

# Safety Standard Advancement Toward Mobile Robot Use Near Humans

R.V. Bostelman, T.H. Hong, R. Madhavan, T. Y. Chang

**Abstract**— As mobile robots have increasingly improved onboard intelligence, they are being used in more flexible manufacturing, warehouse and/or military environments where humans may intervene and interact with these robots frequently causing increased hazards. The US ASME B56.5 - 2004 Safety Standard for industrial trucks was recently changed and now more closely meets the existing British EN 1525 - 1998 Safety Standard for driverless industrial trucks by allowing the use of non-contact safety sensors. Standard-size, material-covered objects, resembling human limb (arm and leg) lengths and diameters positioned in vertical and horizontal orientations, respectively and located within the vehicle path, must be detected and allow the vehicle to react before the vehicle frame contacts these objects. The National Institute of Standards and Technology (NIST) supports the automated guided vehicle industry to not only promote advancement of the ASME standard to use non-contact safety sensors but, to also provide performance evaluation of new 3D real-time range sensor technology toward implementing and further advancing these standards. This paper will provide details of: the US and British safety standards, a new 3D range camera, sensor experiments with ground truth comparison, and obstacle detection and segmentation algorithms and results, and provide further safety standard advancement recommendations to protect humans as they work near mobile robots.

**Index Terms**—ASME B56.5 safety standard, British EN1525 safety standard, 3D range camera, human-robot interaction, obstacle segmentation, intelligent vehicles.

## I. INTRODUCTION

IN Isaac Asimov's 1942 [23] short story called, "Runaround," he stated three laws that robots must obey.

The first of the three laws states that "a robot may not harm a human being ..." Although this was a science fiction story, it has relevance to the real world of robotics and automation today.

Robots can now be found in even the consumer market with uses in entertainment, home health care, vacuum cleaning, and lawn mowing. Robotic assistants already act as guards, help fight fires, deliver materials on construction sites and in mines, and distribute goods or help consumers in retail stores. Robots might even provide high-interaction services such as taking blood and coloring hair [15].

Robots are ever more likely to be fully mobile, bringing them into physical proximity with other robots, people, and objects. Mobile robots will have to negotiate their interactions in a dynamic and sometimes physically challenging environment.

Toward military applications, Project Alpha, a U.S. Joint Forces Command rapid idea analysis group, is in the midst of a study focusing on the concept of developing and employing robots that would be capable of replacing humans to perform many, if not most combat functions on the battlefield [21].

In the service industry, for example health care, robots are still delivering pharmaceuticals to patients rooms using the Helpmate [4] robot developed in the early 1990's by Transitions Research Corporation (now Pyxis Corporation) with funding from the National Institute of Standards and Technology (NIST). This was the first service robot to be widely deployed in American hospitals. NIST researchers were able to advance the original sonar guidance technology on the HelpMate with a LADAR (laser detection and ranging)-based navigation system. The NIST project review suggested that a HelpMate robot made its deliveries faster and more reliably than its human counterparts and produced cost savings (above the rental costs of the robot) of between \$5,000 and \$10,000 per year per robot in the 1990's. Approximately one hundred HelpMates were in use in American hospitals by the end of the decade in clinical laboratories, pharmacies, medical records departments, and central supply rooms.

For manufacturing, Automated Guided Vehicles (AGVs) are the vehicles of choice and are equipped with automatic guidance systems and are capable of following prescribed paths. In automated factories and facilities AGV's move pallets and containers. In offices they may be used to deliver and pick up the mail. They are even used to transport patrons around in airports.

The main benefit of AGVs is that they reduce labor costs. But in material handling facilities there is another benefit. Material handling has always been dangerous. Injuries occur due to a driver's lack of attention, drivers driving too fast, or other personnel not paying attention. Obstacle detection is therefore a key to allowing AGV's to interact with personnel safely while optimizing vehicle speeds [17]. Emergency controls are then required which would stop the vehicle if an object is detected in the direction of travel.

Although workers are trained to mark AGV travel paths clearly, to watch out for AGV's keeping clear when vehicles approach, equipping AGV's with virtual bumpers such as LADAR systems can be beneficial. LADAR systems must be

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R.V. Bostelman, T.H. Hong, R. Madhavan, T. Chang are with the National Institute of Standards and Technology, Gaithersburg, MD 20899 USA (phone: 301-975-3426; fax: 301-921-6165; e-mail: roger.bostelman@nist.gov).

able to detect 3D objects such as humans and the controller must understand what they are to be safe.

