Obstacle Avoidance Wheelchair System

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***Abstract*— We present a collision avoidance system for powered wheelchairs used by people with cognitive disabilities. Such systems increase mobility and feelings of independence, thereby enabling reversal of some symptoms of depression and cognitive impairment and improvement of quality of life. We use a novel 3D sensor developed by Canesta Inc. that allows the wheelchair to "see" obstacles, avoid collisions, and suggest alternatives to users. The Canesta sensors are ideal, as they combine accuracy with efficiency in the distance range necessary for collision avoidance.**

I. Motivation

High quality of life is of the utmost importance and mobility is a key component of a positive quality of life. Unfortunately, many older adults face various impairments and disabilities that result in their mobility being compromised. Furthermore, many of these people require a powered wheelchair because they lack the strength to manually propel themselves. However, powered wheelchairs are not appropriate for older adults with a cognitive impairment, such as Alzheimer's disease, as they do not have the cognitive capacity required to effectively and safely manoeuvre the wheelchair. In addition, their sometimes aggressive and unpredictable behaviour makes wheelchair use unsafe for both themselves and others. Currently there are an estimated 15 to 18 million people worldwide who have been diagnosed with dementia with this number expected to reach 34 million by 2025 [1].

If we can provide these users with some level of independence, irrespective of ability, without placing the person or others at unreasonable risk, then it may be possible to reverse some symptoms of depression and cognitive impairment and improve quality of life. The goal of this project is the application of a novel 3D sensor system to adapt a powered wheelchair, specifically, the Nimble Rocket™ so that it can be driven safely by users with cognitive and other complex impairments. Figure 1 shows an artist's rendition of the Canesta sensor mounted on the wheelchair.

There have been numerous prototypes for automated wheelchairs in the literature. Perhaps the most well known are the stereo-vision guided *Wheelesley* [2], and the sonar guided *NavChair* [3]. Further investigations into shared control were presented in [4], and ultrasound was studies as a failsafe collision avoidance system in [5]. Our work is distinguished for these in that we use audio prompts as our method of communication with the user: the system itself has no control over the motors other than simply stopping the wheelchair. This type of interaction fits into our broader goals for assistive technologies [6].

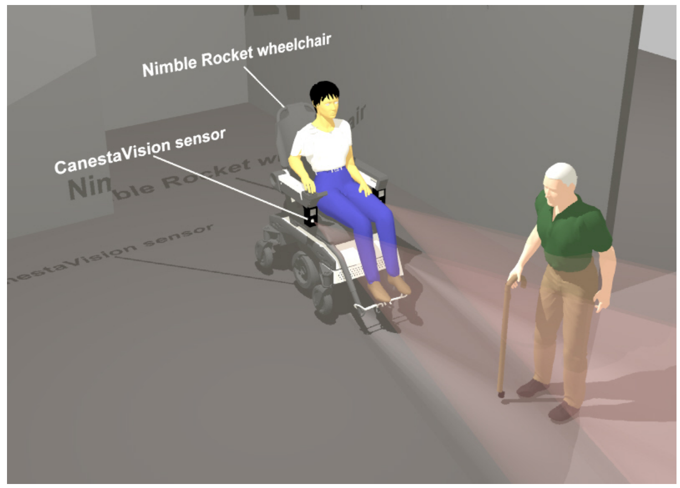


Fig. 1. Nimble Rocket™ wheelchair with Canesta 3D perception sensors.

II. System Overview and Results

A. Sensor & System

An overview of the system is shown in Figure 2.

The primary sensor is a 3D time-of-flight infrared laser range sensor built by Canesta [1]. The sensor uses a pulsed laser and measures the phase shift of the pulse in the reflected light over a 64×64 CMOS sensor chip. This chip allows the depth processing to be done in hardware, giving fast and accurate results. The Canesta sensor is an ideal choice for this application. For example, its advantages over a laser range sensor are its 3D and imaging capabilities, smaller footprint, and low power requirements.

The input layer is the *depth image manager*, which takes output from the Canesta sensor and produces a 64×64 depth image, in which each pixel gives the depth of that location. This depth image is then passed to the *map manager*, which constructs an occupancy grid map. We describe occupancy grids in Section II-B. The occupancy grid is then input to the

