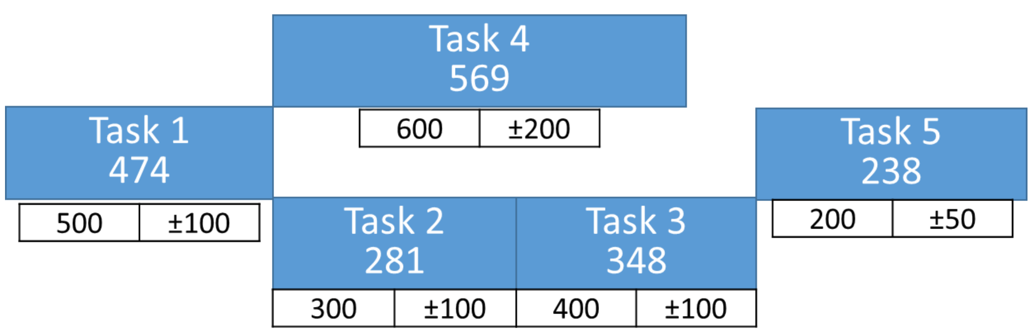


Figure 27. Simple Example NPP Outage Workflow

4.3.2 Analogy between TSA framework & proactive progress monitoring

Previous research studies proposed five steps for achieving TSA: Identify the overall team goal; identify the relationship between the sub-goals; each team member acquires individual SA; communication; and TSA interpretation. If the team goal is defined as "understand the progress of the workflow," the TSA framework can be applied to progress monitoring tasks. TSA defines the process of how to acquire needed information to achieve the team goal in dynamic environments, which provides the reference of modeling the information needs of progress monitoring in a workflow. In NPP outage projects, resilient project monitoring is achieving good TSA in the dynamic project workflows. Based on the TSA model I propose five steps to achieve resilient progress monitoring, which is shown in Figure 28:

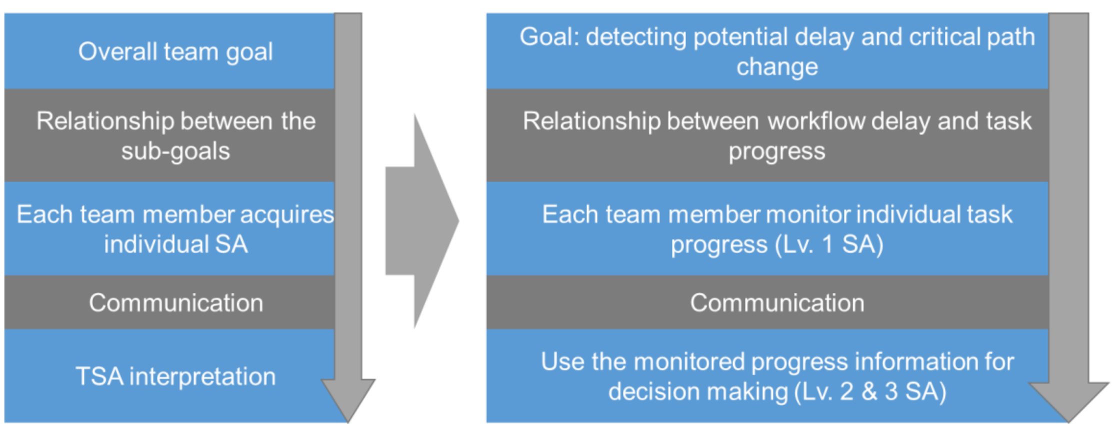


Figure 28. Analogy between TSA Framework & Proactive Progress Monitoring

1. *Modeling the information need of workflow progress monitoring*. The information need of progress monitoring is to identify the percent of overall workflow is done and then estimate the finishing time of the workflow.

2. *Modeling the relationship between workflow progress and progress of individual tasks*. In this step, I need to identify the relationship between the progress and each task and the overall progress of the workflow per the as-planned schedule.
3. *Each worker monitors the progress of his/her task continuously*. In this research, the situation information of each team member refers the as-is progress information of each task in the workflow. The worker working on each task knows the ground truth of their task progress. Therefore, this step is automatically completed.
4. *Determine the communication protocol between team members for proactive progress monitoring*. The ideal case of progress monitoring in this problem is that the supervisor continuously monitors the progress of all tasks, which is not achievable in most of the workflows. This step can derive which task to monitor its progress at what time based on 1 and 2.
5. *Use the monitored progress information for the early detection of workflow delays and critical path changes*. This step will calculate the estimated workflow progress according to acquired progress information. Then the supervisor can calculate the expectation and distribution of workflow finishing time according to the as-planned schedule of tasks not completed for early detection of workflow delays and critical path changes.

4.3.3 Proactive progress monitoring based on modeling the task progress uncertainties

The key steps of proactive progress monitoring include: Step 1 - Modeling the information need of workflow progress monitoring. Step 2 - Modeling the relationship between workflow progress and progress of individual tasks, and Step 3 - Determine the communication protocol between team members for proactive progress monitoring. This is because these steps will help the decision making about which task to monitor and when to monitor and the knowledge enabling these steps does not exist yet. This section will introduce how to achieve these steps by modeling the information needs, the relationship between sub-goal and overall team goal, and the communication protocol.

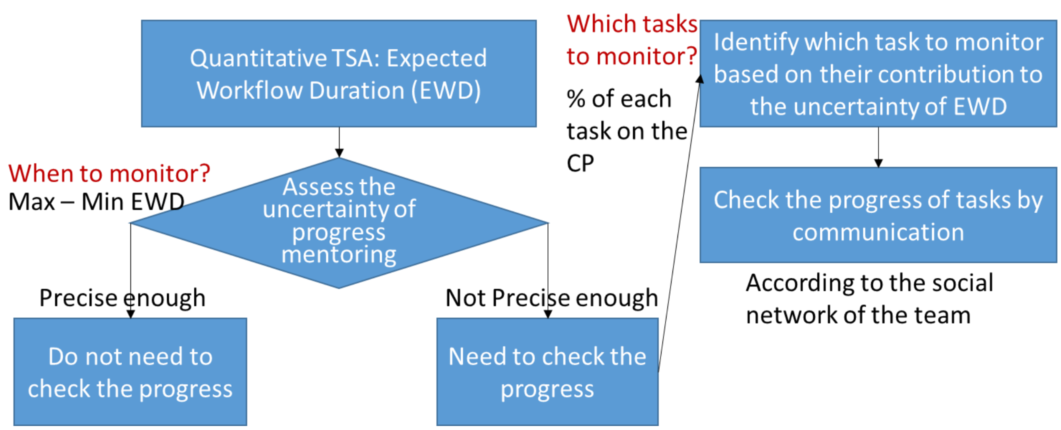


Figure 29. Framework of Proactive Progress Monitoring

4.3.3.1 Modeling information need of overall workflow progress monitoring

The overall goal of progress monitoring is to identify the percent of overall workflow is done and then estimate the finishing time of the workflow. I first identify two ways to define the project progress:

Percentage of progress ($P_{progress}$): Progress of completion is defined as the finished amount of work divided by total amount of work. For example, if one worker need to complete building 10-meter masonry wall and he/she has finished 6 meters, his/her progress of completion is 60%.

