NAVIGATION ASSISTANCE FOR INTELLIGENT WHEELCHAIRS

Pooja Viswanathan[1], Parnian Alimi[1], James Little[1], Alan Mackworth[1], Alex Mihailidis[2]

[1]*Department of Computer Science, University of British Columbia*

[2]*Department of Occupational Sciences and Occupational Therapy, University of Toronto*

INTRODUCTION

Many elderly residents in long-term care facilities lack the cognitive or visual abilities to safely maneuver powered wheelchairs, and are thus not permitted to use them. This leads to reduced mobility and an increased dependence on caregivers. We propose intelligent powered wheelchairs to address this issue. Computer vision methods are used to avoid collisions and provide audio prompts for navigation. We show that the system performs with high accuracy and precision in a realistic indoor setting.

RELATED WORK

Intelligent wheelchairs capable of collision avoidance and path planning have been developed recently [1-4], however these wheelchairs navigate autonomously, thus taking control away from the user. On the other hand, wheelchairs that leave planning and navigation to the user and only provide collision avoidance support are not appropriate for users with cognitive impairment since they often lack planning abilities. We thus suggest a control strategy that combines artificial intelligence of the wheelchair with driver abilities to provide supportive, passive navigation assistance that increases independence and ensures safety.

We seek to build a system that can be easily added to any commercial wheelchair, is cost-effective, and performs reliably in real-world settings. Existing smart wheelchairs have used various active sensors (acoustic, sonar, infrared, laser, etc.). However, these sensors are often large, expensive, power-hungry, unsafe, and prone to cross-talk issues. We thus rely on a stereo-vision camera to detect obstacles due to its low power consumption, ability to perform in natural environments, and relatively low cost. In addition, cameras capture and provide a richer dataset than can be used for high-level scene understanding (to build maps and determine what type of room the wheelchair is in, e.g., kitchen).

METHODS

In this paper, we discuss a prototype intelligent wheelchair that prevents collisions and provides navigation assistance through audio prompts to assist the user in reaching desired locations. A system diagram is provided in Figure 1. We discuss each of the components in the system diagram in the following sections.

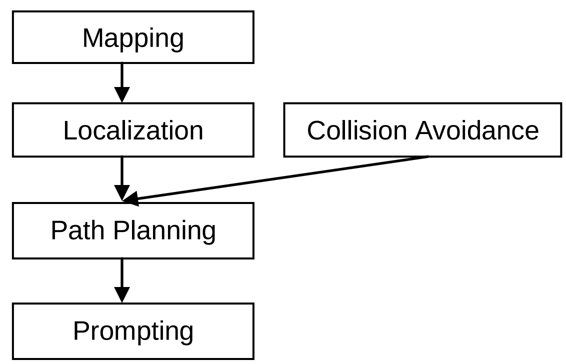

Figure 1: System diagram of intelligent powered wheelchair

Collision Avoidance

In order to detect imminent collisions, we first compute the distances from the wheelchair to visible objects in the environment. Stereo pairs of images are used to construct a *local occupancy map* (Figure 2), a 2D bird's-eye view representation of obstacles in front of the chair, using existing techniques in computer vision [5]. In this map, obstacles are black, free space is white, and grey areas represent unknown regions. The *occupancy map* is updated as the wheelchair moves through the environment. When an obstacle is detected within a pre-specified distance threshold on the occupancy grid, the wheelchair is stopped to avoid a collision. The area around the obstacle with the most amount of free space is then computed and suggested to the driver through an audio prompt (e.g., "try turning right") until the driver successfully avoids the obstacle.

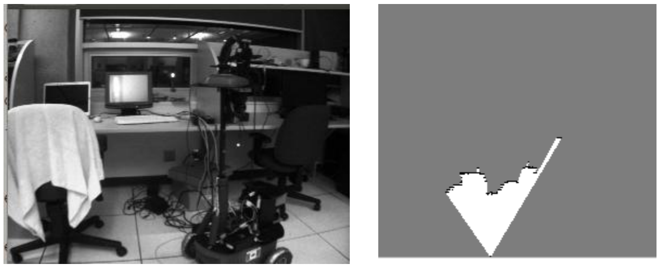

Figure 2: Camera image (left), Occupancy map representing bird's-eye view of obstacles (right)

Mapping

A map of the environment is automatically created through the use of a technique in robotics called Simultaneous Localization and Mapping (SLAM). This technique requires a robot to explore the environment autonomously or in a tele-operated fashion, collecting laser scans or images in order to create *global occupancy maps*. These maps are created by stitching together multiple *local occupancy grids* using odometry information in order to represent larger environments [6]. This map must only be constructed once for each home or long-term care facility. Figure 3 shows the map of the laboratory created as described above and used by subsequent components.

