Measuring Operator's Situation Awareness in Smart Operation of Cranes

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Abstract –

Equipment operators play an integral role in the safe and efficiency operation of heavy equipment. They observe the environment, understand the situation, and make decisions and actions accordingly. Compared with other types of equipment, operating a crane is more sophisticated and mentally demanding, and thus crane operators are more vulnerable to human errors. Therefore, special considerations to mitigate operator errors should be taken when designing an operator-assistance system for construction cranes. With the goal of improving the operators' situation awareness (SA) of safety risks, this research presents a technical framework and practical system architecture for an operator-assistance system by leveraging real-time motion sensing and 3D modeling of dynamic workspaces. An approach for evaluating operators' SA was proposed to validate the effectiveness of the assistance system in actual lifting operations. Results in a series of field tests indicated that the prototype system improved the operators' SA which resulted in an improved lift performance.

Keywords –

Crane Operation; Situation Awareness; Operator; Safety

1 Introduction

Cranes play an integral role in construction projects, responsible for most vertical and horizontal transportation of construction materials, equipment, and personnel. Crane lifting operations are unique among other heavy equipment as they demand huge workspaces and have a significant impact on the safety and efficiency of the entire construction projects. As such, the consequences of crane accidents are catastrophic as they very often result in significant cost overrun, schedule delay, and serious injuries and fatalities. Based on statistics from the U.S. Bureau of Labor Statistics (BLS) from 1997 to 2015, the number of fatalities in crane-related accidents totaled 1259 for all industry sectors [1]. The U.S. construction industry was responsible for 586 fatalities (47%), in which 55% involved mobile cranes (e.g., truck-mounted, crawler cranes). Another source reported that 78% of crane-related accidents in the construction industry from 1992 to 2006 were associated with mobile cranes [2]. Unlike other types of construction accidents, the victims in crane-related accidents are not necessarily limited to construction workers but also pedestrians walking-by as observed in many crane-related accidents.

Behind the poor crane safety records, crane experts consider operator errors a prevailing source of risks in crane lifting operations [3]. It was found that 43% of the crane accidents from 2004 to 2010 were due to the operator failure in their responsibilities [4]. Mechanical failures aside, 75% of crane overturn accidents are due to operator error [5]. A recent investigation on risk factors in crane-related near-misses and accidents reveals that inattention is the most prevalent type of risk that accounts for 19% of the incidents, and errors by operators and signalpersons total 24% of the 212 investigated incidents [6]. These numbers are not surprising as operating a crane is inherently a sophisticated job that requires the operators have extensive training and experience. Repetitive lift tasks and extended work hours make them vulnerable to distraction and fatigue. In addition to the errors of crane operators, lifting safety can also be jeopardized by poor coordination and communication with personnel such as riggers, signal persons, and ironworkers.

With the development of information technology, researchers realized that technology can provide another layer of protection in construction to improve safety performance. Crane operations can benefit from technologies similar to the advanced driver assistance systems (ADASs) deployed on automobiles that provide real-time support to drivers based on surrounding situations [7]. With the goal of providing real-time assistance to crane operators, researchers in construction have explored the use of sensing, visualization, and simulation technologies. However, a holistic synthesis of existing technologies and a framework outlining further development is missing. In addition, previous efforts in evaluating a crane assistance system mainly focused on measuring accuracy, reliability, and ease of use of the introduced technologies [8]. Very few emphasized on the system's effectiveness on helping the operators understand the situation and the safety risks [9]. This is partly because that the situation awareness (SA) of crane operators during lifting operations is difficult to define and measure in such complex and dynamic environment. This also leads to the fact that most of the techniques in previous research were only validated in a simulated environment instead of utilizing real lift tasks [10].

2 Literature Review

2.1 Critical Components in Operator Assistance for Mobile Cranes

The very first step in providing operator assistance is to accurately capture crane motions in real-time. The motions of a crane are essential to carry out a variety of spatial and temporal analyses for load capacity, crane stability, and collisions. Real-time location systems (RTLS) such as Radio-frequency Identification (RFID) have been utilized for tracking mobile assets (e.g., materials, equipment, workers) on construction sites [11]. For capturing crane motion, Ultra-wide Band (UWB), a more precise position tracking technology, were investigated and tested in controlled lab tests [12] and outdoor full-scale tests with real cranes [13]. Using computer vision techniques, the motions of a crane and other articulated equipment can be captured by tracking markers deployed on equipment parts [14] or mapping image to the 3D model of the crane [15]. Similarly, the 3D geometry of a piece of equipment in the form of point cloud can be mapped to its 3D model to achieve equipment motion capture in 3D [16]. Cranes can be considered as giant robots with multiple degrees of freedom in a rigid body or kinematic relationships. Therefore, the entire motion of a crane can be capture by measuring critical motions (e.g., swing, lifting, and extension of the boom, extend/retract hoist cable). These critical motions can be easily measured by inexpensive rotary encoders, laser distance finders [17] and inertia measurement units (IMUs) [18].

