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Design and Implementation of a Nursing-Care Walking Assistant for the Elderly

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Abstract

This paper develops methodologies and techniques for system design and control of a nursing-care walking assistant. Three main topics, including path planning, self-localization and safe navigation, are solved in the paper. A global path planning algorithm based on the criterion of the shortest distance is presented via the dynamic programming method. A self-localization algorithm based on the EKF approach and the minimalistic environmental model is proposed by measurements obtained from a 2-D laser scanner and an odometer. A hybrid navigation approach uses the nature of the reactive navigation together with the identification of the environment model utilizing the 2-D laser scanner, and real-time sensing information from semi-ring ultrasonic ranging finders. Numerous simulations and experimental results are conducted to verify the efficacy and usefulness of the proposed methods.

Keywords: Dynamic programming**,** hybrid navigation, laser scanner, path-planning, navigation, self-localization.

1. Introduction

With the advent of medical science and technology, the number of the elderly people over sixty-five years old is increasing year by year; it is predicted that, in Taiwan, the population of the senior citizens over 65 years old is 9% by the year 2005, and will be 15% by the year 2020. Thus, many governments over the entire world have been attempting to find many alternatives to assist and help the elderly people willing to live in their homes where makes elderly feel private, safe, comfortable and convenient. Among these alternatives, nursing-care and home-care mobile robots are regarded as powerful means to accomplish this goal [1-2].

There are a lot of referred papers and reports concerning with how to apply intelligent control methods for autonomous mobile robots. The dynamic programming approach has been shown capable of providing a global optimal solution for the optimal path planning problem [4]. This paper will employ the dynamic programming approach based on shortest distance to find the optimal path planning. Wong [5] developed methodologies for pose tracking and pose initialization method of a wheeled mobile robot with laser scanning technology. Jensfelt and Christensen [6] presented a Kalman filter-based approach utilizing 2-D laser scanner for pose-tracking of a mobile robot. In this paper, we will propose an extended Kalman filter approach combining with the least square approach to keep trace of the current pose of a nursing-care walking assistant. The concept of hybrid navigation was first introduced by Mandow et al. based on high-level fuzzy path planning and low-level reactive behavior-based control. Gachet et al. [7] suggested a distributed neural network approach to achieve reactive navigation. Lee and Wang [8] proposed the ultrasonic module of detecting the moving obstacles, and then combined a fuzzy obstacle avoidance rule for developing a simple multisensor-based behavior. Ye and Yung [9] presented a navigation strategy based on the behavior fusion method, which performs well in complex and unknown environments through a virtual world simulation. Lai [10] proposed a double fusion policy of fuzzy behavior-fusion control. As the authors' best understanding, the hybrid navigation method based on laser scanner and ultrasonic sensors has not been done yet. Chiu [11] presented a fuzzy hybrid navigation approach for a mobile robot.

The important function of the nursing-care walking assistant for the elderly is to assist the elderly to walk from one position to another position. Such a robot guides the elderly to move along with a designed path. In doing so, the localization of the vehicle, optimal path planning and safe navigation method will be three main core technologies. The contributions of this paper are to construct a complete nurse-caring walking assistant system with multiple sensors, design a dynamic programming approach for finding a global optimal path, use an extended Kalman filter approach with least square approach to track the pose of a nursing-care walking assistant. Finally, we employ the fuzzy hybrid navigation fuse laser scanner and ultrasonic sensors to guide the elderly people safely reach the desired destination.

The remainder of the paper is organized as follows. Section 2 describes the physical configuration of the nursing-care walking assistant system. Section 3 briefly describes the dynamic programming path planning. In Section 4, a map-based self-localization