Our proposed approach to obstacle detection uses a low cost, real time, Centre Suisse d'Electronique et de Microtechnique (CSEM) range camera called the SwissRanger 2<sup>1</sup> (SR2). The 3D range camera is based on the Time-Of-Flight (TOF) principle [13] and is capable of simultaneously producing intensity images and range information of targets in indoor environments. This range camera is extremely appealing for obstacle detection in industrial applications as, when it becomes commercially available, it will be relatively inexpensive as compared to similar sensors. It can deliver range and intensity images at a rate of 30 Hz with an active range of 7.5 m and has no moving parts, such as a spinning mirror as in many off-the-shelf laser sensors.

Since obstacle detection plays a critical role in autonomous driving, there has been much research on many different types of sensors, such as sonar [22], color/gray level cameras [5], FLIR (Forward Looking InfraRed) cameras [20], and stereo cameras [19], [3], [24], [11]. Most of the vision approaches are not applicable to indoor scenes due to lack of texture in the environment. Other researchers have proposed LADAR (Laser Detection And Ranging) sensors for detecting obstacles [9], [7], [10]. However, one dimensional LADAR, which has been used in the AGV industry, is not suitable for the 3D world of factory environments and other complex volumes without moving the sensor during operation.

NIST recently developed an obstacle detection and segmentation algorithm using the CSEM 3D range camera. Our approach has been tested successfully on approximate British safety standard recommended object sizes covered in cotton material placed in the vehicle path. For this paper, the AGV remained stationary as the measurements were collected.

The U.S. American Society of Mechanical Engineers (ASME) B56.5-2004 standard [2] was recently changed to allow non-contact safety sensors as opposed to contact sensors such as bumpers to be used on AGVs. Prior to the change, the B56.5 standard defined an AGV bumper as a “mechanically actuated device, which when depressed, causes the vehicle to stop.” With the current B56.5 standard change and with state-of-the-art non-contact safety sensors, vehicles can be shorter in length, excluding mechanical bumpers, allowing shorter turning radii and the potential to move faster as objects can be detected well before the vehicle reaches them.

Ideally, the U.S. standard can be changed to make it even more similar to the British EN1525 safety standard requirements [6]. Furthering the US safety standard will also provide support toward a unified, global safety standard for AGV's and other driverless vehicles.

The paper is structured as follows: Section II describes the concept of obstacle detection and segmentation including the 3D range camera, algorithm, and a modulation issue using range camera images. Section III explains the results when employing the detection and segmentation algorithm on standard size objects. Section IV provides an explanation of

the indoor autonomous vehicle testbed and the experimental setup and algorithm results. Section V briefly discusses simultaneous localization and mapping and how AGV's will benefit from it. Section VI explains the probability obstacle map. Section VII provides a summary and conclusion followed by acknowledgments and a reference list.

## II. OBSTACLE DETECTION AND SEGMENTATION

### A. 3D Range Camera

In this section, we describe an algorithm to detect and segment obstacles in the path of the AGV using a solid-state Time-Of-Flight (TOF) range camera. The 3D range camera shown in Figure 1 is a compact, robust and cost effective solid state device capable of producing 3D images in real-time.



**Figure 1** - The TOF 3D range image camera. The camera simultaneously generates intensity images and range information of targets in its field-of-view at a rate of 30 Hz with an active range of 7.5 m [25].



(a)



(b)

**Figure 2** - Experimental setup (a) vertical test apparatus where the center object most closely matches the British standard size test piece measuring 65 mm dia. x 400 mm long. The remaining vertical objects are all thinner. (b) horizontal test apparatus (mannequin leg) measuring a segment approximately tapered from 80 to 160 mm dia. x 600 mm long including the leg ankle to the thigh. Both (a) and (b) objects are covered in cloth as also specified in the standard.

