Navigation assistance for a semi-autonomous smart wheelchair

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ABSTRACT

Semi-autonomous smart wheelchairs can enable visually impaired users to drive a wheelchair safely. In collaboration with wheelchair manufacturer Glide, a navigation assistance system for a smart wheelchair was designed. This smart wheelchair uses a CentroGlide wheelchair base and a ZED Mini RGB-D camera to detect the surrounding environment. The system identifies drivable areas using machine learning and identifies obstacles using 3D point cloud data. A RGB-D wheelchair driving dataset was collected around Curtin University and used to evaluate this system. Identification of drivable areas is effective in outdoor areas, but less effective indoors. Obstacle detection is effective at identifying static obstacles such as walls. This obstacle information was encoded into an occupancy map of the surrounding environment and used to implement a basic assistive control algorithm.

INTRODUCTION

The use of powered wheelchairs has enabled greater independence for people with disability, however can be inaccessible or unsafe for people with visual impairment. Smart wheelchairs add intelligent sensing and control to an existing powered wheelchair in order to avoid obstacles in the environment. These wheelchairs can be fully-autonomous, moving the wheelchair to an end goal, or semi-autonomous, where input from the user is blended with the control unit to improve safety.

Previous smart wheelchair implementations have used a variety of sensors to detect their environment. Many have used RGB-D cameras (Wang et al. 2021), with other implementations utilizing 2D Lidar, ultrasonic sensors, or mmWave radar. The compute element inside a smart wheelchair generally consists of a microcontroller to process user inputs and control the motors, a general-purpose computer to run pathfinding algorithms and log information, and an AI accelerator (such as an Nvidia Jetson or Google Coral) to improve the performance of machine learning algorithms.

These machine learning algorithms process input from sensors to understand the surrounding environment. Object localisation involves classifying an object while also identifying its position within an image. Semantic segmentation involves the classification of each pixel in an image, which is often used on objects that cannot be cleanly identified with a bounding box. The Hybridnets model (Vu, Ngo, and Phan 2022) is an object localisation and segmentation model which identifies drivable areas.

Assistive control algorithms can be used to navigate the user through the environment once obstacles are detected. Path-based algorithms such as A* plan a path between a start and goal pose, aiming to reduce the distance travelled by the user. In contrast, local algorithms such as VFH+ (Ulrich and Borenstein 1998) set the wheelchair's current direction using a target direction, while avoiding nearby obstacles.

The overall aim of the project team, which consists of multiple project students and interns, is to fully implement a smart semi-autonomous wheelchair using an existing CentroGlide powered wheelchair. This wheelchair was provided by Glide, who was a collaborator in this research and guided the initial direction of the research projects. The specific aim of this thesis is to implement navigation assistance, which involves both avoiding environmental obstacles such as walls and stairs, and guiding the user along pathways.

RESULTS AND DISCUSSION

A ZED Mini RGB-D camera was mounted to the wheelchair using a 3D printed mount to enable it to sense the surrounding environment. To test the performance of the navigation assistance system, a 47 min wheelchair driving dataset was collected around Curtin University. The navigation assistance system involves identifying pathways and obstacles, and placing these obstacles onto a 2D birds-eye view occupancy map of the surrounding environment. Hybridnets was used to identify drivable areas; the model was retrained on the Cityscapes dataset for 20 epochs to improve its performance. Most gains in model accuracy are achieved after only 1 epoch; results are shown in table 1. Hybridnets was able to run at 10 fps on an RTX 3080 GPU, however, was CPU limited during testing.

To identify static obstacles such as walls, a custom algorithm was used to process 3D point cloud data and place these obstacles onto the occupancy map. Figure 1 shows this algorithm in use, with the wheelchair's location identified with an 'X' and obstacles shown in black. This image also demonstrates drivable area segmentation, shown in light grey on the occupancy map and as a pattern on the original image. The algorithm correctly identifies the right wall and left handrail as obstacles and has a mean processing latency of 550 ms on a test laptop. Due to the FOV of the camera, drivable areas and obstacles directly in front or to the side of the wheelchair are not stored in the map.

Table 1: Hybridnet performance metrics before and after retraining

Metric (Cityscapes)	Pre-trained	After training
mIoU	26.6%	87.5%
Road Recall	30.6%	96.2%
Sidewalk Recall	1.5%	68.2%

A proof of concept semi-autonomous wheelchair control algorithm was implemented using VFH+. This algorithm successfully modifies the wheelchair's direction to avoid obstacles using the occupancy map. VFH+ does not change the wheelchair's speed, making it unsuitable for use in a final smart wheelchair implementation. The ZED Sensors API and Positional Tracking API were tested to obtain the position of the wheelchair, with the Positional Tracking API found to be much more effective for this purpose.

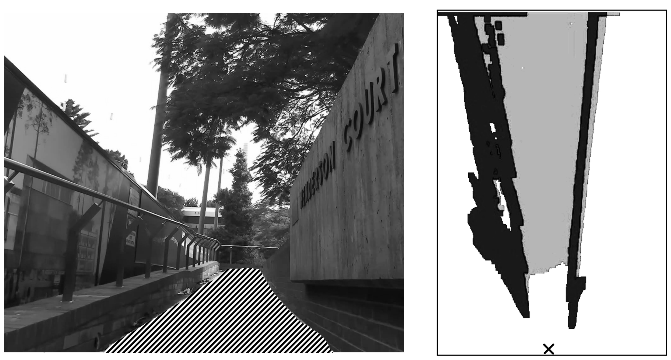

Figure 1: Drivable area segmentation and obstacle detection (top-down occupancy map)

CONCLUSIONS

The results indicate that image segmentation is effective at identifying drivable areas outdoors. The custom 3D point cloud processing algorithm works well at identifying walls, however, is not yet fast enough for moving obstacles such as pedestrians. The navigation assistance technology developed and tested in this thesis can be integrated with other thesis students' work to create a semi-autonomous wheelchair. To work around the FOV of the RGB-D camera, a SLAM algorithm could be used to keep obstacles in memory.

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