[1] www.canesta.com

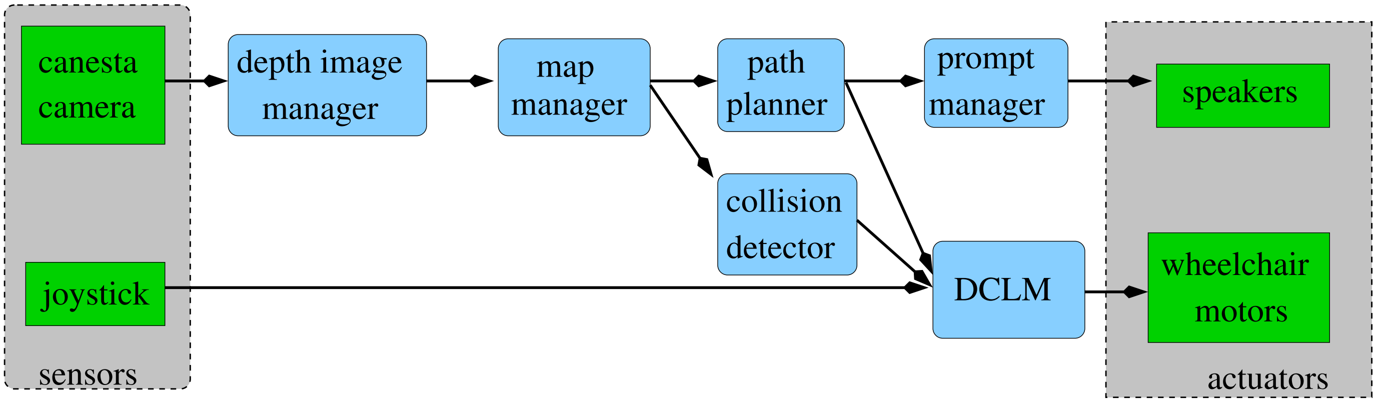


Fig. 2. Schematic of the major components of the wheelchair mobility assistance system. The map manager takes 3D images from the depth manager and builds an occupancy grid. If a collision is imminent, the wheelchair is stopped through the directional logic control module (DCLM), and the prompt manager issues an audio prompt to the user through a set of speakers.

collision detector and to the *path planner*. The *collision detector* estimates if there is a collision imminent by comparing the distance to the closest object in the map to a pre-defined threshold. If an object is too close, then a signal is sent to the *Directional Control Logic Module* (DCLM) [2]. The DCLM acts as a filter for the control signals from the joystick to the motors, only allowing those through that will not lead to a collision. The collision detector sends the direction of the hazardous direction to the DCLM, thereby restricting the motion of the wheelchair in that direction. Internally, the DCLM consists of a programmable PICSTK-2k chip, using 2 lines of analog input, 2x output, 8x digital input and 8x digital output. The *path planner* computes the best direction around the obstacle from the occupancy grid using the *direction of greatest freedom* (DGF). The DGF is the direction around the obstacle with the largest number of unoccupied grid cell. The DGF is then sent to the *prompt manager*, which selects an audio prompt to play, suggesting a possible alternative action for the wheelchair user.

B. Occupancy Grid Maps

An occupancy grid is a method for robotic mapping which represents obstacles in the world using a 2D map of *cells*. Each cell has a value from 0 (known obstacle) to 256 (free space) with 128 representing unknown. We say that a cell is ¡i¿occupied¡/i¿ when it has a value less than a threshold (50 in our system). The *map manager* constructs a local occupancy grid from a range image in three stages, as shown in Figure 3. First, the depth image (Figure 3(b)) is projected to the floor, where the closest depth in each column is used, as shown in Figure 3(c). Given the known camera geometry, the resulting 1D array of depths can be mapped into the 2D horizontal plane by ray tracing, Figure 3(d). The occupancy grid cell values, $G(i)$ for each cell i, are then updated using the method of [7], by adding a constant $-K$ if the cell is in the occupied region of a radial map, and by $+K$ if its in the clear region. The constant K controls how quickly the map evolves over time and responds to changes.

[2]Designed & developed by Gerald Griggs, Centre for Studies in Aging, Sunnybrook & Women's College, Toronto, Canada

The accuracy of the Canesta sensor (and hence, the resolution of the occupancy grid) depends on the range: more accurate depth is obtained at closer range. The accuracy can also be adjusted for a particular depth range. We optimised the sensor for a fairly close range (from about 50cm-150cm from the wheelchair), and get a depth resolution of approximately 5cm in this range. More details on the accuracy of the Canesta sensor can be found at `www.canesta.com`.

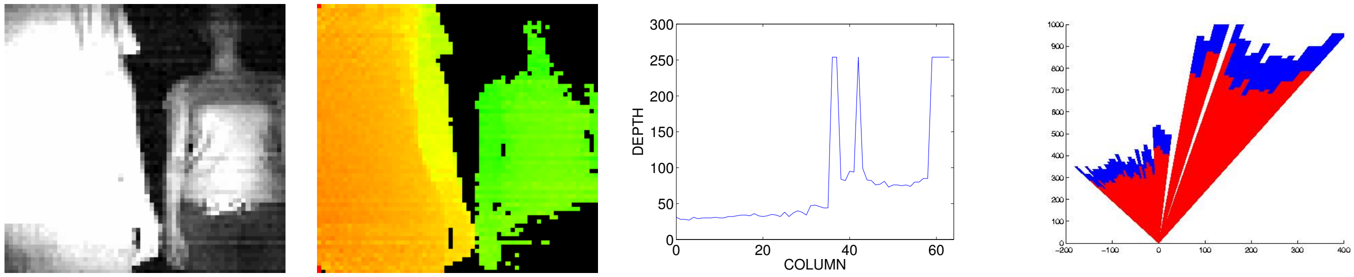
C. Results

Figure 4 shows an example as the wheelchair approaches a large obstacle. The top row shows a view of the scene from a different camera, while the second row shows the depth image output by the depth image manager, and the bottom shows the occupancy grid constructed. When cells too close to the chair become occupied (as in frame 190 in Figure 4), the chair stops and a prompt is issued to suggest a possible direction to the user. Figure 5 shows a further example as the wheelchair approaches a cane. This example demonstrates one of the strengths of the Canesta sensor: the ability to pick out small obstacles rapidly. Clearly, however, a laser range finder would also perform well in this situation. Further results can be found at `www.ot.utoronto.ca/iatsl/projects/canesta.htm`.

