**A Framework for Real-time Pro-active Safety Assistance for Mobile Crane Lifting
Operations**

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ABSTRACT

Despite many safety considerations addressed in lift pre-planning, the ability to provide real-time safety assistance to crane operators and to mitigate human errors during the lifting operation is missing. This research developed a framework for an operation-level safety assistance system enabled by continuous crane motion capturing, pro-active hazard analysis, and real-time 3D visualization. A sensor system captures the critical motions of crane parts, based on which the entire crane motions are reconstructed in real-time with as-is lift site conditions modeled based on point cloud data. The risk of colliding the crane parts and lifted load to surrounding obstructions is analyzed and warnings are provided to the operator through a user interface. A prototype system was developed based on the framework and deployed on a mobile crane. Field test results indicate that the system can accurately reconstruct crane motion in real-time and provide pro-active warnings that allow the operator to make timely decisions to mitigate the risk.

KEY WORDS

Crane safety; human error; real-time; crane motion capturing; collision hazard analysis; 3D reconstruction; point cloud; sensor.

1. INTRODUCTION

A crane is one of the most essential and commonly used type of machinery in the construction industry. In the United States alone, approximately 125,000 cranes of different types are in operation everyday among all sectors of the construction industry, from single houses to international mega projects [1]. Throughout the entire construction phase of a project, cranes are responsible for a great portion of vertical and horizontal transportations of construction resources including material, equipment, and personnel. Lifting operations are inherently a sophisticated job given that the crane is a highly complex piece of machinery that requires extensive experience and skill to operate. For example, crane parts (e.g., boom, jib, trolley, hook) operate independently based on different modes of motion (e.g., swing, translate, lift). Although manipulated individually, every component is interrelated with one another implicitly. Every single motion of one component may affect the movement of other crane parts and the stability of the load.

A crane operator is one of the most well paid jobs in the construction industry because of not only extensive skills and experience required but also the risks and responsibility associated with crane operations. Unsurprisingly, cranes are considered the most dangerous piece of equipment on construction sites by general site employees [2]. Given the magnitude of crane weight and the huge workspace cranes occupy, the potential loss of property and life due to incidents related to crane is tremendous. From 1992 to 2006, crane-related accidents in the United States led to 632 worker deaths in 610 cases, an average of 43 deaths per year [3]. Statistics from Bureau of Labor Statistics (BLS) reveals that from 1997 to 2013, 1171 fatalities were observed in crane-related accidents in all industry sectors. Unfortunately, the construction industry alone was responsible for 544 fatalities in the period, which accounts for almost half of

the deaths in all industry sectors combined. It should be noted that mobile cranes, as the most commonly used type of crane in construction industry, are responsible for 70% of these accidents [3]. Unlike other accidents on construction sites, the victims in crane-related accidents are not necessarily limited to construction labors and crane operators but also pedestrians as observed in many crane-related accidents [4].

The causes of crane-related accidents can be complicated and it usually takes months to fully investigate and uncover them. The Center for Construction Research and Training (CPWR) revealed that 61% of 632 fatalities involved crane parts or loads colliding with obstructions (e.g., power lines, personnel, structure) [3]. Based on the crane accident data from the Occupational Safety and Health Administration (OSHA) from 1997 to 2003, Beavers et al. concluded that struck by load (32%) and failure of boom/cable (12%) together accounted for 44% of the total number of fatalities [2]. It should be noted that 24% of these fatalities occurred during lifting/moving equipment and materials, being the second to mobilization (31%). In most cases, the “struck by” accidents occur mainly due to spatial conflicts existing between crane parts and the surrounding obstructions. Within the large workspace of cranes, the presence of built building structure, storage of materials, and power lines all induce potential spatial conflicts during crane lifting operations. Suruda et al. [5] reported that 40% of the deaths in crane-related accidents were related to spatial conflicts. Furthermore, when analyzing crane-related spatial conflicts, one must consider the dynamic crane motions and changes in the surrounding environment as the project proceeds [6].

Although various techniques are available for mitigating hazards in the lift pre-planning phase, crane safety in the construction phase mainly relies on crane operator skills and experience. Operator proficiency was considered the highest degree of influence that will affect

crane safety by construction equipment and safety experts [7]. King found that 32 out of 75 crane accidents from 2004 to 2010 (43%) were due to the operator failure in their responsibilities [8]. Neitzel et al. pointed out that the crane operator has the most direct influence on the safety of crane lifting operations, and thus they must have the technical and performance proficiency in operating cranes [4]. Operator errors occur because of human frailties such as distraction or fatigue, or because of misjudgement due to lack of experience or inadequate time to react to an unexpected event [7]. Since many construction activities are highly dependent on crane rigging/lifting for material delivery and structure erection, crane operators usually start their work much earlier than other crews. Crane operators, therefore, would be generally more fatigued and thus more prone to making errors when it approaches the end of the day. In addition, crane operators operate huge machines with loads based on limited information obtained from other labor, typically the riggers or signalmen [9]. Construction sites are often very congested with materials, equipment and structures of different heights and shapes. These obstructions introduce massive blind spots into crane lifting operations. Sitting high in a tower crane cabin or low in a mobile crane cabin, operators often find it difficult to determine the absolute height or relative distances between the lifted load and surrounding objects. The limited visibility and poor depth perception lead to the poor situational awareness of the hazards associated with the lift operation, which greatly limits their abilities to identify potential hazards, choose risk-free paths, and timely react to emergencies [10]. It has been well recognized that real-time information and assistance for decision making are necessary and sometimes critical for many construction tasks involving human-machine interaction [11].

