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A Goal-oriented Fuzzy Reactive Control for Mobile Robots with Automatic Rule Optimization

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***Abstract*— To realize real-time goal-oriented navigation for a mobile robot in unpredictable environments, a fuzzy reactive system is proposed in this paper. Besides the establishment of the fuzzy logic system, this paper focuses on the the physical meaning of the parameters in the fuzzy system, and proposes a systematic method to automatically suppress redundant fuzzy rules from the rule base. Under the control of the proposed system with automatic redundant fuzzy rule removal, the mobile robot can preferably avoid obstacles autonomously, and generate reasonable trajectories toward the target in various situations. The effectiveness and efficiency of the proposed approach are demonstrated by simulation and experimental studies.**

I. Introduction

Mobile robot navigation using only onboard sensors is an essential issue in robotics and artificial intelligence. Many approaches to steering mobile robots have been developed, *e.g.*, map-based methods [1], artificial potential field methods [2], vector field method [3], neural network based approaches [4], and some other methods. Many of them deal with only one aspect of the problem, *e.g.*, path planning or path tracking.

Fuzzy logic is known to be an organized method for dealing with imprecise knowledge. Using linguistic rules, the fuzzy logic system mimics human decision-making to deal with concepts which cannot be expressed in a clear or precise method, to deal with imprecise or imperfect information, and to improve knowledge representation and uncertain reasoning. Therefore, fuzzy logic approaches are proposed for controlling a mobile robot in unknown environments. Yang and Patel [5] developed a navigation algorithm for a mobile robot by combining a fuzzy logic architecture with a virtual centrifugal effect algorithm (VCEA). In this model, the goal seeking sub-problem and obstacle avoidance sub-problem are solved by two separate fuzzy logic systems. This algorithm focus on the direction control without considering velocity control. Aguirre and Gonzalez [6] proposed a perceptual model based on fuzzy logic in a hybrid deliberative-reactive architecture. It improved the performance in two aspects of robot navigation: perception and reasoning, where fuzzy logic is used in different parts of the perceptual model. However, the model focuses on map building, and thus is computationally expensive.

Fuzzy logic offers a framework for representing imprecise, uncertain knowledge. It makes use of human knowledge in the form of linguistic rules. However, the disadvantages are that fuzzy logic needs highly abstract heuristics, it needs experts for rule discovery with data relationships, and more importantly it lacks self-organizing and self-tuning mechanisms. The first problem is that it is difficult to decide the parameters of the membership functions, which can be resolved by adding neural network learning capability as in our former paper [7]. Another drawback is the lack of a systematic procedure to transform expert knowledge into a rule base. This results in many redundant rules in the rule base, *e.g.*, Park and Zhang [8] proposed a dual fuzzy logic approach, but the design of the two 81 fuzzy rules is not systematism, and redundancy is obvious.

In this paper, a fuzzy reactive system with automatic suppression of redundant rules is presented for navigation of mobile robots in unpredictable environments. To generalize the proposed fuzzy reactive system, an extension of our previous work [7] is studied. The inputs of the system are the environment information around the robot, including the target direction, the obstacle distances obtained from the left, front and right sensor groups, and the current robot speed. A fuzzy rule base with initial 243 linguistic fuzzy rules is developed to implement expert knowledge under various situations. The output signals from the system are the velocities of left and right wheels, respectively. Furthermore, A comparison algorithm is developed to autonomously suppress the redundant fuzzy rules based on the understanding of the physical meaning of the parameters in the fuzzy system. Under the control of the proposed fuzzy reactive system, the mobile robot can generate reasonable trajectories toward the target in various situations, while at the same time eliminating redundant rules.

II. The Proposed Fuzzy Reactive System

Navigation is a very easy task for human beings or animals, but it is not easy for robots. While a mobile robot is moving in an unknown and changing environment, it is important to the compromise between avoiding collisions with obstacles and moving towards targets, depending on the sensed information about the environment.

