Behavior-Based Navigation Using Heuristic Fuzzy Kohonen Clustering Network for Mobile Service Robots

Ching-Chih Tsai, Chin-Cheng Chen, Cheng-Kain Chan, and Yi Yu Li

Abstract

This technical note presents a behavior-based navigation method for a mobile service robot with a three-wheeled omnidirectional mobile platform. A heuristic fuzzy Kohonen clustering network (FKCN) is presented to obtain laser area weights and desired robot motion heading for all types of indoor environments. An efficient behavior-based navigation structure is then proposed to merge the heuristic FKCN with three fuzzy behaviors in order to navigate the robot without any collisions in crowded and cluttered indoor environments. Simulation and experimental results are conducted to verify the feasibility and effectiveness of the proposed method.

Keywords: Behavior Navigation, fuzzy Kohonen clustering network (FKCN), Mobile robot, Omnidirectional.

1. Introduction

Recently, it has been a promising trend that people have mobile service robots which can help them in their daily life in order to make their life comfortable, easy and convenient. Over past decades, omnidirectional mobile platforms have been proven useful and effective in various applications, such as material handling, home service, nursing-care, entertainment, medical equipment and etc. One of the main reasons is that omnidirectional mobile robots are capable of moving to any positions and attaining desired orientations simultaneously. With these benefits, several mobile service robots with the kind of omnidirectional mobile platform have been constructed and used to coexist with people. Such mobile service robots are designed to be particularly helpful and pragmatic in cluttered and crowded indoor environments because the indoor working space with some indoor facilities (for example, furniture) may become narrow and restricted.

Navigation methods of such mobile robots have attracted much attention in both academia and industry, and those techniques can be roughly divided into two types: model-based and behavior-based [1]. Behavior-based navigation [2] has been well-known as a main branch of reactive navigation methods. Such a behavior-based navigation structure is a bottom-up approach inspired by biology, in which several behaviors act in parallel accomplishing tasks [3-4]. Behavior-based navigation approaches were founded on the subsumption architecture [3], which has been regarded as a powerful methodology for designing autonomous mobile service robots [2-4]. This architecture imposes a general biologically inspired, distributed, bottom-up philosophy, allowing for a certain freedom of interpretation. In this approach, the robot task is decomposed into several modules, called behaviors, such that the robot can accomplish and execute desired tasks concurrently. Behavior-based approach has been successfully shown to cope with the problem that the robot needs to interact in dynamic and unpredictable environments. However, behaviors-based control may produce conflicting actions that are seemingly irreconcilable in one particular time, which is known as action selection problem [5-6]. The problem arises because it is necessary to decide which behaviors should control the mobile robot at any given time to select among the actions that most satisfy navigation purposes. In order to overcome the action selection problem, several control approaches have been provided, including simple and conventional logic up to intelligent control approaches, such as fuzzy logic, neural network, fuzzy-neuro network, ant colony algorithm, and evolutionary programming [6-13]. Fuzzy Kohonen clustering networks (FKCNs) have been proposed to accomplish image processing [14-15]. However, as the authors' best understanding, this approach has not been applied to navigate omnidirectional mobile service robots yet!

The objective of the technical note is to propose a behavior-based navigation method by integrating FKCN and three fuzzy behaviors for a three-wheel omnidirectional mobile service robot. The method contributes to reduction of the number of the fuzzy rules

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and the fusion of suitable well-constructed behaviors to generate an appropriate control action to steer the robot without collisions in any indoor environments.

The rest of this technical note is organized as follows. Section II briefly introduces the system structure and inverse kinematic modeling of the experimental omnidirectional mobile service robot. In Section III, the heuristic FKCN is described as well, and laser area weights and the robot motion heading for navigation purpose are obtained from the heuristic FKCN. Section IV elucidates the behavior-based navigation structure by fusing three fuzzy behaviors and the heuristic FKCN. Section V presents experimental results of the proposed behavior-based navigation. Section VI concludes the paper.

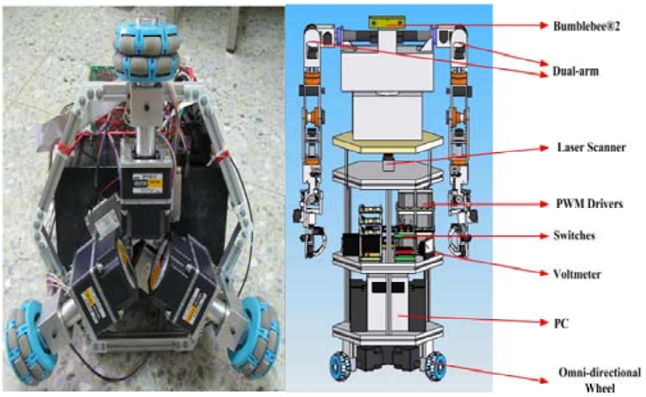


Fig. 1. Pictures of the mobile service robot with the three-wheel omnidirectional mobile platform.