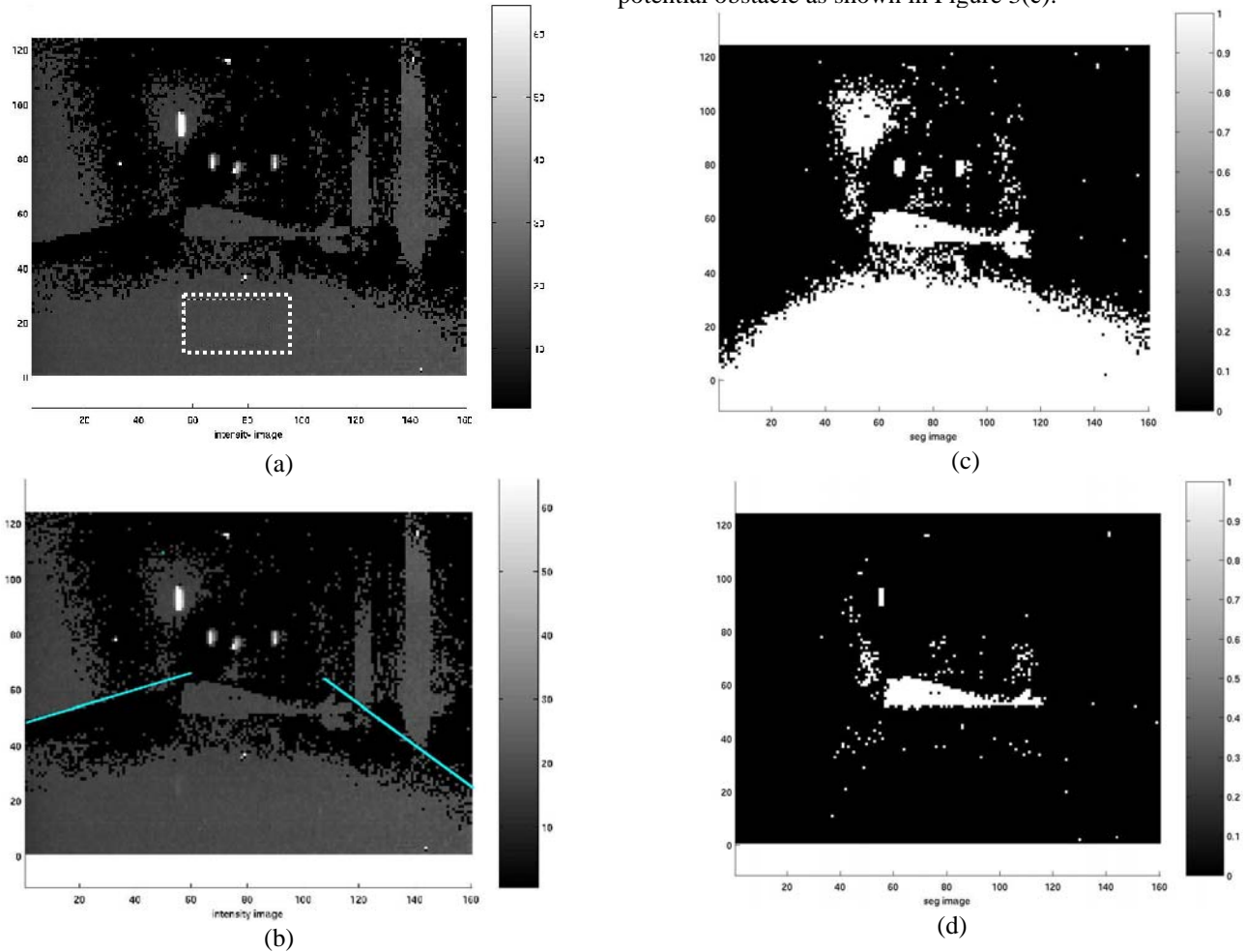
<sup>1</sup> NIST does not endorse companies, organizations or their products. Commercial equipment used is for research purposes only.

The camera measures 14.5 x 4 x 3 cm (5.7 x 1.6 x 1.2 in), has a field-of-view of 42° (horizontal) x 46° (vertical), and is capable of producing range images of 160 x 124 pixels over a 7.5 m range. For a brief overview of the characteristics and operating principles of the camera, see [18]. Approximately sized British standard test obstacles, shown in Figure 2, were placed in the travel path.

The British EN1525 safety standard specifies that horizontal test pieces used to test sensors shall be 200 mm diameter x 600 mm long lying perpendicular to the vehicle path and vertical test pieces shall be 70 mm diameter and 400 mm tall completely within the vehicle path.

### B. Algorithm Details

Generally, the obstacle detection and segmentation algorithm combines intensity and range images from the range camera to detect and estimate the distance to the obstacles. We first calibrate the camera with respect to the AGV so that we can convert the range values to 3D point clouds in the AGV coordinate frame.