A. Mobile Robot Model

In this study, the main sensors of the mobile robot are shown in Fig. 1. The robot has two front co-axle wheels

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driven by different motors separately, and a third passive omni-directional caster. Adjusting the velocities of the two driven wheels respectively, controls the motion of the mobile robot. Nine ultrasonic sensors are placed on the robot (front left, front right, and front middle) to cover a semicircular detection area around the front half of the robot and protect the robot from collisions. These sensors are divided into three groups to measure the distance from obstacles to the left, right and front of the robot. Each group has three sensors for the distance measuring correctly and noise removing efŒciently. In order to reach a target, a simple optical range Œnder with a directing beam and a rotating mirror, a global positioning system GPS, or a indoor positioning system would be used to obtain the target direction. A speedometer is equipped on the robot to measure the current robot speed.

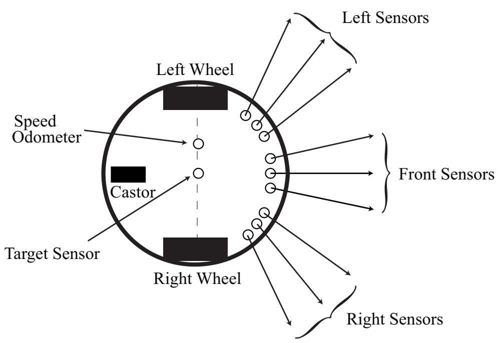


Fig. 1. The mobile robot model with onboard sensors.

The robot motion is controlled by adjusting the speeds of two driven wheels. At Œrst, the robot system has to judge the distance as farƒ or closeƒ, the speed as fastƒ or slowƒ and so on, and then decide the motion commands. This information (farƒ, closeƒ, fastƒ, slowƒ, etc) is uncertain and imprecise. It is also difŒcult to be represented by conventional logic systems, or mathematical models. However, these adjustments are easy for human beings, as people do not need precise, numerical information to make a decision, and they are able to perform highly adaptive control measures. This is due to a human s knowledge and ability to use fuzzyƒ concepts.

B. Structure of the Fuzzy System

The structure of the proposed fuzzy reactive system is shown in Fig. 2. The inputs of the fuzzy system are the obstacle distances d_l, d_f and d_r obtained from the left, front and right sensor groups, the target direction θ_d (that is the angle between the robot moving direction and the line connecting the robot center with the target), and the current robot speed r_s. The output signals from the fuzzy system are the velocities of left and right wheels, v_l and v_r, respectively.

First, all sensor signals have to be translated into linguistic values, which is called fuzziŒcationƒ. Second, the so-called fuzzy inference step evaluates the set of IF-THEN rules, identiŒes the rules that apply to the current situation, and computes the values of the output linguistic variables. The result of this step is to obtain linguistic values for the output variables. The last step is called defuzziŒcationƒ which translates the linguistic values into real values.

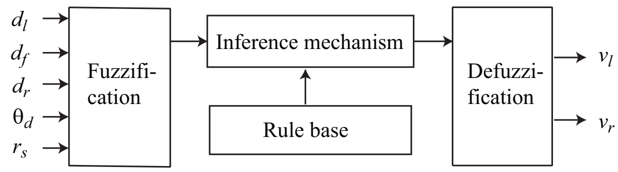


Fig. 2. Structure of the proposed fuzzy reactive system. d_l, d_f, d_r: obstacle distances to the left, front and right of the robot; θ_d: target direction; r_s: current robot speed; v_l, v_r: velocities of the left and right wheels.