III. Conclusion and Future Work

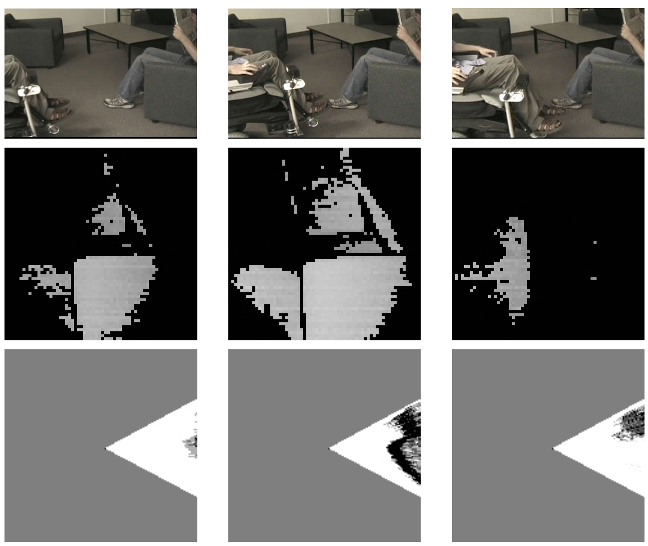
We have presented a method for wheelchair obstacle avoidance using the Canesta 3D sensor. The wheelchair stops before collisions, and suggests alternatives for mobility. The Canesta sensor's speed and accuracy make it ideal in this setting. This system has great potential to improve health and independence in an increasingly elderly population.

Our current work involves integrating our current system with global mapping and localisation methods [8], and with control methods using partially observable Markov decision processes, or POMDPs [6]. The wheelchair will build a global map of its environment and be able to locate itself within the



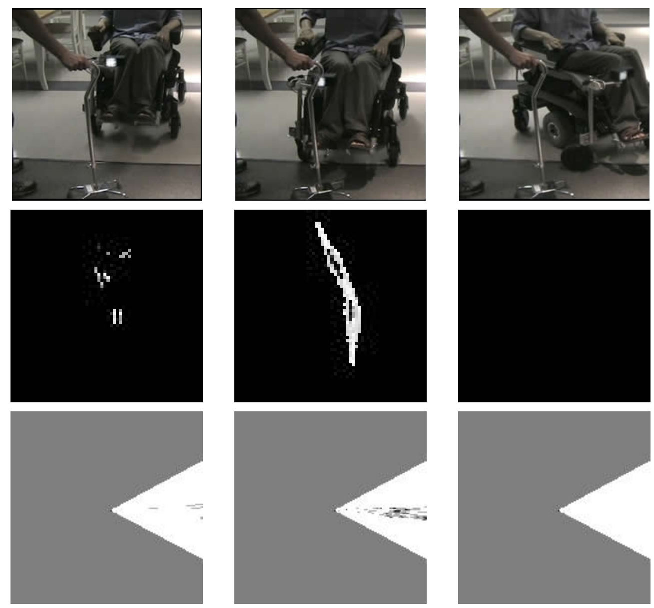
(a) (b) (c) (d)

Fig. 3. Constructing a map from a depth image. A depth image(b) is produced by the sensor from the scene (a), and projected onto the ground (c). Rays are then computed from the sensor position to give the radial map (d).



187 190 194

Fig. 4. Example of avoiding a collision. Scene view (top row), depth images(top row) and corresponding occupancy grids (bottom row). The chair approaches (frame 187), stops (190), a prompt is issued, suggesting a right turn, which the user takes, and the obstacle moves to the left (frame 194).



382 385 389

Fig. 5. Avoiding a collision with a cane. An audio prompt to turn left is issued after the chair stops at time 385, and the user complies at time 389.

map. The POMDP will model the chair's location, obstacles in the map, as well as other context such as the time of day, the user's schedule, etc. A policy of action will then seamlessly combine assisted planning for improved user mobility with obstacle avoidance. The actions the system can take will be combinations of physical control of the wheelchair and audio prompts for the user. We are also investigating adding haptic feedback to the wheelchair joystick, as an additional (to prompting) method for imparting information to the user.

Acknowledgments

The authors thank James Tung, Hai Huang, Gerald Griggs, Jen Boger, Jasper Snoek and Don Murray. This work was supported by a grant from the Canadian Institutes for Health Research (CIHR).

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