Rapid Human-Assisted Creation of Bounding Models for Obstacle Avoidance in Construction

by

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ABSTRACT: State-of-the-art construction equipment control technology creates the opportunity to implement automated and semi-automated object avoidance for improved safety and efficiency during operation; however, methods for constructing models of local objects or volumes in real-time are required. A practical, interactive method for doing so is described here. The method: (1) exploits a human operator's ability to quickly recognize significant objects or clusters of objects in a scene, (2) exploits the operator's ability to acquire sparse range point clouds of the objects quickly, and then (3) renders models, such as planes, boxes, and generalized convex hulls, to be displayed graphically as visual feedback during equipment operation and/or for making proximity calculations in an obstacle detection system. Experimental results indicate that bounding models can be created rapidly and with sufficient accuracy for obstacle avoidance with the aid of human intelligence and that human-assisted modeling can be beneficial for real-time construction equipment control.

KEYWORDS: construction automation, workspace modeling, bounding box, convex hull, obstacle avoidance, laser range finder

1. INTRODUCTION

Recent research indicates that several applications such as earth moving, heavy lifting, and material handling can benefit from the use of graphical models of equipment and workspace [1], [2], [3], [4]. Real-time interference checking for obstacle avoidance is also possible using local area graphical models. Laser range scanners are fast becoming popular tools for collection of three-dimensional range data for construction site modeling [5]. These methods can produce very detailed models of the scanned scene, which are useful for obtaining as-built drawings of existing structures, however the computational and data acquisition time burdens preclude the methods from being used on site for the real-time decision-making. Overall, modeling times for these laser range scanners are on the order of hours or days. The dynamics of a construction site require modeling times on the order of seconds or minutes.

The dynamic nature of the construction environment requires that a real-time local area modeling system be not only rapid but also capable of handling the changing and uncertain work environment. The approach taken in this research relies on a human's cognitive ability to recognize and classify objects in the workspace.

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Much research has been conducted on automatic object recognition for model generation, but these methods are neither robust nor efficient enough for real-time modeling in construction. The goal here is to balance human discernment and efficient range data acquisition with the proper exploitation of the computer in the areas of model generation, interference checking and avoidance control.

2. RAPID WORKSPACE MODELING

The following three sections describe three modeling methods that were developed and found to be useful for rapid workspace modeling for obstacle avoidance: 2.1) workspace partitioning, 2.2) convex hulls, and 2.3) tight-fitting bounding boxes. It should be emphasized that all of the above methods were developed for compliance in a local obstacle detection system. Since high numbers of objects in a workspace compounds the effects of slow distance computations, because pair-wise comparisons of all manipulator links to all objects must be made continuously, all the modeling methods described below take advantage of low numbers of range points for fast data acquisition and modeling as well as planar surfaces for quick proximity calculations.

2.1 Workspace Partitioning

The first and simplest model described is a finite plane (or infinitely thin wall) used for partitioning a workspace. Only three points in space are necessary to define a plane. However, a least-squares approach using more than three points is very useful to ensure that the plane is placed where the operator had intended it to be. The mathematics implemented are described in [6]. Floors, walls, and ceilings (i.e., rooms) can be quickly modeled this way by picking just a few points.

2.2 Convex Hulls

In three-dimensional space, the convex hull of a set of points is the smallest convex volume that contains the points. There are good reasons for using convex hulls for rapid obstacle avoidance modeling:

- Convex nature makes the hull inherently conservative
- Any number of points can be picked, anywhere
- The resulting hull consists of planar faces for fast distance computation

The algorithm used in this research is an incremental algorithm by Barber, Dobkin, and Huhdanpaa that successively adds a point to the convex hull that was generated by using the previously processed points [7]. The details of the algorithm are not discussed here for the sake of brevity.

2.3 Tight-Fitting Bounding Boxes

Much of the same benefits of convex hulls also hold for bounding boxes. Like generalized convex hulls, boxes are convex polyhedrons. Boxes are useful for acting as a simple outer shell that can hide a more detailed and precise model underneath. The primary reason for doing this, relative to obstacle avoidance, is so that at large distances, where manipulator movements are small compared to the overall distance from the manipulator base to the object, the manipulator's detection system is not forced to deal with a complex model. As the manipulator approaches the object, the object's details become more relevant, so the outer box is removed. This multi-layered modeling approach is useful in cluttered environments where high numbers of complex models would stifle an obstacle detection system. The algorithm developed to create the tight-fitting bounding box is described in [6].

3. EXPERIMENTS

Modeling experiments were conducted to determine the applicability of the modeling methods above. The actual mechanism used by the operator for the point collection and the interface issues therein were not the focus of this research. Rather, the human's ability to recognize the important features in a scene as well as the points needed to define models of prescribed geometry of those features was the focus. Twenty test subjects performed the modeling experiments. The experiments aimed to satisfy two sub-objectives as well. First, the relation between speed and accuracy was sought. While speed is obviously the driver, adequate accuracy is essential to obstacle avoidance and must not be abandoned for the sake of speed. Second, test subjects were asked to repeat certain tasks so that a learning curve could be observed.