The fuzziŒcation procedure maps the crisp input values to the linguistic fuzzy sets with membership values between 0 and 1. To simplify the description of the fuzziŒcation procedure and reduce the redundant rules systematically, Gaussian functions, Sigmoid functions, and anti-Sigmoid functions are chosen to represent fuzzy membership functions. The outputs of the fuzziŒcation procedure p_{ij}, which provide numerical values for the i-th input variable, are given as follows: For a Gaussian function:

$$p_{ij} = e^{\frac{-(u_i - m_{ij})^2}{2\sigma_{ij}^2}}; \tag{1}$$

for a Sigmoid function:

$$p_{ij} = \frac{1}{1 + e^{-(m_{ij} - \frac{\sigma_{ij}}{2})(u_i - m_{ij})}}; \tag{2}$$

and for an anti-Sigmoid function:

$$p_{ij} = 1 - \frac{1}{1 + e^{-(m_{ij} - \frac{\sigma_{ij}}{2})(u_i - m_{ij})}}, \tag{3}$$

where $i = 1, 2, \cdots, 5$ is the index of input signal; $j = 1, 2, 3$ is the index of sets of the input variables; u_i is the i-th input signal to the fuzzy system (*e.g.*, $d_l, d_f, d_r, \theta_d or r_s$); m_{ij} is the center of the membership function corresponding to the i-th input and the j-th set of the input variable; and σ_{ij} is related to the width of the membership function corresponding to the i-th input and the j-th set of the input variable.

based on experience, the membership functions with all sets of input and output variables are designed. Usually the number of input and output variables is Œxed along with the structure of the system. However, the sets of each variable are œxible, which is dependant upon the experience of the designer. The more sets of each variable, the more exact the control, but the more complex the system. In this paper, the membership functions are designed as shown in Fig. 3.

After the design of the membership functions, the inference mechanism with a fuzzy rule base is designed. The inference mechanism is responsible for decision-making in the fuzzy system using approximate reasoning. According to the human driving experience, the rule base is created for the system, which governs the input and output relationship of the proposed fuzzy system. In this paper, the inference rules are designed in the form, such as

IF the obstacle distance on the left is near and
the obstacle distance on the front is far and

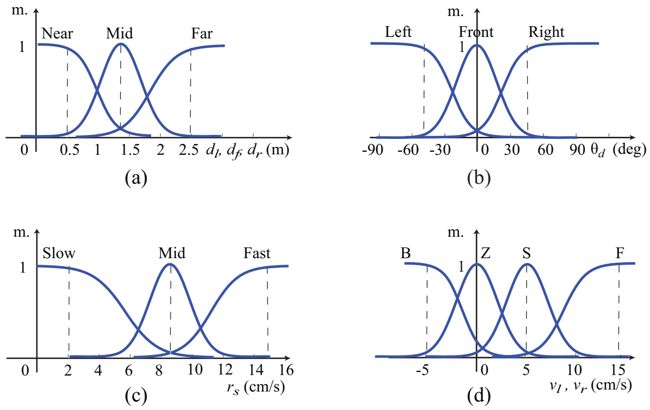


Fig. 3. Membership functions. (a) obstacle distances; (b) target direction; (c) current robot speed; (d) velocities of two wheels.

the obstacle distance on the right is far and
the target direction is right and
the current robot speed is slow
THEN the velocity of the left wheel is fast and
the velocity of the right wheel is slow.

The number of rules in the rule base will be different, as indicated by variations in the deﬁnition of the sets of input membership function variables. If the membership functions have three distance variables with three sets (far, middle and near), one angle variable with three sets (left, front and right), one recent speed variable with three sets (fast, middle and slow), and two output variables with four sets (fast, slow, zero and back), 243 rules will be formulated theoretically. A portion of this set of rules is given in Table I.

TABLE I
THE RULE BASE. N: NEAR; F: FAR; L: LEFT; C: CENTER; R: RIGHT; S: SLOW; F: FAST; Z: ZERO, B: BACK.

