Shared Control Strategies for Obstacle Avoidance Tasks in an Intelligent Wheelchair

Hoang T. Trieu, Hung T. Nguyen, *Senior Member, IEEE* and Keith Willey, *Member, IEEE*

***Abstract*—In this paper we present a method of shared control strategy for an intelligent wheelchair to assist a disable user in performing obstacle avoidance tasks. The system detects obstacles in front of the wheelchair using a laser range finder sensor. As the wheelchair moves the information from the laser range finder is combined with data from the encoders mounted in its driving wheels to build a 360º real-time map. The accuracy of the map is improved by eliminating the systematic error that would result from both the uncertainty of effective wheelbase and unequal driving wheel diameters. The usable wheelchair accessible space is determined by including the actual wheelchair dimensions in producing the real-time map. In making a decision the shared control method considers the user's intentions via the head-movement interface, accessible space of the environment and user safety. The experiments show promising results in the intelligent wheelchair system.**

I. INTRODUCTION

Reports show that the number of elderly people and people with disabilities are increasing significantly [1]. 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, intelligent wheelchairs are 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 to both children and adults in their individual lives [2].

Several platforms for intelligent wheelchairs to assist people with disabilities to manoeuvre their wheelchair have previously been reported. These include *Tinman* [3], *Navchair* [4], *SENA* [5],etc. These systems typically consist of a standard power wheelchair integrated with an intelligent computer based system that receives inputs from both the user and sensors. The inputs are used intelligently to assist the user to safely navigate the wheelchair by avoiding collisions while being guided by the user's intentions. However, most of these platforms still require further developments so that can be operated in real-time in dynamic environments.

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Hoang T. Trieu is with Faculty of Engineering, University of Technology, Sydney, Broadway, NSW 2007, Australia (phone: +612-9514-2451; fax: +61 2 9514 2868; e-mail: thtrieu@eng.uts.edu.au).

Hung T. Nguyen is with Faculty of Engineering, University of Technology, Sydney, Broadway, NSW 2007, Australia (e-mail: Hung.Nguyen@uts.edu.au).

Keith Willey is with Faculty of Engineering, University of Technology, Sydney, Broadway, NSW 2007, Australia (e-mail: kwilley@eng.uts.edu.au).

In this paper, we propose a shared control strategy that uses a new method of building a real time map of the local operational environment. The map is constructed by combining information from a laser range finder and encoder sensors mounted on the wheelchair. As the wheelchair moves information from the laser sensor is combined with previously received information, modified using the encoder data, to build a 360º real-time map.

In determining the accessible space our method also considers the actual dimension of the wheelchair. It can eliminate errors from the common approximation of the wheelchair boundary as a circle that may indicate that there is no accessible space to move safely without incurring a collision. This common approximation can be particularly problematic in critical situations such as passing through a narrow space for example a doorway.

The decisions are made from our shared strategy. It combines user's intensions, accessible space of the environment and user safety to provide goal directions. And then an obstacle avoidance neural network generates paths to the goal. Experiments with an intelligent wheelchair system have produced encouraging results.

The paper is organised as follows. The second section covers the building of the real-time map and accessible space. The following two sections introduce the shared control strategy and report our initial experiment results. In the last section we present our discussion and conclusions.

II. REAL-TIME MAP

A. Real-Time Calibrated 360º Map

In this paper, we propose a novel method of building a real time map of the local operational environment using information from a laser range finder and encoder sensors mounted on the wheelchair's driving wheels. The laser range finder sensor is used to collect information about the environment in front of the wheelchair. As the wheelchair moves information from the laser sensor is combined with the stored information modified using the encoders mounted on the driving wheels to build a 360º real-time map. The five steps process is depicted in fig. 1. It is performed in real-time assisting the wheelchair to navigate in a dense and dynamic environment. The result of this method is presented in fig. 2.