Percentage of time (P_{time}): Progress of time is defined as the time spent on the task divided by the total amount of time spend on the task:

$$\mathrm{P}_{time} = \frac{t_{current}}{t_{expected}} = \frac{t_{current}}{t_{current} + t_{future}}$$

wherein P_{time} is the percentage of time. $t_{current}$ is the time the team have worked on the workflow currently, which is a known variable. t_{future} is the expected duration the team need to work on this workflow in the future. $t_{expected}$ is the expected duration of the entire workflow. For example, normally the worker needs 10 hours to finish the 10-meter masonry wall. However, the worker spends 8 hour on the first 6 meters because of some rework and he/she can finish the rest 4-meter masonry wall with normal speed. At this time, the progress of time is 8/(8+4) = 66%.

This research assumes that the future is independent of the past because this research focuses on making decisions about progress monitoring instead of estimating the uncertainty in the future part of the workflow. In this case t_{future} equals to the expectation of the duration of the unfinished part of the workflow. With such assumption I can represent the relationship between $\mathrm{P}_{completion}$ and P_{time} of the same task:

$$\mathrm{P}_{time} = \frac{t_{current}}{t_{current} + \left(1 - \mathrm{P}_{progress}\right) \times t_{asplanned}}$$

Wherein $t_{asplanned}$ is the as-planned task duration. The information need of project progress monitoring is estimating P_{time} or t_{future} by monitoring $\mathrm{P}_{progress}$ with accuracy, precision and efficiency. I will quantitatively define the accuracy, precision and efficiency of progress monitoring activities in the next section.

4.3.3.2 Modeling the relationship between information needed for the team and each team members

The previous section introduced how to calculate P_{time} (or equivalently calculate t_{future}) for single-task workflows by directly monitor its $\mathrm{P}_{progress}$. However, in a workflow, the $\mathrm{P}_{progress}$ of workflows with multiple tasks loses its meaning. The supervisor can only acquire the $\mathrm{P}_{progress}$ of each task included by the workflow by communicating directly with the worker working on each task. This section will define how to calculate t_{future} of the overall workflow using the $\mathrm{P}_{progress}$of tasks in the workflow.

The duration of a workflow is decided by the length of its critical path. If the critical path of a workflow does not change from the as-planned, the supervisor can easily monitor the $\mathrm{P}_{progress}$ of crucial path tasks and calculate the t_{future} of the entire workflow. However, in real NPP outage workflows, the critical paths can change due to the dynamic environment. Therefore, the supervisor needs the progress information of all the tasks to estimate the as-is critical path and then calculate the t_{future}.

Calculate t_{future} of the workflow using current task progress information

Without losing generality, I use the example workflow to show the identified three level of progress information quantitatively. Figure 30 shows the status of the workflow in Figure 27 at the time of 800 min. At this moment, Task 1 and two have finished; workers are working on Task 3 and Task 4 for 45 and 326 min, respectively; Task 5 has not started yet. The workers of each task can directly perceive the Level 1 progress information: task 1 has been 100% finished; Task 2 has been 100% finished; The as-is progress $\mathrm{P}_{progress}$ of Task 3 is 12.9%, which is directly observed by Worker 1; The as-is progress $\mathrm{P}_{progress}$ of Task 4 is 57.3%.

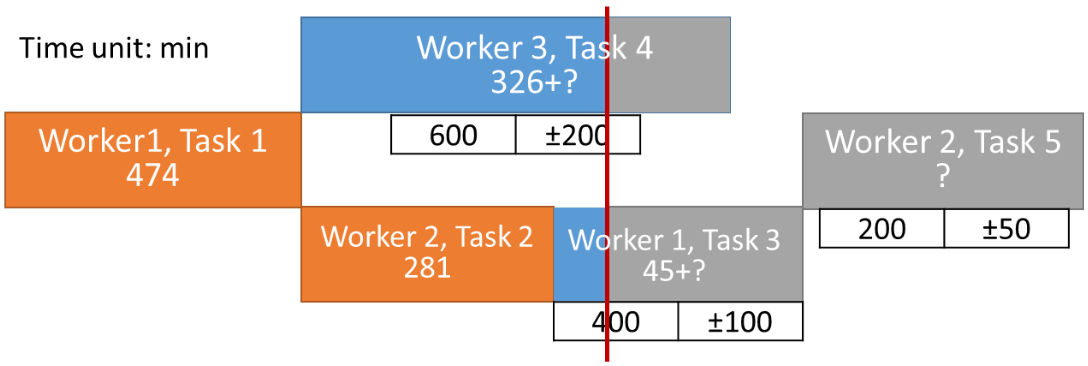


Figure 30. The Status of the Workflow at the Time of 800 Min.

The calculation of t_{future} needs the input of the progress information of all ongoing tasks, as-planned task duration of on-going tasks and future tasks, and the pre-requisite relationship between tasks. The rest of Task 3 will finish in (100%-12.9%)*400= 348.4 min. The rest of task 4 will finish in (100%-57.3%)*600= 256.2 min. Therefore, Task 3 is on the critical path. The total workflow will finish in 348.4 min (the rest of task 3) plus 200 min (task 5), which is 548.4 min. I can also calculate the estimated progress of the entire workflow at this moment, which is 800/(800+548.4) = 59.3%

Estimate t_{future} of the workflow using past task progress information

The supervisor can also calculate t_{future} using past task progress information. If the supervisor does not call Worker 1 and Worker 3 to get the as-is $\mathrm{P}_{progress}$ of Task 3 and

Task 4 at 800 min, he/she only knows that Task 1 and Task 3 started at the time 755 min and 474 min, respectively. Therefore, the supervisor can estimate the $\mathrm{P}_{progress}$ of Task 3 and Task 4 based on the as-planned task duration.

