

# A Human-Like Robot Intelligent Navigation in Narrow Indoor Environments

Bin Hua, Endri Rama, Genci Capi, and Mitsuru Jindai

**Abstract**—Fast and automatic detection of the free pathway in a narrow indoor environment is an important task in assistive and autonomous wheelchair robot navigation. Many studies have shown different methods to control the wheelchairs, from joystick to human brain signals. These techniques require a lot of physical or mental work to be done by the disabled people. This paper presents a human-like intelligent robot navigation technique based on neural networks. In the proposed method, the robot has to rely on the Laser Range Finder (LRF) data and camera data to navigate in the narrow environment and to avoid the obstacles. At first, the wheelchair robot is controlled by using a joystick, where the camera and LRF data are collected. The gathered data are used to train the neural controller. The proposed intelligent navigation method is evaluated in real indoor environments with different settings. Experimental results are presented which demonstrate an efficiency and robustness performance of neural network, resulting in a human-like robot navigation.

**Index Terms**—Wheel-chair robot, navigation, indoor environment, neural networks, laser range finder, camera.

## I. INTRODUCTION

Latest studies on the world population have shown a significant increase of population ageing. As shown in Fig. 1, the proportion of persons aged 80 years or over within the older population is increased from 7 percent in 1950 to 14 percent in 2013. According to the medium-variant projection, this proportion is expected to reach 19 percent in 2050 and 28 percent in 2100 [1].

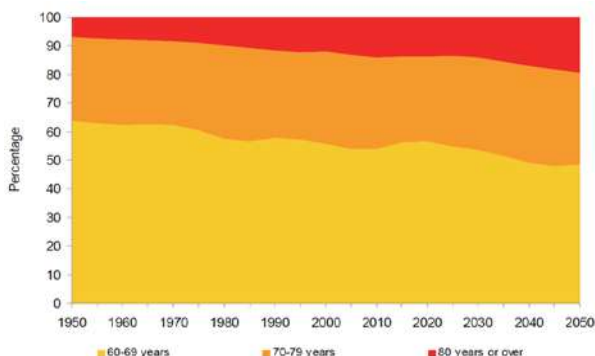


Fig. 1. Distribution of population aged 60 years or over by broad age group: world, 1950-2050.

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As population age, health expenditures tend to grow rapidly, older persons usually require more health care in general and more specialized services to deal with their more complex pathologies. The major disabilities and health problems in old age are non-communicable diseases including: memory loss, falls or immobility, as well as some communicable diseases and injuries.

Regardless how fast the technologies improves, we cannot push back the aging process, but we can provide aged and disable people a good quality of life. This can be done by building assistive robots which makes them easy the everyday life, such as an intelligent wheelchair robot.

Most of the people with immobility problems use the wheelchair in order to move to a specific destination in indoor and outdoor environments. However, they are assisted by other caring person. Therefore, it is important to build intelligent wheelchair robots that can safely navigate and reach goal locations. This means that a robot not only has to be able to move in its environment, but also able to adapt in different types of environments. The intelligent robot must be capable of sensing (perceiving its environment), thinking (planning and reasoning), and acting (moving and manipulating). Before the autonomous robot decides its action, it is necessary to plan it optimally and safely, depending on its task [2], [3]. Also, while planning a collision free path, from a starting point to a target goal, it is necessary to consider some key points, such as: the minimization of time, energy and distance.

Furthermore, while building such intelligent robots, researchers and engineers should consider the usage of low cost sensors and devices, in order that the cost of these robots to be as low as possible.

Many researches in robotics are currently dealing with different problems of motion of autonomous wheelchair robots and motion control of autonomous wheelchair robots in outdoor and indoor environments.

Some researchers have developed different techniques to control the wheelchair, starting from joystick to human brain signals [4]. However, they require a lot of physical and/or mental work to be done by the impaired people.

To solve this problem, different researchers use proximity sensors, such as LRF, camera, Global Positioning System (GPS), and artificial intelligence [5], [6].