The common method of using encoders to estimate the wheelchair's position suffers from the severely inaccuracy of an unbounded accumulation error. This error results from both imperfections in the design, electrical, mechanical implementations (systematic errors) and operating conditions such as wheel slippage (non-systematic errors) [6]. For our case of an indoor wheelchair that travels in even

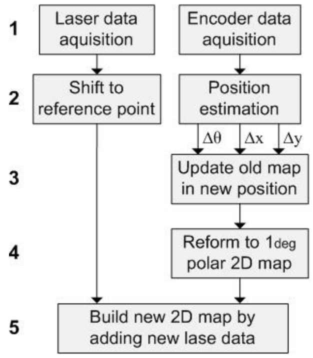

Fig. 1. Five steps to build a 360° real-time map. The procedure is performed whenever the laser data is acquired, every 10 times per sec.

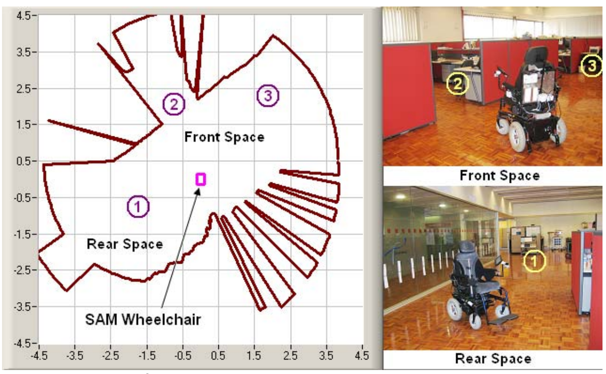

Fig. 2. The 360° real-time map. The front space is explored by laser range finder sensor. The rear space is remembered by encoders.

floors, the most notorious source of errors is typically systematic errors.

Borenstein introduced the University of Michigan Benchmark (UMBmark) to deal with the uncertainty of effective wheelbase and unequal driving wheel diameters, the main contributors to systematic errors [6]. These are caused by errors in the specified diameters of the wheelchair's wheels and the fact that the tyres flatten out so that contact with the floor is not a single point. The spirit of this method is the bi-directional square path experiment, fig. 6a,b. This calibrating procedure is applied for the wheelchair to reduce the error in building the real-time operating map.

B. *Accessible Space Determination (ASD)*

If a motion planner is designed to work in the Cartesian coordinates it would have to perform continually several complicated operations, such as collision checking task. We propose a method that accurately calculates the available space for a mobile vehicle by accommodating the vehicle's actual dimensions. This both reduces computations and identifies more accurately available space by eliminating the errors associated with approximating the vehicle's boundary as a circle. The procedure consists of a number of steps.

1- The obstacle is extended by including the actual wheelchair's dimensions.
2- Update the shortest polar distance to that new obstacle.
3- Perform step 1 and 2 for the entire 360° map to acquire the accessible space.

This method can be easily implemented into either embedded and computer based systems.

III. Shared Control Strategy

A. *Real-Time Obstacle Avoidance Neural Network*

Our Bayesian learning neural network was fist introduced in [7] to perform obstacle avoidance tasks for the intelligent wheelchair system. The inputs of this network are laser data and goal direction and the outputs are steering and velocity to drive the motors, Fig. 3. The Bayesian framework was first applied to determine the most suitable structure of the neural network. The probability of a nominated network structure is given by the equation 2, where H_i is a network and D is training dataset.

$$p(H_i \mid D) = \frac{p(D \mid H_i)\, p(H_i)}{p(D)} \qquad (2)$$

The evidence of the network is calculated by estimating the integration below over the set of network parameters, *w*.

$$p(D \mid H_i) = \int p(D \mid w, H_i)\, p(w, H_i)\, dw \qquad (3)$$

The evidence is estimated using equation 4, [7]. Different network structures are evaluated by comparing their evidences. The optimal network structure being the network with the highest evidence. Using the method the network with 6 hidden nodes to be the most suitable.

$$\ln p(D \mid H_i) = -\alpha_{MP} E_W^{MP} - \beta_{MP} E_D^{MP} - \frac{1}{2}\ln|A| + \frac{W}{2}\ln\alpha_{MP} + \\ + \frac{N}{2}\ln\beta_{MP} + \ln M! + 2\ln M + \frac{1}{2}\ln\frac{2}{\gamma} + \frac{1}{2}\ln\frac{2}{N-\gamma} \qquad (4)$$