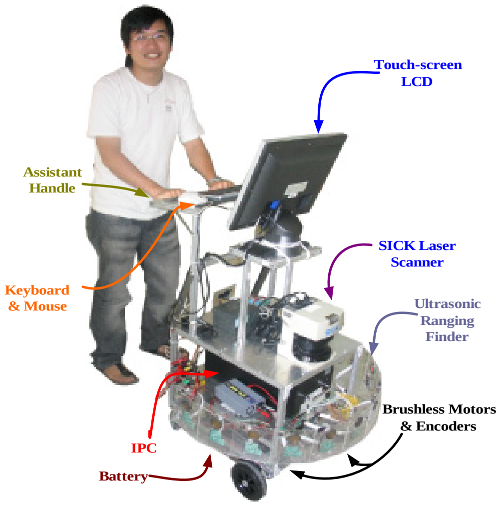

Figure 1. Physical configuration of the proposed nursing-care walking assistant system

method of the nursing-care walking assistant using laser scanner and an odometer is presented. Section 5 proposes the fuzzy hybrid safe navigation approach utilizing cooperation/competition coordination models and environment information. Section 6 concludes the paper and presents some interesting topics for future study.

2. Description of the Nursing-care Walking Assistant

Figure 1 shows the control architecture of the nursing-care walking assistant and control system whose mobile platform is based on the basic structure of a wheeled vehicle. There are two motors mounted on the right and left wheels, thereby giving rise to differential driving motion. The vehicle can move only on any even terrain. The length of the vehicle is 55cm, the width 44cm, the height 100cm, and the weight 50kg. The walking assistant comprises five parts: the power management module, the IPC-based computational unit, the motion control system, ultrasonic ranging system and the laser scanning system.

The main function of the motion control system is to provide precise PI velocity control for the two DC 24V brushless motors. Two internal encoders of the motors are used to obtain the speed and traveling distance of the vehicle. Two quadrate pulses, ϕ_A and ϕ_B, are further processed by a fast counter and then sent out the motor's velocities and rotation directions to the industrial IPC via an 8255 digital interfacing card. The industrial PC uses the dead-reckoning method to find the current position and orientation of the nursing-care walking assistant.

The vehicle drivers and IPC require a DC 24V power offered by two serial DC 12V batteries. The batteries must have sufficient power to drive the two brushless motors. This DC 24V power supply delivers a maximum DC current of 15.5A. The laser scanner subsystem requires also an AC 110V power that is obtained from the AC power inverter with an input of DC 12V. The ultrasonic ranging module is supplied by 12V

The Laser Measurement System (LMS) is a non-contact measuring system, which scans its two-dimensional surroundings. The LMS is based on a time-of-flight measurement principle. A single laser pulse is emitted and reflected by an object surface within the range of the sensor. The elapsed time between emission and reception of the laser pulse serves to calculate the distance between any object and the LMS. The laser scanner does not need any reflectors to function as a scanning system. The laser pulses sweep a radial range in front of the LMS platform via an integrated rotating mirror.

The FPGA-based ultrasonic ranging subsystem is used to provide the vehicle about its surrounding obstacle information. The ultrasonic modules are simultaneously controlled by the IPC through an 8255 card and they are arranged in a back-to-back manner in order to receive signals with minimum noise and to increase shoot frequencies. The FPGA-based control board counts the ultrasonic TOFs. The three TOF values are stored every shoot and then passed on to IPC via the 8255 digital interfacing card.

3. Global Path Planning

This section considers the problem of planning optimal paths for a mobile robot traveling in a known environment. To solve the optimal path problem, we use a dynamic programming approach. The dynamic programming approach utilized herein does not suffer the difficulties associated with virtual local minima that the artificial potential field approach do. In fact, a globally optimal solution is guaranteed found via dynamic programming. In order to enable having a best route from any node to terminal point, the algorithm notes down the node that the best the next one linked for each node. The dynamic programming method is to begin from terminal point, search to the starting point direction. It notes down the best next route to the destination for each passing node. When this reverse searching method reached the starting point, all nodes have been already noted down its best next node to the destination and the searching algorithm is terminated. Therefore, we just only advance towards the next node that is noted down step by step from the starting node, we can find an optimal route.

Our optimal path planning algorithm is based on the shortest distance criterion. To do so, define the following cost function

$$MinDistance(v) = \min_{u \in \delta(v)} \{w(v,u) + MinDistance(u)\}$$

where MinDistance is the shortest distance of the node up till now; u is the previous node and v is the current node; $\delta(u)$ is the set of nodes in close proximity to node v; $w(v,u)$ is the distance from node v to u.