The algorithm utilizes the intensity and 3D structure of range data from the camera and does not rely on the texture of the environment. The segmented (mapped) obstacles are verified using absolute measurements obtained using a relatively accurate (0.25 degrees angular and 10 mm range resolutions) 2D scanning laser rangefinder (shown in Figure 4).

Specifically, the steps of the algorithm are illustrated for a sample image from the camera:

- 1) A patch of data with high intensity values (i.e., the intensity value is greater than 20 of 60) in front of the robot is used to fit a plane for estimating the floor surface as shown in Figure 3(a).
- 2) The left and right edges of 3D robot paths are projected to the range and intensity images such that only obstacles on the path can be considered as shown in Figure 3(b).
- 3) All the intensity pixels between the left and right edges are used to hypothesize the potential obstacle. If the intensity value of the pixel is greater than half of the average of the intensity in the image then the pixel is considered as a potential obstacle as shown in Figure 3(c).

Next, we segment the objects which have high intensity and whose elevation values are above the floor of the operating environment on the AGV path. The segmented 3D points of the obstacles are then projected and accumulated into the floor surface-plane.

**Figure 3 - Obstacle segmentation algorithm illustration.**

- 4) Each potential obstacle pixel in the range image is used to find the distance to the floor plane when the distance to the

floor is greater than some threshold as shown in Figure 3(d). The threshold is dependent on the traversability of the robot.

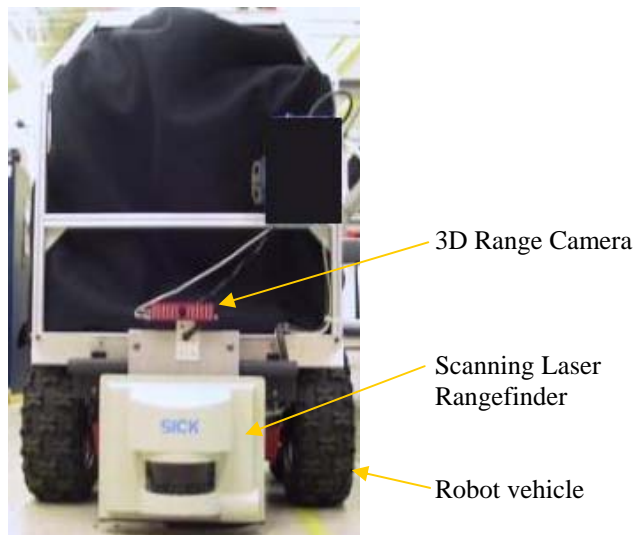
Potential obstacles in the world model can be accumulated as the AGV drives and placed in an obstacle map representation that is part of the world model. Nearly all the obstacles are found, although at the cost of false positives from the reflected objects. To increase the accuracy of obstacle detection, the obstacles in the map and information obtained from an added color camera may be temporally integrated. Such integration has proven to be a very useful cue for obstacle detection [14].

### III. EXPERIMENTAL SETUP AND RESULTS

The experiments were conducted under two scenarios as stated within the (now American and) British Standards:

- A test apparatus with a diameter of 200 mm and a length of 600 mm placed at right angles on the path of the AGV. The actuating force on this test apparatus shall not exceed 750 N.
- A test apparatus with a diameter of 70 mm and a height of 400 mm set vertically within the path of the AGV. The actuating force on this test apparatus shall not exceed 250 N.

Figures 2(a) and (b) show the experimental setup for the two aforementioned scenarios. The camera lens was centered approximately horizontally and vertically on the apparatus for all measurements. The scanning laser rangefinder was offset from the camera by 0 mm vertically, 250 mm horizontally, and to the left of the camera as viewed from the camera to the test apparatus. The range camera was used to detect a known test apparatus mounted on a stand and moved to different locations with respect to the camera.



**Figure 4** - Experimental setup of the AGV, the scanning laser rangefinder, and the range camera.

The obstacle detection and segmentation algorithm was tested on two British standard test objects as described in [2],

and was evaluated against ground truth and placed at 0.5 m to 7.5 m distances to the sensor.

A single-line scanning laser rangefinder, shown in Figure 4, mounted below the range camera, was used to simultaneously verify the distance to the test apparatus for each data set and served as ground truth. The rangefinder produces 401 data points over a  $100^\circ$  semi-circular region in front of the robot.