This network is then trained by Bayesian framework. This framework can restrict the over-growth of network weights improving network's generalization by evaluating the most probable values of hyper-parameters α^{MP}, β^{MP}

$$\alpha_{MP} = \frac{\gamma}{2E_W^{MP}},\ \beta_{MP} = \frac{N-\gamma}{2E_D^{MP}},\ \gamma = \sum_{i=1}^{W} \frac{\lambda_i}{\lambda_i + \alpha} \qquad (5)$$

where λ_i is the eigen value of the Hessian matrix of network's performance error function. The trained network can be used to control the wheelchair.

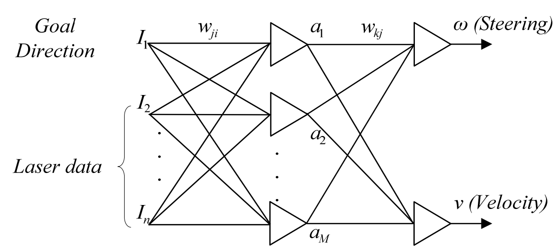

Fig. 3. The obstacle avoidance neural network. The inputs of this network are laser data and goal direction and the outputs are steering (ω) and velocity (v) to drive the motors.

B. *Shared Control Strategy*

Our shared control strategy first combines user's intentions and environment information to determine the navigation directions. A head-movement sensor is used as the user's interface. The 360° real-time map provides information on the operational environment presented as a polar histogram (fig. 5). This continuously updated information improves collision-free wheelchair travel, even in dynamic environments, fig.4.

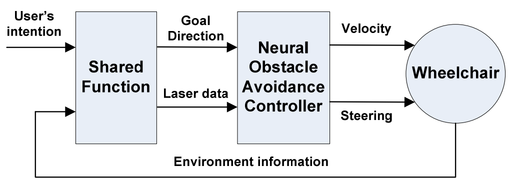

Fig. 4. Shared control strategy.

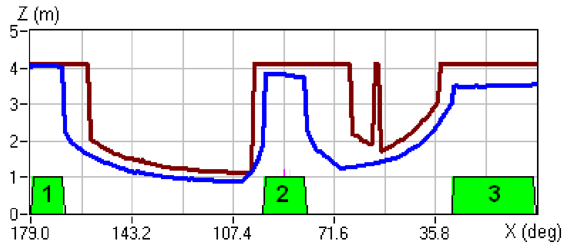

Fig. 5. 2D map (upper line) and accessible space (lower line) histograms of the environment shown in fig. 2. Laser sensor detects a door (2) in front and corridors to the left (1) and right (3).

A cost function is introduced to choose the most suitable free-space (being the one that returns the smallest value for the function C_{share}) when a command I_c, arrives (equation 6).

$$C_{share} = k_1(D_i - I_C) + k_2(D_i - D_C) \quad (6)$$

Where:

D_i: direction to nominated free-space (deg),

I_c: value of user's command: $I_c = \{0^\circ; 90^\circ; 180^\circ; 270^\circ\}$ = {RIGHT; FORWARD; LEFT; BACKWARD} commands,

D_c: current navigating direction (deg),

k_1, k_2: coefficients of terms' relations ($k_1 > k_2$).

The first term chooses the free-space most closely matching the orientation given by the user's command, whereas the second term partially maintains the current direction of travel smoothing the wheelchair's motion when changing direction.

The head-movement interface only outputs commands when provided by the user. To prevent the wheelchair from changing direction, to move to the largest free space, the user's intention must be preserved. To achieve this, another cost function is used. In the absence of a new user command this cost function directs the wheelchair as it moves (and hence observes new free space and or obstacles) towards the free space that most closely resembles the size and direction of the free space selected when the previous user command was received.

$$C_{Tar} = k_3(\Delta B_i + \Delta E_i) + k_4(D_i - D_C) \quad (7)$$

where

ΔB_i, ΔE_i: begin and end boundary differentials of nominated direction to current direction,

k_3, k_4: coefficients of changing size and travel direction respectively (to keep the current direction $k_3 < k_4$)