2. System Structure and Modeling

As shown in Fig.1, the experimental mobile service robot is equipped with a three-wheeled omnidirectional mobile platform, a laser scanner, twelve ultrasonic ranging sensors, an industrial personal computer, an embedded motion controller using Nios Ⅱ from Altra, and dual arms. Moreover, the omnidirectional mobile platform is constructed by a synthesis of three DC 24V brushless servomotors which drive the omnidirectional wheels beneath the platform, three 12-bit digital-to-analog (D/A) converters which transform digital speed commands to analog ones, and the embedded controller which is responsible for computing motion control law and sending speed commands via the D/A converters to the servomotors' driving modules. Three omnidirectional wheels are driven by three DC 24V brushless servomotors via gear-reduction boxes. On the mobile platform, two kinds of internal and external sensors are mounted; three wheel encoders are used for dead reckoning and a laser scanner is employed for fuzzy behavior-based navigation task. The industrial personal computer is adopted to execute the proposed behavior-based navigation algorithm.

A. *Inverse Kinematic Model of the Three-Wheel Omnidirectional Mobile Platform*

This subsection is aimed at simply describing an inverse kinematical model of the three-wheeled omnidirectional mobile service robot moving at slow speeds less than 1 m/sec.

Fig.2 depicts the platform's geometry where the pair (x, y) represents the robot position and θ denotes the robot orientation which is positive in the counterclockwise direction. Moreover, the parameter L is the distance from each wheel to the geometric center of the robot, and V_i denote the translational speeds of wheel *i*, *i=1,2,3*.. With the aforementioned notation, the inverse kinematic model of the platform is then expressed by the following vector-matrix form [16].

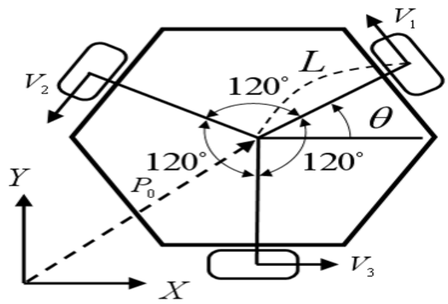


Fig. 2. Geometry of the omnidirectional mobile platform.

$$\begin{bmatrix} V_1 \\ V_2 \\ V_3 \end{bmatrix} = P(\theta)\begin{bmatrix} \dot{x} \\ \dot{y} \\ \dot{\theta} \end{bmatrix} \qquad (1)$$

where the matrix $P(\theta)$ is always nonsingular for any θ and given by .

$$P(\theta) = \begin{bmatrix} -\frac{2}{3}\sin\theta & -\frac{2}{3}\sin(\frac{\pi}{3}-\theta) & \frac{2}{3}\sin(\frac{\pi}{3}+\theta) \\ \frac{2}{3}\cos\theta & -\frac{2}{3}\cos(\frac{\pi}{3}-\theta) & -\frac{2}{3}\cos(\frac{\pi}{3}+\theta) \\ \frac{1}{3L} & \frac{1}{3L} & \frac{1}{3L} \end{bmatrix} \qquad (2)$$

Note that once the three speeds, $\dot{x}, \dot{y}$ and $\dot{\theta}$, have been determined by the proposed navigation system designed in Section IV, the three wheel translational speeds will be obtained from (1).

B. *Laser Scanner*

The used laser scanner, URG-04LX from Hokuyo Automatic Co., Ltd, Japan, is taken to measure the distance between the laser light source and the target object surrounding the robot; the distance measurement is based on calculation of the phase difference between the transmitted infrared laser beam of wavelength 785nm and the reflected beam from the target surface. Fig.3 shows that the scanning area of the laser measurement system is a 240-degree semicircle whose maximum radius is 4 meters and with the angle resolution of 0.36 degrees. Worthy of mention is that the ranging measurements from the ultrasonic ranging sensors and the laser scanner are fused together to acquire more exact distance information from the robot to the surrounding objects.