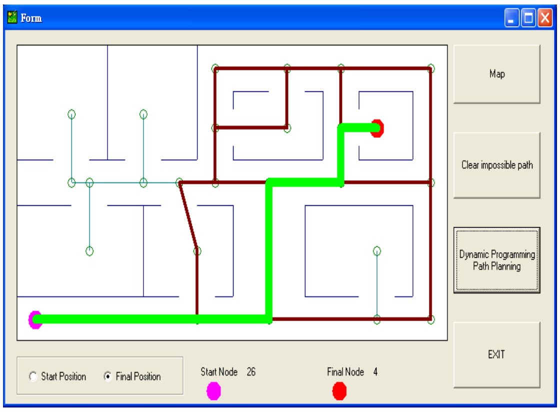

Figure 2. Experimental results of the proposed method for showing the findings of the optimal path via dynamic programming.

Figure2 shows the found optimal path highlighted by green color using the dynamic programming.

4. Map-based Self-Localization Using Laser Scanner

In this section, we will discuss the problem of developing methodologies and techniques for pose-tracking of a nursing-care walking assistant using a 2-D laser scanner. In our application the initial estimate of the nursing-care walking assistant pose and environment model are known, and we use an extended Kalman filter (EKF) to update the estimate of the nursing-care walking assistant pose. In addition, we use a kind of validation gate to filter out the noise and to match measured information with the environment model in order to enhance measured precision. Furthermore, we adopt a least-squares method to extract the parameters of the modeled walls from the have already classified data.

4.1 Self-Localization Algorithm Using Laser Scanner

This subsection describes the measurement model using the well-known extended Kalman filter (EKF) framework and how the wall features are represented and extracted. This method integrates more than two kinds of sensors; one is the odometer, and other is the laser scanner employed to extract the features of environment. Figure 2 displays a block diagram of a general feature-based pose tracking algorithm. The odometer gives information about the relative motion of the nursing-care walking assistant. The feature-based localization can be divided into three parts to update. The raw data from ranging sensors are clustered and matched according to the environment model and a priori pose estimate. Afterward, we extract the parameters of features from the matched data, and then compare with the parameters of predicted features. Finally pairs of extracted and predicted features through the EKF to update the pose estimate. In this chapter, we have two measurements from the odometer and the laser scanner to localize the nursing-care walking assistant, and employ the walls as the features of environment.

In a feature-based pose tracking algorithm, the feature extraction is a very important task for the subsequent state updating algorithm. Due to we use walls as features of environments, and lines can be used to describe the walls. We express a line equation with the two parameters ρ and α as

$$\rho = x\cos\alpha + y\sin\alpha \tag{1}$$

By using the well-defined parameters of a line: ρ, the perpendicular distance from nursing-care walking assistant to the line, α, the orientation of the normal.

The data which concluded with noise will be very difficult to extract the information we wanted. Validation gate method is a common way to handle this kind of problem. A validation gate defines an acceptable region around the predicted value in each measurement will be associated to the corresponding feature. The validation region is described by the four-tuple

$$G = (\hat{\rho}, \hat{\alpha}, \delta, \gamma) \tag{2}$$

where $\hat{\rho}$ is the predicted distance to the wall and $\hat{\alpha}$ is the predicted angle of the normal to the wall, δ is the smallest width of the gate and γ is the opening angle. The region of each validation gate is defined by the pairs of parameters (δ, γ).