Table 1 shows the performance of the range camera for detecting the distance to the test apparatus placed at several distances from the range camera out to about 3 m. As can be seen, the accuracy (mean) of the range decreases as the distance of the apparatus placed in front of the range camera is increased. Ranges between approximately 3 m and 7.5 m maximum as specified by the camera manufacturer were left off intentionally as the results require further investigation into the best camera settings to provide clear data.

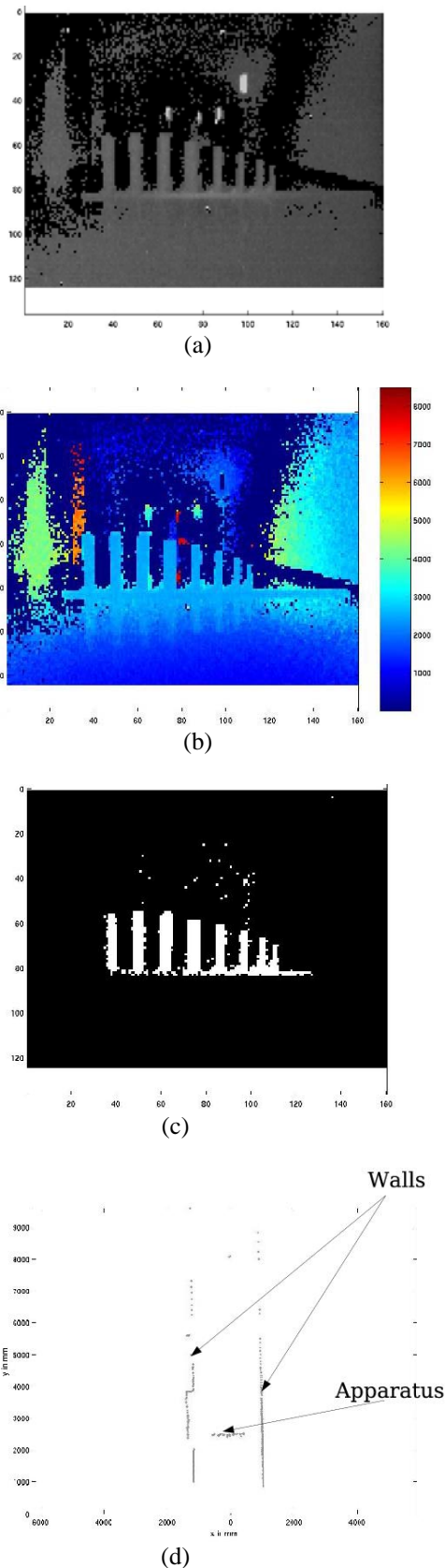
**Table 1** Quantitative Comparison of Performance

<i>Nominal Obstacle Distance (cm)</i>	<i>3D Range Camera Mean (cm)</i>	<i>2D Rangefinder Mean (cm)</i>
64	64.1	64.7
111	111.0	111.3
160	161.4	160.7
210	204.0	210.0
259	249.5	259.1
310	284.7	310.2

In Figure 5, the test apparatus was placed at a distance of 2.5 m from the range camera. Each object in the test apparatus was clearly detected even though the range camera was also sensitive to the reflectors on the wall of the hallway.

The resultant intensity, range, and segmented images are shown in Figures 5(a), (b) and (c), respectively. The ground truth provided by the scanning laser rangefinder is shown in Figure 5(d) and has been rotated to show a top-down view.

Similar to Figure 3, [14] shows additional data taken with the test apparatus being a mannequin leg placed on the floor with an approximate diameter of 200 mm and a length of 600 mm. This test apparatus is more challenging for the algorithm because the entire object is close to the floor. The legs are detected, but at the cost of detecting farther objects. This deficiency can be eliminated by using two different modulation frequencies (such as 10 MHz and 20 MHz) where the detected objects would be coarsely represented at a more appropriate distance. The control algorithm can then intelligently delete them.