Given the spatial and temporal scale of crane lifting operations, crane workspace is subject to constant changes in its surrounding environment (e.g., presence of vehicles and workers, newly erected structures). Therefore, modeling the as-is condition and dynamics of crane workspace is of great importance to successful operator assistance. Building Information Models (BIM) can provide a general spatial context for the crane workspace [17] but fails to model the dynamics and changes in the surroundings. As-is conditions such as geometry and color of nearby objects can be capture by laser-scanned point cloud and updated by a hybrid visualization approach that takes advantages of the efficient data collection and computation from computer vision and comprehensive 3D geometric information contained in point cloud [19].

The interface presented to the operator by assistance system plays a pivotal role in operator assistance. A user interface provides visual feedback to augment the operator's understanding of lift tasks [17]. To this end, numerical feedback provided by traditional operator-assistance systems such as Load Limit Indicators (LMI) is limited. At the other end of the spectrum, vivid pictures from crane camera systems may lead to distraction and increased mental workload when the operator struggles with the depth perception and limited field of view [20]. The user interface (UI) needs to provide just-in-time alerts in multiple forms (e.g., visual, auditory, haptic) with the right amount of information that supports operator to make decisions to mitigate hazards [18].

Although an array of safety devices are available in the market, the effectiveness and utilization of these devices in the industry are unclear [9]. It is important to evaluate the effectiveness of these safety devices in actual lift tasks in order to identify potential challenges and suggest further improvement. Previous efforts predominantly focused on addressing technical limitations, while the impact of such systems on reducing the operator error and improving their SA remains unknown.

2.2 Operator Error and Situation Awareness

From the perspective of cognitive psychology, a human error is considered a result of one or multiple failures in the human cognition process. This process can be described by the sequential stage model created by Furnham [21]. This model simulates the development of accidents as a sequential chain that consists of three cognition stages: hazard perception, hazard recognition, and decision/ability to avoid a hazard. It is helpful to understand the causation of cognitive failures in the development of crane accidents by applying this model to the cognition process of crane operators. When a crane operator is exposed to one or multiple hazards, they need to first perceive the presence of the hazards, mainly through the status, attributes, and dynamics of relevant elements in the environment. Based on the information acquired and their understanding of hazards, the operator should recognize the type, severity, and consequences of the hazards. Finally, the operator needs to make appropriate decisions and actions to mitigate or avoid the hazard from further development. Operator success in all cognition stages will result in safe behaviors. Failure in any of the stages will result in unsafe behaviors that may lead to accidents.

Successful hazard perception involves an acute state of alertness and high level of sensory skill from the operators, and it requires them to maintain a good Situation Awareness (SA) during the operation. Once the operators perceive the hazard in the first stage and proceed to the next stage of hazard recognition, they need to correctly recognize the type and severity of the hazards using their experience and knowledge as well as a comprehensive SA. Therefore, failures to perceive and recognize hazards are generally categorized as an SA problem [22], which has a high likelihood of leading to performance failure [23]. SA is defined by Endsley as "a person's perception of the elements of the environment within a volume of time and space, the comprehension of their meaning and the projection of their status in the near future" [24]. During crane operations, crane operators' SA depends on an understanding of both the crane (e.g., crane motion, capacity, malfunctions) and the physical characteristics of the environment (e.g., wind speed, blind spots, clearances to obstructions).

2.3 Measurement of Situation Awareness

A number of measurement methods for situation awareness have been developed and each measure has its advantages and applied circumstances. These measures can be classified into three categories: 1) process indices-based, 2) performance-based, and 3) query-based techniques.