The supervisor can calculate that the minimum, expected, and maximum of $\mathrm{P}_{progress}$ of Task 3 is at least 45/500 = 9% , 45/400=11.25%, and 45/300=15%, respectively. Similarly, the minimum, expected, and maximum of $\mathrm{P}_{progress}$of Task 4 is 40.8%, 54.3%, and 81.5%, respectively. Without calling the workers to inspect the progress of task 4 and task 3, the $\boldsymbol{t_{future}}$ of the workflow based on the expected $\mathrm{P}_{progress}$ of ongoing tasks is 200+ max(45.7%*600, 88.75%*400) = 555 min. Similarly, the $\boldsymbol{t_{future}}$ of the workflow based on the most optimistic and pessimistic estimation of ongoing tasks is 540 min and 564 min. Therefore, If the supervisor calls the workers to monitor their as-is $\mathrm{P}_{progress}$ of task 3 and 4 at time 800, the possible range of the t_{future} of the workflow will change from a range [540, 564] to a number 548.4 min (calculated in the last section).

I can define the accuracy and precision and efficiency of $\boldsymbol{t_{future}}$ based on past task progress information to evaluate the performance of progress monitoring in a workflow:

- The Level of Accuracy (LoA) is defined as the deviation between the t_{future} of the workflow calculated using current workflow information and past workflow information. In this example the accuracy of progress monitoring at 800 min is 555 – 548.4 = 6.6 min.

- The Level of Precision (LoP) is defined as the difference between maximum and minimum possible t_{future}. In this example the precision of progress monitoring at 800 min is 564 – 540 = 24 min.

4.3.3.3 Determine the communication protocol in progress monitoring

The precision and accuracy of t_{future} describes the information quality of progress monitoring, which can serve as the requirement of progress monitoring activities. In order to monitor the workflow progress with effectiveness and efficiency, the supervisor can define the progress information requirement according to the need of the workflow, and plan minimum progress monitoring activities that can satisfy the precision and accuracy requirement of activity. The detailed steps are described below using the example shown in Figure 30:

Step 1: Define the information requirement of progress monitoring. The supervisor can set up a threshold of acceptable LoP and calculate the LoP of the progress monitoring result in the future. If the acceptable LoP is 100 min in the example workflow (shown in Figure 30), the supervisor needs to monitor the current workflow if the difference between maximum and minimum $\boldsymbol{t_{future}}$ is larger than 100 minutes.

Step 2: Identify the next time that the progress monitoring result will exceed the precision requirement. Without losing the generality, assume the supervisor needs to decide the next progress monitoring time at time = 755 min, which is the time task 3 starts. At this time the supervisor can calculate the LoP = 0 min. Then the supervisor will calculate that at the time = 944 min. the LoP = 100 min. Therefore, time = 944 min is the time when the supervisor should process the next progress monitoring activity.

Step 3: monitor the task which is most likely on the critical path to improving the accuracy of progress monitoring estimation. At the identified progress monitoring time, the supervisor will use the as-planned distribution of task duration of unfinished tasks to calculate the possibility that each ongoing task is on the critical path. Correctly estimated critical path task would lead to 0 min of LoA when the processing the progress monitoring activity. The supervisor will monitor all the on-going tasks the probability of which becomes on the critical path above a certain threshold. Figure 31 shows the progress monitoring result of the example workflow following the resilient progress monitoring method. The supervisor will receive the task finishing information from the worker of each task. Also, the supervisor monitored the progress of task 1 at 240 min., task 2 at 609 min., and task 3 and four at 944 min per the resilient progress monitoring method. The picture shows that this method controls the LoP of the progress monitoring result under defined threshold.

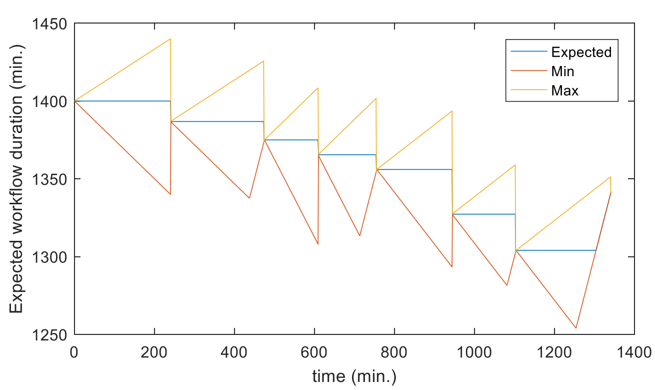


Figure 31. Progress Monitoring Result of the Example Workflow

4.4 Validation

This section uses the simulation result to show how different communication protocols will influence the duration of the entire workflow and probability of critical path change. Shorter workflow duration means less time cost during communication or human errors. Lower chance of critical path change means the management team can only focus on the progress of a few critical tasks to control the progress of the overall workflow so that the labor and resource can be saved. Section 4.4.1 and 4.4.2 will compare these two optimization functions under different error rate of human (i.e. the probability of the worker or supervisor forgetting to call when they need to) and different follow-up call intervals.

4.4.1 Example NPP outage workflow for validating the proactive progress monitoring method

This section introduces the experiment site layout and the as-planned schedule used in this experiment. The tasks simulated in this research are valve maintenance during an NPP outage project on three different sites (they are on Site A, B, and C, respectively) which are shown in Figure 32. The workers need to complete five tasks on each site. Each task is assigned to a specific worker. In this workflow, the workers can only work on one site at a time, which makes them the shared resources.