3. Heuristic FKCN Network and Laser area Weights

This section introduces the heuristic FKCN network and uses it to obtain laser area weights and desired robot heading for navigation. The physical meanings of the laser area weights are delineated as follows. First, the laser area weights are a set of seven weights corresponding to seven different regions shown in Fig.3. Second, all the weights lie with the interval between 0 and 1. Third, the value of each weight shows the level of importance for robot navigation. In what follows, the heuristic FKCN network is described which combines a conventional FKCN structure with a rule table for calculating these weights.

A. Fuzzy Kohonen Clustering Network (FKCN)

FKCN is indeed an unsupervised learning neural network to do pattern classification and recognition. Fig.4 shows the structure of the FKCN equipped with three layers fully connected between the neurons of each layer. The first layer is an input layer used for input patterns. The second layer is the distance layer that is employed to calculate the distance between an input pattern X_i and a prototype pattern W_j; d_{ij} represents the Euclidean error distance between an input pattern X_i and a prototype pattern W_j. Notice that the bigger difference between X_i and W_j has, the bigger d_{ij} becomes; $d_{ij}=0$ means $X_i=W_j$. The last layer is a membership layer for computing the membership function μ_{ij}, where the membership degree μ_{ij} represents the similarity between X_i and W_j, where $\mu_{ij}\in(0,1]$. In the off-line training phase, several known input patterns are used, and the learning rules are described in the following steps:

Step1: Generate the initial weight W_j randomly, and set the magnitude of the neighboring region (*NE*) as $c/2$ if *c* is even, and as $(c+1)/2$ if *c* is odd, where c is the number of the output neurons in the third layer. Set the initial updating weight increment ΔW_j be zero, and select the positive learning rate η between 0 and 1.

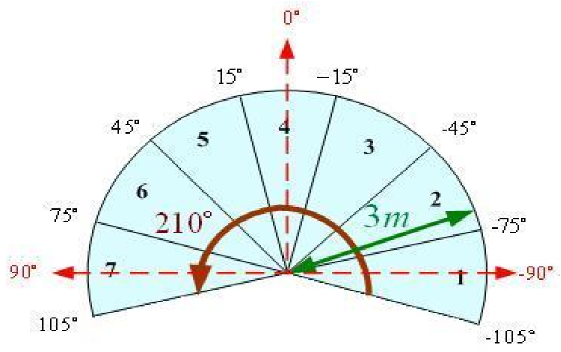


Fig.3. LMS URG-04LX scanning range and seven regions.

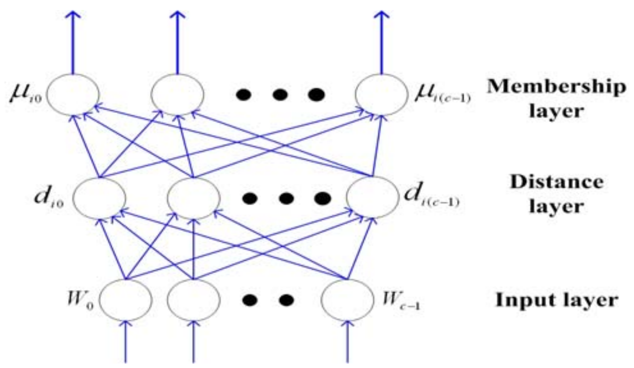


Fig.4. FKCN structure.

Step2: Input the training pattern X_i, and calculate the Euclidean error distance d_{ij} as in (3).

$$d_{ij}=\left\|X_j-W_j\right\|^2=(X_j-W_j)^T(X_j-W_j) \tag{3}$$

and calculate the membership degree value μ_{ij} via (4) and (5).

$$\mu_{ij}=\begin{cases}1 \text{ if } d_{ij}=0\\ 0 \text{ if } d_{ik}=0 \text{ ,(k}\neq 0\text{,k}\geq 0\text{,j}\leq c\text{-1)}\end{cases} \tag{4}$$

and otherwise, if $d_{ij}\neq 0$,

$$\mu_{ij}=\left(\sum_{l=0}^{c-1}\left(\frac{d_{ij}}{d_{il}}\right)\right)^{-1} \tag{5}$$

Step 3: Select an output neuron j^* for each input pattern, where $j^*\in(0,c-1]$, such that $d_{ij^*}=\min(d_{i1},d_{i2},d_{i(c-1)})$, and then renew the weight W_j according to (6) and (7).

$$W_j(k)=W_j(k-1)+\eta\times\Delta W_j(k) \tag{6}$$

$$\Delta W_j(k) = \Delta W_j(k-1) + \mu_{ij}(X_j - W_j(k-1)) \quad (7)$$

Repeat Step 2 and Step 3 until $W_j(k)$ remain unchanged.

