CRANE OPERATOR VISIBILITY OF GROUND OPERATIONS

Tao Cheng and Jochen Teizer*

School of Civil and Environmental Engineering, Georgia Institute of Technology, Atlanta, USA
** Corresponding author (teizer@gatech.edu)*

ABSTRACT: Construction accidents that involve cranes often relate to struck-by incidents, when the crane or its load is in too close contact with personnel, objects, and/or other equipment. In these incidents, limited or poor visibility of resources in the surrounding work space is often the cause of the problem. The result is often the death, serious injury of worker(s), and/or significant collateral damage to property. This paper presents a framework to increase the situational awareness of tower crane operator(s). Research is presented that quantifies the spatial visibility of tower crane operators in a typical building construction project. A visibility measurement tool is presented that utilizes range point clouds from laser scanners to accurately measure the size and location of the operator's invisible spaces of a jobsite (blind spots). Results to a field trial demonstrate how important the proper selection of the location of equipment can be when safety is prioritized.

Keywords: *Blind spot, Crane, Laser Scanning, Point Cloud, Equipment Operator, Planning, Design, Safety, Site Layout, Visibility.*

1. INTRODUCTION

The dynamic and complex nature of building processes and multiple resources performing activities on the jobsite at the same time are often based on sophisticated work site layout and task planning. As tower crane operations require well-coordinated activities of related site processes and resources involving workers, equipments and materials, its operation is mostly a manual process [1]. This means crane operator's interpret a visual two-dimensional (2D) scene (since from their tower crane cabin they do not see ground operations in their spatial configuration) and require in most ground operation situations some feedback from the ground personnel through hand or radio signals.

Although recent application of semi-automatic navigation systems helps improving the operator's judgment and potentially enables real-time feedback [2], the operator's limited or poor visibility of ground operations poses severe risks to all resources present in the vicinity of a tower crane.

According to the classification system of the U.S. Bureau of Labor Statistics' Census of Fatal Occupational Injuries [3], the majority of construction deaths usually result from falls and transportation accidents (e.g., 38% and 24%, respectively, in 2007). The most common crane accidents are related to contacts with personnel, objects, and/or other equipment (e.g., struck-by swinging load, etc.). In 2006 alone, there were 72 crane-related fatal occupational injuries, of which 61% were contacts with objects or equipment, of which 30 were caused by falling objects (nine of these were due to collapsing crane or parts of cranes, and the remainder were due to loads attached to the crane). A total of 632 crane-related construction worker deaths occurred between 1992 and 2006. Of these, 21% were related to struck-by loads and other crane parts [3].

Many of the recommendations issued by industry, equipment manufacturers, or regulators indicate that crane safety could be improved when the workforce involved in mobilizing, demobilizing, and operating is properly trained. One factor that impacts the operational safety is to increase the operator's situational awareness. The basis for optimizing the visibility of crane operators is a proper site layout and equipment location. Although generating a safe construction plan is often a challenging and time consuming tasks, multiple variations typically exist to come up with efficient and productive construction methods for operations. Therefore, it is necessary to take spatial (available construction space) and working behavior (resource trajectory) aspects into account during safe construction site layout and task planning.

Crane operations are constrained by the construction space [4]. The construction spaces are divided into three categories: Resource space, topology space, and process space [5]. Resource spaces are required for workers, equipment, and materials which accomplish a construction work task. Topology spaces involve the building structure, the site layout, and the environment. Topology spaces are time-dependent, as they change dynamically during the construction progress. Process spaces are considered as the process-related spatial aspect such as working spaces, hazard spaces, and protected spaces.

The spatial constraints generated by construction spaces are always inter-dependent. An well-known example that poses safety risks is the operation of a tower crane over a working crew. Other spatial constraints are less known. For example the blind spots to the crane operators that are caused by objects that obstruct the operator's field-of-view (FOV). These can be derived from the geometric dimensions of the respective objects in the topology space.

This paper aims to automatically distinguish visible from invisible spaces to a tower crane operator. Range point cloud data from a laser scanner is utilized to automatically measure the crane operator's perspective, and furthermore detect the location and size of blind spaces that obstruct his/her FOV. The algorithm and its performance are illustrated using data from a typical multi-level building construction site. A discussion towards the end of the paper demonstrates the future work ahead in safety planning in construction while taking advantage of existing of emerging automated technology.

2. BACKGROUND

A tower crane is one of the most frequently used pieces of construction equipment, and in particular in the construction of high-rise buildings. Compared to the mobile crane, the tower crane operators seems to always have a wide FOV (panoramic view), which is particularly helpful in a variety of construction activities such as rigging, loading, and unloading [6]. A clear and non-obstructed FOV obviously also improves the crane efficiency and safety.

