
A Laser Based Semi-Autonomous Wheelchair Using Bayesian Theory

By

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Certificate of Authorship/Originality

I, Tuyen Hoang Trieu, certify that the work in this thesis has not previously been submitted for a degree, nor has it been submitted as part of the requirements of a degree, except as fully acknowledged within the text.

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Abstract

Reports show that the number of elderly people and people with disabilities in society are significantly increasing. These people have a wide range and variety of functional impairments. The aim of rehabilitation technology is to improve the quality of life of people with disabilities. In particular, smart wheelchairs have been developed to accommodate people with mobility impairments. The provision of independent mobility can produce substantial benefits, such as the development of physical, cognitive, communication and social skills for both children and adults in their daily lives.

In this thesis, we present a method of constructing a 360° real-time environmental map for the smart wheelchair. It combines the information from a laser range finder and encoders mounted in the driving wheels. As the wheelchair moves, the obstacles in front of the wheelchair that are detected by the laser sensor are updated to this map, after a modification based on the encoder data. This mapping method is 13-fold more accurate than the common use of encoders.

Also, a method of determining accessible free-space for the obstacle avoidance task is implemented. This accommodates the actual dimensions of the wheelchair and then determines the collision-free area available for the wheelchair. The data of accessible free-space can be used to simplify the obstacle avoidance controller and improve its real-time capabilities. It eliminates errors from the common approximation of the wheelchair boundary as a circle, which may lead to the assumption that no accessible space is available to move safely without incurring a collision.

We introduce an advanced obstacle avoidance technique that utilises separate Bayesian neural networks for specified tasks. The obstacle avoidance task is divided into three sub-tasks: passing through a door, corridor and wall following, and general obstacle avoidance. This enables the network to respond to the particular features of each task, thereby improving performance. Specific data acquisitions are performed to collect the patterns used to design the neural network for each task. Bayesian framework is then applied to determine the optimal network structures. The training patterns are subsequently used in conjunction with the Bayesian training process to improve the generalisation and performances of each network. Our method was able to successfully accomplish difficult navigation tasks smoothly following a near optimum trajectory.

Furthermore, we developed an adaptive shared control method for an intelligent wheelchair based on the Bayesian recursive technique to assist disabled users when performing obstacle avoidance tasks. Three autonomous tasks have been developed for different types of environments to improve the performance of the overall system. The system combines local environmental information gathered using a laser range finder sensor with the user's intentions to select the most suitable autonomous task in different situations. The evidences of these tasks are estimated by the Bayesian recursive technique during movements of the wheelchair. The most appropriate task that is selected automatically by the wheelchair controller is the one that has the highest value of evidence.

Finally, a method of classifying the environmental model is introduced for this shared control strategy. The features of the environment such as doorways, corridors and walls, and general obstacles have to be recognised. This method is based on the Bayesian neural network to recognise the environmental features from the laser images that were acquired from the onboard sensors. This environmental feature information is one of the main inputs of the adaptive shared control strategy to effectively improve the accuracy of autonomous task selection.

Various experiments are conducted to evaluate the performance of our smart wheelchair system. Eight able-bodied people are recruited, including four males and four females whose ages range from 27 years to 60 years. They have had no experience of driving a

wheelchair before. Three experiments are arranged with increasing difficulties. These users are asked to drive the wheelchair in both manual mode via a conventional joystick and in semi-autonomous mode with the shared control strategy and autonomous obstacle avoidance controller.

The evaluation results show the advantages of our wheelchair's control system compared to the manual control method. Our intelligent wheelchair, which was equipped with a reliable obstacle avoidance method and an effective shared control strategy, was able to successfully accomplish difficult navigation tasks not only by following a near optimum trajectory but also by generating smooth movements (maintaining stable velocities) in different types of environments. It is able to successfully support people with various types and levels of impairment.