3.1 Experimental Setup

Figure 2 is a picture of the mock scene that was set up in the construction automation laboratory for this and other modeling experiments. Referring to the figure, four models were used in the experiments described here:

1) A vertically constrained wall obtained by picking points on each of the three orange construction cones in the rear of the scene
2) Three convex hull/tight-fitting bounding box combination models of the wood box, pipe rack, and junk pile

The three construction cones were placed somewhat linearly so that the resulting vertical wall, as seen in the graphic display window by the test subjects, would unambiguously coincide with the cones. The width of the wall was arbitrarily forced to equal the distance between the two furthest cones and the height was arbitrarily set to six feet to be definitive. The wood box, pipe rack, and junk pile were each used for the convex hull and bounding box modeling. These three objects were chosen for their variations in geometry, complexity, size and the number of points required to define the convex hull. The junk pile was just a random assortment of pipes, boards, and a pick ax.

Data acquisition was accomplished using a laser range finder mounted on a two degree-of-freedom pan and tilt unit (PTU). The laser was directed via a trackball controller and the graphical models were displayed on the computer screen using the Matlab™ GUI (Figure 3). For details on the retrieval of the laser distances and pan and tilt angles as well as the forward kinematics of the system see [6].

3.2 Experimental Method

Prior to performing any of the modeling, each test subject was given some motivation by explaining the nature of the research project and rapid world modeling in general. They were asked to imagine themselves with the task of the equipment operator who needs to quickly create a graphic model of the workspace scene by picking various points on the objects using the PTU-mounted laser range finder. The operator as visual feedback would then use this graphic model during the manipulation task as well as by the obstacle detection system. Next, the test subject was introduced to the data acquisition system (Figure 3). Once the subject felt comfortable with the system, modeling began. Each model was displayed graphically using the Matlab™ GUI immediately after it was modeled so that the experimenter could see the results and the effects of the decisions that were made. The graphic workspace model was updated with each new model so that by the end of the last object model, the experimenter had a complete local graphical workspace model of the scene.

The time was recorded for each modeling exercise and commenced on the registration of the first distance measurement of the laser and ended on the registration of the last distance measurement. Qualitative observations were made and recorded as each test subject used the system. A means of quantifying the accuracy or conservativeness with which a test subject could model an object or objects by picking points to create a convex hull was also necessary. This was accomplished by developing a ray-tracing algorithm. This algorithm essentially compares the smallest convex volume that could encompass an object with the convex hull created by the test subject. It is detailed in [6].

3.3 Scoring Function

In addition to the ray-tracing algorithm, which enabled quantification of the convex hull modeling accuracy, a means of quantifying the overall convex hull modeling performance of each of the test subjects was necessary. Four related criteria emerged as the most significant in determining the effectiveness of a convex hull modeler:

1) Accuracy - as discussed above
2) Time - total elapsed time acquiring points per object
3) Efficiency - the number of convex hull points versus the total number of range points per object

4) Number of Missed Points - the number of missed points as detected by the ray-tracing algorithm

A scoring function was formulated that combines these factors and is detailed in [6].

3.4 Experiment Results

Referring to the picture of the workspace scene in Figure 2, Figure 4 is an example of the completely modeled scene done by one of the test subjects of the first group. Notice that each of the objects has been modeled with the appropriate method (wall - planar fit, wood box/pipe rack/junk pile - convex hull/bounding box). Modeling the pipe as a cylinder is described in [2], [6] and is not discussed here due to length restrictions.

The learning curve was not monotonic for about half of the subjects. In fact, it was observed in most of these cases that as the subject's understanding of the convex hull modeling approach grew stronger and enthusiasm for performing the experiment diminished, the test subject would attempt to model the object with a minimum number of points. This led to some missed points and lower accuracies, which despite an improved time, resulted in a lower score. This is apparent in Table 1, which shows the averages for each of the four metrics and the resulting score for both attempts of the second group. Notice that the average number of missed points for the second attempt at modeling the junk pile was actually higher than the first attempt, despite an overall improvement in score. The improvement in score was most dramatic for the pipe rack, which makes sense since it was modeled first in the sequence.

The most significant result, as shown in Table 1, is the average deviations of the experimenter's convex hulls from the control hulls. These average deviations were roughly an inch after two attempts for both the pipe rack and junk pile. Moreover, the median deviations were even smaller than the averages (0.92" for the pipe rack and 0.80" for the junk pile). Deviations this small are quite negligible with respect to large construction manipulators where the closest allowable distance from the manipulator to an obstacle would be larger.