In order to improve the situational awareness of crane operators, video cameras have been installed to transmit vertical views of ground level operations. The signals are then send to a monitor in the crane cabin [7, 8]. Another technology focused on a 3D animation and visualization system that was developed to simulate crane hoisting processes during the work task planning stage or constructability review [9, 10]. Aside from these efforts, cranes today utilize load capacity and collision waning detectors in simulated or operational environment [11]. However, its effectiveness is not near the desired success rate, for example, the long-known problem of crane/overhead power line collision has not been solved reliable to today. Several additional studies [among them 12, 13] have conducted research in human factors and root cause analysis.

Approaches, including technology, yet have to be developed that allow rapid assessment and control of site safety conditions at the pre-task planning or operational level [14, 15, 16]. A true pro-active safety warning alert system for workers and equipment operators will then be in place, once effective and efficient communication of blind spots, visible and non-visible spaces to equipment operators and pedestrian workers, and warning and alert mechanism are integrated and work together.

3. RESEARCH OBJECTIVES AND SCOPE

The objectives of this research were to automatically visualize the blind spaces that surround a tower crane and to measure the limited FOV the operator has. The goal was to develop an automated blind space algorithm for tower crane operator visibility based on range point cloud data from a laser scanner.

4. METHODOLOGY

This research utilized a commercially-available laser scanner for as-built and topographic surveys of a building structure. A flowchart of the developed algorithm that detects objects that obstruct the FOV of the tower crane operator is presented in Figure 1. Details to the major phases are presented next.

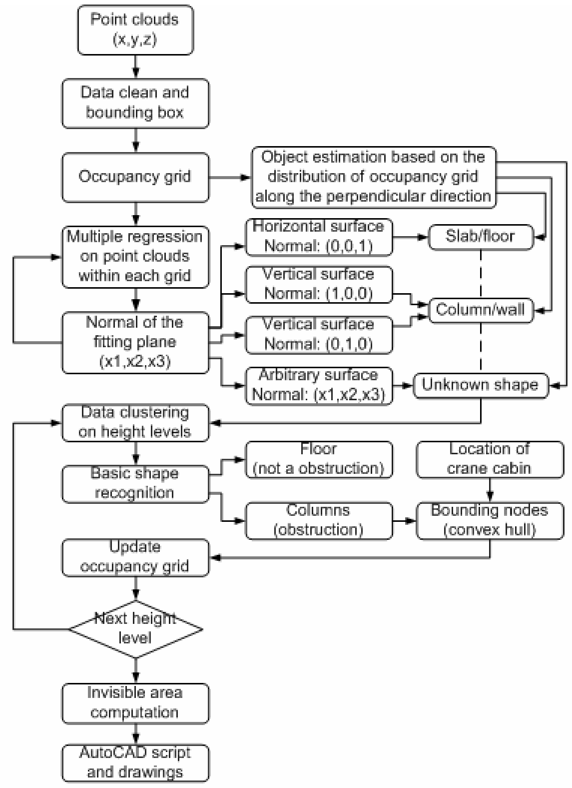

Fig. 1 Process to automatically detect FOV obstructions

4.1 OCCUPANCY GRID

The 3D as-built data collected by the laser scanner is cleaned and export as point file, while the spatial information is store in a 2D matrix as "x,y,z". The spatial information is then structured into 3D occupancy grids, which are established along the X, Y, and Z axis. Each grid is called a voxel (volume pixel) which has a user-defined size [15]. The size of the voxel determines the resolution of the blind spots map. Finer grids result in more accurate blind spot space maps but demands higher computational complexity.

Depending on the construction schedule, for example, the number of voxels that represent the top floor (a large open area that is generally visible to the crane operator to place materials or other assist other resources) would be significantly larger than those observed from columns, walls, and other temporary objects.

4.2 SURFACE DIRECTION

Since the spatial data collected by the laser scanner only represents surface detail (millions of unrelated points), generating complex solid models based on surface data is challenging. Furthermore, very detailed solid modeling is eventually not necessary in computing the blind spaces. A simplistic but computationally efficient geometric approach to locate entities, such as boxes for material carts or cylinders for round columns might be already good enough.

The selected approach calculates the basic geometric entities. The surface direction is computed using multiple-regression within each occupancy grid. Three types result: Horizontal surfaces when the vectors of the fitting plane are vertical (tolerating a ±5° error); vertical surfaces when the vectors of the fitting plane are horizontal (tolerating a ±5° error), and arbitrary surface when a random/unknown surface direction is observed.

