Real-time Spatial Detection and Tracking of Resources in a Construction Environment

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REAL-TIME SPATIAL DETECTION AND TRACKING OF RESOURCES IN A CONSTRUCTION ENVIRONMENT

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ABSTRACT

Construction accidents with heavy equipment and bad decision making can be based on poor knowledge of the site environment and in both cases may lead to work interruptions and costly delays. Supporting the construction environment with real-time generated three-dimensional (3D) models can help preventing accidents as well as support management by modeling infrastructure assets in 3D. Such models can be integrated in the path planning of construction equipment operations for obstacle avoidance or in a 4D model that simulates construction processes. Detecting and guiding resources, such as personnel, machines and materials in and to the right place on time requires methods and technologies supplying information in real-time.

This paper presents research in real-time 3D laser scanning and modeling using high range frame update rate scanning technology. Existing and emerging sensors and techniques in three-dimensional modeling are explained. The presented research successfully developed computational models and algorithms for the real-time detection, tracking, and three-dimensional modeling of static and dynamic construction resources, such as workforce, machines, equipment, and materials based on a 3D video range camera. In particular, the proposed algorithm for rapidly modeling three-dimensional scenes is explained. Laboratory and outdoor field experiments that were conducted to validate the algorithm's performance and results are discussed.

KEY WORDS

Occupancy Grid Algorithm, Range Sensing, Real-Time 3D Modeling, Resource Detection and Tracking, Safety, Voxel

INTRODUCTION

Real-time three-dimensional modeling of construction environments is of fundamental as well as technological interest to the construction community. Fundamentally, three-dimensional

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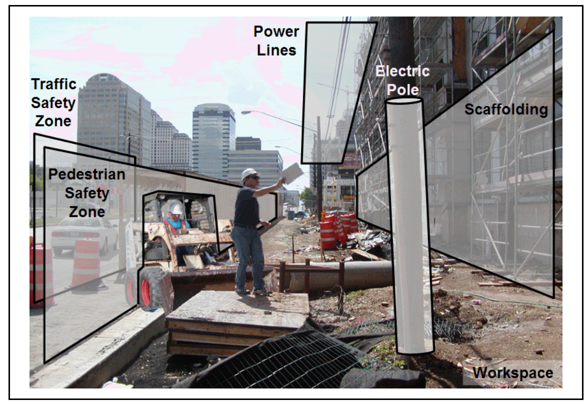
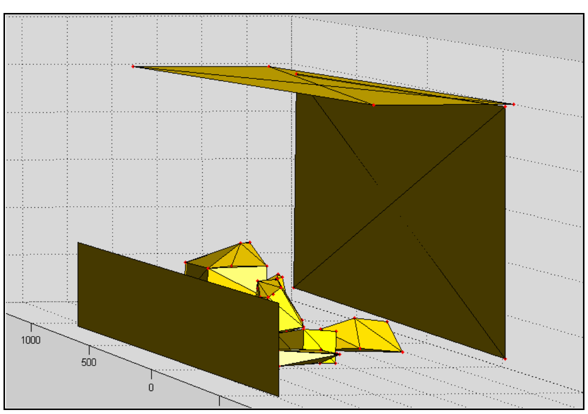
modeling enables the comparison between the planned and actual spatial status of complex systems in order to support better management decisions. Technologically, the development of ever smaller and cheaper electronic components for safer and faster operation of heavy equipment or for materials tracking requires the investigation of multi-disciplinary fields and principles from areas such as manufacturing, logistic, remote sensing, and transportation. Ultimately, such an approach can assist in solving some of the current problems in construction and make construction processes more effective and efficient by reducing accidents, cost, schedule, and waste (Goodrum and Haas, 2002).