The research in artificial intelligence/neural networks is increased dramatically, and has been widely used in many engineering fields [7], [8]. Some researchers use different neural networks to control the robots, and they have shown a good performance [9]. However, the neural network training takes too much time, especially when the training starts from scratch.

In this paper, we develop a human-like robot navigation in narrow indoor environments. We are focused on robot navigation by neural controller, using the LRF data and camera data. The vision system data is considered as a passive sensor and possesses some fundamental advantages over the active sensors such as infrared, laser, and sonar sensors.

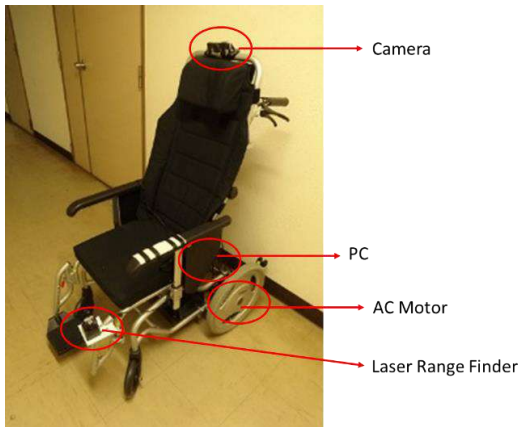


Fig. 2. Wheel-chair robot and sensors.

By using passive sensors such as camera, we can obtain more information than active sensors. Computer vision techniques capable of extracting such information are continuously being developed and more and more real-time vision-based navigation systems for mobile robots are being implemented now.

In our work, we implement the Back Propagation Neural Network (BPNN) in order to learn the human-like robot motion. Initially, a skillful user controls the robot using a joystick. During robot navigation the LRF, camera and robot speed and steering data are collected. Then, BPNN is utilized to map the sensors data to robot action. The BPNN gives a good performance on the robot navigation resulting in a navigation trajectory similar to the user based navigation.

The remainder of the paper is organized as follows. The experimental environments and tasks are presented in Section II. The proposed method is introduced in Section III. Experimental results and analysis are described in Section IV. Finally, conclusions are given in Section V.

## II. EXPERIMENTAL ENVIRONMENT AND ROBOT TASK

In this study, we built an intelligent wheelchair robot, as shown in Fig. 2. It consists of a control PC, one LRF, one camera, two Yamaha AC motors for right and left wheels. The LRF range is 3 meters and the angle between two laser rays is 1 degree. LRF sensor is fixed in the left-front part of the wheel-chair, 37cm from the ground. The control PC is in the back of the wheel-chair robot. The camera is fixed in the upper part of the robot, 120 cm from the ground.

We are focused more on robot navigation in long narrow corridors. The dimensions of the environment where we collected the data are as follows: the length from the starting position to the end of the experimental environment is 12m, and the width is 2.14m.

Fig. 3 represents three environments with different settings, in which we collected the sensors data and then performed the experiments. As shown in the figure, there are different static

obstacles on the robot pathway with different dimensions.

Our wheelchair robot task is to navigate from the starting to the goal position. As mentioned above, in the experimental environment there are different types of obstacles, so while the robot navigates it must avoid the collision.



Fig. 3. Experimental environments.

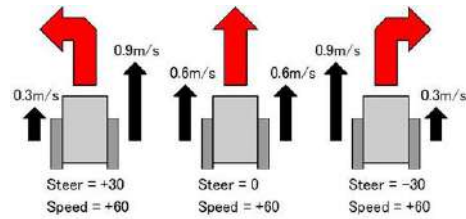


Fig. 4. Rotation speed of the wheel.



Fig. 5. Data collection.