The following least-squares algorithm is proposed to fit the measured data to an estimated straight line by minimizing the sum of squared errors between the estimated points and the perpendicular distance to the wall. In doing so, let the distance d_i from the valid measurement (r_i, ϕ_i) to the line parameters (ρ, α)

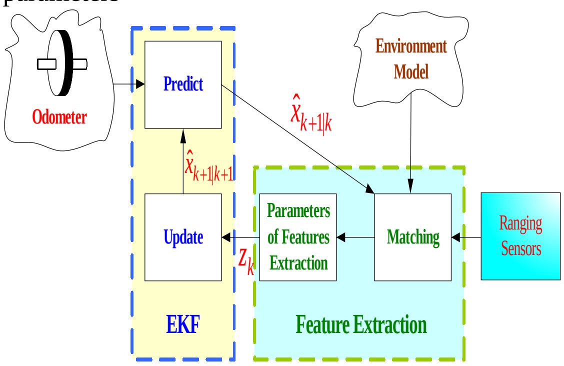

Figure 2. Block diagram of the feature-based pose estimation.

be given by

$$d_i = r_i \cos(\phi_i - \alpha) - \rho \tag{3}$$

and the best fit (ρ, α) is thus given by

$$\arg(\rho,\alpha)\min\sum_i (r_i\cos(\phi_i-\alpha)-\rho)^2 \tag{4}$$

The solution of the optimal (ρ,α) is easily obatined from

$$\begin{cases} \dfrac{\partial \sum_{i=0}^{n-1}[r_i\cos(\phi_i-\alpha)-\rho]^2}{\partial\rho}=0 \\ \dfrac{\partial \sum_{i=0}^{n-1}[r_i\cos(\phi_i-\alpha)-\rho]^2}{\partial\alpha}=0 \end{cases} \tag{5}$$

which leads to the sequel best solution

$$\rho=\frac{1}{n}\sum_{i=0}^{n-1} r_i\cos(\phi_i-\alpha) \tag{6}$$

$$\tan(2\alpha)=\frac{\sum_{i=0}^{n-1} r_i^2\sin 2\phi_i-\sum_{i=0}^{n-1}\sum_{j=0}^{N-1}\frac{1}{N}r_i r_j\sin(\phi_i+\phi_j)}{\sum_{i=0}^{n-1} r_i^2\cos 2\phi_i-\sum_{i=0}^{n-1}\sum_{j=0}^{N-1}\frac{1}{N}r_i r_j\cos(\phi_i+\phi_j)}$$

$$\alpha=\frac{1}{2}A\tan 2(q/p) \tag{7}$$

where p and q represent the denominator and numerator respectively. Finally, we get the line parameters (ρ,α). In addition, if the statistical relationships between (ρ_i,α_i) and (ρ_j,α_j) ,for $i\neq j$, are independent, then the covariance matrix of the line parameters is given by

$$\begin{bmatrix}\sigma_\rho^2 & \mathrm{cov}(\rho,\alpha)\\ \mathrm{cov}(\alpha,\rho) & \sigma_\alpha^2\end{bmatrix}=\begin{bmatrix}\frac{\partial\rho}{\partial r} & \frac{\partial\rho}{\partial\phi}\\ \frac{\partial\alpha}{\partial r} & \frac{\partial\alpha}{\partial\phi}\end{bmatrix}\begin{bmatrix}C_r & 0\\ 0 & C_\phi\end{bmatrix}\begin{bmatrix}\frac{\partial\rho}{\partial r} & \frac{\partial\rho}{\partial\phi}\\ \frac{\partial\alpha}{\partial r} & \frac{\partial\alpha}{\partial\phi}\end{bmatrix}^T \tag{10}$$

where $C_r=diag(\sigma_{ri}^2)$ and $C_\phi=diag(\sigma_{\phi i}^2)$.

After accomplishing the line extraction, we use the well-known Extended Kalman Filter to fuse the internal position estimation and external measurements to the features. Since the initial pose of the nursing-care walking assistant is known, the priori pose information and the environmental model can be adopted to update the nursing-care walking assistant pose estimate through the EKF-based pose-tracking algorithm is proposed.