IV. Experiment Results

A. Real-Time Mapping and Accessible Space Results

The UMBmark calibrating procedure is applied for the wheelchair. To minimise the position error from slippage, the speed of the wheelchair is limited to 0.4(m/s). The calibrating values are estimated as follows,

$D_{eff\text{-}L}$ = 0.350266 (m); $D_{eff\text{-}R}$ = 0.349734 (m);

$L_{eff\text{-}WB}$ = 0.528661 (m),

where $D_{eff\text{-}L}$, $D_{eff\text{-}R}$, $L_{eff\text{-}WB}$ are effective diameters of left and right wheels and effective wheelbase respectively.

The test results using this calibration method are shown in fig. 6. Before calibration, the wheelchair shows a significant error in final position, figure 6a, whereas after calibration the wheelchair tracks the square more accurately (fig. 6b). This result represents a 4-fold increase in accuracy with the average error before calibration being 3.5634m reducing after calibration to 0.8298m.

The calibration method also significantly improves the accuracy of the real-time map. For example, the wall indicated in area A (fig. 6c) for the uncalibrated wheelchair is shown to protrude out into the actual free space area while the same wall after the calibration procedure shown in fig. 6d is more accurately detected.

The calculated accessible free space (for the calibrated wheelchair) is shown in fig. 7. The advantage of accurately interpreting the wheelchair's boundary (fig. 7a) as a rectangle as opposed to approximating it as a circle (fig. 7b) is clearly demonstrated. The rectangular boundary allows the wheelchair to pass through the doorway as it is detected as accessible free space. Conversely the circle boundary fails to

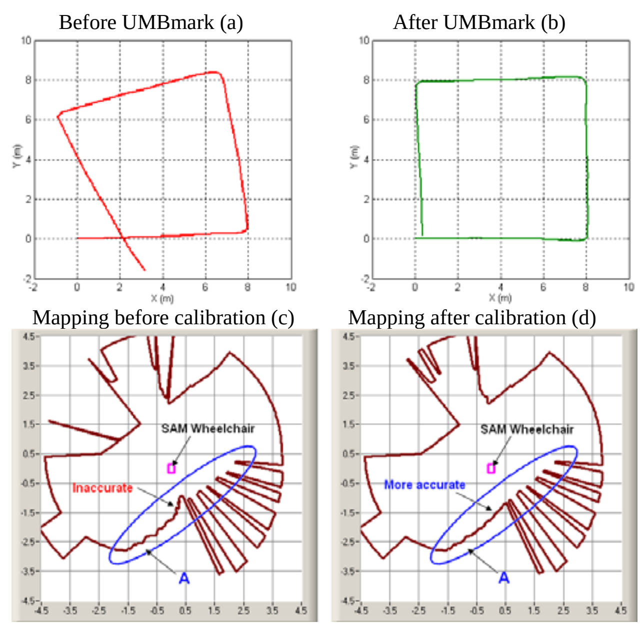

Fig. 6. The calibration results. a and c are results before calibration. The better results of the calibrated wheelchair are shown in b and d.

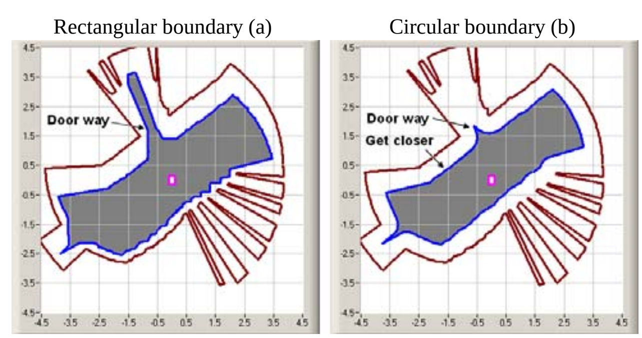

Fig. 7. The accessible space, gray areas. The wheelchair's rectangular boundary provides accurate result of accessible space in a, and b shows accessible space determined by circular boundary approximation.

detect the doorway preventing the user from accessing this space. This accessible space information is fed to the obstacle avoidance neural network.