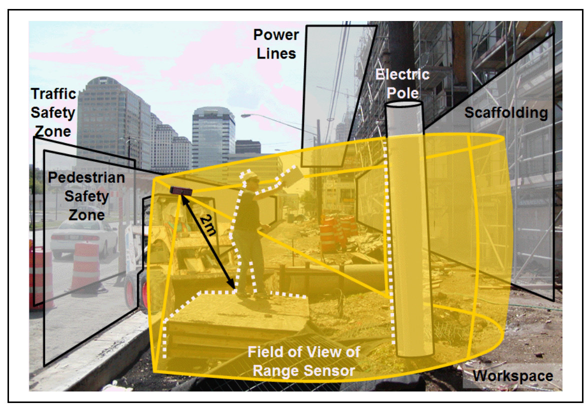
(a) Original scene of potential hazards



(b) Sparse point cloud modeling approach



(c) Sparse point cloud model of static objects



(d) 3D range camera modeling approach

Figure 1: Real-time 3D Modeling Approach for Obstacle Avoidance System

The approach of this research is explained in Figure 1. To make construction sites safer, faster, and at higher productivity levels, an obstacle avoidance system was designed to increase the limited perception of heavy equipment operators through real-time three-dimensional modeling. The obstacle avoidance system is based upon five steps: (1) Acquire range information of construction scenes using existing or emerging technologies (Figure 1a), (2) create 3D models of objects with permanent hazardous nature (Figure 1b and 1c), (3) detect and track 3D models of objects with a temporary hazardous nature ~~location element~~ (Figure 1d), (4) integrate 3D models in a so called World Model, that includes all scene relevant information of object location, dimension, velocity, and direction, and (5) run and operate an obstacle avoidance system based on range sensing in a simulated environment and on realistic construction job site equipment. Since research steps 1 and 2 were developed in previous research efforts, this paper discusses research step 3.

BACKGROUND REVIEW

Construction layouts usually host multiple sources of objects with hazardous potential, which in general are of permanent static nature (street with ongoing traffic, pedestrians in walkways, high voltage in power lines), of temporal static nature (erected scaffolding walls and structures, and at various locations placed and stored materials), or of moving nature (workforce, equipment and machines). All of which might have the potential to become dangerous in cross relationship to other objects (Figure 1a).

Reach-in and interference of machines, workers or construction related materials into vehicular and pedestrian traffic space can cause collateral damage as well as bodily injuries or fatalities. As a result, the typical construction environment needs boundaries to divide the "civil space" from the "construction workspace". The civil space is the area in where construction work is generally not permitted unless certain safety protection guidelines are followed. The civil space is usually separated from construction workspace by installing safety fences, protective barriers such as traffic cones, or covered pedestrian sidewalks. The original scene image in Figure 1 shows that the construction workspace itself is not protected but still offers a hazardous potential to resources such as workforce, materials, and equipment. Variously placed materials, moving workforce and objects such as power lines make it difficult for heavy equipment, such as a skid steer loader or crane, to navigate on a job sites safely.

An obstacle avoidance system which is based on the generation of rapid three-dimensional models must be able to detect, track, and characterize each object within the workspace. The idea of rapidly building three-dimensional barriers (Figure 1b) to areas where construction equipment faces elevated danger, e.g. street, walkway, power lines, scaffolding walls, or electric poles, allows granting i.e. machine access to work only in safe zones.

In this research approach objects can be modeled in 3D by using two different approaches. Permanently located objects that don't frequently change their position and shape ~~less frequent than once per week~~ are modeled after the Sparse Point Cloud approach (Song, 2004 and Kim, 2004). All other objects which very frequently change their location or geometric shape ~~more frequently~~ may need real-time ~~and greater than 1Hz~~ updates to accurately determine their position in the construction workspace. Integrating both approaches allows building an obstacle avoidance system.

Range Data Acquisition of Static Scenes

One step towards the generation of a more rapid three-dimensional modeling approach was successfully demonstrated using a Sparse Point Cloud approach. The basic modeling principle is described in Figure 1b. This approach focuses on single range point data acquisition, processing, and modeling.~~-~~

LAser Detection and Ranging (LADAR) sensing technology such as commercially available laser scanners capture millions of range points of static scenes (Leica, 2006). The range data acquisition process of laser scanners involves a manual sensor installation and allows the automated acquisition of range values to image pixels of entire scenes within several minutes. Many more hours or days are needed to process the range data to meaningful three-dimensional object information, which then can be included in 3D or 4D CAD models. A wider range of applications, e.g. comparison of as-built to planned information, becomes possible once a three-dimensional model exists (Teizer et al. 2005). Object dimension and location, however, cannot be ~~received~~ analyzed instantly due to the lack of real-time data acquisition and processing and new sensing and modeling methods are required for application where objects have a dynamic nature.

The manual selection of range points using the commercial Laser Range Finder technology characterizes elements of the geometry of an object, such as significant object corners to determine size and dimension. Sparse Point Cloud modeling allows a rapid semi-automated approach to create three-dimensional boundaries surrounding static objects on job sites leading to 3D models within a few minutes. However, this approach does not allow the 3D modeling of any kind of object that has a frequent change in location including moving objects such as workforce or equipment (Teizer et al., 2005).

Range Data Acquisition of Static and Moving Objects

Using emerging technology like 3D video range cameras mounted on heavy equipment, this research intends to create an obstacle avoidance system based on three-dimensional modeling of the ~~moving~~ environment in real-time.