Rule No.	Input					Output	
	d_l	d_f	d_r	θ_d	r_s	v_l	v_r
1	F	F	F	L	S	S	F
2	F	F	F	L	F	B	Z
3	F	F	F	C	S	F	F
4	F	F	F	C	F	F	F
···	···	···	···	···	···	···	···
240	F	N	F	L	S	B	S
241	F	N	F	L	F	S	Z
242	F	N	F	C	S	Z	B
243	F	N	F	C	F	S	Z

In every rule, the IF part is deﬁned alternatively: IF condition A is true, AND B is true, AND C is true, AND $\cdots$ with ﬁve conditions. Using the fuzzy logic operators, the AND can be represented mathematically by the min operator in the aggregation step. The output of the aggregation procedure, which is the conjunction degree of the IF part of the k-th rule, is given as

$$q_k = \min\{p_{1k_1}, p_{2k_2}, p_{3k_3}, p_{4k_4}, p_{5k_5}\}, \tag{4}$$

where k =1, 2, $\cdots$, 243; and p_{ik_i} is the degree of the membership for the i-th input contributing to the k-th rule, i = 1, 2, $\cdots$, 5; k_i = 1, 2, $\cdots$, 5.

The defuzziﬁcation procedure maps the fuzzy output from the inference mechanism to a crisp signal. The center of gravity (CoG) method is used in the proposed system, combining the outputs represented by the implied fuzzy sets from all rules to generate the gravity centroid of the possibility distribution for a control action. The value of the output variables v_l and v_r are given as

$$v_l = \frac{\sum_{k=1}^{243} v_{k,1} q_k}{\sum_{k=1}^{243} q_k}, \tag{5}$$

$$v_r = \frac{\sum_{k=1}^{243} v_{k,2} q_k}{\sum_{k=1}^{243} q_k}, \tag{6}$$

where $v_{k,1}$ and $v_{k,2}$ denote the estimated values of the outputs provided by the k-th rule, which are related to the center of membership functions of the output variables.

C. Algorithm to Suppress Redundant Rules

The rule base is designed depending on the environments and human experience, after the structure of the fuzzy system and the membership functions are created. However, there are no systematic methods to design the rule base and to suppress the useless rules. For example, Godjevac [9] proposed a neuro-fuzzy model for a mobile robot to avoid obstacles. More than 600 rules are formulated, where many of them are redundant and there are no methods to suppress the useless rules. Marichal *et al.* [10] presented a neuro-fuzzy controller by a three-layer NN with a competitive learning algorithm for a mobile robot. It automatically extracts the fuzzy rules and the membership functions through a set of trajectories obtained from human guidance, but it is difﬁcult to determine the fuzzy rules for complex environments with obstacles. Song and Sheen [11] developed a heuristic fuzzy neural network using a pattern-recognition approach. This approach can reduce the number of rules by constructing the environment (*e.g.* obstacles) using several prototype patterns. It is suitable for simple environments, because the more complex the environment is, the more difﬁcult it becomes to to construct the patterns. Rusu *et al.* [12] proposed a neuro-fuzzy controller for mobile robot navigation in an indoor environment. However, the design of the rule base for the controller is not clear. The meanings of system parameters are vague when being trained by Neural network. In this paper, the physical meanings of the variables and parameters in the proposed fuzzy reactive system are explained in detail, and then a weight comparison method is used to suppress the useless rules.

Figure 4 shows the physical meanings, where $[d_l, d_f, d_r, \theta_d, r_s]^T$ is the input vector; and $[v_l, v_r]^T$ is the output vector. The variable p_{ij} is the degree of membership for the i-th input corresponding to the j-th set of the input variable obtained by Eqns. (1-3) according to different membership functions. The variable q_k is the conjunction degree of the IF part of the k-th rule obtained by Eqn. (4). The variable $w_{i,k}$ denotes the center of the membership function corresponding to the i-th input and