No.	Task name	Resource
1	Remove the valve	Insulator
2	De-term the motor operator	Electrician
3	Perform valve maintenance	Mechanic
4	Re-term the motor operator	Electrician
5	Re-install the valve	Insulator

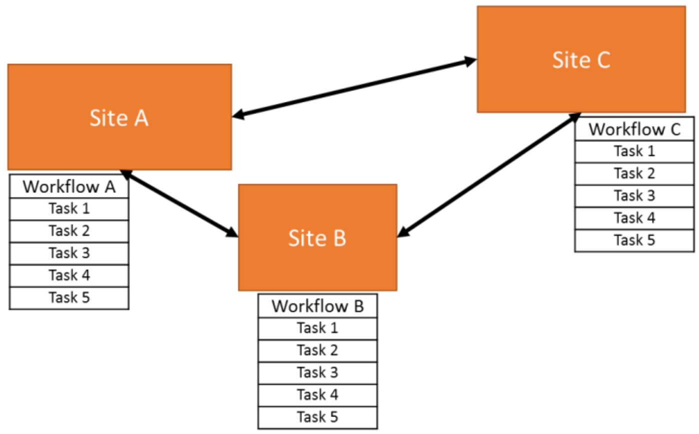


Figure 32. Spatial and Temporal Relationship between Tasks in Outage Workflows

4.4.2 Agent-based simulation platform

Two types of human agents are in this simulation model: worker and supervisor. A worker agent can be of three types: the insulator, the electrician, and the mechanics. Each type of worker is responsible for certain tasks in the workflow. The supervisor is responsible for communication and collaboration with the workers. Such collaboration work includes receiving the task progress information from the workers and inform the corresponding worker which task is ready for him/her to do.

To finish the tasks, I should have the "worker" agent. Each worker can do the following things:

1. The worker can move at a certain speed.
2. Each worker can do certain tasks according to his/her worker type. Specifically, the insulator can remove or re-install the insulation (Task 1 and Task 5). The electrician can de-term or re=term the motor operator (Task 2 and Task 4). The mechanics can do the maintenance work (Task 3)

3. The worker can communicate with each other or with the supervisor. They can report their progress of their current task or receive information about the progress of other tasks.
4. The worker can decide what to do next after they finish their current tasks based on the currently available tasks.

Based on these features of workers, I can generate the "worker" class. Each worker has five statuses, which are visualized in Figure 33.

- Waiting. If no task is available to the worker, it will stay in the waiting status. Whenever a task is available for the worker, the status of this worker will become "traveling."
- Traveling. After the worker identifies the "current task," it will move toward the location of the current task for 1 step. If the current location of the agent is the same as the location of "current task," the status of the worker agent will transfer from "moving" to "working."
- Working. When the worker agent is in the working status, the remaining time of the current task starts counting down. After the remaining time becomes zero, the status of the worker will become "Reporting," and the status of the valve will be changed according to the current task.
- Reporting. When the agent enters the reporting status, the remaining time of the worker's reporting activity starts counting down. When the remaining time of the worker's reporting activity reaches zero, the supervisor will receive a message

saying that the "current task" of the worker is finished. Then the status of the worker becomes waiting.

- When the worker is receiving a call from the supervisor, its status will temporarily become "Receiving the call from the supervisor." In this status, the worker will receive the available task information.

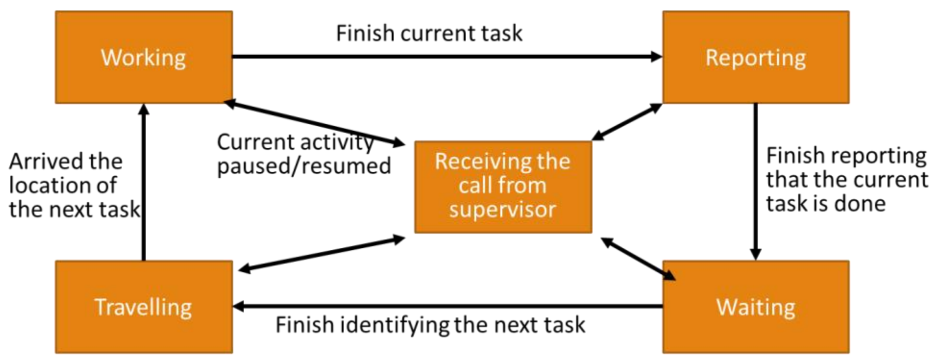


Figure 33. Status Transition of the Worker Agent

In this NPP outage scenario, the task of the supervisor is to 1) answer the phone calls from the worker and record the information about the finished tasks. 2) inform the worker of the following task that following task is ready to be worked on after the supervisor received a phone call reporting a completed task. Based on the behavior of the supervisor, I generate the supervisor agent (shown in Figure 34), which has the following status:

- Waiting. The supervisor will stay in the "waiting status" when no one is calling the supervisor and the supervisor is not calling any worker.
- Communicating. After the worker agent call the supervisor, the supervisor's status will become "communicating". After the worker agent finishes calling, the supervisor will add the task that the calling worker just finished into the finished task list. After the supervisor finishes answering the incoming phone-call from

worker A, the supervisor will check all tasks which have not been started to see which one is ready. Then the supervisor will “make a phone call” to inform the worker agent B who is responsible for the successor task, which means B will add the successor task to its available list.

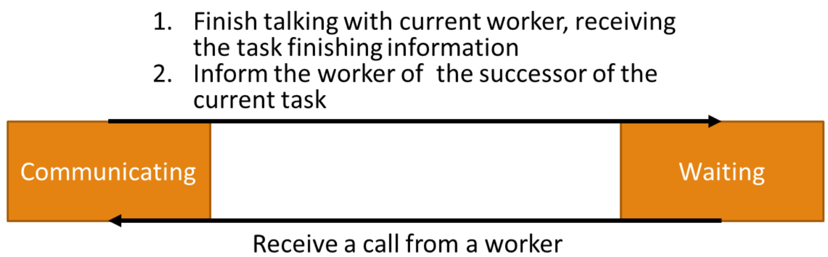


Figure 34. Status Transition of the Supervisor Agent

4.4.3 Comparing the performance of different progress monitoring plan

This research will validate the progress monitoring result on an NPP outage workflow the critical path of which is changed. Table 6 shows the as-planned task duration of the NPP outage workflow in the simulation model. The fourth column of Table 6 shows the baseline duration of the task duration of all tasks in the simulation model. The as-planned critical path of the simulation model is A1-A2-A3-B3-C3-C4-C5 (visualized in Figure 35), which is calculated using the mean value of the task duration. Figure 35 shows all the possible changes of the critical path. Among 1000 runs of the simulation model, 72% runs to hold the same critical path as planned. However, in other cases, the as-is critical path may change. The critical path of the example simulation run is A1-B1-B2-A4-C2-C3-C4-C5. The uncertainty of workflow duration not only causes the critical path change but also cause the task sequence change (task A4 and task C2).