Step 4: Terminate the off-line training phase if $NE = 0$; otherwise decrease NE by $NE = NE - 1$, and return to *Step 2*.

Notice that the sum of the membership degree μ_{ij} is equal to unity as in (8)

$$\sum_{j=0}^{c-1} \mu_{ij} = \sum_{j=0}^{c-1} \left(\sum_{l=0}^{c-1} \frac{d_{ij}}{d_{il}} \right)^{-1} = 1 \quad (8)$$

B. Heuristic FKCN Network

Fig.5 depicts the block diagram of the heuristic FKCN network; at the bottom of the structure is the FKCN structure used to recognize input patterns, and at the top of the structure is the inclusion of the target direction T and the rule table to find the laser area weights and desired robot heading for the three fuzzy behaviors developed in Section IV. The acquired laser scanning data are divided into seven regions, each of which the resultant distance is calculated by averaging all the measurements in the region, and then quantified into four linguistic levels. Let q_i denote the linguistic level of each region; and the vector *S* be thus formed by $S = \{q_1, q_2, \cdots, q_7\}$. Note that the vector *S* is the input pattern mentioned in Section 3.1, and S_i means the input pattern measured at the i-th sampling instant. For each input pattern S_i, the heuristic FKCN network will generate a set of weights W_j which is close to its corresponding prototype pattern. After the learning phase, the heuristic FKCN structure is then employed to recognize all input patterns, in which (3) is employed to calculate the difference degree d_{ij} between an input pattern S_i and its corresponding prototype pattern W_j, and (4) and (5) are utilized to compute the membership degree μ_{ij} between S_i and W_j.

Since each prototype pattern represents one special type of the environments, the laser area weights and the robot motion heading can be obtained in each type. Hence, appropriate fuzzy rule tables should be constructed before the heuristic FKCN network is off-line trained; in each rule, the inputs of the IF-PART are input patterns and target direction, the outputs of the THEN-PART are the laser area weights and the robot motion heading θ_{HFKCN}. Notice that the target direction, ϕ, represents the direction of any obstacle with respect to the robot. Finally, the resultant laser area weights are obtained from summing of the laser area weights and robot motion orientation multiplying by their membership degrees.

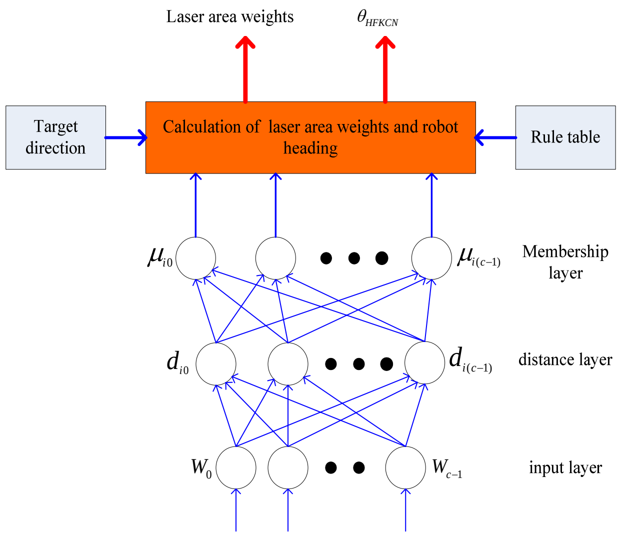


Fig.5. Heuristic FKCN network structure.

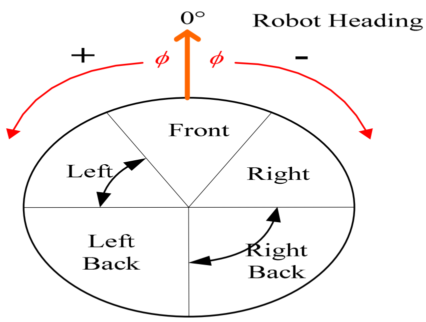


Fig.6. Fuzzified target direction.