Process indices-based techniques examine the way subjects process information obtained from the environment such as by analyzing gaze movement using eye tracking technology [25]. Another type of process indices is physiological measures such as electroencephalographic (EEG) activity, eye blinks, and cardiac activity, which represent the subject's overall functional state [26]. Although the changes in the subject's physiological states may be associated with cognitive activities, there is not necessarily a direct link between physiological states and the level of SA. In performance-based techniques, the level of SA is inferred from the performance outcomes based on the assumption that better performance indicates better SA. Commonly used performance metrics include productivity level, time to perform the task, and the accuracy of the response or, conversely, the number of errors committed. The main advantage of performance measures is that they yield objective, quantitative results without disrupting task performance. Although in many cases there is a positive relation between SA and performance, this connection is not always direct and explicit [27].

In query-based techniques, subjects are asked directly about their perception of certain aspects of the situation. The queries are usually designed by domain experts based on the characteristics of the tasks. One of the most widely used query-based techniques is the Situation Awareness Global Assessment Technique (SAGAT) [28]. The operation is frozen at randomly selected times and subjects are queried about their perception of the situation at that instant. SAGAT is popular as it produces a quantitative assessment of SA and it can benchmark the result with similar data in a similar context [29]. However, SAGAT is criticized as it interrupts the natural flow of the task. To address these limitations, Durso et al. developed the Situation Present Assessment Method (SPAM) based on the premise that SA involves simply knowing where to find a particular piece of information in the environment [30]. In addition to being less intrusive than other techniques [31], the benefits of using SPAM lie in it uses response time to indicate the level of SA so that the results reflect the real-time dynamic SA of the operator.

3 Methodology

To direct further development of operator-assistance systems for mobile cranes, this research proposes a framework to identify major technical layers and requirements. A system architecture is presented based on the framework to address key technical challenges in this endeavor. In addition, this research proposes an assessment approach to quantify the effectiveness of such operator-assistance systems by defining and measuring operators' SA and lift performance.

3.1 System Architecture for Real-time Operator Assistance

With the goal of improving crane lift safety, a system architecture is developed to enable real-time operator assistance. The system architecture consists of three components: crane motion capturing, site condition modeling and updating, and user interface and interaction (Figure 1). To capture crane motion in real-time, a combination of wired rotary encoder sensors and a wireless inertia measurement unit (IMU) sensor are adopted to measure the critical motions of crane modules (e.g., boom lift angle, boom extension length, boom slew angle, load sway) [32]. The data from the encoders are first synchronized in a processing unit so that the game engine program on the tablet receives the packet that includes the measurements from all encoders. In addition, the processing unit will detect and reject corrupted or incomplete packets. In site condition modeling and updating, the format of a point cloud, collected by a laser scanner or other photogrammetry technologies, is used to represent the as-is lifting site

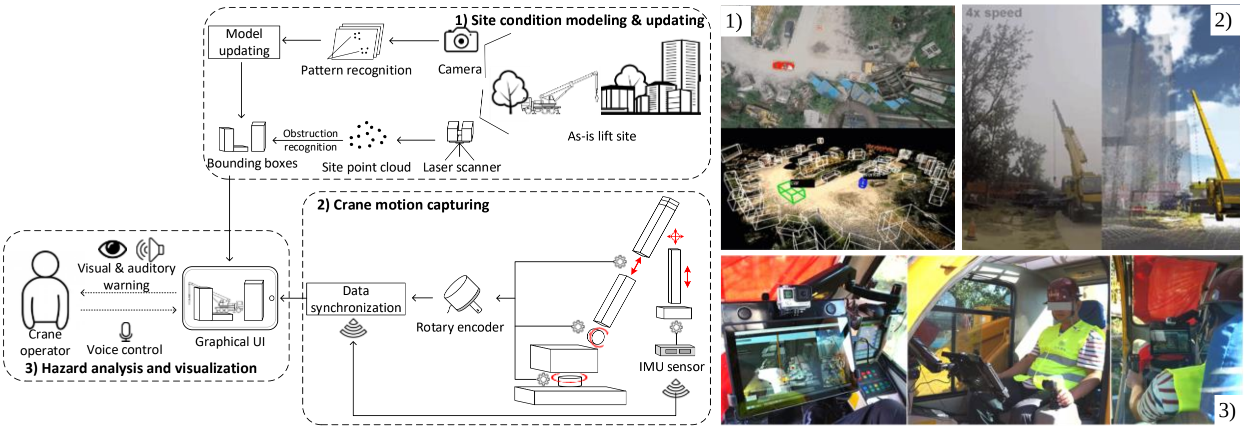

Figure 1: System Architecture

condition as it can be efficiently acquired. To reconstruct an as-is lifting site, the site point cloud needs to be converted to bounding box objects to represent site obstructions. Bounding boxes will be automatically constructed to represent the obstruction through multiple steps of point cloud processing. With the point cloud and bounding boxes serving as base 3D information, updating the lifting site condition, more precisely the location change of obstructions (e.g., vehicles, materials), can be achieved by correlating the 2D images captured by a camera with the known 3D information. Based on the crane motion data and the site condition data, the on-board computer will virtually reconstruct and realistically visualize the lift scene using a game engine, and analyze the hazards based on the real-time data. Once a hazard is detected, warnings will be delivered to the operator through both visual and auditory means. Throughout the operation, the operator is able to interact with the UI through voice commands The related details in team's previous work can be found in [19][33].