This paper discusses experiments and results in detecting and tracking moving targets in the field of view of a 3D video range camera and demonstrates the general feasibility of applying this research approach to other areas, such as comparison of as-built to as-planned range data or in the integration to 3D or 4D CAD models.

All of these applications require overcoming the discussed difficulties of existing three-dimensional modeling approaches. The research objective was to find and address the three-dimensional geometric characteristics of static or moving objects within a larger field of view of a range camera.

The developed approach uses 3D video range camera, a.k.a. Flash LADAR that is based on a contactless distance measurements principle. In this research a SwissRanger 2 range sensor emits a continuous near-infrared light wave (880nm) in a scene at a modulation frequency of 20Mhz. Amplitude samples of the reflected wave help ~~to~~ determine the distance to each of the 160x124 pixels (resolution) after the phase-shift principle. Range image frames are collected at frame update rates of up to 30Hz in a field of view of horizontal 42° and vertical 45°. The range accuracy is less than 5cm at a non-ambiguous distance of 7.5m. One of the current limitations of the 3D video range sensing technology is the prototype stage of the hardware. More importantly, range image processing algorithms needed to be developed to accurately detect and track objects in the field of view of a range camera (CSEM, 2004).

THREE-DIMENSIONAL OCCUPANCY GRID ALGORITHM

Initial developments in processing the raw range data were based on existing image processing techniques, such as Canny edge detection and clustering techniques such as k-means. Results were successful, however, the duration to process a single range frames in a MatLab® environment was up to 4 minutes. Moreover, k-means clustering and other clustering techniques required a priori knowledge to supply and detect the correct number of objects contained in a scene. These downsides of knowledge based approaches did not allow further relying on these processing techniques and thus asked for a more robust range data processing algorithm.

Three-dimensional occupancy grids offered a potential solution. The working principle of an occupancy grid can be seen in Figure 2. In a first step the three-dimensional occupancy grids allocates the originally collected range matrix of range points into so called voxels (volume pixels). A voxel is defined by the grid size of the Local Model, also known as the field of view of the sensor. The developed algorithm used a variety of empirically found thresholds to filter noise measurements and to cluster the remaining range values.

With this 3D occupancy grid approach an object can be detected and tracked by collecting by the following information:

- Location (Position of the center of gravity of each cluster in 3D)
- Dimension (Size of object in all dimensions)
- Velocity (Speed of object)
- Direction (Orientation of velocity vector)

The knowledge of where objects are, knowing their accurate dimension, and in case of a potential moving object can help to plan the path of heavy equipment operation. Furthermore it allows detecting and tracking objects such as materials for tracking purposes.

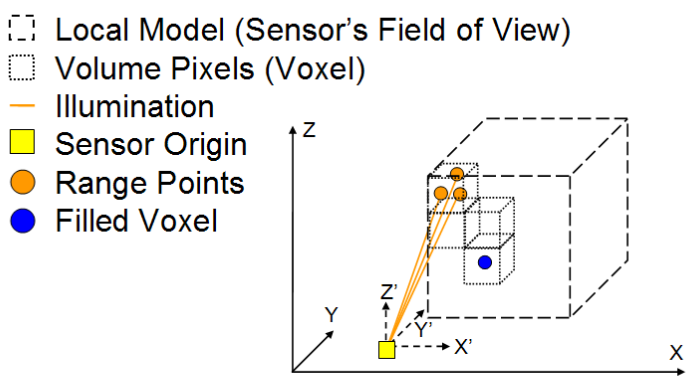


Figure 2: Three-dimensional occupancy grid

An occupancy grid with the grid size of 0.1m in all axes (X, Y, and Z) was used to analyze the raw data from experiments. The grid size was based on empiric values and allowed to capture small sized objects as well as reduced the overall number of range points for processing. The basic working mechanism of the algorithm is described next: Two range points in each voxel were needed to keep the voxel filled. If more than six neighbors were filled, the voxel was kept, otherwise deleted with no further computational burden. Segmentation into single clusters was based on grouping at least 10 voxels together and if the distance to the next group was less than 2 voxels, or respectively 20cm, the cluster was combined with its neighbor cluster ~~after~~ using ~~an~~ hierarchical agglomerative clustering (Elfes, 1989). The center of gravity was used to track moving objects. If a cluster volume from one frame to the next did not change more than 25% the cluster was supposed to be the same. If the difference in the location of the center of gravity of each cluster changed between one or two voxels the cluster was identified moving, otherwise identified as a static object or assumed to be a new object.