C. Fuzzification of Ranging Readings and Target Direction

Since the input patterns of the heuristic FKCN are the fuzzified and quantized ranging readings from the laser scanner and ultrasonic ranging sensors, all the scanning data from -105° to 105° are divided into seven regions, as shown in Fig.3. For sake of simplicity, each region has its four linguistic variables, N (Near and $d_i \in [0, 100\text{cm}]$), MF (Middle Far and $d_i \in [80\text{cm}, 170\text{cm}]$), F (Far and $d_i \in [150\text{cm}, 220\text{cm}]$), and VF (Very Far and $d_i \geq 200\text{cm}$), where d_i is the averaged distance reading in region *i*, and the trapezoidal membership functions are respectively chosen for the four linguistic variables. It is worthwhile to mention that the four linguistic variables in the fourth region are essentially important for robot navigation, in order to detect the collision level from the robot to its front obstacles, thereby preventing any possibly immediate collisions from the front obstacles. Worthy of mention is that too many linguistic variables increase difficulty to construct the rule table. In addition, the target direction in the rule table also requires fuzzification; as shown in Fig. 6, the target direction T based on the detected ϕ is then fuzzified into five linguistic variables: Front ($\phi \in [-45^o, 45^o]$), Right ($\phi \in [-30^o, -100^o]$), Left ($\phi \in [30^o, 100^o]$), Left Back ($\phi \in [90^o, 180^o]$), and Right Back ($\phi \in [-180^o, -90^o]$), where the trapezoidal membership functions are again adopted for fuzzification.

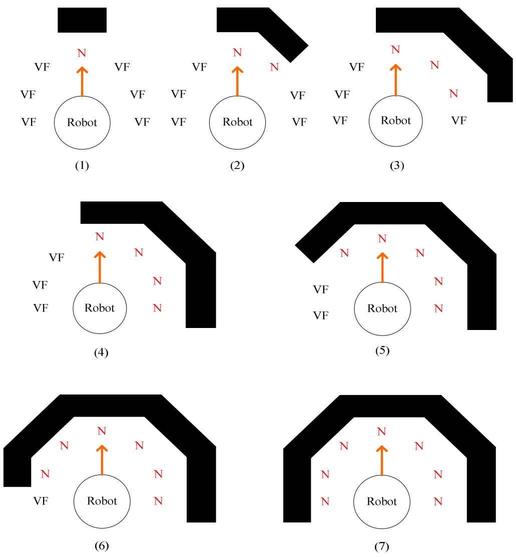


Fig.7. Seven illustrative examples of environment types.

D. The Rule Table and Laser Area Weights

From the environment types as shown in Fig. 7, the rule table is constructed for the heuristic FKCN network, in order to obtain the laser area weights and the desired robot motion heading θ_{HFKCN}, where θ_{HFKCN} can be easily determined according to environment types. For example, a simple rule for the first type environment and the prototype pattern W_1 is described in the following two examples.

$Example 1: IF\ \ W_1 = \{VF, VF, VF, N, VF, VF, VF\}, T\ is\ Front$

$Then\ \ laser\ area\ weight = \{S, M, L, Z, L, M, S\},$

$\theta_{HFKCN} = Right\ or\ Left$

$Example 2: IF\ \ W_1 = \{VF, VF, VF, N, VF, VF, VF\}, T\ is\ Right$

$Then\ \ laser\ area\ weight = \{L, L, L, Z, Z, Z, Z\},$

$\theta_{HFKCN} = Left$

where four linguistic variables, Z (zero), S (small), M(middle) and L (large), are used for the outputs of the laser area weights. Moreover, in *Example* 1, the robot can either turn right or turn right, but in *Example* 2, the robot goes toward the left direction. Similarly, forty-three rules are then established in the rule table in order to navigate the robot efficiently.

Once prototype patterns and the rule table for the heuristic FKCN network have been established, the heuristic FKCN network will produce laser area weights and desired robot heading for each input pattern. For any input pattern, the Euclidean error distance d_{ij} can thus be obtained from (3), and (4) and (5) are employed to compute the membership degree μ_{ij} for the input pattern. Thus, the resultant laser area weights are the product of the membership degree value μ_{ij} and the laser area weights in the rule table.

4. Design of Behavior-based Navigation

This section is devoted to briefly describing three fuzzy basic robot behaviors, called obstacle avoidance, wall following and goal seeking, respectively, and to develop the behavior-based navigation structure by fusing the heuristic FKCN and the three behaviors. Using the information acquired from the laser scanner and ultrasonic ranging sensors, the obstacle behavior intends to find a safe way to circumvent any collision, the wall following behavior moves along walls with desired clearances, and the goal seeking behavior go toward a pre-specified location and orientation. The conventional fuzzy logic control (FLC) method can be easily adopted to synthesize the three fuzzy behaviors where the only three simple fuzzy rules are established for each behavior, and their membership functions are almost the same. Note that the used fuzzy inference for the three fuzzy behaviors is of Mandani type. For detailed designs of the three fuzzy behaviors, the reader is referred to [17].