The kinematics model of the wheeled mobile robot with pure rolling can be described by the following discrete-time nonlinear state equation:

$$X(k+1)=f(X(k))+W(k) \tag{11}$$

or,

$$\begin{bmatrix}x_c(k+1)\\ y_c(k+1)\\ \theta(k+1)\end{bmatrix}=\begin{bmatrix}x_c(k)+\Delta d\cos\theta(k)\\ y_c(k)+\Delta d\sin\theta(k)\\ \theta(k)+\Delta\theta\end{bmatrix}+\begin{bmatrix}w_x(k)\\ w_y(k)\\ w_\theta(k)\end{bmatrix} \tag{12}$$

where $\Delta d=\Delta T\cdot v_c$, $\Delta\theta=\Delta T\cdot w_c$, ΔT is the sampling interval, v_c and w_c is the linear and angular velocities of the robot, respectively. The process noises $w_x(k)$, $w_y(k)$ and $w_\theta(k)$ denote the uncertainties due to the wheel slippage, surface roughness, etc., and they are modeled as uncorrelated zero-mean white Gaussian processes with covariance matrix

$$Q(k)=diag\{\sigma_{wx}^2,\sigma_{wy}^2,\sigma_{w\theta}^2\}.$$

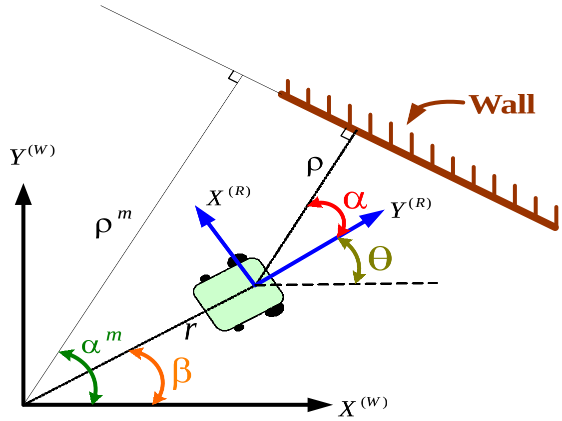

Figure. 3. The parameters definition of a wall.

4.2. Measurement Model

For the pose estimate in an extended Kalman filter framework, we need to predict the parameters of the walls to be extracted from the current state of the robot and the environmental model. Therefore two parameters ρ and α are considered to be measurements in the EKF framework. A wall measurement equation can be modeled as

$$z(k)=h(x(k))+v(k) \tag{13}$$

or,

$$\hat{z}_i=\begin{bmatrix}\hat{\rho}_i\\ \hat{\alpha}_i\end{bmatrix}=h_i(X,M)+v_i \;,\; i=1,2,\ldots,N \tag{14}$$

where v_i is the measurement noise, M denote the model of the walls and subscript i represents the ith walls. The measurement function $h_i(X,M)$ can be expressed by

$$h_i(X,M)=\begin{bmatrix}\rho_i^m-\sqrt{x^2+y^2}\cos(\alpha_i^m-\beta)\\ \alpha_i^m-\theta\end{bmatrix} \tag{15}$$

where ρ_i^m is the distance to the ith modeled wall with respect to the world coordinate system and α_i^m is the corresponding angle. Figure 3 shows an illustration of the parameters defining a wall, where r is the distance between the current poses of the robot and the origin of the world coordinate system, and β is the corresponding angle.

The measurement function can be expressed as the following linear term:

$$z_i=H_i X+m_i \tag{16}$$

where the Jacobian matrix H_i with respect to the state X is given by

$$H_i = \left.\frac{\partial h}{\partial X}\right|_{X=\hat{X}(k/k-1)} = \begin{bmatrix} H_{11} & H_{12} & 0 \\ 0 & 0 & -1 \end{bmatrix} \quad (17)$$

where the elements of H_i are given by

$$H_{11} = -\frac{x}{r}\cos(\alpha_i^m - \beta) - \frac{y}{r}\sin(\alpha_i^m - \beta) \quad (18)$$

$$H_{12} = -\frac{y}{r}\cos(\alpha_i^m - \beta) + \frac{x}{r}\sin(\alpha_i^m - \beta) \quad (19)$$

Note that $r = \sqrt{x^2 + y^2}$, $\beta = \arctan\left(\frac{y}{x}\right)$

4.3 Extended Kalman Filter Algorithm

In order to obtain the best pose estimate of the mobile robot, a discrete-time extended Kalman filter algorithm is briefly proposed as follows:

Step 1: At the time $k = 0$, select a good estimate $\hat{X}(0/0)$ and an initial error covariance matrix $\tilde{P}(0/0)$, where $E\{X(0/0)\} = \hat{X}(0/0)$

$$E\left\{\left|X(0) - \hat{X}(0)\right| \cdot \left|X(0) - \hat{X}(0)\right|^T\right\} = \tilde{P}(0/0)$$

Step 2: Let the optimal estimate of $X(k)$ at time k be $\hat{X}(k/k)$ and its error covariance matrix be $\tilde{P}(k/k)$. Use Eqs. (20) and (21) to calculate the best prediction, $X(k+1/k)$ and its propagation error covariance $\tilde{P}(k+1/k)$

$$\hat{X}(k+1/k) = f(\hat{X}(k/k)) \quad (20)$$

$$\tilde{P}(k+1/k) = F(\hat{X}(k/k)) \cdot \tilde{P}(k/k) \cdot F(\hat{X}(k/k))^T + Q(k) \quad (21)$$

where
$$F(\hat{X}(k/k)) = \left.\frac{\partial f(X(k))}{\partial X(k)}\right|_{\hat{X}(k/k)} = \begin{bmatrix} 1 & 0 & -\Delta d\sin\theta \\ 0 & 1 & \Delta d\cos\theta \\ 0 & 0 & 1 \end{bmatrix} \quad (22)$$

Step 3: At time k+1, the location system reads the measurement data $Z(k+1)$ and then uses Eqs. (23) and (24) to obtain the updating estimate $\hat{X}(k+1/k+1)$ and the error covariance matrix $\tilde{P}(k+1/k+1)$

$$\hat{X}(k+1/k+1) = \hat{X}(k+1/k) + K(k+1)\cdot\left[Z(k+1) - h\left(\hat{X}(k+1/k), M\right)\right] \quad (23)$$

$$\tilde{P}(k+1/k+1) = \left[I - K(k+1)_i \cdot H_i\right]\cdot\tilde{P}(k+1/k) \quad (24)$$

$$K(k+1) = \tilde{P}(k+1/k)\cdot H_i^T\left[H_i \cdot \tilde{P}(k+1/k)\cdot H_i^T + R(k+1)\right]^{-1} \quad (25)$$

where
$$H_i = \left.\frac{\partial h}{\partial X}\right|_{X=\hat{X}(k/k-1)} = \begin{bmatrix} H_{11} & H_{12} & 0 \\ 0 & 0 & -1 \end{bmatrix} \quad (26)$$

Step 4: Repeat *Step* 2 to *Step* 3.

4.4 Experimental Results and Discussion

This subsection aims to examine the feasibility and efficiency of the proposed self-localization algorithm through experiments. The experiments built an F-style environment model composed of 10 flat walls, which using 10 straight lines to represent. These parameters of environment model are shown. Assume the initial state be $\hat{X}(0/0) = [30, 50, 30^\circ]^T$ and the ranges of the validation gate be $\delta = 3$cm, $\gamma = 2^\circ$.The walking assistant started at the pose

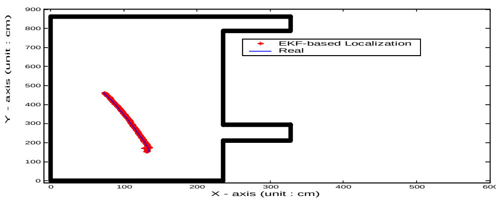

Figure 4 The x-y robot trajectory and the experimental environment.

$(133.5, 153, 90^\circ)$ and then passed through the via-point $(133.5, 180)$ toward the direction 102° to reach the final pose $(74, 463, 102^\circ)$. The motion trajectory with respect to the world coordination is depicted in Figure 4.