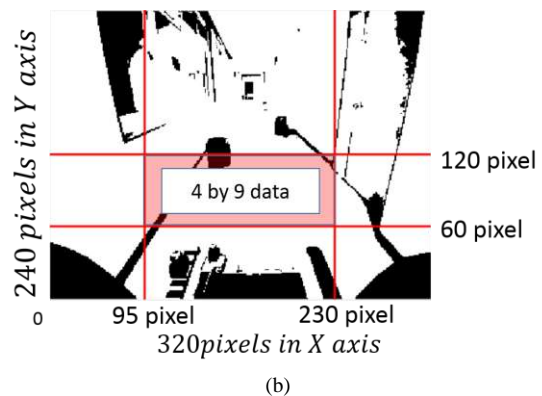
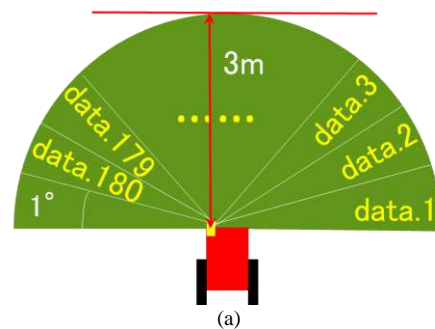


Fig. 6. (a) LRF data and (b) Processed camera image.

## III. ROBOT NAVIGATION CONTROLLED BY NEURAL NETWORKS

### A. Data Collection

Initially, we convert rotation speed of two wheels to two

parameters: speed and steer, as shown in Fig. 4.

The rotation of the left wheel is:  $(Speed - Steer) \times 0.01$ , right wheel is  $(Speed + Steer) \times 0.01$ . The rotation unit is meter per seconds.

Then, by controlling the robot with a joystick in different indoor environments, we collect the LRF sensor, camera and the wheel rotation data (Fig. 5).

As shown in Fig. 6 (a) and (b), we collected 181 laser data from LRF and 36 data from camera, at various locations and orientations within and around the destination position. We recorded the speed and steer data every 0.27 seconds. In total, we recorded 780 data to train the neural networks.

We used a cheap camera which its maximum resolution is 1280 x 640 pixels. However, for our navigation purpose, we collect image data from 95 pixel to 230 pixel in X axis, and from 60 pixel to 120 pixel in Y axis.

This area makes possible to explore the 3 meters length area in front of the robot, which is same distance with LRF. Hereof, we calculate  $15 \times 15$  pixels average value into 1 data. Thus, we collect 9 by 4, 36 data from camera in total.

The RGB camera image is converted to grayscale image, as follows:

$$\text{Grayscale values} = 0.2989 * R + 0.5870 * G + 0.1140 * B$$

The grayscale image is converted into a binary image as shown in Fig. 6 (b).

### B. Neural Network-Based Dynamic Control

At the end of data collection, we performed off line training of different neural networks to find out the best neural network matching for our model.

In the neural network we used the maximum epoch is 20000, learning rate is 0.00001 and the number of hidden layer neurons is 700. During the training process, the relative weights of the connections between nodes are adjusted to reduce differences between teaching data and network output.

In order to compare the human based and neural network navigation, the robot location during navigation is important to be generated. We used a LRF sensor to recognize the robot location during navigation.

The architecture of the neural network is shown in Fig. 7. It consists of three parts: input layer, output layer and hidden layer. The input layer has 217 neurons, hidden layer has 700 neurons and output layer has 2 neurons. We implemented the Back Propagation Neural Network (BPNN) in order to learn the human-like robot motion. In the BPNN, all the input units are directly connected with the hidden units. The output units of the neural network are used to control the steering and speed of the wheel-chair robot.

The activation function of each unit is a sigmoid function as follows:

$$y_i = \frac{1}{1 + e^{-x_i}} \quad (1)$$

where, the incoming activation for node  $i$  is:

$$x_i = \sum_j w_{ji} y_j \quad (2)$$

and  $j$  ranges over nodes with weights into node  $i$ .