In order to improve the operators' situational awareness to the potential hazards associated with crane lifting, this research developed a framework of a safety assistance system

for mobile crane lift operations enabled by real-time crane motion monitoring, pro-active hazard analysis and 3D visualization. This paper starts with a thorough review of current lifting safety practices and technologies. Then, a framework of the pro-active safety assistance system is introduced with details in sensory systems, lift site modeling and updating, and hazard analysis and visualization. The proposed framework is then demonstrated with the prototype pro-active safety assistance system deployed on a telescopic boom mobile crane. Based on the collected field test data, the performance of the prototype system is evaluated with respect to reconstruction accuracy, latency, and ease of use. Finally, the potentials and limitations of the proposed framework approach are discussed.

2. RELATED WORK

2.1. Crane Lift Planning

Crane lifting planning is an essential planning mission that is critical for the productivity and safety of the entire project [12]. Tasks in crane lifting planning usually include two basic components: crane location planning and lifting path planning. The crane location or layout planning aims to maximize crane utilization in transporting construction resources. This is a complicated optimization problem involving various spatial-temporal constraints. In current practices, a crane location is typically determined by experienced lift coordinators through trial and error, given the site shape and topography, and the distribution of estimated lifting tasks [13]. This manual process can be assisted or validated by simulation technologies [14] [15] and optimization algorithms [16] [17][18][19].

The goal of path planning is to plan a collision-free and efficient lift path based on load data (e.g., size, weight) and site geometric constraints. Traditionally, the lift path is planned

mainly depending on the planners' intuition and experience and this process is often labor intensive and error prone [20]. Recently, researchers have adopted the knowledge and techniques in robotic motion planning to automate the lift planning process. In this approach, a crane is treated as a multi degree-of-freedom robotic manipulator and various algorithms (e.g., Probabilistic Road Map [21], Rapidly Exploring Random Tree (RRT) [22][23][24][25]) were tested to optimize a lift path to ensure a collision-free travel while guaranteeing a respectively short lift path. It should be noted that the computer-aided path planning only works when provided with accurate and comprehensive site geometric information. Site geometry, however, is not always available or accurate in the early planning phase. In addition to static obstructions, when analyzing crane-related spatial conflicts, one must consider the dynamic crane motions and changes in the surrounding environment as the project proceeds [6]. Design changes occur throughout the planning phase and even during the construction phase, and thus site drawings or models used for lift path planning no longer represent all the geometric constraints existing in the actual lift site. These variances between planned and actual site conditions inevitably compromise the validity of the planned lift paths.

2.2. Real-time Lift Safety Assistance

With the development of information technology, researchers realized that technology can provide another layer of protection in construction safety [26]. Crane operations can benefit from technology similar to the advanced driver assistance systems implemented on vehicles that provide real-time support to the driver based on surrounding situations. The following sections introduce three technologies that have been investigated or implemented in crane lifting operations.

2.2.1. *Load moment indicator (LMI)*

A load moment indicator (LMI) is a system that aids the crane operator by sensing (directly or indirectly) the overturning moment on the crane, i.e., load multiplied by radius [27]. It compares the current lifting condition to the crane's rated capacity or load chart, and indicates to the operator the percentage of capacity at which the equipment is working. This system has become standard in heavy-duty cranes from many crane manufacturers and its performance in the field has proved its effectiveness in preventing accidents due to overloading. However, the LMI system cannot address other hazards associated to crane operation such as collisions and excessive load sway.

2.2.2. *Camera system*

Using a camera is a simple solution for enhancing the visibility and situational awareness of crane operators. Typically, a camera system involves a wireless camera mounted on crane trolley or hook block directed downwards, and a monitor in the crane cabin (sometimes also in the management office) showing the lifted load and the workspace underneath. Lee et al. [28] proposed a tower crane motion monitoring system equipped with wireless video camera and LCD cabin monitor enabled by a wireless local area network (WLAN). The system provides the crane operator with an enhanced view of the workspace and the lifted load. Shapira et al. [29] developed a vision system for tower cranes to increase the operators' visibility to the load during loading and unloading. Based on the feedback from domain experts, it was concluded that the vision system offers potential benefits in safety enhancement and productivity improvement especially during blind lifts and lifts in the proximity of obstructions. In addition to monitoring

the lifted load, Putnik et al. [30] proposed a more comprehensive system with multiple cameras streaming from different angles to cabin monitors.

Camera-based methods are effective in terms of providing alternative views to enhance operator visibility and situational awareness. However, the monitor in the cabin provides only 2-dimensional images without depth perception. This means the operator cannot determine the height of load at the lower level or the proximity from the load to surrounding objects. Despite the function of zooming in/out, cameras are fixed to the crane parts that makes it less flexible in complicated lifting scenarios such as blind lifts. In addition, the attachments including sheath blocks, hooks, slings, and loads can block the camera views. Furthermore, camera systems provide no automatic warning function, and thus the operator has to constantly check the monitor while operating the crane. This introduces additional mental workload and distractions to the operator, which could ironically increase the risk of accidents.

2.2.3. *Real-time location system*

A real-time location system (RTLS) is a technology that automatically identifies and tracks the location of objects in real-time. In construction, it has been used for various applications such as site security, resource location tracking, and equipment safety. Zhang et al. employed a high-precision RTLS technology named Ultra-wide band (UWB) for estimating mobile crane poses in near real-time [31]. In this system, UWB readers were deployed around the lifting scene and UWB tags were mounted on different spots of crane boom and lifted objects. The system is able to estimate crane poses in near real-time through noise filtering and missing data filling. Using the same technology, Hwang [32] explored methods for tower crane collision prevention. He studied the characteristics of different types of collisions and developed a computer program for

monitoring crane motions and sending warnings if a potential collision hazard was detected. Li et al. took advantage of Global Positioning System (GPS) and Radio Frequency Identification (RFID) for developing a real-time crane motion monitoring system [33]. Tracking crane parts and construction workers, this system aims to assist the safety operation in blind lifts by detecting the presence of unauthorized workers within a risk zone.