Localization

Given the *global occupancy map*, and an estimate of the wheelchair's starting position, the wheelchair's location at any given time can be computed as follows. Landmarks from incoming stereo images are matched to previously seen landmarks. The wheelchair's position and orientation are then computed using information about the camera's geometry (a process known as visual odometry) [6].

Path Planning

We assume that goal locations are provided (by a caregiver, for example) through a graphical user interface, which displays the *global occupancy map*. Goal locations are specified by clicking on the map. The optimal route to the goal from the wheelchair's current location is computed at every step using techniques in [7], and used in computing the driver's progress towards the goal.

Prompting

Once the optimal route is determined, the heading of the driver is computed by comparing the wheelchair's current orientation (obtained from the localization step) to the required orientation. Appropriate audio prompts are then issued - "off route – turn left", "off route – turn right", "off route – turn around", and "on route – move forward" (if the wheelchair is heading in the correct direction but has not made progress towards the goal). Wheelchair motion (e.g., stopped or moving) is determined by computing the change in wheelchair position. In addition, the optimal route is analyzed for upcoming turns by discretizing the optimal route into direction vectors, and computing the angle between subsequent vectors. If a turn is detected within a pre-specified distance, an appropriate prompt is delivered, such as "upcoming left turn" or "upcoming right turn".

RESULTS

We have previously demonstrated the performance of the vision-based collision avoidance system in [8], which performed with 96% accuracy while detecting several objects in a controlled setting. In this paper, we thus focus on the other components of the system. Specifically, we show the performance of the planning and prompting system on 12 unique routes traveled by the wheelchair, containing several deviations, stops and turns. The wheelchair was driven by an able-bodied user, at a speed of 0.15 m/s, which was determined to be a safe driving speed for the intended user population. The environment chosen was realistic, containing dynamic obstacles (people walking around in the lab). In addition, the experiments were conducted during varying times of the day (morning, evening, and night) in order to test the robustness of the system to different lighting conditions. We determine true positives (TP), false positives (FP), and false negatives/missed detections (FN) for each of the different types of detections as shown in Table 1.

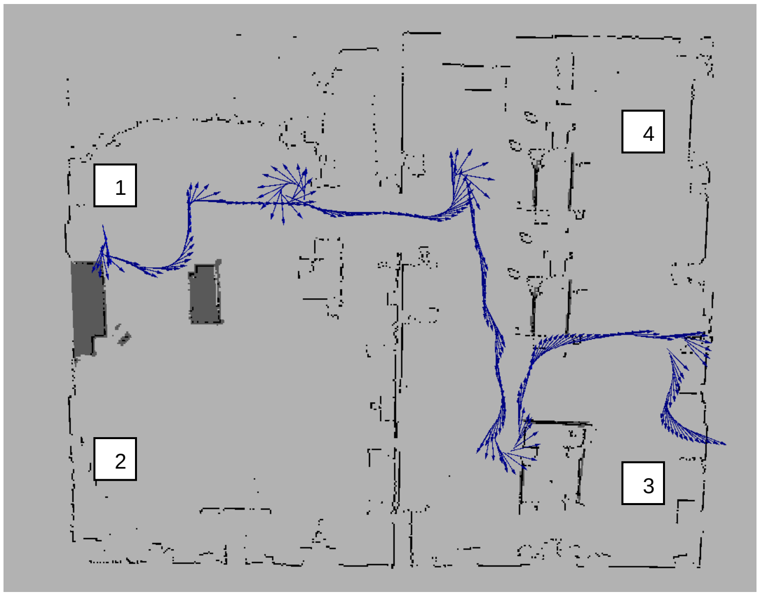

Figure 3: Map of laboratory created by the mapping component. Locations chosen as start and end positions are numbered 1-4. Blue arrows denote wheelchair position and heading as estimated by the localization component while driving along route "1-3".