The back propagation is used to calculate derivatives of

performance in respect to the weight and the bias variables  $X$ . Each variable is adjusted according to the following:

$$X = X + a * dX \quad (3)$$

where,  $dX$  - is the searching direction value.

$$dX = -gX + dX_{old} * Z \quad (4)$$

$gX$  - is the gradient and  $Z$ , the conjugate gradient, can be computed in several different ways. We used the Polak-Ribière variation of conjugate gradient which is computed as follow:

$$Z = ((gX - gX_{old})' * gX) / \text{norm\_sqr} \quad (5)$$

$\text{norm\_sqr}$  - is the norm square of the previous gradient, and  $gX_{old}$  - is the gradient on the previous iteration [10].

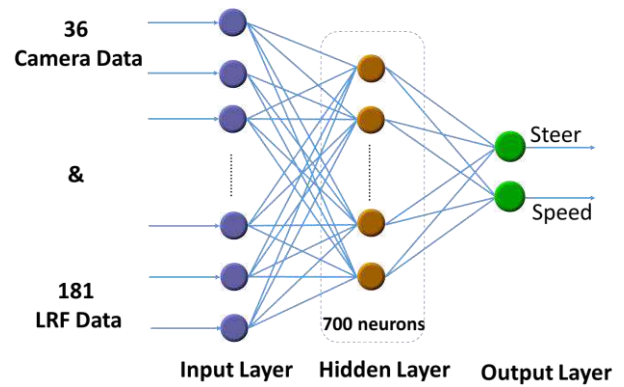


Fig. 7. Neural network architecture.

## IV. RESULTS

The BPNN, which used the Polak-Ribière conjugate gradient updates, shows the best performance to our navigation model, as shown in Fig. 8 (a). The best validation performance is 15.12. In Fig. 8 (b) is shown the gradient descent back propagation training result, where the best validation performance is 265.5872. Fig. 8 (c) shows the performance of the back propagation with Fletcher-Reeves conjugate gradient updates, where the best validation performance is 20.5035.

Therefore, based on the validation performance, we considered the BPNN with the Polak-Ribière conjugate gradient updates to perform our experiments.

After the neural network off-line training we assessed the wheel-chair robot performance in real environments, as shown in Fig. 9. Moreover, in the figure are shown the LRF data and the camera image in different position of the robot during the navigation task.

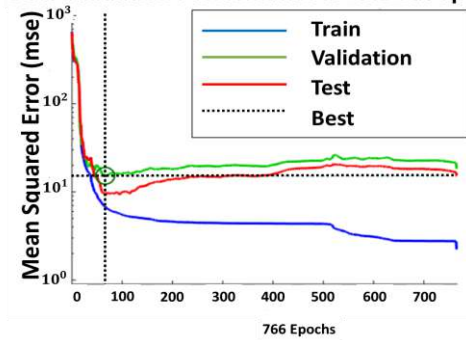
The wheelchair robot moves forward from the starting position toward the goal position with a smooth motion and without hitting any obstacle.

When the robot detects any obstacle, by using its sensors, it changes the direction in order to avoid collisions and continues the navigation. This performance is shown more clearly in Fig. 10. There are shown three environments with different settings and two trajectories of the robot, respectively: the black line show the robot trajectory

controlled by human (with joystick) in training session, the red line show the robot trajectory controlled by neural network. The red and black squares show the real-time position of the wheel-chair in two trajectories.

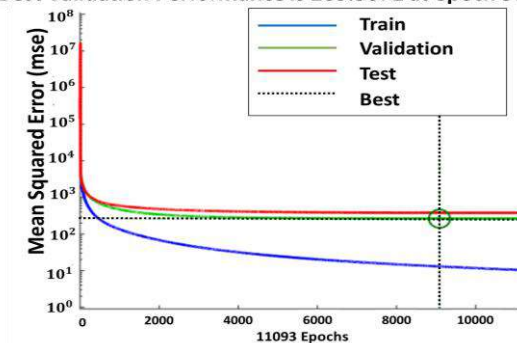
obstacles. The robot performance controlled by neural network is similar with the trajectory of the robot during the training session.