Figure 36 shows the progress monitoring result in the format of estimated workflow duration at different times. The resilient progress monitoring result can control the uncertainty under a limited amount.

Table 6 Task durations in the simulation model

No.	Task name	Resource	As-planned Duration
1	Remove the valve	Insulator	30-60 min
2	De-term the motor operator	Electrician	45-75 min
3	Perform valve maintenance	Mechanic	60-90 min
4	Re-term the motor operator	Electrician	45-75 min
5	Re-install the valve	Insulator	30-60 min

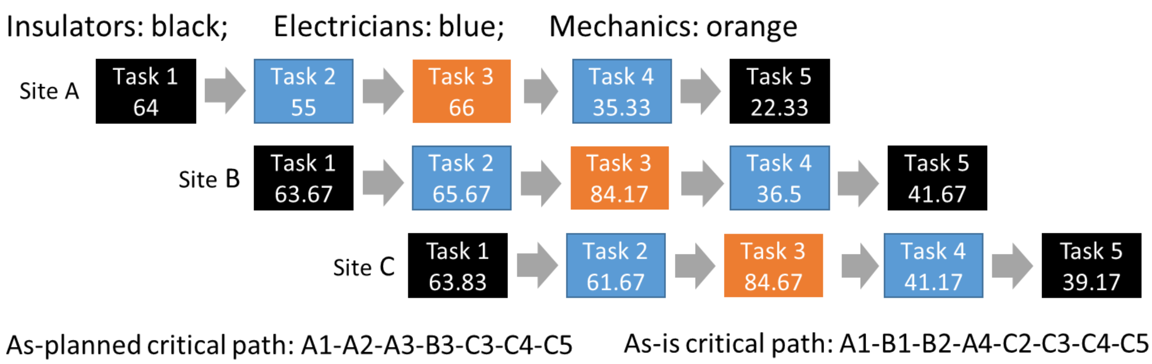


Figure 35. A Changed Critical Path Due to Uncertainties of Task Durations

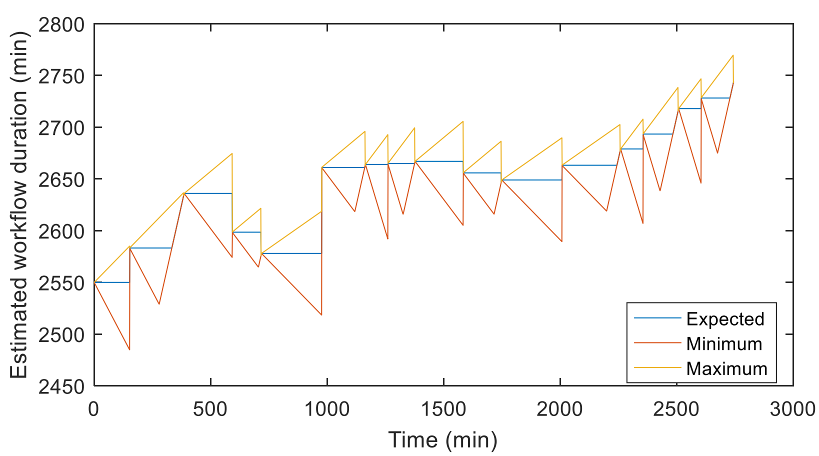


Figure 36. Estimated Workflow Duration Based on Resilient Progress Monitoring

Figure 37 compares the progress monitoring result of the different strategy. I still use estimated workflow duration as the performance function. The blue line shows the estimation of workflow duration under ideal progress monitoring approach, which means the supervisor can monitor all of the on-going tasks in real time. The orange line and the gray line visualize the estimation of workflow duration under resilient progress monitoring or only use workers' report of task finishing time. Figure 37 shows that the orange curve is much closer to the blue line compared to the gray line, which means the result of resilient progress monitoring is better than the progress monitoring result only based on workers' report of task finishing time. With the proposed proactive progress monitoring method, the management team can predict the risk of critical path change at 36 minutes before a worker make the wrong decision due to he or she choosing the incorrect task after finishing the current one. This risk of critical path change will cause 20 minutes' delay of the entire workflow. On the other hand, if the management team only focus on the progress of the tasks on the as-planned critical path, they will identify the mistake after the unreliable decision has caused the workflow delay. This result means the resilient progress monitoring method can proactively detect the potential critical path change and workflow delay to maintain the resilient management of NPP outage project.

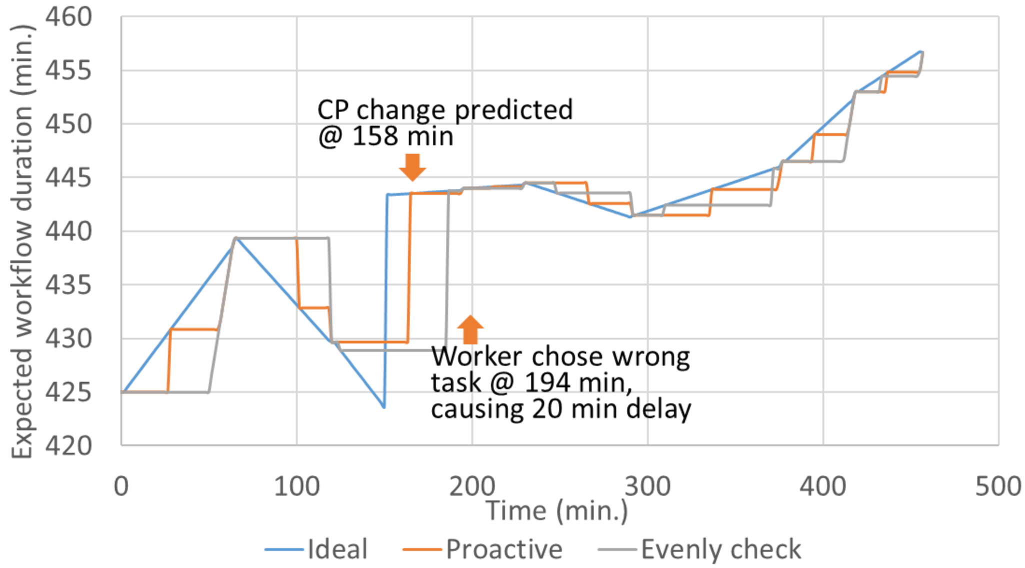


Figure 37. Comparing Different Progress Monitoring Strategy

4.5 Discussion

4.5.1 Extendibility of the proactive progress monitoring method

This proactive progress monitoring method should also be potentially useful for automated control of other shutdown projects, such as the turnaround of petrochemical plants, shutdown maintenance of other types of power plants and water supply system, and fast bridge maintained and construction on highways. To achieve early detection of workflow delay or critical path change in other shut down projects, the management team can use the as-planned schedule, and the organization structure of the project team to identify which tasks need more frequent monitoring and what is the optimized time to monitor these tasks.