4. OBSTACLE AVOIDANCE SIMULATION

An obstacle avoidance simulation was performed to demonstrate the applicability of the modeling methods to obstacle detection for the purposes of equipment operator feedback and control. Since construction equipment tends to be large and massive, inertia is an extremely important factor to be monitored for safe navigation. Thus, the simulation was designed to monitor manipulator link velocities as well as positions. The simulation consisted of a three-dimensional, three degree-of-freedom robot traversing over a box. Initial and final joint angles and a total elapsed time were specified. The joint paths were then forced to follow smooth fifth-order curves. The Gilbert, Johnson, and Keerthi algorithm for computing the minimum distance between convex polyhedra in three-dimensional space was used as a fast method of proximity calculation [8]. The velocity was accounted for by running a forward dynamic sub-simulation at each control time step (100 Hz) to see where the manipulator would stop given its current joint angles and velocities as initial conditions. The actual positions as well as the projected positions from the sub-simulation were put into an artificial potential function as feedback output [6]. The simulation indicated that obstacle avoidance for a construction manipulator instrumented with feedback control would be feasible in real-time given the relatively simple models described in this paper.

5. CONCLUSIONS

Three modeling methods were found to be useful for construction site modeling: workspace partitioning, convex hulls, and bounding boxes. The low deviation values (about one inch), and the low modeling times (about 2-3 minutes) in Table 1 indicate that a human-guided laser range finder can model construction site objects significantly faster than current methods and with sufficient accuracy. In contrast to an autonomous scanner, the human can quickly recognize the important features of the scene and then direct the laser accordingly, decreasing data acquisition time and, consequently, computational time due to the lower number of points.

6. REFERENCES

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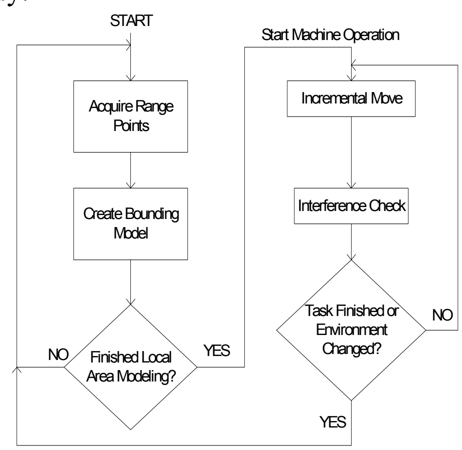

Figure 1. Overall Construction Equipment Operation Modeling Process

Figure 2. The Scene for Experimental Modeling

Figure 3. Laser, PTU, Trackball Control, and Data Acquisition Software Interface

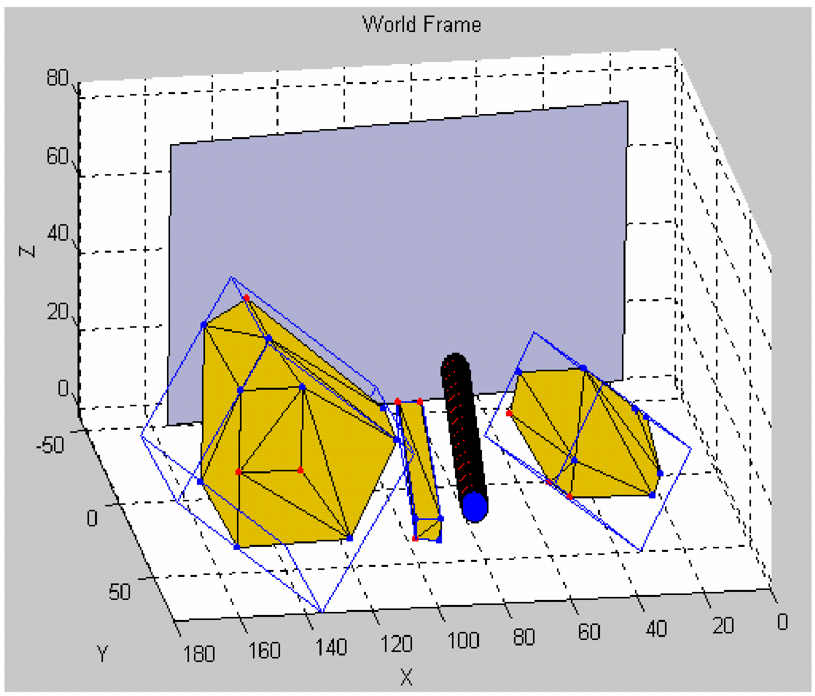

Figure 4. Graphic Model of Workspace Scene (dimensions are inches)

Table 1. Average Values for the First and Second Attempt at Modeling the Pipe Rack and Junk Pile

	Pipe Rack		Junk Pile	
Averages	**1st**	**2nd**	**1st**	**2nd**
Deviation (in)	2.42	1.16	1.12	0.97
Time (min)	5:51	2:33	3:30	2:17
# Range Points	26.3	14.6	16.6	13.1
# Hull Points	16.0	11.9	13.3	11.6
H/R Ratio	0.68	0.86	0.86	0.90
# Misses	1.0	0.1	0.4	0.7
Score	**39**	**76**	**72**	**76**