Fig.8 shows the overall behavior-based navigation structure. As depicted in Fig. 8, the four outputs of each behavior are the fusion weight (FW), the linear speed (V), the angular speed (ω), and the robot heading (θ), respectively. Moreover, the subscripts O, W and G respectively stand for the obstacle avoidance, wall following and goal seeking behaviors. For example, FW_O, FW_w and FW_g denote respectively the fusion weights of the obstacle-avoidance, wall-following and goal-seeking behaviors. The fusion weight for each behavior has the following properties: (i) each fusion weight is real and positive; (ii) the value of the fusion weight represents the degree of the behavior matching the current environment type. Note that a larger fusion weight for each behavior represents a higher degree of fitting for that behavior in the environment.

In Fig. 8, the tournament selection module is used to determine the robot motion orientation and angular speed of the mobile robot by merging the outputs of these three behaviors, i.e., the tournament selection module is used to select resultant robot orientation, θ_{HSR}, and angular speed, ω_{HSR},merged from these three behaviors, and find out the resultant θ_{HSR} and ω_{HSR} by comparing these fusion weights. Moreover, the tournament selection module mentioned in Fig.8 is adopted to select the fused behavior to match well the environment types according to the fusion weights. For instance, if $FW_O > FW_G > FW_W$, then $\omega_{HSR} = \omega_O, \theta_{HSR} = \theta_{OHFKCN}$, where ω_O represents the output angular speed of the obstacle avoidance behavior.

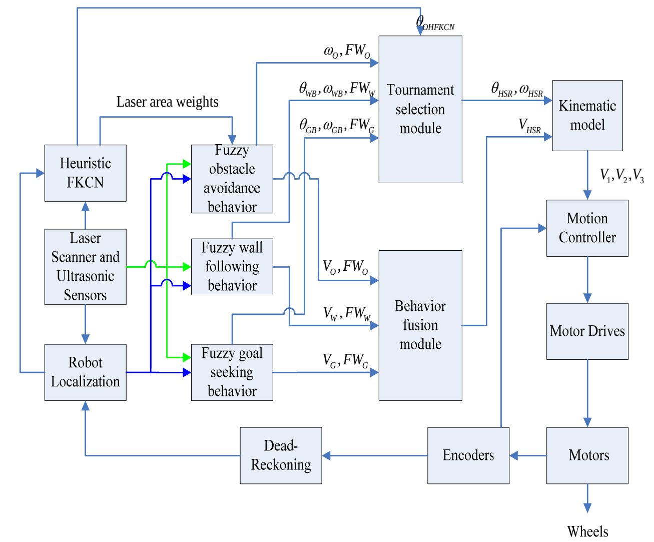


Fig.8. Proposed navigation structure.

Furthermore, the behavior fusion module depicted in Fig.8 is employed to determine the resultant linear speed V_{HSR} of the robot by (9).

$$V_{HSR} = V_O \times \frac{FW_O}{FW_O + FW_W + FW_G} + V_W \times \frac{FW_W}{FW_O + FW_W + FW_G} + V_G \times \frac{FW_G}{FW_O + FW_W + FW_G} \tag{9}$$

where V_O, V_W and V_G are respectively the output linear speeds from the three fuzzy behaviors. Once the resulting linear and angular speeds, and robot heading of the robot have been obtained from (9), the inverse kinematics model (1) is then utilized to convert three outputs, $\theta_{HSR}, V_{HSR}, \omega_{HSR}$, into corresponding three wheel translational velocities, V_1, V_2, V_3, by setting $\dot{\theta} = \omega_{HSR}$, $\dot{x} = V_{HSR}\cos(\theta_{HSR})$ and $\dot{y} = V_{HSR}\sin(\theta_{HSR})$. Afterwards, the kinematic motion controller will output three control signals to corresponding servomotors for navigation purposes.