4.5.2 Limitation and future studies

This research has the following limitations. First, current proactive progress monitoring method is based on simulated workflow data created by researchers working on NPP process optimization in the stead of real NPP outage data. I model the distribution of each task in the workflow as uniform distribution, and the progress monitoring performance could be improved if I use the database real NPP outage schedule to generate the task duration distribution.

Second, the uncertainties involved in this research is only the task duration uncertainty. In reality, human errors are major sources of uncertainties, especially in communication activities (Hobbins et al. 2016). Furthermore, the complex organization of NPP outage team creates a larger number of communication activities compared to normal construction projects, which enlarges the impact of human error on the effective and efficient monitoring and management of the project. Therefore, in the future, I will integrate human error model into the progress monitoring.

Considering these two limitations, I propose BIM-based simulation platform can improve the performance of the current progress monitoring method (Ben-Alon and Sacks 2017). BIM will help visualize the progress of the project and the behavior of different agents (e.g. workers, supervisors, management team, and so on). Also, BIM model can connect to the historical outage workflow database and improve the precision of the simulation result. Most importantly, BIM adds more types of agents to the simulation environment thus enables the interaction between the building component agents, environmental agents, and human agents. Such enrichment of agent interaction enables simulating more types of uncertainties on the NPP outage workflows, such as workers being not familiar with the environment, error in perception of the as-is progress of certain tasks in the night because of the low ambient light, and so on. In a word, the integration of BIM, simulation, and human factor science can greatly help the efficiency and effectiveness of decision making in busy construction projects.

4.6 Conclusion

This research proposes the proactive workflow progress monitoring methodology in NPP outage workflows. Using the concept of TSA from cognitive science domain, this method optimizes the communication protocol between field workers and management team according to the as-planned workflow and the previous as-is progress monitoring information. This method can support the early detection of the delay of the workflow and the prediction of critical path changes by modifying the time and tasks to monitor in progress monitoring activities. Simulation results show that the proposed method can provide valid guidance for resilient workflow control in NPP outage workflows.

CHAPTER 5 CONCLUSIONS AND FUTURE RESEARCH

In this research, aimed at achieving resilience for acquiring information in dynamic construction job sites, I developed a computational framework for enabling human acquiring timely, detailed information through sensor based inspection, manual inspection, and communication. Further, I validated this framework by applying it to specific applications of collecting laser scanning data collection for geometric information, job site risk information, and workflow progress information. The following sections described the contributions and corresponding validations, practical implications and recommended future research work.

5.1 Summary of Research Contributions and Validation Results

5.1.1 A laser scan planning for dynamic construction environments

In construction environments, laser-scanning technologies can perform rapid spatial data collection tasks, such as streamlining field activities, monitoring construction progress, and controlling construction quality. However, even the most skilled of surveyors cannot guarantee comprehensive laser scanning data collection on a construction site due to its constantly changing environment, wherein a large number of objects are subject to different data-quality requirements. The current practice of manually planned laser scanning often produces data of insufficient coverage, accuracy, and details. Although redundant data collection can improve data quality, this process can also be inefficient and time-consuming. There are many studies on automatic sensor planning methods for guided laser-scanning data collection in the literature. However, fewer studies exist on how to handle the exponentially large search space of laser scan plans that consider data quality requirements, such as accuracy and levels of details (LOD). This paper presents a rapid laser scan planning method that overcomes the computational complexity of planning laser scans based on diverse data quality requirements of various objects in the field. The goal is to minimize data collection time while ensuring that the data quality requirements of all objects are satisfied. An analytical sensor model of laser scanning is constructed to create a “divide-and-conquer” strategy for rapid laser scan planning of dynamic environments. In this model, a graph is generated having specific data quality requirements (e.g., levels of accuracy and detail) in terms of nodes and spatial relationships between these requirements as edges (e.g., distance, line-of-sight). A graph-coloring algorithm then decomposes the graph into sub-graphs and identifies “local” optimal laser scan plans of these sub-graphs. A solution aggregation algorithm then combines the local optimal plans to generate a plan for the entire site. Runtime analysis shows that the computation time of the proposed method does not increase exponentially with site size. Validation results of multiple case studies show that the proposed laser scan planning method can produce laser-scanning data with higher quality than data collected by experienced professionals, and without increasing the data collection time.

5.1.2 A crowdsourcing-based safety risk analysis method using job site images

Risk assessment based on imagery data is becoming popular in construction project management because cheap imaging devices can capture reality in real time. One challenge is that image-based safety risk identification heavily relies on the subjective image interpretation. Well-trained inspectors could be a limited resource to meet the inspection requirements for construction safety. “Crowdsourcing” is one of the ideal approaches collecting identified risks through online image interpretation games and aggregate answers from game players into comprehensive and reliable risk recognition results. Unfortunately, inputs provided by non-professional players can distort the aggregated results. This paper presents a study showing that without knowing the actual risks on construction sites, human-image interaction behavior analyses of anonymous online image interpreters can overcome the influences of mixed reliable and unreliable answers from anonymous online players and acquire reliable risk evaluations of job site imageries. I conducted this study with the following steps: 1) train anonymous assessors in a few minutes on limited safety rules and have them assess some images for collecting crowd-based risk detection data, 2) collect assessment results using an online crowdsourcing platform, and 3) automatically aggregate risk assessments using a Bayesian network model into the risk detection results. Results from an online image-based elevator installation risk assessment experiment show that the proposed method can overcome the limitation of the majority-based voting and achieve comparable results as experienced safety inspection professionals.

5.1.3 A qualitative model to evaluate information for progress mongering in NPP outage workflows

Nuclear power plant (NPP) outages are challenging construction projects that involve a large number of maintenance and repair activities with a busy schedule and zero-tolerance for accidents. During NPP outages, the communication activities can be time-consuming and error-prone due to the complicated organization of outage processes and crews, the extremely busy schedule with a 10-minute level of detail, and a large number of people working simultaneously on the job site. Furthermore, such busy schedules and the complicated organizations could cause communication-related delays or mistakes to propagate to even more tasks, which could compromise the productivity of the entire workflow. Therefore, precisely predicting and controlling the time wasted during communications and remedying miscommunications caused by human errors can improve the NPP outage productivity.