These efforts demonstrated the feasibility of using RTLS for crane pose/motion monitoring. However, the RTLS technology suffers from several limitations that compromise its performance in the application of crane motion monitoring. Firstly, most RTLS system requires setting up hardware including readers, cables for data transmission and synchronization, power supply, and computer for data collection and processing. Depending on the range of the RTLS readers, the number of readers needed to cover the site needs to increase accordingly as the size of the crane to be monitored increases. In addition, crane lifting is a 3-dimensional operation that requires the RTLS system to be deployed at various heights in order to tracking the vertical movement of crane parts and load. This not only requires setting up a big amount of RTLS antennas around the lift site ahead of time, but also means a big investment in hardware given that the cost of UWB is approximately \$140/m² [34]. Secondly, the site security and vandalism for the installed sensing system would be another concern unless the components are installed and retrieved every day. Thirdly, the RTLS technology inherently suffers from signal interference due to electromagnetic interferences, multi-path propagation, fading and scattering of signals [35]. This problem becomes more significant in metallic and densely packed construction environment. As recognized by Zhang et al. [31], their UWB tracking system failed to reliably track the load position because the tags on the crane load cannot be detected and tracked continuously due to serious signal loss.

2.3. Direct Motion Measurement

Another method that has been extensively investigated for crane motion monitoring is integrating sensors of different types to capture critical crane motions. Critical crane motions stand for the key freedoms of major crane parts that, when combined are able to represent most possibilities of crane maneuvers. Lee et al. developed a laser-based lifting path tracking method for a robotic crane system to improve the crane lifting productivity [36]. This system employs multiple sensors including a laser device for measuring the load elevation, and an encoder and an accelerometer for measuring horizontal and vertical angles of crane boom. A major limitation of this system is that it does not consider the load sway and, as pointed out by the authors, the configuration of laser sensor and reflection board cannot reliably measure the load elevation during excessive load sway. Advanced from the previous attempt, Lee et al. augmented the crane motion monitoring system by introducing multiple sensors and a BIM-based method for incorporating the surrounding environment [37]. They further analyzed the ease of use and usefulness of the developed system. After 71 days of implementation on a tower crane, the operators heavily relied on the developed system (93.3%) compared to traditional load moment indicator (LMI) system. However, the operator had to use a 19-key mini keypad to change the crane view angle on the user interface, which very likely compromises the lifting safety and efficiency, as the operator is distracted from the main task. Ren and Wu developed a real-time anti-collision system for mobile cranes that creates a safe lift zone during lifting based on the location and shape of static obstacles collected prior to the lift [38]. However, this process involves extensive manual input and additional data collection time prior to the lift.

Compared to the RTLS-based and camera-based crane monitoring methods, the direct sensor-based solutions hold several apparent advantages. Firstly, hardware employed in sensor-

based systems is usually more cost-effective and durable in long-term use. Once securely installed on the crane, the sensors require little maintenance efforts and with proper enclosure they can work properly in harsh environmental conditions. Secondly, sensor-based methods do not require external hardware deployment on the site, and thus it introduces minimal interruption to other construction activities. Thirdly, sensors-based system can captures crane motions more effectively and comprehensively.

3. METHODOLOGY

Despite several research efforts that have been devoted to improving crane lift safety in pre-planning and execution phases, very few of them can provide crane operators with effective information to enable real-time operational assistance and pro-active hazard warnings. To fill this gap in knowledge, this research designed and created a novel framework that enables pro-active safety assistance for mobile crane lift operations through the integration of real-time motion capturing, rapid lift scene updating, pro-active safety analysis, and visual and audio warnings. As shown in Figure 1, the proposed framework consists of three major components: critical motion capturing, site condition modeling, and hazard analysis and visualization. Real-time actions are indicated by boxes in solid line, which include crane motion capturing and hazard analysis and visualization. Pre-lift actions include crane model preparation and as-is site point cloud acquisition. The following sections introduce each component in the framework in detail.

Figure 1: A framework for real-time pro-active safety assistance for crane lifting operation

3.1. Critical Motion Analysis of Crane Manipulation and Suspension Modules

A crane is comprised of multiple rigid bodies connected by different types of joint, depending on the crane type and capacity. In this study, the type of telescopic-boom mobile cranes was selected as they usually have more degrees of freedom than others (e.g., tower cranes or lattice boom mobile cranes), and thus the design of mobile crane motion capturing proposed in this research can be easily altered to apply to other types of cranes. A telescopic mobile crane can be decomposed to two independent modules: the manipulation module and the suspension module (see Figure 2). The manipulation module is comprised of three rigid bodies including a truck base, a crane body, and a telescopic boom. Then, the telescopic boom is further broken down into two rigid bodies (i.e., main boom and sub-booms) and a prismatic joint that only allows translational movement between these two rigid bodies. The connection between the truck base

and the crane body as well as the connection between the crane body and the main boom are modeled by a revolute joint that only allows one rotational degree of freedom between the two rigid bodies. The suspension module consists of a normal rigid body, the lifted load, and an extensible rigid body for the hoist line. Although hoist line itself is elastic and thus can be hardly considered a rigid body, when used in a pulley system where double (four cables) or triple tackle (six cables) serve together for lifting, the cable bundle is actually resistant to twisting and bending, especially when the lifted load performs a 3-dimensional pendulum motion in a very small magnitude (less than 10 degree). The connection between the suspension module and the sub-booms is modeled by a spherical joint that allows rotation in all direction and only constraints translational movement. Based on the critical motion analysis, a telescopic boom mobile crane is simplified as six rigid bodies connected by five joints. This means that any motion that can be possibly performed by a crane is able to be kinematically represented by measuring the boom slew angle, boom lift angle and boom extension length in the manipulation module and the length of the hoist line and load sway in the suspension module.