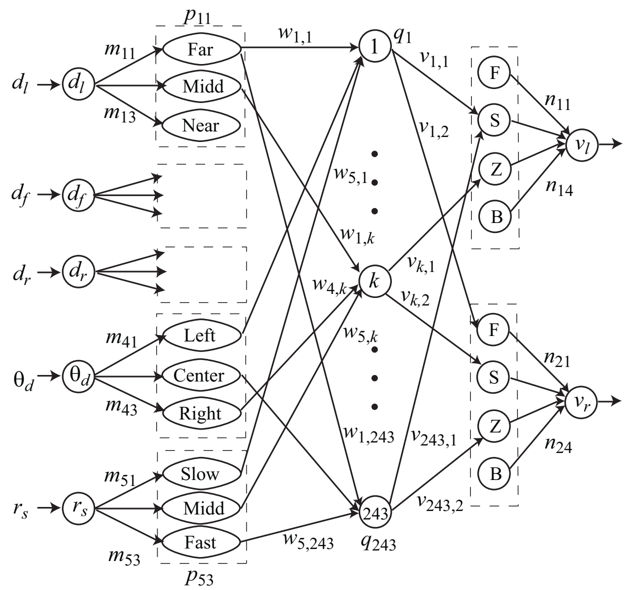


Fig. 4. The physical meanings of the variables and parameters.

the k-th rule, which can be assigned to one of the m_{ij} according to the rule base. For example, from Fig. 4 it is easy to get $w_{1,1} = m_{11}$, $w_{1,x} = m_{12}$, $w_{1,243} = m_{11}$, $w_{4,x} = m_{43}$, $w_{5,1} = m_{51}$, $w_{5,x} = m_{52}$, and $w_{5,243} = m_{53}$. The variables $v_{k,l}$ are the estimated value of the outputs provided by the k-th rule, which are related to one of the centers of membership functions of the output variables. Assume n_{ls} denotes the centers of the membership functions of variable v_l and v_r. Assume the width of the membership functions are constant (*e.g.* 1). Then $v_{1,1} = n_{12}$, $v_{1,2} = n_{21}$, $v_{x,1} = n_{13}$, $v_{x,2} = n_{22}$, $v_{243,1} = n_{12}$, and $v_{243,2} = n_{23}$.

A rule base with 243 rules is defined in the fuzzy reactive system. However, it is difficult to define the system rules accurately and without redundant rules, if the number of input variables increases, or the number of the sets of variables increases to fit a more complex environment. To solve this problem, a selection algorithm is added to the fuzzy system to suppress redundant fuzzy rules automatically.

It is clear from Fig. 4 that the variables $w_{i,k}$ and $v_{k,l}$, which can be obtained from the parameters m_{ij} and n_{ls} described above, determine the response of the fuzzy rules to the input signals. Every rule is related to a weight vector

$$W_k = [w_{1,k}, \cdots, w_{5,k}, v_{k,1}, v_{k,2}]^T, \quad k = 1, 2, \cdots, 243. \tag{7}$$

If the Euclidean distance between two weight vectors is small enough, both vectors will generate similar rules in the sense that a similar result is obtained for the same input. So, by calculating the Euclidean distances between the weight vectors, the redundant rules can be reduced. Based on this idea, the proposed algorithm is summarized in Fig. 5. First, design the center values of the membership function by experience, then get the weight vectors, normalize the weights, and set the tolerant rates. After that, compare the Euclidean distance of each pair of vectors. If the distance is less than the tolerant value, remove one of the rules, which relate to the pair of vectors. Although the number of the reduced fuzzy rule set is unpredictable, which depends on the environments and the tolerant rate, the proposed method gives a significant method to simplify the fuzzy rule system.

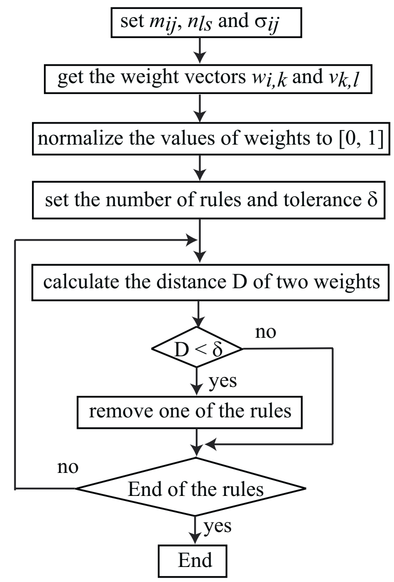


Fig. 5. The algorithm to suppress redundant rules.