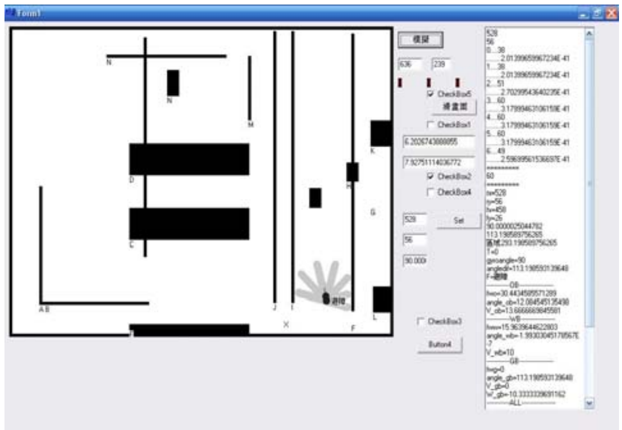
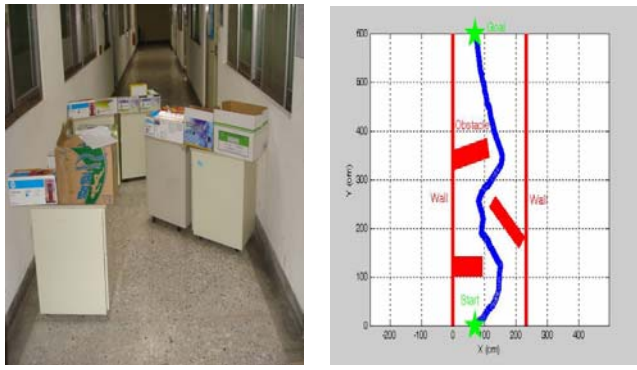


Fig. 9. Simulation of the proposed behavior-based navigation.



(a) (b)

Fig.10. (a)Experimental environment with three obstacles; (b) experimental result of the proposed behavior-based navigation structure.

5. Simulation, Experiments and Discussion

This section conducts one simulation and two experiments to show the effectiveness and performance of the proposed behavior-based navigation system. Before experimentation, the parameters of these fuzzy membership functions for the three fuzzy behaviors were obtained by simulations. Fig. 9 shows how to proceed with simulation of behavior-based navigation by C++ programming language. Once the three fuzzy logic controllers were established and verified, the two experiments were then conducted on the experimental omnidirectional mobile service robot. The sampling period of the navigation computer was 0.05 seconds, while the sampling period of the motion controller was 0.001 seconds.

In the first experiment the starting position and the goal position were set by (70, 0) and (70, 600) (unit: cm) for the mobile platform. These three obstacles were respectively installed at (45, 120), (170, 210) and (55, 340) (unit: cm) inside the experimental environment, as shown in Fig.10(a), and the size of the experimental environment was given by 234cm×600cm. As shown in Fig.10(b), in the beginning, the mobile robot encountered with the first obstacle and moved with the right direction. When the laser scanner detected the first obstacle, the fusion weight FW_O increased and then activated a combined behavior of fusing both goal-seeking and obstacle-avoidance behaviors. By appropriately merging these two fuzzy behaviors, the mobile robot quickly reached its goal posture. The result in Fig. 10 reveals that the proposed navigation method is capable of smoothly steering the robot over this crowded and cluttered indoor environment.

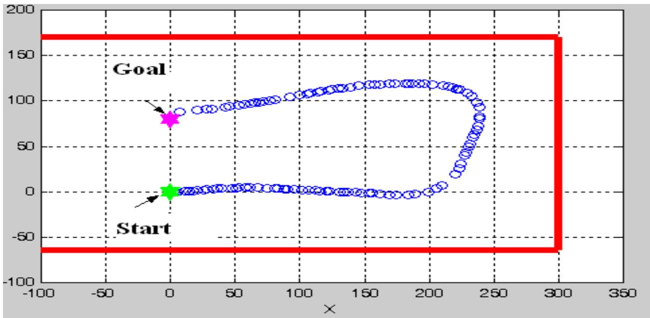


Fig. 11. Experimental result of the proposed behavior-based navigation by fusing both wall following and goal seeking behaviors.

The second experiment was performed to show the performance of fusing goal both seeking and wall following behaviors. Fig. 11 presents the experimental result of the merged behavior, indicating the effectiveness and applicability of the proposed method.

6. Conclusions

This paper has presented a behavior-based navigation method using a heuristic fuzzy Kohonen clustering network (FKCN) together with three fuzzy behaviors to smoothly steer a three-wheeled mobile robot to reach desired destinations in crowded and cluttered indoor environments. The laser area weights have been employed to calculate the resultant fusion weights of the three fuzzy behaviors, and finally these fusion weights have been adopted to decide the degree of which behavior to be used. With the laser scanner and ultrasonic sensors, the heuristic FKCN structure has been proven to be effective in reducing the number of the fuzzy rules so that the proposed behavior-based navigation strategy has been proposed to steer the mobile service robot to reach desired poses by fusing the three fuzzy behaviors. Through one simulation and two experimental results, the effectiveness of the proposed heuristic FKCN and behavior-based navigation method has been successfully confirmed. An interesting topic for future research might be to design fuzzy tournament selection and behavior modules for improving navigation performance.