Figure 2: Kinematics configuration of a typical telescopic boom mobile crane

3.1.1. Manipulation module motion capturing using rotary encoders

Rotary encoders are electromechanical devices that are used in various electronic and mechanical devices for measuring angular position or motion of a shaft or axle in the device. Rotary encoders can be classified into incremental and absolute encoders, or mechanical, optical, and magnetic encoders based on how the digital code is produced [39]. For typical magnetic absolute encoders, strips of magnetized material are placed on the rotating disc and are sensed by a Hall-effect sensor or magneto resistive sensor. The prototype system adopted rotary magnetic absolute encoders to measure three critical motions of the crane manipulation module: boom slew and lift angles, hoist line extension and boom extension. The boom lift angles can also be measured by an inclination sensor alternatively. Although the proposed motion capturing method adopts commercially available encoders, it is more flexible than other commercial solutions [40] in that

the selection and deployment of the sensors are also suitable for retrofitting existing cranes in service.

3.1.2. *Suspension module motion capturing using an inertia measurement unit*

An inertial measurement unit (IMU) is an electronic device that measures velocity, orientation, and gravitational forces, using a combination of accelerometers and gyroscopes, sometimes magnetometers. IMU sensors were originally developed for the maneuver of aircraft and spacecraft, such as an unmanned aviation vehicle (UAV) and satellites, to report inertial measurements to the pilot system. Recently, IMU sensors have been widely used as orientation sensors for measuring human body motions in sport athlete training and movie production. A typical IMU sensor contains angular and linear accelerometers for tracking the changes in position and gyroscopes for maintaining an absolute angular reference. Generally, an IMU sensor has least one accelerometer and one gyroscope for each of the three axes: pitch (nose up and down), yaw (nose left and right) and roll (clockwise or counter-clockwise). When rigidly mounted to an object, the IMU sensor measures the linear and angular acceleration and automatically calculates the orientation of the attached object. In the particular case of load sway, it is assumed that the cable length is known and the cable is rigid. Therefore, the load sway motions can be simplified to a typical 3-dimensional (3D) pendulum motion (Figure 3a). Given the measured angular orientation on each axis (Figure 3b) and the cable length, the estimated position of the load relative to the fixed point can be calculated by converting the Euler angle measurements to Cartesian coordinates in the local coordinate system (Figure 3c).

Figure 3: Transforming the angular measurements to absolute positions (adapted from [41])

This process of converting the Euler angle measurements to Cartesian coordinates is demonstrated in the following steps. Firstly, one single load orientation measurement can be represented by three independent rotations: yaw, pitch, and roll. The yaw, pitch, and roll rotations can comprehensively represent a 3D rigid body in any orientation. These three independent rotations are defined as follows: a yaw is a counterclockwise rotation of α about the z-axis; a pitch is a counterclockwise rotation of β about the y-axis; a roll is a counterclockwise rotation of γ about the x-axis. Therefore, a single rotation matrix $R(\alpha, \beta, \gamma)$ can be formed by multiplying the yaw, pitch, and roll rotation matrices.

Since the load sway motion is a simple 3-dimensional pendulum motion, the load trajectory actually lies on the internal surface of a virtual sphere with the radius of the cable length. Hence, the unit vector on a local z-axis always points to the center of the sphere. Therefore, converting the Euler angle measurements to Cartesian coordinates is simplified by converting this unit vector on the local z-axis to a vector on global coordinate system according to the rotation matrix containing the three independent rotations. Thus, the load position can be estimated by multiplying the rotation matrix with the unit vector $(0, 0, 1)$ and the length of the hoist line L using Eq. (1).

$$P(x, y, z) = R(\alpha, \beta, \gamma) \cdot \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} \cdot L = \begin{bmatrix} \cos\alpha \cdot \sin\beta \cdot \cos\gamma + \sin\alpha \cdot \sin\gamma \\ \sin\alpha \cdot \sin\beta \cdot \cos\gamma - \cos\alpha \cdot \sin\gamma \\ \cos\beta \cdot \cos\gamma \end{bmatrix} \cdot L \quad (1)$$

359

360 It should be noted that the initial orientation measurement (α, β, γ) is not necessarily the
 361 origin since the surface where the sensor is placed might not be completely leveled. Therefore, a
 362 deviation from the origin can be expected in the estimation of the load trajectory based on this
 363 method. To minimize this error, the initial load orientation is taken into consideration. The
 364 orientation data measured when the load is static is averaged and introduced to the calculation as
 365 an offset for correcting the deviation.

366

367 3.2. Site Condition Modeling

368 3.2.1. Crane modeling

369 Cranes are different in types, sizes, and capacities, and thus it is important for the lift assistance
 370 system to model the critical crane configurations according to the actual crane geometry and
 371 movements. This can be accomplished by modifying an existing crane model according to
 372 specifications of the actual crane that will be used for the job. Key dimensions to be considered
 373 include the sizes of crane base and cabin, limits of boom length, pivot point of crane's
 374 superstructure, and the size and shape of the lifted load.