The directional values to each occupancy grids are saved in a 3D matrix, which is called the surface direction matrix. It is utilized to distinguish the object types. For example, points observed on the floor level with a perpendicular surface normal vector are considered as the as-built data representing the floor; points observed above the floor level with horizontal surface normal vectors are considered as the spatial data for the columns and walls; points with arbitrary surface normal vectors indicate a complex or unknown object.

4.3 CLUSTERING

A clustering algorithm (Density-Based Spatial Clustering of Applications with Noise – DBSCAN) is implemented on the surface direction matrix. Pre-defined heights were selected to separate the constructed objects from each other.

4.4 CONVEX HULL

A convex hull is constructed to identify the boundary nodes on the clustered objects. The nodes form the smallest convex polyhedron that contains the set of points from one object. Nodes indicating the boundaries of objects are export to a script file, which is utilized further for visualizing the blind areas in a CAD environment.

When the convex nodes have been found on one clustered object, the surface direction matrix is updated.

Voxels that are inside the convex hull are then removed from the data set to reduce the computational burden. The process repeats until all clusters in the pre-defined elevation range have been visited, and repeats thereafter for all other elevation ranges.

4.5 BLIND AREA AND SPACE MAP

The generated script file contains the bounding nodes of all detected objects. Taking advantage of crane geometry and crane cabin location (simplified as one point) a ray tracing algorithm was applied to the nodes of each object. The blind areas were visualized as seen in a conceptual sketch in Figure 2.

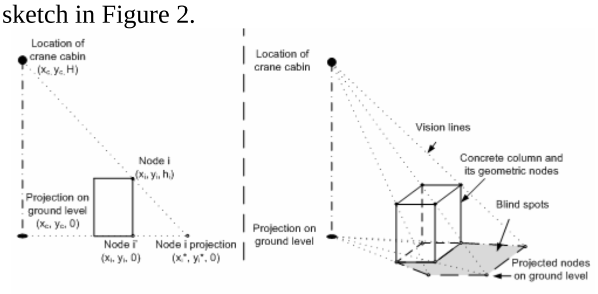

Fig. 2 Blind spot caused by a column

The area of the blind spots was then calculated using the following formulas:

$$x_i* = \frac{Hx_i - h_i x_c}{H - h_i}, \quad y_i* = \frac{Hy_i - h_i y_c}{H - h_i}$$

$$Blindspots\ area = \frac{1}{2}\sum_{i=0}^{n-1}(x_i y_{i+1} - x_{i+1} y_i)$$

5. EXPERIMENT AND RESULTS

5.1 DATA COLLECTION

This section details the results to an experiment conducted on a building construction site of the size of approximately 100 m in length and 40 m in width. A crane was positioned at one of the sides in the middle of the rectangle (see the generated range point cloud in plan view in Figure 3). The two dark circles in the center of the plan view indicate the location of the laser scan stations. Data from both scans were automatically registered (in the long run a laser scanner might be mounted at the crane cabin to automatically monitor and record the construction progress). The color of the point indicates the reflectivity of that spot. Dark areas with irregular shapes were the areas that were out of the line-of-sight of the laser scanner.

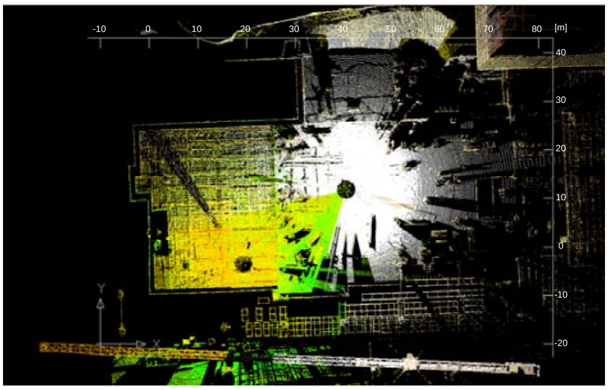

Fig. 3 Plan view of range point cloud

Points outside the work space of the crane were manually removed including the adjacent building, or any other environmental objects that have no relevance to this research method, such as bushes and temporary construction resources such as moving vehicles, workers, as well as the tower crane structure itself. The cleaned data set contained still about two million data points of the as-built scene.