3.2 SA-based Effectiveness Assessment

Given the lack of effectiveness assessment in previous operator-assistance systems, this research proposes an assessment approach to quantify the effectiveness of assistance systems by defining and measuring operators' SA during lift tasks. The level SA is expected to have a direct impact on the lift performance. To investigate the correspondence of SA and performance, this research adopts the performance assessment method introduced in [33] which quantifies lift performance with respect to safety and efficiency by five key performance indexes (KIPs). In addition, the complexity of the lift task (e.g., mental, physical, and temporal demands) will affect the level of SA and the lift performance. The relationship between SA, lift performance, and task workload is illustrated in Figure 2. The following section will describe specific methods used to measure SA, lift performance, and task workload in crane lifting operations.

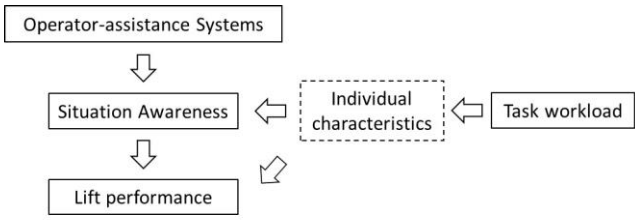

Figure 2: Relationship between SA, lift performance, and task workload in lift operations

3.2.1 Query-based Assessment of Situation Awareness

SA has been widely considered as an important factor in dynamic decision-making, and several indirect or subjective methods (e.g., physiological measurement, performance measures, self-rating) have been proposed and used in the SA research of aircraft pilots and air traffic controllers. This research employed a query-based SA measurement method adapted from SPAM [34]. In this method, the operator will be presented with queries about the situation while the situation remains present and while they continue to perform the primary task. During the query process, the questioner will indicate the operator that he intends to ask a query. Once the operator is ready to take the query, he or she will suspend the operation and indicate the questioner that he is ready. Then, the questioner will ask the question. The duration between the time the questioner finishes the question and the time operator start answering the question is considered the response time. Once the questioner records the operators' answer to the query, he will indicate the operator to resume the operation. In addition to response time as the sole measure of SA in traditional SPAM, the operator's level of SA is measured by both the response time and response correctness. Response correctness is quantified by the percentage of variance of the operators' answer to the correct answer recorded by the system.

Two major challenges that are addressed in this research when using this method are 1) designing proper queries that can effectively reflect the level of SA in crane lifting operations, and 2) choosing the proper timing to make the queries so that it does not interfere the primary lift tasks while remains effective for real-time SA assessment. A list of queries is shown in Table 1, in which two queries focus on past events, three queries focus on present events, and one query focuses on future events. These queries were designed based on panel discussions with safety experts, crane supervisors, and crane operators to ensure these queries reflect the most essential understandings of the lift tasks and their associated risks. During each lifting operation, one of the queries is chosen to ask according to the concurrent situation. For example, when the load is being lifted above a tree, the questioner asks the current clearance between load or boom and tree.

Table 1: Query list for the query-based SA measurement

Type	Query
Past	What is the maximum sway distance so far?
Past	How many warnings have you received from the system so far?
Present	What is the current boom reach?
Present	What is the current clearance between load/boom and obstructions?
Present	How far is the load placed from its target placement location?
Predictive	How long do you anticipate this lift task will take?

3.2.2 Assessment of Task Workload

During the crane lifting operation, operators' performance and SA can be affected by the workload imposed by the assigned lift task including mental, physical, and temporal demands. Given the same lift task, different operators may perceive different workload because of subjective, individual differences in training, experience, and cognitive capability. The perceived workload of the individual operator can be measured using NASA Task Load Index (NASA-TLX) [35]. The NASA-TLX is a widely used, subjective, multidimensional assessment tool that allows users to perform subjective workload assessments on operators working with various human-machine systems. NASA-TLX derives an overall workload score based on a weighted average of the ratings on six dimensions, including Mental Demands, Physical Demands, Temporal Demands, Own Performance, Effort, and Frustration.