After applying the algorithm, a minimum number of rules is obtained. Thus, the minimum number of nodes in the second layer of the structure in Fig. 4 is obtained. For example, if the environment is simple, the tolerance can be chosen to be relatively large. Consequently some of the rules will be suppressed and the number of useful rules will be smaller than 243. This algorithm has obvious benefits over rule bases with thousands of fuzzy rules.

III. Simulation Studies

To demonstrate the effectiveness of the proposed fuzzy logic based system, simulations using a mobile robot simulator (MobotSim Version 1.0 by Gonzalo Rodriquez Mir) are performed. The robot is designed as shown in Fig. 1. The diameter of the robot plate is set to 0.25 m, distance between wheels is set as 0.18 m, wheel diameter is 0.07 m, and wheel width is 0.02 m. In addition to the target sensor and the speedometer, there are nine ultrasonic sensors mounted on the front part of the robot. The angle between sensors is 20^o. The sensor ring radius is 0.1 m. The radiation cone of the sensors is 25^o. The sensing range of the ultrasonic sensors is from 0.04 m to 2.55 m. The upper bound of the wheel speed is 0.18 m/s. In every case, the environment is assumed to be completely unknown for the robot, except the target location; and the sensing range of the on-board robot sensors are limited.

A. Removing Redundant Rules

As mentioned above, every rule is related to a weight vector in Eqn. (7), and the weight vectors depend on the parameters of the membership functions. Table II shows the weights related to some of the rules, which can be obtained from Fig. 4 and/or Table I.

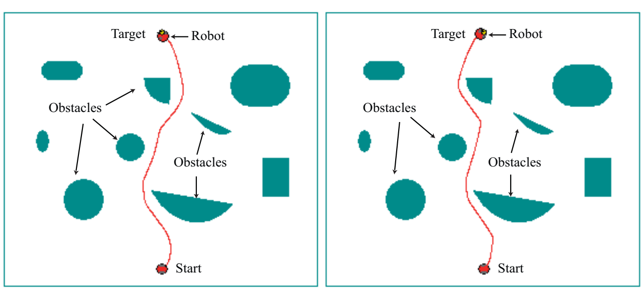
TABLE II

THE WEIGHTS RELATED TO THE RULES AFTER THE TUNNING.

No.	w_{1k}	w_{2k}	w_{3k}	w_{4k}	w_{5k}	v_{k1}	v_{k2}	Red.
1	2.5	2.5	2.5	-60	5	1	2	
2	2.5	2.5	2.5	-60	18	-1	0	
3	2.5	2.5	2.5	0	5	2	2	
4	2.5	2.5	2.5	0	18	0	0	
...	...	...	...	...	...	...	...	
240	2.5	0.5	2.5	-60	5	-5	5	
241	2.5	0.5	2.5	-60	18	5	0	*
242	2.5	0.5	2.5	0	5	0	-5	
243	2.5	0.5	2.5	0	18	5	0	

After the applying of the weight comparison algorithm summarized in Fig. 5, the number of the rules will be less than the original number (such as 243), depending on the tolerance δ. As δ increases, the number of rules decreases, however the performance also decreases. In this simulation, when the tolerance $\delta = 0.05$, only 38 rules are useful. The others (such as the rule 241 in Table II) are redundant and can be removed.

The robot trajectories are shown in Fig. 6 when $\delta = 0$, which having 243 rules (a); and $\delta = 0.05$, which having 38 rules only (b). It is obvious that the trajectories in Figs. 6(a), and (b) are almost the same in this environment. This means that with only 38 rules, the system can obtain a reasonable result with respect to robot navigation. There are many redundant rules that the system automatically removes.