375

376 3.2.2. Site condition modeling and updating from Point cloud

377 Cranes' lift capability and maneuverability are greatly affected by the geometric constraints in
 378 the surrounding environment, especially for mobile cranes as their location and workspace
 379 change quite frequently as a project proceeds. Therefore, it is necessary to integrate lift site
 380 environment data into the lift assistance framework. A major limitation in traditional lift

planning approaches is the lack of information to represent the as-is lift site condition. Recent advances in rapid geometry data acquisition make it possible to obtain massive 3-dimensional geometric data in a short amount of time with minimal efforts. This is realized in the proposed framework by rapid modeling and updating the lift site in the form of point cloud. A point cloud is a set of points containing coordinate data (XYZ) and color data (RGB) representing the geometry of objects in the captured scene. Obtained from a terrestrial laser scanner or aerial photogrammetry technology, point clouds can be used to represent object geometries or to reconstruct a scene with good accuracy ($\pm 2\text{mm}$) and efficiency (up to 976,000 point per second) [42].

To reconstruct an as-is lift site, the site point cloud acquired by a laser scanner is converted into bounding box objects prior to the lifting operation to represent site obstructions for the collision hazard analysis in the next step. The as-is lift site model is updated by manually adding dynamic objects such as vehicles and construction materials on the operator user interface. Research in automating the laser scanning-based site modeling and updating [43] [44] is out of the scope of this research, and advancement in this area will be introduced in future publications. The pipeline of obtaining oriented bounding boxes for various objects in point clouds involves the steps of segmentation, clustering, and orientation estimation. The input point cloud is first down-sampled from its original number of points to around 10,000 points by performing voxel grid filtering. Individual points in the original point cloud are projected onto a grid of 1cm-sized voxels and only a single point representing the center of each occupied voxel is preserved in the point cloud while the extraneous points are filtered out.

Next, ground plane segmentation is performed using Random Sample Consensus (RANSAC) [45]. Points from the ground plane are filtered out so that object points can be

separated nicely in the clustering step. The RANSAC algorithm iteratively computes an estimate of the ground plane parameters by randomly sampling points from the point cloud. The best estimate in terms of number of inliers is determined and all points located within 0.4m of the calculated plane are filtered out.

The ensuing clustering step involves grouping points that are contained within the same neighborhood together and labelling each group as an individual cluster. The threshold parameter used in this study is 0.4m but it can also be manually adjusted so that the points belonging to the same object would not be split into separate clusters and the points belonging to different objects would not be grouped into the same cluster. Even with carefully tuned clustering parameters, this step may occasionally face problems with over-segmentation or under-segmentation, which affects the tightness of fit and orientation accuracy of the bounding boxes. However, the final bounding box span in 3D space to determine collisions remains largely the same.

Finally, an oriented bounding box is computed for each point cluster by considering the physical spread of points in the z-axis (vertical axis) and the x-y-plane. Principal Component Analysis (PCA) [46] is used to determine the two principal directions in which points in the cluster vary the most in the x-y-plane. The principal directions are used to determine the orientation of the objects bounding box in the x-y-plane. The final bounding box is then computed by determining the maximum and minimum length along the vertical axes and the horizontal principal axes. The total computation time for the whole process largely depends on the down-sampling ratio but it only takes a few minutes to down sample a site point cloud of around 30 million points. Regardless of the original point cloud resolution, a final point cloud with a size of around 10,000 points is considered sufficient and efficient for obstruction identification since it is only necessary to recover a rough outline of each detected object.

Once the bounding boxes for obstructions are automatically created, they are prepared for visualization with the adjustment of the surface transparency level and being labeled as obstructions in a game engine. The framework for lift scene reconstruction is illustrated in Figure 4. As the obstructions in the as-is lift site are represented by bounding boxes, the site condition can be easily updated based on actual changes by manually moving or adding bounding boxes through the user interface. The recognized obstructions represent the possible collision risks on the lift site that will be addressed in pro-active hazard analysis and visualization in real-time.

Figure 4: Lift site condition modeling process based on point cloud data

3.3. Pro-active Hazard Analysis and Real-time Visualization

Once crane motions are captured and a lift site is reconstructed with the recognized obstructions, the next task in this framework is to analyze potential hazards in real-time based on a pre-defined proximity threshold. The pro-active hazard analysis is enabled by the four steps as follows. First, the algorithm considers four crane parts as the objects subject to collision hazards: crane cabin, boom, hoist line, and load. Second, the obstructions present on the site are categorized into three levels of severity based on the potential consequences if the collision occurs. For example, power lines in the crane workspace fall into the highest level of severity while trees fall into the lowest level of severity. In the third step, based on safety regulations from the Occupational Safety and Health Administration (OSHA) [47] and industry best practices [7], different safe proximity thresholds are assigned to each severity levels as shown in Table 1. Lastly, the game engine keeps tracks of the proximity between each crane part and each obstruction. The proximity is defined as the distance between the closest points on the surfaces of each object. To minimize the delay in real-time visualization, the hazard analysis needs to be conducted in an efficient manner. As such, the program only monitors the crane parts and the obstructions within a distance less than 5 m; this input can be changed based on size of crane, types of lifting work, and conditions of job site. When the proximity between the crane part and the obstruction is beyond the respective threshold, the program will highlight the objects of interest and send visual and auditory warnings through the graphical user interface to the operator.

Table 1: Proximity thresholds in the hazard analysis based on level of severity

Level of severity	Proximity threshold	Examples
High	4 m	Energized power lines
Moderate	2 m	Building structures, equipment
Low	1m	Trees

4. PROTOTYPE DEVELOPMENT

To validate the proposed framework, a prototype system was developed and deployed on a 70-ton telescopic boom mobile crane. This section introduces how each part of the framework was implemented and the performance of the prototype system was evaluated in field tests.