5.2 OBSTRUCTION DETECTION

The occupancy grid was set that each voxel had the dimension of 0.2m x 0.2m x 0.2m. The size of voxels can be adjusted as needed. The voxel distribution (along the vertical axis) for the top floor of the building (closest and the only floor level visible to the crane operator) is illustrated in Figure 4. The zero meter height level indicates most of the voxels (floor level), with quite a number of voxels up to 1.5 m height (construction materials), and fewer but consistent number of voxels up to 6 m height (columns and walls).

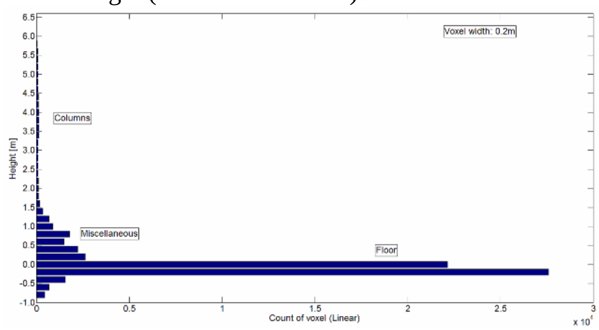

Fig. 4 Distribution of voxels along elevation

In order to improve the estimation of the objects, the direction of each voxel was computed. Within each voxel, a series of the as-built data points were fitted to a flat plane, whose normal vector represents the direction of the voxel. Figure 5 illustrates two voxels that have vertical and horizontal normal vectors respectively.

Voxels within the altitude range of -0.2m to 0.2m and oriented vertically were considered as the surface of the floor, while those within the altitude greater than 1.5m and oriented horizontally were regarded as surface of the walls and columns. The directions of voxels form a 3D matrix associated with the spatial information (Figure 6).

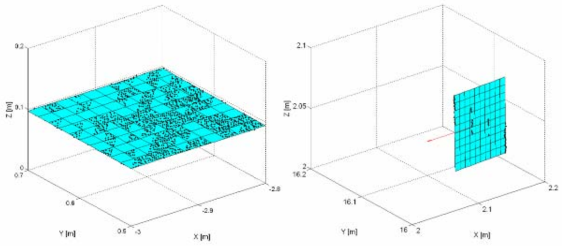

Fig. 5 Voxels with horizontal and vertical direction

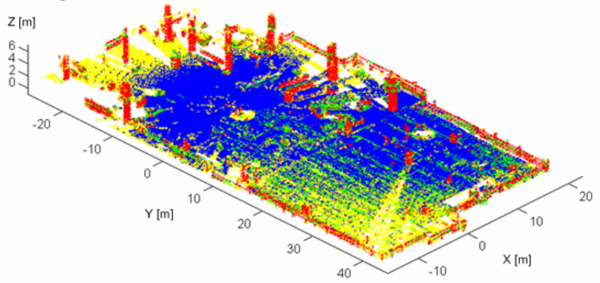

Fig. 6 Directional map of voxels (blue = horizontal, red = vertical, green = arbitrary, yellow = unidentified)

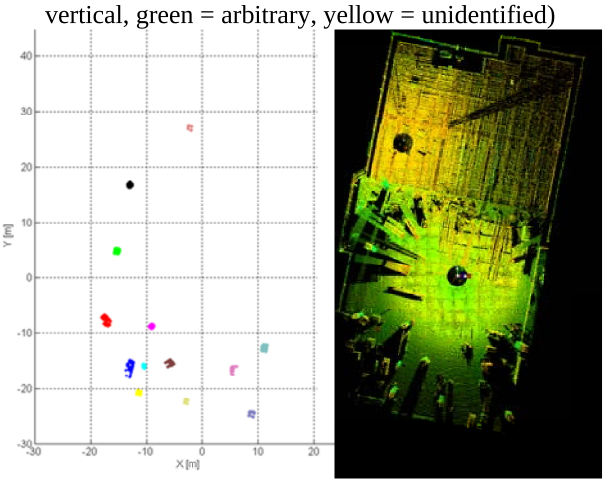

Fig. 7 Objects detected in greater than 1.5m height

Voxels were clustered based on a distance threshold (set to be 1 m) and needed to contain at least eight voxels. Group with less than the minimum number of voxels were treated as noise and removed. The clustering started in the highest altitude range (columns and wall level), and continued to the lower height levels (floor level). Figure 7 shows the result of objects that were detected at a height greater than 1.5m (from zero elevation or slab floor).

5.3 VISUALIZATION OF BLIND SPACES

Once the objects such as the columns were detected, their geometry was represented only by the nodes encompassing the boundary surface of the object. The invisible spaces to the crane operator are therefore determined through the projection principle (ray tracing algorithm). Each obstruction forms an invisible area that itself is projected in form of a polygon in the space and as a blind spot mapped on the floor. Since the position of the crane operator cabin is known, the blind spaces and blind spot areas as they relate to objects in the scene and on the floor, respectively, can be calculated.