In the assessment of perceived workload, participants were instructed to place an "X" on each of the six scales at the point that matches their experience. Each scale has two endpoint descriptors such as "bad" and "good", or "low" and "high". These numerical ratings for each scale reflect the magnitude of the factors in a given task. Then, the participants were presented with a series of pairs of rating scale tiles (for example, Effort vs. Mental Demands) and asked to choose which of the items was more important to their experience of the workload in the lift task they just performed. This was used to evaluate the contribution of each factor (its weight) to the workload of a specific task. Given the numerical rating and the weight of each factor, an adjusted rating can be computed for quantifying the overall perceived workload of the rated task.

4 Field Tests and Results

4.1 Overview

The goal of the field tests was to investigate how operator assistance would affect the operator's SA and performance under tasks with high and low workload. Five crane operators with experiences range from 8 to 16 years were recruited. Prior to the tests, the operators undertook a 30-minute training session to be familiar with the functionalities of the assistance system. To differentiate the complexity level of the lifting operation, two lift tasks were designed with different spatial and temporal constraints. Although surrounded by trees and other spare crane parts, lift task #1 features a simpler lifting operation as no obstructions present between the pick and drop locations. Lift task #2 requires the operator to lift the load over a row of trees of 15 m in height (Figure 3). Sitting in the cabin at ground level, the operators can hardly see the load when it is above the trees. Therefore, estimating the clearance from the trees to the load or boom is very challenging yet crucial for safety. For each task, a control and a test scenarios were created where in control scenario the operators only use traditional LMI system and in test scenarios, the operators use both LMI and the proposed assistance system. In these field tests, in total 60 lifts were conducted with 12 lifts for each operator.

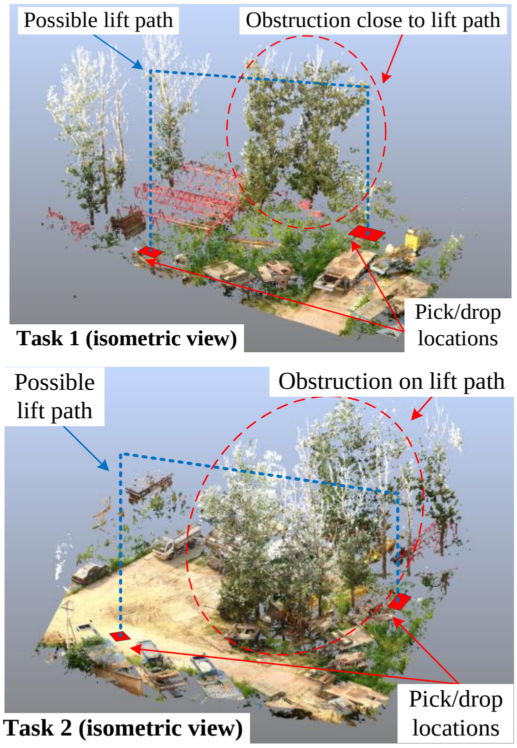

Figure 3: Lift task #1 and #2 in isometric view

4.2 Workload Assessment for Each Lift Task

A NASA-TLX rating package was explained and presented to each operator after the lifting operations. They were asked to fill out the rating and weight sheets based on their experience in the lifts. As the operators vary in individual characteristics such as motivation, risk-taking tendency, and mental and physical capabilities, different operators may perceive the different level of workload given the same conditions and constraints. Therefore, the workload index for each lift task was computed based on an averaged index from the five operators. Overall, lift task #1 received an adjusted rating of 5.42 whereas lift task #2 received 6.65. This result indicates that lift task #2 imposed a larger amount of workload to the operators than lift task #1. This can be further assured by the fact that all five operators rated Task #2 higher than Task #1, with the largest difference of 2 and smallest of 0.73.

In addition to the workload indexes for the lift tasks, it is also interesting to see how the operator rates and weights each workload dimension in general. Among the six dimensions, the largest rating difference between the two tasks lays in mental demand (5.8) whereas the smallest difference in physical demand (0.6). In the meantime, the operators weighted mental demands as the second biggest contributor (second to performance) to the workload and physical demands as the smallest. These results show that mental demand was a dominating source of the workload in the two test tasks, and very likely in crane lifting operations in general as these tasks represented the common characteristics in day-to-day lifting operations.