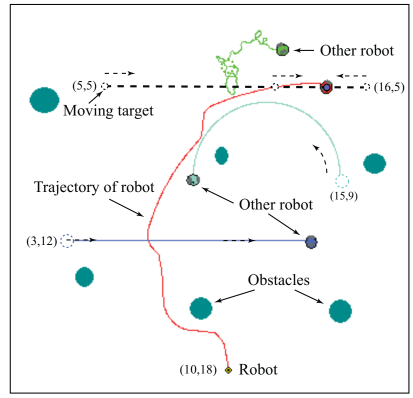


(a) (b)

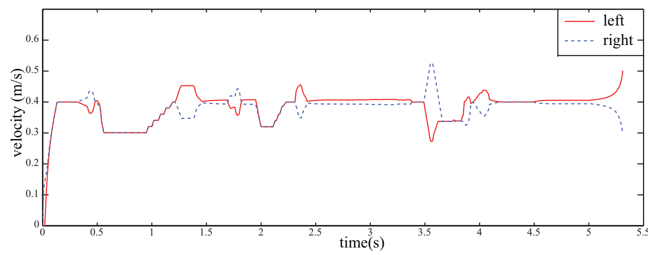
Fig. 6. Robot trajectories with different number of rules when the tolerance δ is selected. (a) 0 with 243 rules; (b) 0.05 with 38 rules.

B. Dynamic Environments and Velocity Analysis

In Fig. 7(a), robot navigation is demonstrated in a complicated environment where the robot meets some static or movable obstacles and a moving target. Assume that the target moves in a line from the position (5, 5) to (16, 5) and then back to (5, 5); besides some static obstacles, one robot considers as an obstacle being moving in a line from the position (3, 12) to (16, 12) and back to (3, 12); one robot is moving in a cycle from the position (15, 9) around the point (11.7, 9) with 3.3 radius and anti-clockwise direction; another robot is moving randomly; and the controlled robot with a direction to the right starts from position (10, 18) in the workspace. A smooth trajectory is executed in which the robot avoids obstacles and travels to the target.



(a)



(b)

Fig. 7. Robot navigation in a dynamic environment with moving target and obstacles. (a) the generated trajectory; (b) the velocities of the robot.

The recorded velocity proﬁle of both wheels in this simulation is presented in Fig. 7(b). It can be seen from this ﬁgure that in the beginning, the velocities of both wheels of the controlled robot increases; and the velocity of the right wheel increases and the velocity of the left wheel decreases when the robot turns to the left to avoid obstacles. The velocity increases or decreases a little when the robot makes a small turn, and changes much more for large turns.

IV. Experiment of Studies

As a test bed, real robots will be employed to test the performance of the proposed fuzzy reactive approach, which navigates autonomously in an unknown environment using onboard sensors. The robots used as a test bed are from Dr Robot Inc. shown in Fig. 8. Because of the limitations of the robot equipments, only three ultrasonic sensors with the range between 0.04 m to 2.55 m are used to obtain obstacle distances from left, front, and right of the robot. The direction of the target, and the distance between the robot and the target, are ignored. In this situation, the robot can wander on a level ﬂoor with obstacle avoidance using the proposed fuzzy reactive system.

In Fig. 9, the robot demonstrates avoidance of an obstacle encounted on its left side. Fig. 9(a) shows the simulated trajectory of the robot in this situation, where the robot turns right to avoid the obstacle on the left side, then goes straight and turns left when it meets obstacles on the right side. Figs. 9(b)-(e) show the pictures of the real robot at positions 1, 2, 3

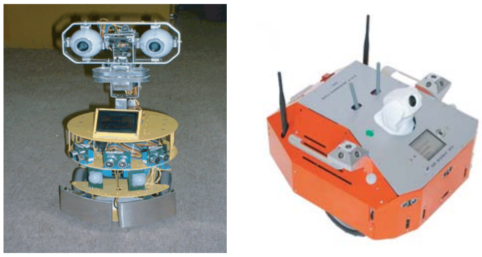


Fig. 8. Robots used as a test bed.

and 4 during its navigation. Fig. 9(f) represents the recorded sensor profiles of the left, front and right sensors. Fig. 9(g) represents the recorded velocity profiles of the left and right wheels.