4.1. Sensor Deployment

The prototype system adopted rotary magnetic encoders to measure three critical motions: boom slew, hoist line extension and boom extension (see Figure 5). The boom slew angle was measured by attaching a small measuring gear on the rotary encoder to the main slewing gear underneath the crane cabin. Similar to the slewing angle, the length of the hoist line was calculated based on rotation of the crane hoist winch measured by another rotary encoder. The boom extension was obtained using another rotary encoder by measuring the length of a wire with one end fixed at the middle of the boom and the other end attached to the tip of the boom. Unlike other motion measurements, the boom lift angle was directly measured by an inclination sensor attached to the crane boom. All the rotary encoders and inclination sensor were powered by the crane battery and connected to a microcontroller.

Boom length/angle
(rotary encoder,
inclination sensor)

Hoist line length
(rotary encoder)

Load sway
(IMU sensor)

Slew angle
(rotary encoder)

Figure 5: Sensor configuration for critical motion capturing

A wireless IMU sensor was used to measure the position of the lifted load. As shown in Figure 6, the IMU sensor was powered by a small power bank battery and they were enclosed in a waterproof case that are NEMA 4X / IP66 rated. The case can be attached to the side of the hook block using heavy-duty tapes or bolts. The wireless IMU continuously measures and transmits load orientation to the tablet for data processing.

Figure 6: IMU sensor configuration for load position measurement

4.2. Error Analysis of Crane Motion Reconstruction

When analyzing the error of the final load positioning, error propagation as a result of the changes in boom lift angle, slew angle, and boom extension must be considered. The goal of this section is to understand how the error in the results of the pose reconstruction is affected by different crane configurations (i.e., a combination of boom angle, slew angle, and boom length). Given that the load position is dependent on boom lift angle, boom length and boom slew angle, a load position in X-Y plane can be calculated as shown in Eq. 2 and 3.

$$x = L_b \cdot \cos \theta_l \cdot \sin \theta_s \quad (2)$$

$$y = L_b \cdot \cos \theta_l \cdot \cos \theta_s \quad (3)$$

in which,

θ_l : boom lift angle

θ_s : boom slew angle

L_b : boom length

Eq. 6 shows a general equation for error propagation. Given that $R = R(X, Y, \dots)$ (X and Y are different measurements) and δX and δY (the uncertainty of measurement X and Y), the standard deviation of R can be calculated by a generic expression as shown in Eq.6. Since the

measurement of each sensor are independent, we assume there is no covariance between each measurement.

$$\delta R = \sqrt{\left(\frac{\partial R}{\partial X} \cdot \delta X\right)^2 + \left(\frac{\partial R}{\partial Y} \cdot \delta Y\right)^2 + \dots} \quad (4)$$

Therefore, substituting the X and Y in Eq. 4 with Eq. 2 and 3, the standard deviations of load position estimation in x and y axes, δx and δy can be calculated as shown in Eq. 5 and 6, respectively.

$$\delta x = \sqrt{\sin^2 \theta_l \cdot \sin^2 \theta_s \cdot L_b^2 \cdot \delta \cos \theta_l^2 + \cos^2 \theta_l \cdot \cos^2 \theta_s \cdot L_b^2 \cdot \delta \sin \theta_s^2 + \cos^2 \theta_l \cdot \sin^2 \theta_s \cdot \delta L_b^2 + \delta x_l^2} \quad (5)$$

$$\delta y = \sqrt{\sin^2 \theta_l \cdot \cos^2 \theta_s \cdot L_b^2 \cdot \delta \cos \theta_l^2 + \cos^2 \theta_l \cdot \sin^2 \theta_s \cdot L_b^2 \cdot \delta \sin \theta_s^2 + \cos^2 \theta_l \cdot \cos^2 \theta_s \cdot \delta L_b^2 + \delta x_l^2} \quad (6)$$

Thus, the error of load positioning in the X-Y plane can be obtained by Eq. 7.

$$\delta P(x, y) = \sqrt{\delta x^2 + \delta y^2} = \sqrt{\sin^2 \theta_l \cdot L_b^2 \cdot \delta \cos \theta_l^2 + \cos^2 \theta_l \cdot L_b^2 \cdot \delta \sin \theta_s^2 + \cos^2 \theta_l \cdot \delta L_b^2 + \delta x_l^2 + \delta y_l^2} \quad (7)$$

According to the sensor datasheet, the measurement error of boom lift and slew angle is ± 0.5 deg, and the measurement error of boom length is ± 0.1 m. Therefore, when boom lift angle $\theta \in (0, 75^\circ)$ and boom extension $L_b \in (11, 45m)$ (maximum range limits according to the tested crane specification), the load positioning error in X-Y plane was calculated based on Eq. 7.

Figure 7 shows the load positioning errors in X-Y plane as a result of the propagation of boom

angle and length measurement errors in different boom slew angles (i.e., 0, 45, 90 degree). It should be noted that the maximum error of load positioning occurs when the boom fully extends (45m), boom lifts up to the maximum angle (75 degree), and boom slews to 90 or 270 degree from the front. This result indicates that crane pose reconstruction is likely to be less accurate in such configuration, and conservative adjustments such as increasing the proximity thresholds in the hazard analysis should be undertaken.

Figure 7: Load positioning errors in X-Y plane due to propagation of boom angle and length measurement errors, when boom slew angle is 0, 45 and 90 degree, respectively.