**Figure 5** - Results of the obstacle detection and segmentation algorithm for the experimental setup shown in Figure 2(a). The resultant intensity, range, and segmented images are shown in (a), (b) and (c), respectively. The ground truth

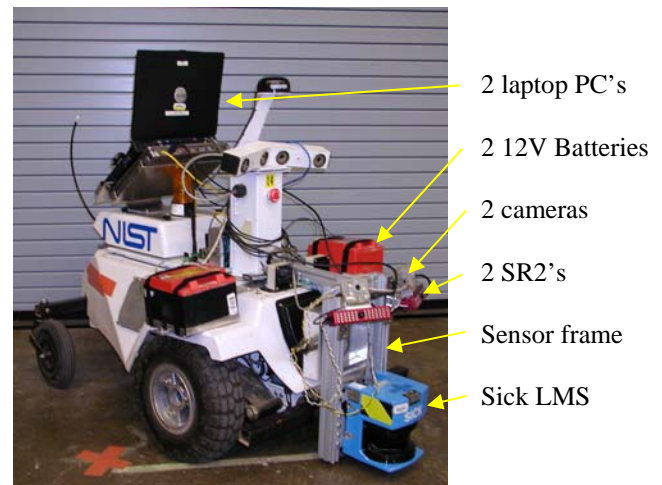
provided by the scanning laser rangefinder is shown in (d) and has been rotated to show a top-down view.

#### IV. INDOOR AUTONOMOUS VEHICLE

Along with the previous standards efforts, NIST has recently done research for the AGV industry through the Industrial Autonomous Vehicles (IAV) Project to provide advances in onboard vehicle intelligence, standard control architectures, and sensors. These project objectives are set to allow AGV users and vendors to do more with AGV's without their following a preplanned, very low tolerance path monitored by an external host computer and without the need to dramatically change facility infrastructure to install AGV's. Infrastructure changes may include clearing wide areas for vehicle paths or to even install laser reflectors to allow laser triangulation for referenced vehicle positioning to the facility.

Figure 6 shows a photograph of the NIST testbed vehicle leveraged from the Defense Advanced Research Project Agency's Learning Applied to Ground Robots (LAGR) Project. Two CSEM SR2's and a Sick LMS (laser measurement system) have been temporarily mounted to the LAGR vehicle for indoor obstacle detection measurements and vehicle navigation testing.

The LAGR vehicle is equipped with stock dual stereo cameras, two infrared sensors, and a physical bumper along with two drive-wheel encoders, an inertial measurement unit (IMU) and a global positioning system (GPS) sensor. DARPA provided this vehicle to NIST and the other seven LAGR project teams as government furnished equipment to be used by each organization to perform outdoor vehicle navigation tests where a new generation of learned perception and control algorithms for autonomous ground vehicles are being developed [16].

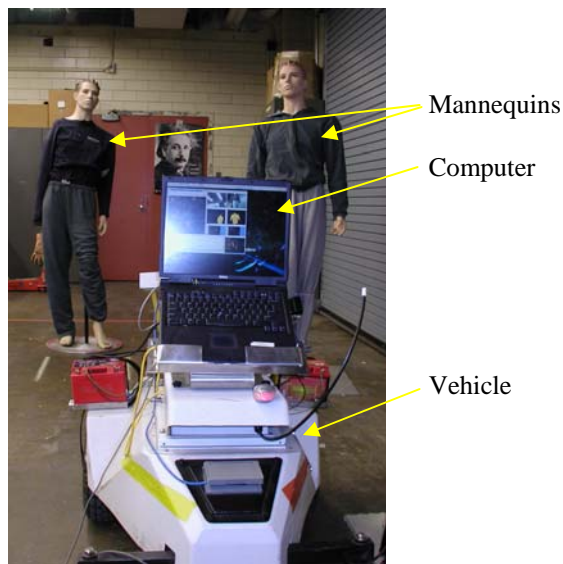


**Figure 6** – DARPA LAGR vehicle equipped with portable NIST sensor suite.

The vehicle is made from a powered wheelchair base with front wheel drive/steering and rear casters and has four onboard computers for control, planning, and left and right stereo vision. NIST has replaced the vehicle behavior

generation, world modeling and sensor processing control software with 4D/RCS (4 Dimensional, Real-time Control System) control architecture software developed at NIST [1]. Also, NIST has developed an Operator Control Unit (OCU) that includes visual feedback from right and left cameras, right and left range sensors, and high and low level obstacle maps. Other sensor data windows can also be added as needed.