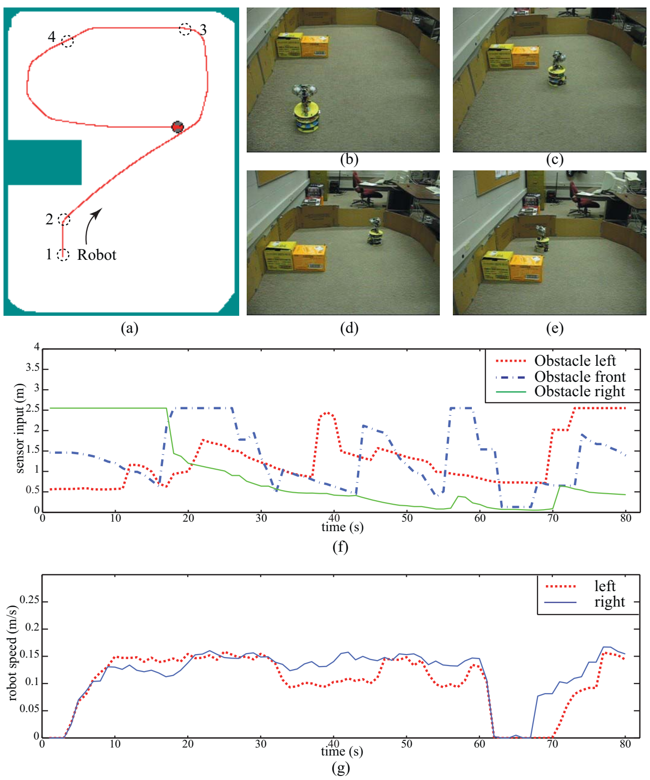


Fig. 9. Robot moves with obstacle avoidance. (a) trajectory; (b)-(e) snapshots; (f) sensor input; (g) robot speed.

From the movies of the experiments, we can see that the robot can operate smoothly, without obvious oscillation in a workspace, despite variations in environmental factors. From the robot speed analysis of the experiments, we can see that the speeds of the left and right wheels of the robot are smooth. In general, "smoothness" is synonymous to "having small high-order derivatives". Smoothness is relative. It can be easily identified from a picture, or defined as a change less than a specific value. In this study, "smoothness" is defined as "without obvious oscillation". It can be defined as a speed change which is less than 0.05 m/s^2 and an angle change which is less than $30^o/s$.

V. Conclusions and Future Work

In this paper, a novel fuzzy reactive system with automatic suppression of redundant rules is proposed for real-time reactive navigation of a mobile robot. The inputs of the system are the target direction, the obstacle distances, and the current robot speed. A fuzzy rule base with initial 243 rules is developed. The output signals from the system are the velocities of left and right wheels respectively. Furthermore, the physical meaning of the parameters in the fuzzy system is explained in detail. Based on this, a comparison algorithm is proposed to autonomously suppress the redundant fuzzy rules. Experiments show that the proposed fuzzy reactive system can control the mobile robot to autonomously reach the target along a smooth trajectory with obstacle avoidance in dynamic environments after automatic suppression of the redundant fuzzy rules. In this paper, the study focuses on the generalization of fuzzy reactive system with fuzzy rule reducing. For the future work, the dead lock problem in U shape environments will be considered. More sensors will be considered in back section of the mobile robot. More sensors and more test environments will be added for real robot experiments.

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