5. Safe Navigation.

One of the ultimate goals of the nursing-care walking assistant is to let the vehicle safely carry out its missions in its dynamic, clustered and populated environments. In other words, walking assistant should be able to react rapidly to unexpected changes, and still perform its task continuously. In general, there are three types of navigation: planned navigation, reactive navigation and hybrid navigation. The main function of the planned navigation is to guide the robot to track the planned path. This type of navigation relies on accurate and unchanged models of the environments, and therefore such a function will be influenced if unexpected obstacles block on planned path. The reactive navigation uses an accurate self-localization system and works with several built-in behaviors to steer the robot to move smoothly from any starting pose to any final pose. Nevertheless, owing to the reactive navigation has not environment information, so that the robot may take a roundabout way. Compared with planned navigation, reaction navigation seems to be more flexible from the starting pose to final pose, and planned navigation always follows the planned route while reactive navigation can have different routes. Hybrid navigation is the integration of low-level reactive behaviors and high-level planning in order to complement mutually the shortcomings of these two navigation methods.

This chapter aims to use fuzzy control methods to establish the two basic behaviors of the nursing-care walking assistant, including goal seeking and obstacle avoidance behaviors, and employ the two basic behaviors to accomplish fuzzy hybrid navigation control for the nursing-care walking assistant. The goal-seeking behavior is synthesized based on the laser scanning readings and the environment model and the obstacle-avoidance behavior is constructed according to the ultrasonic data. How to develop a behavior fusion method to control the vehicle to complete the navigation task is a keystone for designing a hybrid navigation control. A fuzzy cooperation/competition coordination approach is developed to cope with multiple ultrasonic data so as

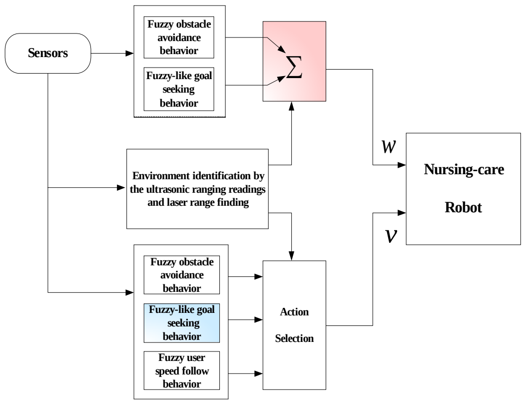

Fig. 5. Block diagram of the hybrid navigation for the nursing-care walking assistant.

to fuse goal-seeking and obstacle avoidance behaviors to generate a suitable or emergent behavior, making the nursing-care walking assistant move smoothly in a dynamic, complicated and cluttered environment. The hybrid navigation method is presented to steer the robot to reach the final pose in an appropriate route by changing fusing behaviors via identification of the environment model from the laser scanning measurements. Fig. 5 illustrates the basic ideas to use the fuzzy hybrid navigation to control the nursing-care walking assistant. That uses the ultrasonic ranging readings and laser range finding to identify the surrounding environment, and employs the behaviors fusion method to inference the output variables v and w.

6. Conclusions

This paper has developed system configuration and control methodologies for the nursing-care walking assistant to assist the elderly safely move towards any destination that the elderly want to go. Such results is divided into three main problems.

The first main problem comprises two parts: the first one is the decision of destination which is usually determined by a user; the second one is the problem of path planning. This paper has proposed a user-friendly operation interface that provides users easy to determine the destination and find out the optimal path. The optimal path planning algorithm is based on the shortest distance criterion and the dynamic programming approach. The simulation results have demonstrated that dynamic programming can be capable of obtaining the optimal path for a mobile robot traveling a known environment.

The second main problem means the problem of localization. To do so, we used a well-known EKF to keep trace of the current pose of the nursing-care walking assistant, which fuses a 2-D laser scanner and odometer information based on the minimalist rectangular model.

The third main problem expresses safe navigation that aids the elderly to walk towards the destination without collision. The fuzzy hybrid navigation method is presented for the nursing-care walking assistant, comprising goal-seeking behavior and obstacle-avoidance behavior. The hybrid navigation method is shown useful in steering the nursing-care walking assistant to reach the final pose in an adequate route by changing fusing behaviors via identification of the environment model. Experimental results are conducted to illustrate the efficacy of the proposed hybrid navigation method.

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