On top of sensor measurement errors, data collection and synchronization might increase the error if they are not handled properly. 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 at a frequency of 50Hz. In addition, the processing unit and the program will detect and reject corrupted or incomplete packet. Given that all the encoders are connected to the processing unit by cables, delay in data collection and transmission is negligible. All these measures ensure the error related to data collection and synchronization is minimized.

4.3. Operator User Interface

In the prototype system, the tasks of hazard analysis and visualization were accomplished using an on-board tablet computer. The tablet is equipped with an Intel Core i7 1.7GHz processor, Intel 5000 integrated graphic card, 8 GB RAM and 512 GB storage. The tablet offered a bright 11 inch display so that the user interface is visible to the operator even under normal sunlight conditions (see Figure 8). The tablet was mounted on a fully adjustable monitor holder, which makes it very flexible to be configured to what the operator considers fit. A game engine Unity 3D [48] was used as the program for real-time data processing and 3D visualization. To minimize the distraction to the main lifting tasks, A commercial voice recognition program was integrated into Unity3D to enable voice control over the user interface.

Figure 8: Graphical user interface deployed in a mobile crane cabin

5. FIELD TESTS AND RESULTS

5.1. Overview

The performance of the prototype system was evaluated in a field test. The prototype system was installed on a 70-ton telescopic boom all-terrain crane manufactured by XCMG Construction Machinery. The objective of the test was to evaluate the performance of the prototype system in the criteria of reconstruction accuracy, latency and ease of use. The field test took place in a

crane parts storage yard congested with obstructions such as truck trailers, lattice boom segments and trees as shown in Figure 9(a). Crane parts such as lattice boom segments and truck trailers were introduced in the scene to simulate the condition in a congested construction site. Figure 9(b) shows the top view of the reconstructed test site with obstructions indicated by the semi-transparent boxes. The two dots indicate the load pick up and placement locations.

Figure 9: Actual test site and top view of the reconstructed test site (two dots indicate pick up and drop off locations)

The point cloud of the lift site was acquired from three laser scans around the site. The point cloud consists of 27 million points, from which 29 obstructions were automatically modeled and three obstructions were manually modeled. The entire process including laser scanning, obstruction recognition, and virtual lift site reconstruction took in total 35 minutes.

5.2. Results of Real-time Hazard Analysis and Visualization

The tablet served as a computation device for hazard analysis while displaying the reconstruction lift site to the operator. Although visualization delay was expected because of data transmission and computation, the test operators observed no noticeable delay during the test. The visualization results were validated by comparing the reconstructed crane boom and load motions to site camera recordings from two view angles: site overview and top view from the crane boom head. The site overview comparison demonstrates the accuracy in reconstructing crane boom motions (see Figure 10) and the top view from boom head comparison demonstrates the accuracy in reconstructing crane load sway motions (see Figure 11). In these figures, the solid cube indicates the lifted load and the circle indicates the target drop off location.

Figure 10: Comparison between actual lifting (upper) and reconstructed lifting process (lower) in site overview

Figure 11: Comparison between actual load sway motion (upper) and reconstructed load sway motion (lower) from the boom's top view.

5.3. Demonstration of Pro-active Safety Assistance

The comparison between the actual crane motion and the reconstruction motion reveals the system's capability in analyzing and visualizing potential hazards during the lift. During the first 10 seconds at the beginning of the lift, the system detected a risk of collision given that the proximity between the lifted load and the trees nearby is within a pre-defined threshold for safe clearance of 2 meters, as highlighted in frame 00s or 10s in Figure 10 and 11. Figure 12 shows the snapshot of the user interface at the moment the potential collision hazard was spotted. Once this hazard was detected, visual and audio warnings were immediately provided to the operator, and the objects involved the collision risk (i.e., lifted load and nearby trees) were automatically highlighted in the system user interface. This allowed the operator to pro-actively review and assess the lift condition in the side and top views, or alternatively move the virtual camera by voice commands to zoom in to the area of interest for a more effective judgement.

Figure 12: User interface of the pro-active safety assistance system

5.4. Reconstruction Error Analysis

Since it is very difficult to measure the error during the lift, the overall reconstruction error of the system was represented by the error of load positioning at the end of each lift. This assumption is reasonable as the final load position is greatly affected by the reconstruction accuracy of both the boom and load motion. Furthermore, it also reflects the overall error that may accumulate during the lift. As the load was always placed at the exact same drop off location, the load positioning error is the horizontal distance between the actual and planned drop off location. Figure 13 plots the load positioning errors in 92 consecutive lifts, and the maximum, minimum, median, first and third quartile of the errors are shown in the box plot to the right. The average error for reconstruction is 0.43 m and the maximum error for reconstruction is 0.93 m. Compared to theoretical error calculated based on the propagation of nominal sensor errors, the average value of the actual errors is slightly higher (0.43m vs. 0.38m) and the variances are bigger as well (0.49m vs. 0.21m). Differences between the actual and theoretical errors are mainly due to

variances in sensor setup or system calibration as well as possible measurement errors. The logarithmic trend line indicates a slight increasing tendency of the errors over the 92 lifts. It should be noted that no re-calibration was conducted during the test lifts. This indicates the system error did accumulate over time in extensive usage conditions, and thus re-calibration is necessary in actual field implementation in the long-term.

Figure 13: Errors of virtual lift reconstruction during 92 lift tasks in scenario 1 and 2

5.5. Operator Feedback

In addition to testing the technical performance, it is important to know how much the operators are receptive to the new system in terms of effectiveness of the assistance and user friendliness.