The LAGR vehicle's stock dual stereo vision did not provide adequate disparity for obstacle detection in the indoor NIST laboratory. Instead, 2D (Sick LMS) and 3D (SR2's) ranging sensors are being used. Figure 7 shows a photograph of a scene as viewed from behind the robot. It shows two mannequins placed in front of and in the path of the robot where the goal the robot is trying to reach is behind them. If programmed to autonomously reach the goal, the vehicle must therefore, sense the objects and plan to go around them.



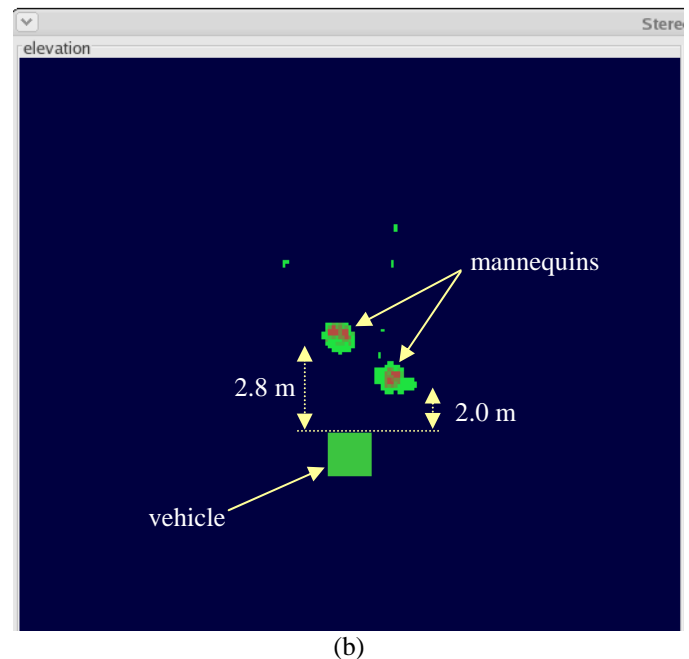
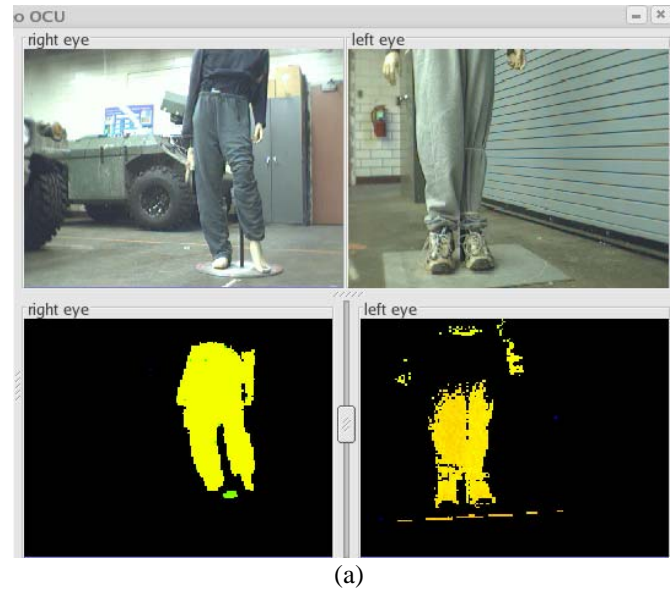
**Figure 7** – Photograph of the scene as viewed from behind the NIST testbed vehicle.

The LADAR sensors are used to detect range to obstacles where a world modeling software module places the obstacles within a low level map for close range vehicle planning purposes. The low level map is a 20 cm per pixel map spanning 20 m to the left and right and forward and back of the vehicle with the robot centered within the map. A high level map is also used to plan paths at longer ranges up to 200 m on all vehicle sides.

Figure 8 shows snapshots of the two mannequins within the low level map as viewed by the SR2's. The SICK LMS data is not shown as it is currently only displayed in the OCU as no LMS sensor processing module has been implemented on this NIST testbed.

The figure clearly shows obstacles placed in the map and can therefore, plan a path to navigate around the obstacles. Obstacles are detected and placed in the map at several meters in front of the vehicle all in one time cycle (10 Hz) of vehicle control. However, without referencing vehicle position with global positioning or even locally through other (e.g., radio frequency identification detection, bar coding, visual

odometry) means, the vehicle IMU will drift so that the map will be incorrect. Since the IMU is also combined with wheel encoder information to provide vehicle pose, it causes the vehicle position to shift relative to the obstacle maps. To compensate for this drift, a simultaneous localization and mapping (SLAM) scheme is being considered at NIST.