To reduce the time wasted and impact of human errors in communication, I propose the communication protocol optimization according to the as-planned workflow. This communication protocol optimization study evaluates how different communication protocols in a team will influence the time wasted under the influence of human error, task duration uncertainty, and communication. This methodology has four steps: 1) define the outage workflow process of an NPP outage workflow; 2) identify the uncertainties in the workflow model, including the task duration uncertainty and random communication errors; 3) design the communication protocol to mitigate the identified uncertainties; and 4) optimize the parameters (e.g. the time interval between phone calls) in the communication protocol. To validate this methodology, this research uses two objective functions to quantify the performance of a communication protocol in a collaborative workflow. The first objective function used for communication protocol optimization is minimizing the duration of the entire workflow. The second objective function is minimizing the probability of critical path change in the schedule. Simulation result shows that the proposed method can provide a reliable reference of designing the communication protocol in NPP outage workflows.

5.2 Practical Implications

This research defines three possible ways to improve the resilience of information acquisition in dynamic construction site through sensor-based inspection, manual inspection, and communication. All three information acquisition techniques can form a resilient information acquisition system.

The laser scan planning algorithm can support a mobile app to guide the laser scanning surveyor's data collection task on the job site. According to engineers in the construction industry, acquiring detailed as-built 3D building information model will cost tens of thousands of dollars, varying with the scale of the projects. As a result, full automation of 3D site inspections will save time and money for contractors. In the future, using the proposed laser scan planning method, unmanned aerial vehicles (UAVs) or robots could enable autonomous robots that carry sensors and process 3D imagery collection with minimum human involvement. This will help autonomous high-quality data collection in remote areas that are dangerous for human inspectors, such as underwater structures, top of skyscrapers, or rescue missions after an earthquake. Automatic laser scan planning will make laser scanning autonomous, safer, more precise, and more efficient on various dynamic sites.

The crowdsourcing-based job site risk assessment system could be useful real-world construction projects. For large public construction projects without confidential issues, the construction workers can collect job site images and upload them online. Then the public can participate in the safety assessment using the proposed crowdsourcing system to improve the effectiveness and efficiency of job site safety management. For the construction projects which have confidential issues such as a nuclear power plant, uploading the job site images to the internet will trigger safety issues. In such cases, the idling employees can work as the participants of the crowdsourcing system to assess the safety risks in job site imageries, which can still reduce the workload and error rate of safety inspectors.

The proposed proactive progress monitoring system can be integrated into the current Automatic Work Package (AWP) system, which is an automation technique that supports micro-level management and control of outage tasks (Blanc et al. 2012). This system enables the workers to track their tasks on a hand-held electronic device (e.g. tablets or smartphones), which can be used as the input of the progress monitoring system. Then the progress monitoring system will automatically push the progress monitoring order to the inspection personnel or even directly pull progress information from certain workers to achieve automatic workflow progress monitoring.

5.3 Recommended Future Research Directions

Although challenges related to information acquisition and modeling exists in achieving HCA in job site information acquisition, many techniques that have not been applied in real-world construction projects are potentially helpful in addressing these challenges mentioned above. I broadly explored various techniques developed in the domains of computer science, human factor and ergonomics, construction engineering, system science, and nuclear industry to find potential solutions to these challenges. Finally, I identified the following research directions as potentially useful for supporting resilient job site information acquisition. Computer-vision-based human tracking can provide human traveling pattern information, and natural language processing can aid the measurement of cognitive factors as well as automatically analyzing operational histories of past NPP outages. The rest of this section will review these future directions to draw a practical research roadmap toward the goal of HCA for resilient construction information acquisition.

5.3.1 Human tracking

Human tracking is using sensing technologies to automatically capture the trajectory of moving people, which can address the challenges of capturing the human traveling pattern information in the complicated construction site. Available human tracking can be divided into two categories: computer-vison based and tag-based tracking. Tag-based human tracking utilizes the trackable devices attached to the human body, which includes RFID, Wi-Fi, global navigation satellite system (GNSS), etc. RFID technology is a well-implemented technology mainly for tracking equipment. The accuracy of human tracking can achieve meter level (Li and Becerik-Gerber 2011; Montaser and Moselhi 2014). However, tag-based human tracking technologies are not suitable for NPP outages because of two reasons: 1) GNSS does not function in indoor and underground environments. Assisted GNSS (A-GNSS) extends GNSS to indoors, but it is limited and unreliable. On the other hand, the performance other tag-based tracking technologies might not satisfy the sub-meter-level tracking need of certain construction workflow, such as NPP outage projects; 3) trackable tasks may cause confidential issues, which is rejected by the labor union.

Meanwhile, computer vision technology can detect the presence/absence of objects as well as their trajectories, which can provide useful information about the motion of workers on the construction job site (Chaquet et al. 2013; Koch et al. 2015; Sato and Aggarwal 2004; Seo et al. 2015; Zaurin and Catbas 2007). Using data fusion of workers' position and upper body postures along with the job site environment information, computer-vision-based approaches can capture the positions activity types of field workers in real time (Chaquet et al. 2013; Cheng et al. 2013). The work activity information is used to perform automatic work sampling to facilitate real-time productivity assessment. Computer-vision-based human tracking may also enable the detection of abnormal human behaviors in workspaces. Using these technologies to detect anomalous behavior of field workers can help anticipate accidents or delays in workflow. It is attempting to explore using computer vision technologies to identify individuals whose behaviors are different from the majority (Chandola et al. 2009; Kratz and Nishino 2009; Patcha and Park 2007; Tang et al. 2016; Zhang et al. 2016).

However, challenges exist in achieving computer-vision-based human tracking. Current construction sites support videos and image as data inputs. However, these imagery sensors cannot be allocated everywhere across the job sites. As a result, to achieve real-time human behavior inspection, a sensor allocation technology and new research focusing on the trade-off between data size and tracking performance is needed to reduce data collected while keeping all the needed information (Spletzer and Taylor 2003; Tarabanis et al. 1995).