Table 1: Navigation Assistance Results

Route	Left deviation			Right deviation			U-turn			Upcoming left turn			Upcoming right turn			Stop		
	TP	***FP***	***FN***	***TP***	***FP***	***FN***	***TP***	***FP***	***FN***	***TP***	***FP***	***FN***	***TP***	***FP***	***FN***	***TP***	***FP***	***FN***
1 – 4	3	0	0	2	0	0	3	0	0	1	0	0	0	0	0	3	0	0
1 – 3	5	1	0	6	2	0	4	4	0	3	0	0	3	0	0	5	0	0
1 – 2	5	0	0	7	0	0	4	0	0	3	0	0	3	0	0	0	0	0
2 – 1	3	0	0	8	1	0	2	2	0	4	0	0	0	0	0	2	0	0
2 – 3	3	0	0	0	0	0	1	0	0	0	0	0	2	0	0	2	0	0
2 – 4	4	0	0	4	1	0	2	0	0	2	0	0	4	0	0	2	0	1
3 – 1	5	0	0	4	0	0	2	0	0	3	0	1	5	0	0	3	1	0
3 – 2	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
3 – 4	9	1	0	3	1	0	1	2	0	4	0	0	2	0	0	3	0	0
4 – 1	4	0	0	0	1	0	2	0	0	0	0	0	1	0	0	2	0	0
4 – 2	4	1	0	8	3	0	4	4	0	2	0	0	3	0	0	3	0	0
4 – 3	3	0	0	2	2	0	2	0	0	4	0	0	1	0	0	3	0	0
Totals	**50**	**3**	**0**	**44**	**11**	**0**	**27**	**12**	**0**	**26**	**0**	**1**	**24**	**0**	**0**	**28**	**1**	**2**
Avg Recall (TP/ TP+FN)	**1.0**			**1.0**			**1.0**			**0.96**			**1.0**			**0.93**		
Avg Precision (TP/ TP+FP)	**0.94**			**0.8**			**0.69**			**1.0**			**1.0**			**0.97**		

DISCUSSION

As seen in Table 1, most deviations and turns are detected with high accuracy and precision. Most of the errors (specifically for right deviations and u-turns) noted during the experiments were caused by the following:

1) Errors made by the localization module due to lack of texture or reflective surfaces.
2) Inaccurate starting position estimates.
3) Obstacles in the map that did not exist in the test environment.

The first error is a common pitfall of vision-based systems, since estimating camera motion requires the matching of landmarks between incoming images. Untextured areas such as blank walls, as well as reflective surfaces such as windows, result in few, incorrect or no matches, thus causing localization errors that persist until the system is able to re-localize using previously-seen landmarks. Future work involves integrating an inertial measurement unit, which measures orientation and velocity, and can be used to determine wheelchair motion in the absence of visual landmarks.

In these experiments, approximate starting positions were specified by clicking on the map through a graphical user interface. Since localization estimates are relative to the starting position, any errors in the starting position propagated throughout the route. Future work will involve verification of these positions using landmarks on the map, or acquiring these positions directly during the mapping process. Alternatively, positions of known landmarks in the environment can be used to correct localization estimates when these landmarks are detected by the camera.

Since the map was generated once several months prior to the experiments conducted in this paper, the positions of many movable obstacles such as chairs and boxes had changed since the mapping process. Thus, the planning and prompting modules occasionally instructed the user to move around 'invisible' obstacles that did not exist in the test environment. These errors can be reduced by reconstructing the global map when the environment changes significantly. Unlike the errors described previously, invisible objects resulted in temporary errors that the system was able to recover from when the user moved away from them.

In the current system, prompts were provided when a deviation, turn, or stop was detected. However, future work involves estimating the user's needs and preferences through a probabilistic model and providing prompts that adapt automatically to the user.

CONCLUSIONS

This paper has shown the effectiveness of a vision-based system for navigation assistance. Experiments are underway to test this system with visually and cognitively impaired users. We expect that this system will benefit them greatly by increasing their mobility and independence.

ACKNOWLEDGEMENTS

We would like to thank NSERC and CIHR for funding this research.

REFERENCES

[1] R.C. Simpson, D. Poirot, and F. Baxter. The Hephaestus Smart Wheelchair System. IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 10, no. 2, pp. 118-122, 2002.
[2] J.P. Odor, M. Watson, P. Nisbet, and I. Craig. The CALL Centre smart wheelchair handbook 1.5. CALL Centre, 2000.
[3] S. McGarry, L. Moir, S. Girdler, and L. Taylor. The smart wheelchair: is it an effective mobility training tool for children with cerebral palsy? The Centre for Cerebral Palsy, Coolbinia, WA, UK, 2009.
[4] W. Honore et al. Human-Oriented Design and Initial Validation of an Intelligent Powered Wheelchair. RESNA Annual Conference. 2010.
[5] D. Murray and J. Little. Using Real-Time Stereo Vision for Mobile Robot Navigation. Autonomous Robots, Vol. 8, No. 2, pp. 161--171, 2000.
[6] K. Konolige, G. Grisetti, R. Kuemmerle, W. Burgard, L. Benson, R. Vincent. Sparse Pose Adjustment for 2D Mapping. IEEE/RSJ Intl. Conf. on Intelligent Robots and Systems (IROS), 2010.
[7] K. Alton and I. M. Mitchell. Fast Marching Methods for Stationary Hamilton-Jacobi Equations with Axis-Aligned Anisotropy. SIAM Journal on Numerical Analysis, 47(1) pp. 363-385, 2008.
[8] P. Viswanathan, J. Hoey, J. Boger, and A. Mihailidis. A comparison of stereovision and infrared as sensors for an anti-collision powered wheelchair for older adults with cognitive impairments. 2nd International Conference on Technology and Aging, Toronto, 2007.