**Figure 8** – Snapshots of: (a) right and left camera images (top) and associated right and left SR2 range data (bottom) of two mannequins in front of the vehicle; (b) Low Level Obstacle Map showing the two mannequins from a top-down perspective. The middle color of each mannequin is an indicator of obstacle height.

## V. SIMULTANEOUS LOCALIZATION AND MAPPING

Towards navigating in an environment without any or minimal modifications to it, we are developing algorithms using onboard laser range sensing for AGV navigation. By combining information from the AGV's internal sensors (wheel encoders and IMU sensors) with external sensing. By combining information from the AGV's internal sensors (wheel encoders and IMU sensors) with external sensing (LADAR), we can construct a map of the environment and in turn use this map for position estimation thereby eliminating the need to either install or to maintain additional infrastructure.

We are developing an estimation-theoretic SLAM scheme where we concurrently build a feature-based map of the environment and use this map to obtain estimates of the location of the vehicle. By tracking the relative position between the vehicle and identifiable features in the environment, both the position of the vehicle and the features can be estimated simultaneously. Given process (vehicle) and observation (sensor) models, the SLAM process consists of generating the best position and map (feature) estimates [8]. This can be accomplished using the recursive Extended Kalman Filter (EKF) wherein the information from the internal and the external sensors is fused to obtain quantifiable estimates of the vehicle position as well as that of features in the operating environment. The proposed algorithm will be tested on the LAGR vehicle in the next few months.

## VI. THE PROBABILITY OBSTACLE MAP

The probability obstacle map (Figure 8 (b)) is the system's internal representation of the external world. It acts as a bridge between sensory processing and behavior generation for representing sensory information in a unified representation. The maps are updated continually from sensor data. If the information is no longer believed to be representative of the world, it will be deleted from the map. In addition, the confidence factors to the map can be adjusted as new data are sensed. Currently, the map implementation fuses information from multiple sensors, including navigation sensors and two SR2 cameras. The navigation system provides information about the vehicle's current position, orientation, speed, velocity, etc. Data from each SR2 camera includes a range image which is used to detect obstacles in the environment as described in Section II Obstacle Detection and Segmentation.

The maps are updated temporally and spatially by the sensed obstacles. The primary use of this information is to plan safe and efficient paths. We currently only demonstrate the feasibility of using the SR2s for obstacle detection. Possible future research directions are to enhance the map capabilities and incorporate an active path planner module to compute safe and task-appropriate routes. Furthermore, a Sick LMS sensor processing module will be added to the system for evaluating the performance of the SR2 in factory environments.

## VII. SUMMARY AND CONCLUSIONS

An obstacle detection and segmentation algorithm for

Automated Guided Vehicle (AGV) navigation in factory-like environments using a novel 3D range camera was described in this paper. The range camera is highly attractive for obstacle detection in industrial applications due to its relatively low cost and it's ability to deliver range and intensity images in real time. The performance of the algorithm was evaluated by comparing it with ground truth provided by a single-line scanning laser rangefinder.

Towards navigating in an environment without any or minimal modifications to it, we are developing algorithms using onboard laser range sensing for AGV navigation.

We are developing an estimation-theoretic SLAM scheme where we concurrently build a feature-based map of the environment and use this map to obtain estimates of the location of the vehicle. The proposed algorithm will be tested on the LAGR vehicle in the next few months.

The probability obstacle map currently fuses information from multiple sensors, including navigation sensors and two SR2 cameras. The maps are updated temporally and spatially by the sensed obstacles. The primary use of this information is to plan safe and efficient vehicle paths.

We envisage the extension of the work detailed in this paper toward:

- Addition of enhanced map capabilities and an active path planner module incorporation to compute safe and task-appropriate routes.
- Addition of a SICK LMS sensor processing module for evaluating the performance of the SR2 in factory environments.
- Moving obstacle detection from a moving AGV for factory applications,
- Combining the sensor with a color camera for detecting and tracking obstacles over long distances, and
- Indoor to outdoor (e.g., factory to materials yard) and return environments obstacle detection.

Some prospective applications include: mapping factory environments ("lights-out") manufacturing inside and outside during night (dark) hours and security and other service mobile robot advancements.

## VIII. ACKNOWLEDGEMENTS

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