Best Validation Performance is 15.12 at epoch 66



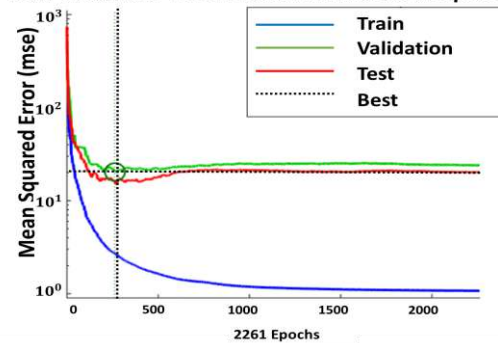
(a)

Best Validation Performance is 265.5872 at epoch 9093



(b)

Best Validation Performance is 20.5035 at epoch 261



(c)

Fig. 8. Neural Network training results.

The wheelchair robot moves forward from the starting position toward the goal position with a smooth motion and without hitting any obstacle.

When the robot detects any obstacle, by using its sensors, it changes the direction in order to avoid collisions and continues the navigation. This performance is shown more clearly in Fig. 10. There are shown three environments with different settings and two trajectories of the robot, respectively: the black line show the robot trajectory controlled by human (with joystick) in training session, the red line show the robot trajectory controlled by neural network. The red and black squares show the real-time position of the wheel-chair in two trajectories.

In the first environment, Fig. 10 (a), the obstacles are in the sideway. The free path is limited between the wall and

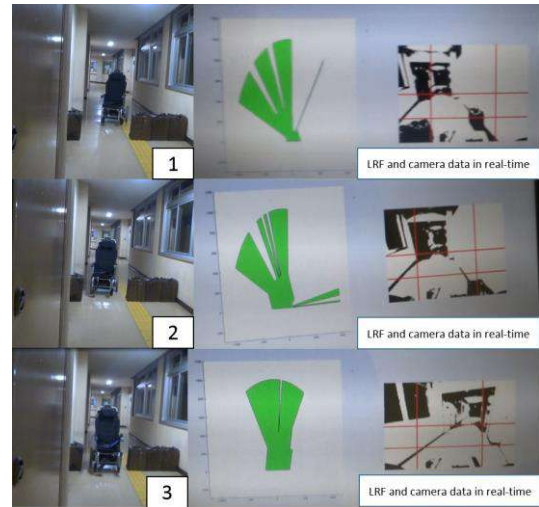


Fig. 9. Wheelchair robot performance in a real environment.

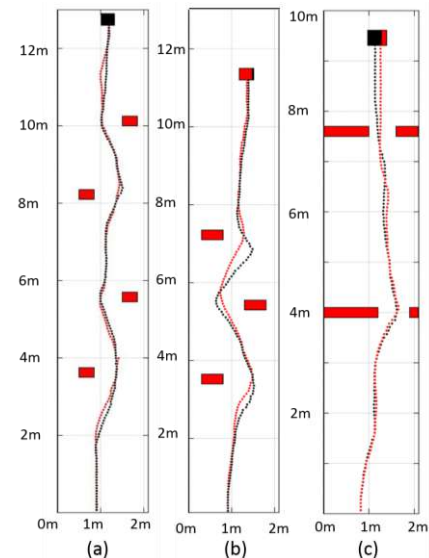


Fig. 10. Robot trajectories in three different environments.

In the second environment, Fig. 10 (b), the obstacles are in the pathway, which makes more difficult for the robot to move forward. During this experiment, the wheelchair robot considers the changing of the steer and speed many times. Comparing the performances of the robot, especially from the 6th m to 8th m of the experiment environment, the wheelchair robot showed a much smoother trajectory, avoiding the obstacles successfully. However, in other parts of the environment the trajectories are quite similar.

Third environment is composed by obstacles in two sides of the pathway, as shown in Fig. 9 (c). Wheelchair robot moved toward the goal position safely and smoothly. The trajectories are almost similar, except the last part of the environment where we got an error around 10 centimeters.