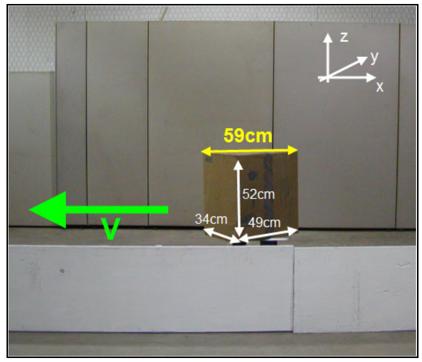
EXPERIMENTS AND RESULTS

The functionality of the developed occupancy grid algorithm was verified in experiments. Range data of static as well as moving objects placed in the field of view of the range camera was collected. The occupancy grid algorithm was used to create 3D models in real-time. The following example output of one experiment is demonstrated in Figure 3.

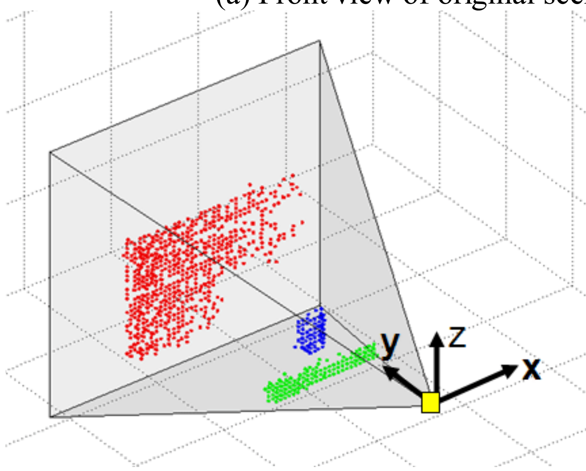
A target object, e.g. a box in Figure 3a, was propelled at various speeds and different angles on a rail through the field of view of the 3D video camera. In the front of the image a fascia board covered the cart which carried the target object. Since the sensor operated at a modulation frequency of 20 MHz, a background wall needed to limit the field of view to non-ambiguous distance measurements of maximal 7.5m. On top of the cart the target object, i.e. a cardboard box, was mounted. Dimensional values of the box were measured with a commercially available laser range finder. The target object varied from different sized boxes, round aluminum pipes, and a human representing a construction worker. Additional collected values characterized the experimental environment, e.g. temperature inside laboratory and humidity level, and were stored in an experimental log book.

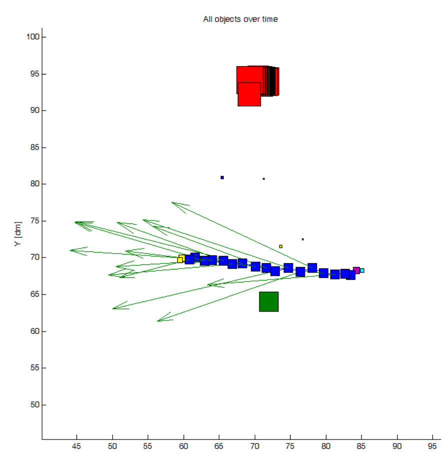
The target object was propelled through the field of view of the range sensor and range images at frame update rates of 15.2 Hz were recorded. The described occupancy grid algorithm converted the raw range data into an occupancy grid model. The result of the algorithm is displayed in Figures 3b to 3e.

In Figure 3b the three-dimensional view of the occupancy grid can be seen. The three objects within the field of view of the range camera were successfully detected. The fascia board, the box, and the background wall are separated in different clusters. To each cluster and each frame a center of gravity is generated. The center of gravity is calculated using the averages of voxel locations in each cluster. The number of voxels in each cluster~~s~~ determines the size of the square of the each center of gravity. In Figure 3c the consecutive plane view of all 52 range frames taken in this experiment are plotted. The trajectory of the box can be seen. The static fascia board received a single location for its center of gravity. The square, demonstrating the center of gravity of the fascia board is bigger than those ones generated from the occupancy grid algorithm for the box. Since the number of points in the "fascia board" cluster is larger then in the "box" cluster this particular displaying and tracking element of the occupancy grid algorithm was successful. The size of the "background wall" cluster is the biggest of all three detected objects. Its location in the plot in Figure 3c is varying slightly, since some parts of the background wall arecovered by the moving box.