B. Shared control strategy

The shared control strategy is tested in the wheelchair for a number of tasks by following user's commands including passing through a doorway, following a wall/corridor and entering a narrow area. The results are shown in fig 8 and 9.

The wheelchair, SAM – Semi-Autonomous Machine, starts moving forward at point A after receiving a forward command, fig. 8, traveling in the middle of the corridor. When the laser sensor detects an available space to the right hand side the wheelchair turns slightly towards it. At point B, SAM can see a doorway (left) and a corridor (right). A right turn command drives the wheelchair toward the corridor. On reaching point C if a right turn command is received the wheelchair will pass through the door way otherwise it will continue to follow the corridor to point D.

In fig. 9, the reception of a right turn command at point D drives the wheelchair into the wide dead-end corridor while a forward command at point D drives the wheelchair to point E. At point E the wheelchair is confronted with two open spaces. If a forward command is received the shared control strategy considers it is more likely that the user wants to access the free space slightly to the right. If a left command is received the wheelchair moves to access the narrow corridor on its left.

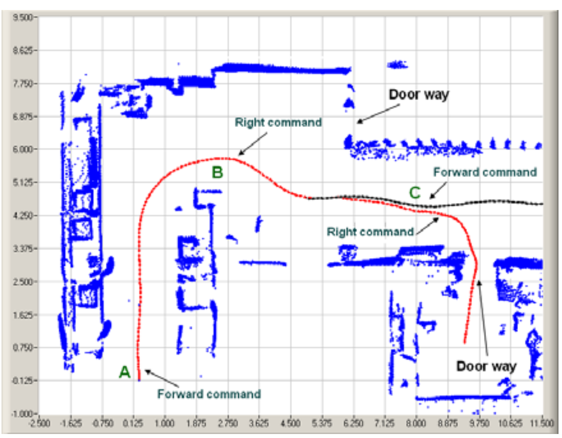

Fig. 8. The wheelchair performs corridor following and passing through a door tasks by following the user's commands.

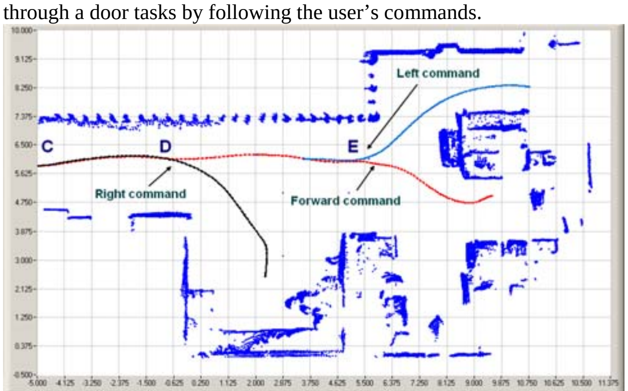

Fig. 9. The wheelchair safely travels along the wall, changes its direction, accesses the narrow space or corridor to adapt to user's commands.

Close examination of SAM's navigated path shows some meandering around the most direct route and that the wheelchair only just fails to collide with the door frame when turning right after point C (fig 8). We are currently exploring using multiple neural networks, each dealing with a specific obstacle avoidance task to improve the overall performance of the SAM system.

V. Discussion and Conclusion

The results demonstrate the real-time map provides an accurate, stable and reliable information source to be used by the wheelchair in performing safe navigation tasks. The application of the calibration procedure contributed significantly to the accuracy of this method. Consideration of the wheelchair dimensions in the free space calculations allows laser range find noise and small un-accessible spaces to be mostly excluded from the real-time map. This feature is particularly useful when using low power laser sensor that tend to suffer from noise when detecting reflective surfaces.

The results of the shared control strategy experiment suggest that one general obstacle avoidance neural network is insufficient to provide optimal performance in all situations. Currently we are developing a system that employs different neural networks designed for specific obstacle avoidance tasks, such as door passing and corridor and wall following. It is hoped that the separate networks will be able to provide a more optimum path in negotiating different tasks than is possible with using one general obstacle avoidance network. In addition, we are exploring the use of a probabilistic reasoning technique such as Bayesian framework [4] to replace the previously discussed cost function to more accurately determine user intentions.

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