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Development of a Bayesian Neural Network to Perform Obstacle Avoidance for an Intelligent Wheelchair

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***Abstract*— This paper presents an extension of a real-time obstacle avoidance algorithm for our laser-based intelligent wheelchair, to provide independent mobility for people with physical, cognitive, and/or perceptual impairments. The laser range finder URG-04LX mounted on the front of the wheelchair collects immediate environment information, and then the raw laser data are directly used to control the wheelchair in real-time without any modification. The central control role is an obstacle avoidance algorithm which is a neural network trained under supervision of Bayesian framework, to optimize its structure and weight values. The experiment results demonstrated that this new approach provides safety, smoothness for autonomous tasks and significantly improves the performance of the system in difficult tasks such as door passing.**

I. Introduction

Commercial electric – powered wheelchairs traced to the 1950s [1] have been providing functional mobility for people with both lower and upper extremity impairments. With the assistance of the wheelchair, these people are capable of moving around their home, going to work or doing their daily tasks independently. However, challenges of safely and independently using their wheelchair can result from various overlapping motor, perceptual, or cognitive impairments such as spinal cord injury, or cerebral palsy. A survey [2] of 200 practicing clinicians indicates that many users have difficulty controlling power wheelchairs. According to the report, nearly half of the people who are unable to control a standard power wheelchair can benefit from the assistance of an intelligent wheelchair.

In the design of an intelligent wheelchair, automatic obstacle avoidance plays a very important function which maneuvers the wheelchair to avoid obstacles while still targeting the goal. Some popular classic obstacle avoidance methodologies were already applied for the intelligent wheelchair application such as potential field [3], or vector field histogram [4]. However, as originally developed for autonomous mobile robots, these methods are far from satisfying all the requirements for a wheelchair system. For instance, the user must feel safe and in control of the wheelchair; the wheelchair's reaction to input must be intuitive enough to inspire confidence and smooth enough for comfortable travel.

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Our intelligent wheelchair has been developed to create a wheelchair system which reduces the physical coordination and cognitive effort required from operating the wheelchair. Based on a standard commercial wheelchair, our wheelchair has been equipped with necessary hardware items such as a portable computer, a laser sensor and assistive navigation system software which assists it in making control decisions related to the user's intention, avoiding obstacles, and performance qualities required to reduce discomfort and provide the user with safety perception.

Like many human-machine systems, our wheelchair is a shared control system which takes advantages of the capabilities of both the human and machine. In our previous work [5], we proposed a method that integrates the human and the machine entity into one unity to navigate the wheelchair based on probability reasoning. In maneuvering the wheelchair, one of the major challenges is of uncertain information which arises both from noise and insufficient measurements of obstacles from the sensors, and inconsistent commands given by the user with disabilities. In our work, the uncertain information is modeled and processed under the Bayesian recursive technique to find the most appropriate direction of travel for the wheelchair.

Being aware of constraints on the behavior of the system for human users, and overcoming shortcomings of existing obstacle avoidance methods, a neural network obstacle avoidance strategy was first proposed for our wheelchair [6]. This method relies on the capability of neural networks to learn how to react in certain difficult situations. After training, the neural network controls the wheelchair to avoid obstacles in real-time. Avoidance maneuvers are automatic and occur in real time. Experimental results have shown that this technique allows the wheelchair to move smoothly through a cluttered environment filled with both moving and stationary obstacles.

The main goal of this paper is to propose and implement an extension of the neural network obstacle avoidance based on Bayesian framework. Instead of calculating free-spaces following the wheelchair dimensions, the network will learn to act based on the raw laser data. This proposal provides safety, smoothness and significantly improves the performance of the system in difficult tasks such as door passing. This paper is organized as follows. An overview of the intelligent wheelchair is provided in Section II. In Section III, a strategy of obstacle avoidance for the wheelchair will be presented. In section IV, experimental results of proposed method are described to demonstrate the performance of the assistive navigation system. Finally, a conclusion of our study is drawn in Section IV.

II. THE INTELLIGENT WHEELCHAIR SYSTEM

A completed hardware description of our intelligent wheelchair is presented in [5, 6]. The wheelchair based on a commercial wheelchair has been modified to attach additional items: a Mac mini computer with 2.66 GHz Core 2 Duo Processor attached behind a chair, user interfaces, and measurement sensors.

User interfaces: Besides a standard joystick, there are a number of a novel user interfaces developed for this intelligent wheelchair including a brain-computer interface (BCI), or a head-movement system which communicate with a computer through NI USB-6008 analog ports or a control system through iPhone 4/iPad employing wireless communication.