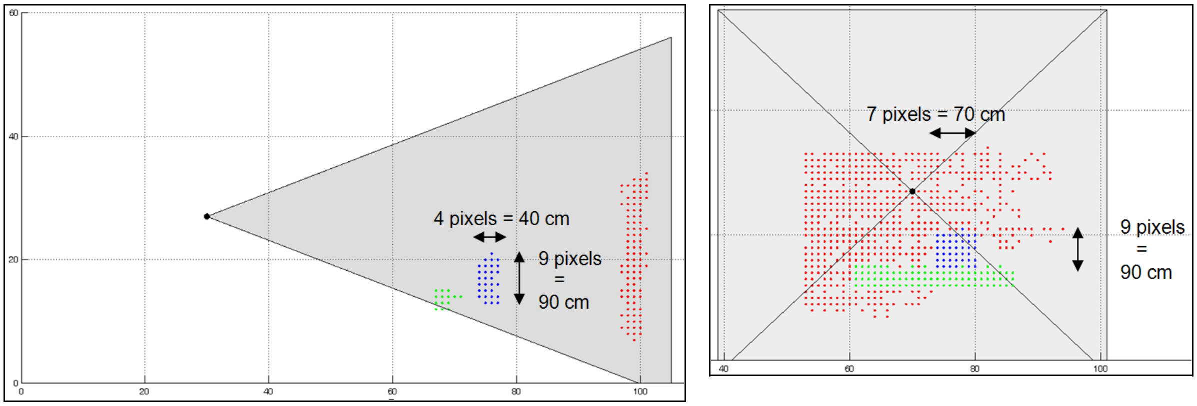
(a) Front view of original scene with propelled box





(b) 3D view of single range frame

(c) Plane view of 52 consecutive frames



(d) Elevation view of single range frame (e) Front view of single range frame

Figure 3: Occupancy grid model ofexperiment (show axes in 3d and e)

In Figure 3d and 3e the elevation view and front view of a single processed range frame is presented. The grey ~~triangle~~ pyramid demonstrates the field of view of the range camera. All voxels generated in the occupancy grid fall into the grey area. The developed algorithm automatically counts the dimensional values of each clusters as well as the number of voxels each cluster contains. Counting the voxels respectively to each cluster allows measuring the position and dimension of objects. Additional algorithm output is the direction and speed of moving objects in a scene.

In Figure 5 the results of the accuracy of the developed are presented. The position error of single points is maximal 8.9% compared to the original position the same points. The dimension of objects varies significantly in y-direction (depth). Since single range cameras capture the face (2½D instead 3D) of objects, this error was expected. Calibration on historical measured error values may allow predicting the correct depth value. Object are maximum 4.8 degrees of the original path. The speed of the measured object compared to the original velocity is maximal 5.4% higher than expected.

In summary, errors are observed mostly in the positive direction of the axes. This may conclude to have systematic errors. As a result, improving steps can be taken by calibrating the range camera, reducing the noise level of measurements, as well as ~~thorugh~~ improving the preliminary measurement environment, such as defining sub degree level of the orientation of the range camera and better hardware to define the exact position of the propelled object.

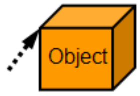
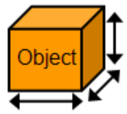
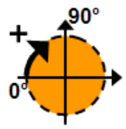
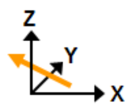
Modeling Accuracy		Axis	AVG Deviation
Position [m]		X	0.03 (+8.9%)
		Y	0.22 (+4.6%)
		Z	0.01 (+1.0%)
Dimension [m]		X	0.09 (+15.9%)
		Y	0.15 (+40.7%)
		Z	0.11 (+9.9%)
Direction [°]		X	0.3
		Y	1.7
		Z	4.8
Speed [m/s]		X	0.08 (+3.7%)
		Y	0.07 (+5.4%)
		Z	0.01 (+1.1%)

Figure 5: Experimental results at grid size 0.1m

CONCLUSIONS

Three-dimensional modeling of construction environments becomes increasingly necessary for good management. It becomes feasible through modeling approaches based on sparse and dense point cloud algorithms which use range data collection methods based on laser scanning and 3D video range cameras.

This paper demonstrated that the real-time detection and tracking of objects in the field of view of a 3D video range camera is possible. The research developed computational algorithms and experimental validation for real-time 3D modeling using emerging technology. A prototype three-dimensional video range camera~~, also called Flash LADAR (Laser Detection and Ranging),~~ was used to capture 3D surface geometry measurements. 3D dense point clouds at frame rates above 15 Hz of resources such as humans, equipment, materials, or structures were collected. This research accomplished two tasks: Distance and position validation to an accuracy level where the technology can be applied to construction applications such as the detection and tracking for safety in obstacle avoidance systems; development of real-time range data processing as well as data analyses algorithms; and verification of its working principle through extensive experimentation in modeling static and dynamic resources. This approach successfully demonstrated complete within the sensor's FOV, accurate, stable, and fast visualization and modeling of complex structures and sites.

ACKNOWLEDGMENTS

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More detail of errors (systematic and random), explain setup is not yet good enough, algorithm uses 0.1 grid, …