Acknowledgments

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References

[1] R. Siegwart and I. R. Nourbakhsh, *Introduction to Autonomous Mobile Robots*, the MIT Press, 2004.
[2] R. C. Arkin, *Behavior-based robotics*, The MIT Press, London, England, 1998.
[3] R. A. Brooks, "Robust layered control system for a mobile robot," *IEEE Journal of Robotics and Automation*, vol. 2, no. 1, pp. 14-23, 1986.
[4] M. J. Mataric, "Behavior-based control: examples from navigation, learning, and group," *Journal on Experimental and Theoretical Artificial Intelligence, Special Issue on Software Architecture for Physical Agents*, vol. 9, no. 2-3, pp. 1-15, 1997.
[5] A. Saffiotti, "The uses of fuzzy logic in autonomous robot navigation," *Soft Computing*, Vol. 1, Springer-Verlag, pp. 180-197, 1997.
[6] B. C. Min, M. S. Lee, and D. Kim, "Fuzzy Logic Path Planner and Motion Controller by Evolutionary Programming for Mobile Robots," *International Journal of Fuzzy Systems*, pp. 154-163, vol. 11, no. 3, September 2009.
[7] C. H. Chao, B. Y. Hsueh, M. Y. Hsiao, S. H. Tsai, and T. H. S. Li, "Fuzzy Target Tracking and Obstacle Avoidance of Mobile Robots with a Stereo Vision System," *International Journal of Fuzzy Systems*, pp. 183-191, vol. 11, no. 3, September 2009.
[8] J. I. Park, J. H. Cho, M. G. Chun, and C. K. Song, "Neuro-Fuzzy Rule Generation for Backing up Navigation of Car-like Mobile Robots," *International Journal of Fuzzy Systems*, pp. 192-201, vol. 11, no. 3, September 2009.
[9] P. Rusu, E. M. Petriu, T. E. Whalen, A. Cornell, and H. J. W. Spoelder, "Behavior-based neuro-fuzzy controller for mobile robot navigation," *IEEE Transactions on Instrumentation and Measurement*, vol. 52, pp. 1335-1340, August 2003.
[10] X. Yang, M. Moallem, and R. V. Patel, "A layered goal-oriented fuzzy motion planning strategy for mobile robot navigation," *IEEE Transactions on Systems, Man and Cybernetics-Part B. Cybernetics*,

vol. 35, pp. 1214-1224, December 2005.
[11] J. S. Chiou and K. Y. Wang, "ACA-based Fuzzy Controller Design for Robot Soccer," *International Journal of Fuzzy Systems*, pp. 164-173, vol. 11, no. 3, September 2009.
[12] C. Y. Hsu, K. T. Chen, and G. H. Tzeng, "FMCDM with Fuzzy DEMATEL Approach for Customers' Choice Behavior Model," *International Journal of Fuzzy Systems*, vol. 9, no. 4, pp. 236-246, 2007.
[13] K. T. Song and L. H. Sheen, "Heuristic Fuzzy-Neuro Network and its Application to Reactive Navigation of a Mobile Robot," *Fuzzy Sets and Systems*, vol. 110, no. 3, pp. 331-340, 2000.
[14] K. H. Chuang, M. J. Chiu, C. C. Lin, and J. H. Chen, "Model-free Functional MRI Analysis Using Kohonen Clustering Neural Networks and Fuzzy-C Mean," *IEEE Transactions on Medical Imaging*, vol. 18, no. 12, December 1999.
[15] W. Lei and Q. Feihu, "Adaptive Fuzzy Kohonen Clustering Network for Image Segmentation," *Proceeding of 1999 International Joint Conference on Neural Networks*, vol. 4, pp. 2664-2667, 10-16 July 1999.
[16] H. C. Huang and C. C. Tsai, "Simultaneous Tracking and Stabilization of an Omnidirectional Mobile Robot in Polar Coordinates: a Unified Control Approach," *Robotica*, Published Online by Cambridge University Press, 30 July 2008.
[17] C. C. Chen, *Behavior-based navigation and task execution of a home-service robot with two arms*, M.S. Thesis, Department of Electrical Engineering, National Chung-Hsing University, Taichung, Taiwan, July 2008.

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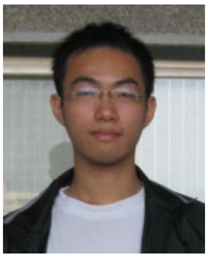

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