Sensors: A laser range finder URG-04LX is mounted in front of the chair to provide information about the distance to the nearest obstacles in the direction of travel. In this application, the sensor is asked to scan a 180^0 front area with maximum radius 4m and angular resolution 1.08^0 in a 10-millisecond loop.

The wheelchair, with this modification, allows the user to operate in both manual mode and assistive mode. By assistive mode operation, the system interrupts the connection between the wheelchair joystick and wheel motor controllers. User interface signals are read by the computer. In this way, the computer can monitor what the user wants the wheelchair to do. Another important information source is the laser-based obstacle detection. The URG-04LX is used to assemble data pertaining to the wheelchair's immediate environment. When they are available, uncertainty of these data is modeled to find the direction of travel where the user is likely to go. Concerned with avoiding obstacles, and other additional requirements, the trained neural network obstacle avoidance makes final decisions about editing the direction of travel and the speed of the wheelchair.

The assistive navigation software is built based on a multithreading technique in Labwindows/CVI platform. All tasks described above are separated into four threads which are performed simultaneously: User interface reading thread, URG-04LX reading thread, Semi-autonomous thread, and display thread. From empirical research, the time interval between executions of the thread without any error is set at 10 milliseconds.

III. METHOD

A. Direction of travel

A set of potential paths for circumnavigation is calculated in a number of ways. One of the methods is to enlarge surrounding obstacles to determine free-spaces [6]. However, the fact that obstacles are extended based on the wheelchair's dimensions, a safe distance, and orientation, makes doorways or narrow paths a challenge. As illustrated in Fig. 1.a, a doorway that is actually traversable by the wheelchair is blocked by extended obstacles. As a result, the wheelchair fails to enter the door. Furthermore, this method is quite complicated and time-consuming due to many calculation steps.

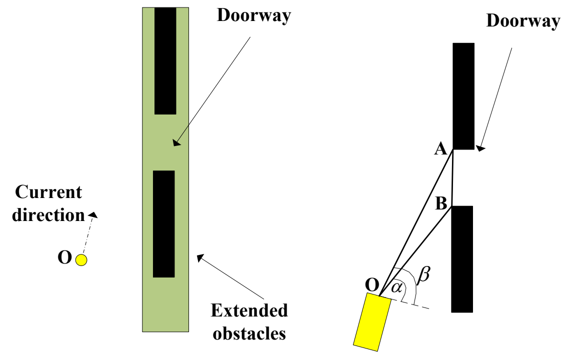

Fig 1. a) The wheelchair at traversable doorway blocked by extended obstacles; b) Determining a potential path

In this paper, the information about surrounding obstacles is used in a direct way to navigate the wheelchair. First, a number of potential paths are determined based on their sizes. As shown in the Fig. 1.b, the wheelchair measures the size of the doorway opening by calculating $AB = \sqrt{OA^2 + OB^2 - 2.OA.OB\cos(\beta - \alpha)}$, if the size is greater than the wheelchair's width size plus a safe distance, it is considered as one of potential paths of travel. These potential paths, then, are combined with a user's command to find the most suitable direction of travel through a Bayesian recursive technique as presented in [5]. This technique uses a probabilistic model to solve uncertainty of signals caused by the limitation of devices and inconsistent commands given by the impaired user.

B. Bayesian neural network obstacle avoidance

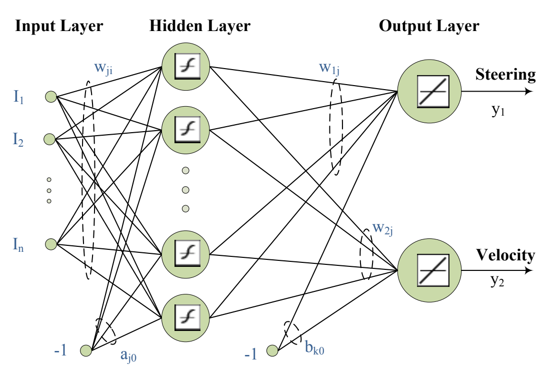

Fig 2. Feed-forward neural network structure for obstacle avoidance

1. Neural network

Fig. 2 shows a feed-forward neural network obstacle avoidance designed to provide a framework for representing non-linear functional mappings between a set of input variables and a set of output variables, 2 outputs corresponding to two electrical signals sent to the motor controller. The input layer, having 37 inputs, includes a direction of travel and 36 inputs of obstacle distances from the laser data. Although the laser data contains 180 data points corresponding to 1 degree resolution, the minimum data point in each 5 degree is chosen as the input value.

$$I_i = \min\{r_{5i+j}\}\ for\ j = 1\, to\, 5$$

The number of hidden nodes is allowed to vary during the training process and Bayesian framework estimates the most probable structure and weight values of the network after training.