4.3 Operator SA Assessment

A query-based SA measure was used to quantify the operators' SA during the operation. The level of SA was quantified by the response time and response correctness for each query. Figures 5 and 6 present the average response time and average response correctness of the 60 queries in different tasks and scenarios. The quantile box plot indicates the variance in the results of response time and correctness. It was observed that the average response time in both the tasks was remarkably reduced when the assistance system was used, 17.5% in Task #1 and 28.6% in Task #2. The quartile box plot indicates that the variances of response time in the control scenario in both the tasks are much smaller than that in the test scenario. This result suggests that the operators have developed a consistent pattern of understanding the situation based on their experience without the assistance. Despite that overall response time was reduced, the introduction of operator assistance may change the way the operators search and understand the situation. Therefore, training plays an important role in the successful integration of the assistance system. Overall, the results show that the introduction of the assistance system facilitated the operator's ability to comprehend the situation, especially the information closely related to lift safety and efficiency.

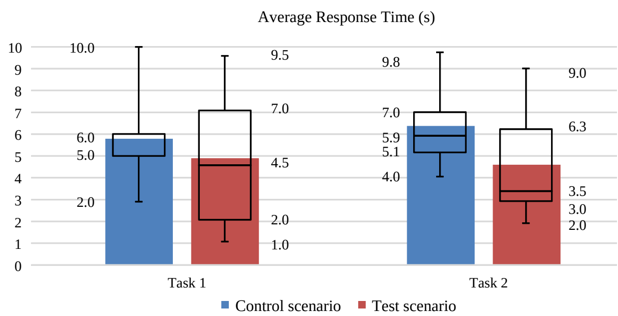

Figure 5: Average response time in two lift tasks under control and test scenarios

The response correctness is shown in percentage and it was computed by comparing the operators' responses to the correct answer recorded in the system. The results show that average response correctness was improved in the test scenario, by 2.3% in Task #1 and 9.5% in Task #2. The box plot suggests that the response correctness in test scenarios was in generally more consistent, especially in Task #2. Although not as obvious as the decrease in response time, the improvement of response correctness suggests that the assistance system was able to provide helpful information to augment the operator's awareness of the lift task so that the accuracy of their decision-making can be increased.

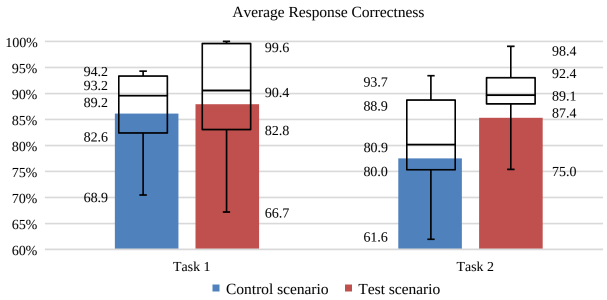

Figure 6: Average response correctness in two lift tasks under control and test scenarios

5 Discussion

From a statistical perspective, the sample size of operators participated in the field tests may not large enough to show the statistical significance of the improvement. Particularly, the variances in the measurements tend to be large due to the limited number of subjects and the significant difference in experience and maneuver pattern among them. That being said, the results in these field tests reflect the general trend in the improvement of lift performance and SA by introducing the assistance system. The conclusions are meaningful to understand the strengths and limitations of the current design and to guide the future work. Another limitation in the SA measurement in the field tests that the query process was not blind to the questioner. This bias in the results can be minimized by asking multiple queries and randomly selecting part of them for SA measurement.

6 Conclusion

To guide further development of operator-assistance systems for mobile cranes, this research presents a framework to identify major technical tasks and requirements. Based on the framework, a system architecture is proposed to address key technical challenges to facilitate implementation. In addition, this research proposes an assessment approach to assess the effectiveness of such operator-assistance systems by defining and quantifying operators' SA and lift performance. These proposed methods were tested and validated in a series of field tests. Results indicate that the assistance system has a positive impact on improving operators' SA during lift tasks, which led to improved lift performance, especially in safety. Overall, it was found that the assistance system facilitated the operator's ability to comprehend the situation, especially the information closely related to site geometric constraints, which led to a safer and more efficient lifting operation. It should be noted that the experiments were conducted in real lift jobs with actual temporal and spatial constraints, and the participating operators were exposed to real lifting safety pressure and risks. Compared to virtual simulation or survey that were commonly used in many other research, the data collected and presented in this research is more realistic and therefore the results are closer to the actual effectiveness of the assistance.

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