5.3.2 Natural language processing

Natural language processing (NLP) is a subfield of artificial intelligence that aims to use natural language text making it understandable to computers so that it is processed in a human-like manner (Dutta 1993). Currently, most cognitive measures used to determine SA and MW are survey-based and require direct input from the test takers. Unfortunately, requiring any additional tasks from the already over-worked operator may cause interruptions of ongoing work. Besides interrupting the operator, manual assessments are also tedious and error-prone. Furthermore, achieving timely, reliable, and comprehensive assessment of field personnel's SA and MW in dynamic construction projects is nearly impossible. NPL has the potential to simplify this measurement process by enabling automatic assessment of the test takers' SA and MW through simple, but effective oral assessments and in turn, reducing management's workload and interruption caused by cognitive factor measurements (Verma et al. 2011).

Additionally, NLP can help achieve the automated extraction of rich, semantic information from the documentation of various events during the operation and maintenance of nuclear plants (e.g. the Licensee Event Report system established by Idaho National Lab (Gertman et al. 1992; Hobbins et al. 2016; Salo and Svenson 2003; Schroeder and Bower 2014)) for supporting the analysis of nuclear power plant incidents. These incidents include technical problems, personnel errors, safety violation, inadequate procedure, radioactive leak, or supervision issues. Automated analysis of documentations can assist in understanding dynamic team processes, such as team cognition during outages, thereby provide insights and information about complex team skills to improve team SA and reduce team MW. Furthermore, this automated analysis can suggest ideal interventions target cognitive underpinnings of team performance, such as training programs and technological support systems to increase team effectiveness (Cooke et al. 2004; Zouaq 2011).

5.3.3 Human-in-the-Loop Cyber-Physical Systems Research

A Cyber-Physical System (CPS) is a mechanism that the physical world is controlled or monitored by computer-based algorithms, tightly integrated with the Internet and human users (Lee 2015; Schirner et al. 2013). In a CPS, computers monitor and control physical processes, usually with feedback loops, where physical processes affect computation processes and vice versa. Domain applications of CPS include automotive systems, manufacturing, medical devices, etc.(Lee 2008). In recent years, researchers proposed the concept of "Human-in-the-Loop Cyber-Physical Systems (HiLCPSs)," which is defined as "*a loop involving a human, an embedded system (the cyber component), and the physical environment wherein the embedded system augments a human's interaction with the physical world*" (Schirner et al. 2013). In HiLCPSs, the sensors and computer systems monitor human activities (both cognitive and physical) and translate the sensory measurements into close-loop control signals to aid and modify the interaction between human and other components in the physical world (Munir et al. 2013). HiLCPS combined with Building Information Modeling (BIM) enables activity-level construction site planning that has the potential to gradually achieve proactive improvements of operational and construction safety in construction projects (Cheng et al. 2013).

The vision of CPS in outage control is to optimize human-automation interactive decision making and achieve the following: 1) the performances of tasks will be automatically tracked in detail with abundant human factor information; 2) schedules will be automatically updated and adjusted while human intervention is fully supported in order to mitigate the impacts of delays, errors, or field discoveries; 3) detailed as-is workflow information including human factors can be restored in supporting data-based decision making for future needs. Furthermore, artificial intelligence techniques, such as statistical learning methods, integrated into HiLCPS for continuous improvements of the system based on learning from historical data and documents (Deng and Yu 2014; Liu et al. 2015; Michalski et al. 2013; Schmidhuber 2015). In the future, I expect that computers would be able to automate more decision-making and control mechanisms, so that release human operators and decision makers to conduct more detailed diagnosis of projects and outage control strategies. Smarter computers and algorithms also should be able to enable automatic learning from human-computer interaction histories to recommend better human-computer interaction interfaces (van der Aalst et al. 2004; Herbst n.d.).

Despite of significant progress into CPS and HiLCPS technology in recent years, building a reliable, self-learning HiLCPS for a complex system such as NPP outage control is still difficult because of three challenges (Lee 2008, 2015; Munir et al. 2013; Schirner et al. 2013): 1) sensing and modeling techniques for each system need to be developed specifically based on the domain needs, which is not yet supported by mature computational and data science (Lee 2008); 2) traditional data analysis tools are unable to cope with the complexity of CPS or adequately predict system behavior (Schirner et al. 2013); 3) integrations of knowledges from different domains (e.g. computer science, mechanical & civil engineering, management science, and phycology science) are difficult to achieve for a reliable HiLCPS because of the natural complexity and uncertainty of human behaviors and physical processes (Lee 2015; Munir et al. 2013). Fully addressing these challenges requires the breakthroughs in computer science, cognitive science, and system science. Therefore, the practical step forward toward HiLCPS is to address the identified information acquisition challenges to precisely monitor the as-is workflow, to comprehend and optimize the decision-making processes.

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APPENDIX A

IRB APPROVAL DOCUMENT FOR THE CROWDSOURCING RESEARCH

EXEMPTION GRANTED

Pingbo Tang
Sustainable Engineering and the Built Environment, School of (SEBE)
480/727-8105
tangpingbo@asu.edu

Dear Pingbo Tang:

On 2/3/2016 the ASU IRB reviewed the following protocol:

Type of Review:	Initial Study
Title:	Online Safety Inspection Games for Crowdsourcing Risk Recognition Capability of Internet Users in Identifying Dangerous Elevator Installation Scenarios
Investigator:	Pingbo Tang
IRB ID:	STUDY00003858
Funding:	None
Grant Title:	None
Grant ID:	None
Documents Reviewed:	• Cheng Zhang CITI training, Category: Other (to reflect anything not captured above); • HRP-503a-TEMPLATE_PROTOCOL_SocialBehavioralV02-10-15.docx, Category: IRB Protocol; • Online_Survey_Form_for_Safety_Image_Analysis.pdf, Category: Participant materials (specific directions for them); • Pingbo Tang CITI training, Category: Other (to reflect anything not captured above); • HRP-502c - TEMPLATE CONSENT DOCUMENT -SHORT FORM.pdf, Category: Consent Form;

The IRB determined that the protocol is considered exempt pursuant to Federal Regulations 45CFR46 (2) Tests, surveys, interviews, or observation on 2/3/2016.

In conducting this protocol you are required to follow the requirements listed in the INVESTIGATOR MANUAL (HRP-103).

Sincerely,

IRB Administrator

cc:

Cheng Zhang