2. Bayesian Framework

The Bayesian approach [7], first introduced by MacKay, provides a framework to find the most probable model corresponding to the training data D in automatic fashion. Instead of finding a single set of values of the network weights as maximum likelihood techniques, the Bayesian learning considers Gaussian probability distribution over weight values. In particular, once the training data D has been observed, the posterior distribution of the weights w in network H can be calculated by using Bayes' theorem.

$$p(w \mid D,H) = \frac{p(D \mid w,H)\,p(w \mid H)}{p(D \mid H)}$$

Where *p(D|w,H)* is the likelihood that contains information about the weights from observations and the prior distribution *p(w|H)* contains information about background weight set. The *p(D|H)* is known as the evidence of the network H.

The most probable value for the weight vector w_{MP}, corresponding to the maximum of the posterior distribution, can be found by minimizing a cost function *S(w)*

$$S(w) = \beta E_D + \alpha E_w$$

Where E_D is an error function, E_w is the sum square of weight value, and α, β know as hyper-parameters.

The hyper-parameters are re-estimated until the cost function value ceases to change significantly between consecutive re-estimation periods. After the network training process is completed, the log evidence of network H_i having M hidden nodes is computed as follows [8]

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

The process is repeated for a number of different networks, and the best network is selected with the highest log evidence value.

IV. Experiment Result

1. Training Neural Network

Acquisition experiments are implemented to collect training data. Software built in NI Labwindows CVI 2010 is used for this purpose. The wheelchair is manually driven to follow a number of pre-designed paths by a standard joystick. At the same time, the software collects all surrounding obstacle distances to the wheelchair by using the laser range finder URG-04 LX and control signals from the joystick with 100ms sampling time. Each sampling time, all data from URG-04LX passed through a low pass filter to remove noise, and a desired direction of travel are recorded as input values. Plus two signals from the joystick are recorded as target values. Total samples gathered during the experiment were 1200 and all data were used for training purposes.

It is noticed that the number of pre-designed paths should include various environmental types such as a narrow space, walls, doorways, moving obstacles. Depending on obstacle clearance level, the wheelchair is driven accordingly. For example, when the obstacles are still at a distance, the wheelchair would be driven to be close to the direction of travel and at a high speed. In contrast, when moving between two closely space obstacles such as the posts of a doorway, the wheelchair would decelerate, and be centered with the doorway. In this situation, a slight difference between a steering angle and the desired direction is usually acceptable.

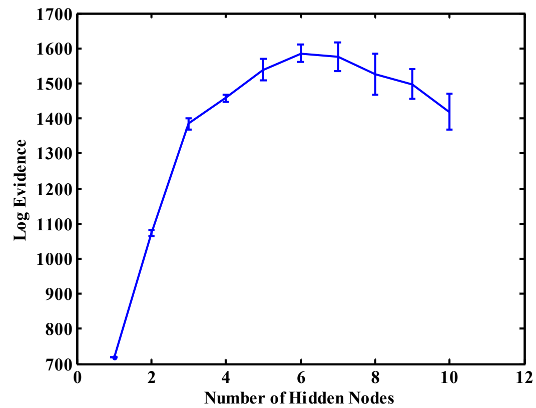

Fig 3. Estimation of log evidence for hidden nodes

A training program based on Bayesian framework was written in Matlab R2009b environment, and the hidden nodes of the network were set to vary from 1 to 10, each network structure was repeatedly trained 3 times for consistency. As shown in Fig. 3, the feed forward neural network architecture with 6 hidden nodes yielded the highest evidence. This structure and its weight values were extracted into a text file, and then loaded into the software to control the wheelchair.