In this test, five crane operator subjects with an average experience of 18 years in crane operation were invited to test the prototype system and their feedback toward the current prototype system is listed in Table 2. Most of the operators expressed that the system was effective in reconstructing the lift scene and providing them hazard warnings. Based on this information, they were able to make timely decisions to mitigate the risk. Overall, the operators believed that using this system would make them feel more confident to execute the lift task

more efficiently and safely. In addition, three operators pointed out that this system is particularly useful in blind lift scenarios where the operator can review the constraints in the lift and make the right decisions instead of totally relying on the signalman.

Table 2: Feedback from subject tests on the performance of the prototype system

Feedback	Positive	Negative
Operator A (15-year exp.)	<ul style="list-style-type: none"> • I am already relying on this system • Reconstruction is fast and accurate 	<ul style="list-style-type: none"> • System setup take quite a while • Better have a shade for the screen
Operator B (13-year exp.)	<ul style="list-style-type: none"> • Very useful for night lifting tasks • I can totally trust this system 	<ul style="list-style-type: none"> • Top view is more useful, should be enlarged • Should display the motion data from LMI
Operator C (20-year exp.)	<ul style="list-style-type: none"> • Very useful for blind and night lifts • It makes me feel safer 	<ul style="list-style-type: none"> • Orientation should be shown more clearly
Operator D (21-year exp.)	<ul style="list-style-type: none"> • It can already replace the LMI system 	<ul style="list-style-type: none"> • It should show the distance between load and obstructions and drop-off location
Operator E (19-year exp.)	<ul style="list-style-type: none"> • Very useful for blind and night lifts 	

6. DISCUSSION

Accurate motion capturing and reconstruction are essential for enabling real-time hazard analysis and visualization. The error of load positioning mainly comes from three sources: sensor measurement error, error propagation in motion reconstruction, and accumulated system error due to sensor setup. Sensor measurement error can be reduced by using sensors that are more accurate and durable. Error propagation in motion reconstruction varies in different crane configurations (e.g., boom length and angle) and thus can be hard to reduce. The accumulated system error can be reduced by improving the way the sensors are deployed. For example, the length of the hoist line is measured by attaching a small wheel to the edge of the hoist line winch. Although the contact between the wheel and the winch is perfectly firm in the beginning, it

might become loose in the long term and thus increase the error in the length measurement of the hoist line. This problem can be solved by deploying a rotary encoder directly on the axle on the winch with an enclosure. Such improvement in system deployment will be addressed in the future study.

Another critical issue that can significantly compromise the effectiveness of real-time systems is the delay or latency in data processing and visualization. Crane lifting operations are so dynamic that an accident can develop in a couple of seconds. The tested prototype system showed no noticeable delay or latency based on the operator feedback and the comparison between the actual and reconstructed crane motion (see Figure 9 and 10). This is partially because the communication between sensors (except the IMU sensor) and the computer were via wired connection. In addition, delay in data processing or lagging in visualization can be expected if a less powerful tablet is used for data processing and visualization.

Ideally, the site condition is preferred to be updated in real-time to capture any tiny changes at any given moment. In reality, technology limitations make real-time 3-dimension geometry updating very challenging and expensive even if possible. At the same time, it is not always necessary to update the site condition in real-time. First, workers as the most dynamic assets on construction site, does not need to be tracked on the lift site considering that workers except the lift crew are not allowed to be in the lift zone. Secondly, although other mobile asset such as equipment and vehicles might be present in the lift workspace for material delivery, their location and movement are fairly predictable and relatively static during the lifting operation. As such, frequent updates for the site condition, as needed, is regarded sufficient to address the changes on the lift site. That said, the site condition should be automatically updated as a new change is introduced. Although this is beyond the scope of this paper, promising strategies for

real- or near real-time lift site condition updating are discussed as below. As stated before, laser scanning is the most efficient method for acquiring a large amount of 3D geometric data in a short period of time. Many state-of-the-art laser scanners can be remotely operated and wirelessly transfer the scan results to remote computers for processing. Therefore, such terrestrial laser scanners can continuously scan the lift site and update the condition changes with the obstruction recognition algorithm. As a future study, the authors are planning to use a mobile robot equipped with a laser scanner to add a mobility of scanner for a better scan view for the changes of the lift site.

7. CONCLUSIONS

Despite many safety considerations embedded in lift pre-planning, the ability to provide real-time safety assistance to crane operators during the lifting is missing in the state-of-the-art. This paper introduces a framework of a safety assistance system for crane lift operations. The framework consists of three components: real-time crane motion monitoring, pro-active hazard analysis and 3D visualization. Critical motions of crane manipulation and suspension modules are captured by a hybrid sensor structure, based on which entire crane motions are reconstructed in a visualization platform in real-time with as-is lift site conditions. The risk of colliding the boom and load to obstructions in the lift site is analyzed pro-actively and warnings are provided to operators when a potential hazard is detected. The framework was validated by a prototype deployed on a real crane and a field test was conducted to evaluate the system performance with respect to reconstruction accuracy, timing, hazard analysis and visualization effectiveness. Test results indicate that the prototype system was able to reconstruct crane motions with an average error of 0.43 m for load positioning in X-Y plane. It also proved that the system is effective in

providing pro-active hazard warnings that allows the operator to make timely decisions to mitigate the risk. The feedback from five experienced test subjects show a great potential of the pro-active safety assistance system in enhance the existing lift safety practices, especially in blind and night lifts. This paper broadens the focus of crane lift safety from pre-planning phase to the operation phase. The framework introduced in this paper successfully addresses various challenges in enabling real-time pro-active safety assistance in crane lifting operations. The error analysis approach is useful for not only crane monitoring systems, but also other construction heavy equipment.

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