In order to better understand the differences between the performances of the robot during the training session and when the robot is controlled by the neural network, Fig. 11 show the error between two trajectories, for each environment. There are many reasons which affected the robot performances.

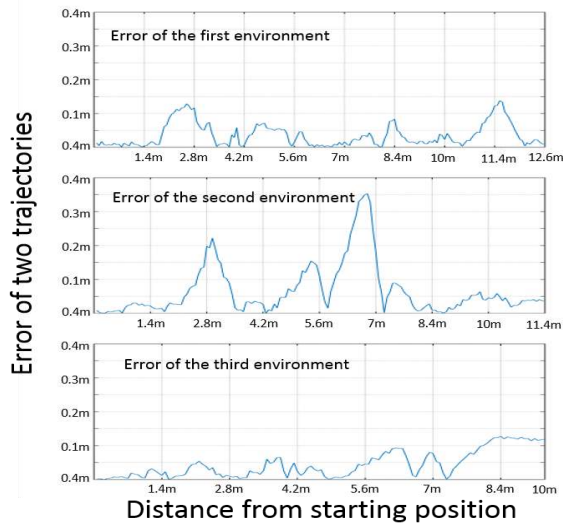


Fig. 11. Error between two trajectories in three different environments.

One of them is the usage of a low cost camera, which is easily affected by the light and shadows during the experiment. The result shows that the robot performed a fast navigation, and which is the most important in this paper, it tries to imitate the human-like robot trajectory.

## V. CONCLUSIONS

In this paper, we compared the performance of different neural controllers for robot navigation in three different indoor environments. First, we collected data from the LRF sensor and camera, and together with the collected steer and speed data we trained the neural network. The results showed that the back propagation neural network, with the Polak-Ribière conjugate gradient updates, gave the best performance.

The robot was able to navigate toward the goal position avoiding hitting the static obstacles. In our experiments, the human-like robot trajectory and the neural controlled robot trajectory almost matched with each other.

In our future work, we will try to do a higher level of image processing in order that the robot not only detect the obstacles but also recognize and gather more information about them. We are also testing our robot in more complex environments.

## REFERENCES

[1] United Nations, Department of Economic and Social Affairs, Population Division, *World Population Ageing 2013*, 2013.  
 [2] S. Thrun *et al.*, "Stanley: The robot that won the DARPA grand challenge" *Journal of Field Robotics*, vol. 36, pp. 1–43, 2007.  
 [3] M. Montemerlo, S. Thrun, H. Dahlkamp, D. Stavens, and S. Strohband, "Winning the DARPA grand challenge with an AI robot," in *Proc. AAAI Conference On Artificial Intelligence*, 2006, vol. 1, pp. 982–987.

[4] M. Mano and G. Capi, "An adaptive BMI based method for real time wheelchair navigation," *International Journal of Innovative Computing, Information and Control*, vol. 9, no. 12, pp. 4963–4972, 2013.  
 [5] G. Capi, M. Kitani, and K. Ueki, "Guide robot intelligent navigation in urban environments," *Advanced Robotics*, 2014.  
 [6] S. L. Phung, M. C. Le, and A. Bouzerdoum, "Pedestrian lane Detection in unstructured scenes for assistive navigation," *Computer Vision and Image, CVIU-15-298R1*.  
 [7] M. Minsky and S. Papert, *Perceptrons: An Introduction to Computational Geometry*, 1969.  
 [8] D. E. Rumelhart, G. E. Hinton, and R. J. Williams, "Learning internal representations by error propagation," *Parallel Distributed Processing: Explorations in the Microstructure of Cognition*, vol. 1, pp. 318–362, 1986.  
 [9] M. Z. Li, G. Capi, T. Oshima, and E. Rama, "Evolution of neural controllers for exploration of dynamic environments," vol. 10, pp. 85–91, 2014.  
 [10] E. Dennis and R. Schnabel, *Numerical Methods for Unconstrained optimization and Nonlinear Equations*, Englewood Cliffs, NJ: Prentice-Hall, 1983.



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