2. Experiment 1

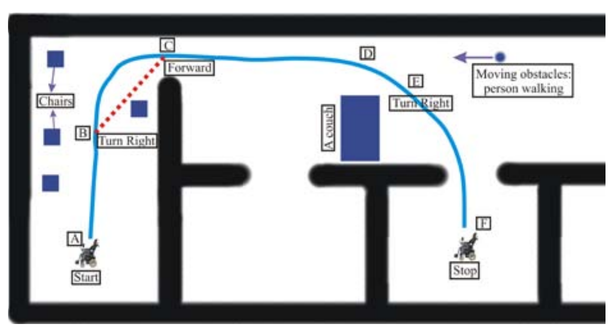

Fig 4.The automated assistive navigation system's performance

Experiment 1 was performed in order to evaluate the performance of the automated assistive navigation system of the wheelchair. The user commands activate the wheelchair to move forward at start, then turn right, forward, turn right again and stop, all through the iphone interface control. The experiment was conducted in the laboratory room in which both static obstacles (walls, chairs, a couch) and dynamic obstacles (person walking) are present. The figure 4 showed the trajectory of the assistive navigation system performance (the blue path). Starting from A, the wheelchair smoothly moves to B with an average speed 0.78 m/s. As a turn right command and a right path are available, the direction BC heading to the middle of the door is determined. However, concerning the distances to obstacles, the neural network obstacle avoidance strategy modified the direction BC to safely avoid obstacles and create a curve to enter the center of the doorway. The speed of the wheelchair in section BC slowly decreased while approaching the door with an average speed 0.34 m/s. After performing section DC parallel to the wall with 0.65 m/s, the wheelchair slightly turns right to avoid the person walking, then enters the next door with an average speed 0.31 m/s.

3. Experiment 2

Another experiment was conducted to demonstrate the ability of the new method to pass between closely spaced obstacles such as a door. In this experiment, a door having a changeable width from 0.65m to 1.2m (the wheelchair's width is 0.64m) was used. For a performance comparison purpose, the wheelchair was steered through the door by three different objects: An experienced human user employing a joystick (assume as a "perfect performance"), the assistant navigation software using the neural network obstacle avoidance based on the laser raw data via iphone interface, and the software using the neural network obstacle avoidance based on the compensate data developed in [6] via iphone interface. Each object repeatedly steered the wheelchair through the door 10 times for each door's width. The percentage of successful passing per each door's width was record in the Fig. 5.

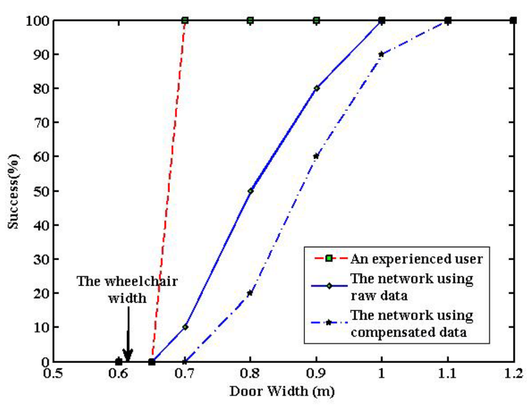

Fig 5.Results of the performance for door passing task

The Fig. 5 showed that, with the new method, the performance of the wheelchair for the door-passing task is significantly improved. The percentage of successful passing increases from 20% to 50%, 60% to 80%, and 90% to 100%, corresponding to door's width 0.8m; 0.9m; 1m, when comparing to the method developed in [6]. This results from the advantages affected by the new method. First, the wheelchair always heads to the door as long as the opening of the door is greater than the chair's width plus a safe distance. With the method using compensated data, the blocked door caused by extended door pots prevents the wheelchair from successfully entering the door during the navigating process. Second, the faster and more accurate response of the new method would make the system more stable and contributes to passing door success.

However, the experiment also shows while an experienced user can consistently steer the wheelchair to pass through the door with small widths (0.7m or greater), the software with the new algorithm still has a low successful percentage of passing with 10% and 50% corresponding to width of the door of 0.7m and 0.8m respectively.

V. CONCLUSION

This paper presents a new approach to reduce computational cost and improve the stability of the algorithm in real-time. The experimental results suggested that the performance of the system with the new approach was significantly improved, especially in difficult tasks such as door-passing. Overall, our wheelchair based on the Bayesian neural network obstacle avoidance strategy has proved its potential as an effective approach to provide independent mobility to people with impairments.

However, there are still unsolved problems. As shown above, the wheelchair is not consistently able to pass through the doorways of the width which is less than 1m. In addition, the laser range finder URG-04LX cannot detect transparent obstacles and only detects obstacles the same height as the sensor. To solve these problems, the current focus of our research is to develop a special neural network obstacle avoidance strategy which is only active to control the wheelchair in narrow spaces like doorways. Also, a combination of the URG-04LX with different types of sensors is being considered to overcome the shortcomings of the URG-04LX.

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