Figure 8 shows the geometric representation of a column and its blind area as it is projected on the ground. The red marked area is invisible to the crane operator as well as any space between the blind area and the column. The column was automatically calculated as a 5.42 m tall obstruction. The blind area on the floor was 5.08 m long. The red solid area indicates the shade which was a polygon enclosed by the projections of the column's convex nodes. The column created a blind area (red) of 4.98m^2 in size.

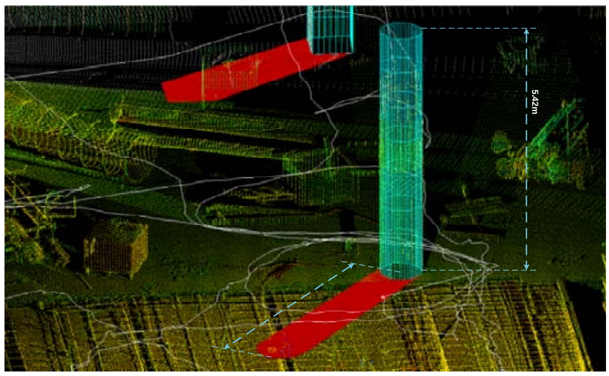

Fig. 8 Geometric representation of columns and shades

All obstruction present at the time of the measurement generated blind spaces/areas (including the walls, the columns, any temporary construction objects such as materials, and even the slab itself since it was already on the second floor). The total area of the blind spots caused by the constructed columns on the second floor was determined to be 56.2 m^2 large. The areas of blind spots caused by the slab edges (projected to the first level) were 514.5 m^2, respectively. Figure 9 is a visual interpretation of the generated results.

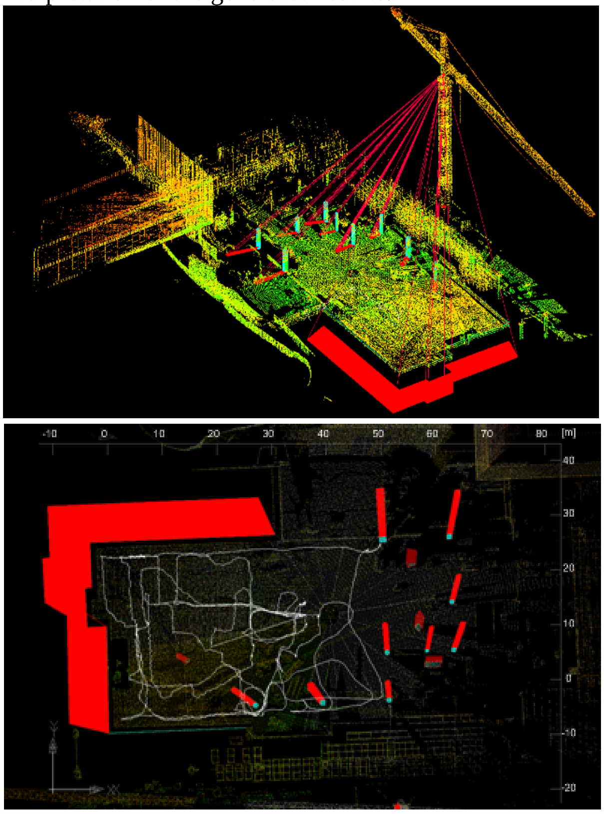

Fig. 12 Blind spots generated by objects taller than 1.5m

6. CONCLUSIONS

Advanced topographic survey technology (laser scanning) made it possible to quickly and accurately document as-built conditions. As such technologies become available they lead to novel solutions in identifying and resolving potential design and operational issues. This paper demonstrated the capability of automatically detecting objects in a large as-built spatial data set. The objective was to use the objects for locating and quantifying the blind spaces/areas and furthermore to alert equipment operators of obstructions which limit their field-of-view and eventually cause other hazards. Assuming that several potential mobilization locations for tower cranes exist on a jobsite (some might not be cost-effective since longer jibs would be necessary), optimization of crane efficiency can be achieved not only for productivity and cost factors, but also for safety. While it is possible the demonstrate the capability and the benefits of utilizing spatial information to improve tower crane operator visibility, further and more detailed study is necessary, in particular how well existing safety practices and design can be improved. This research is only a first step in multiple (safety) research efforts that are being addressed currently at the Real-time Automated Project Information and Decision Systems (RAPIDS) laboratory at the Georgia Institute of Technology.

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