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Fuzzy-Logic-Based Reactive Behavior Control of an Autonomous Mobile System in Unknown Environments

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This paper presents a method for fuzzy-logic-based reactive behavior control of an autonomous mobile system in unknown environments. Difficulties in behavior-based control arise mainly from the quantitative formulation of reactive behavior as well as from the need for efficient coordination of conflicts and competition among multiple types of reactive behavior. The main idea of the present study is to incorporate fuzzy logic control with behavior-based control such that types of reactive behavior are formulated by fuzzy sets and fuzzy rules, and conflicts and competition among different types are coordinated by fuzzy reasoning. The inputs to the control scheme consist of a heading angle between the robot and a specified target and the distances between the robot and the obstacles to the left, front, and right locations, acquired by an array of ultrasonic sensors. The outputs from the control scheme are commands for the speed control unit of two rear wheels of a mobile robot. Simulation results show that the proposed method can be applied to efficient robot navigation in complex and unknown environments by weighting different varieties of reactive behavior, such as avoiding obstacles, following edges, moving towards a target, and so forth. In addition, this method is suitable for robot navigation by multisensor fusion and integration.

Keywords: Robot navigation, fuzzy logic control, behavior-based control, uncertainty, sensor-based motion planning.

1. INTRODUCTION

A key issue in building a control system for an autonomous mobile robot is the search for an efficient algorithm for robot navigation in unknown and complex environments. In this case, sensors must be used to acquire information on unknown obstacles in the real world. Such information, however, is very difficult to use in building a precise and entire world model in real time for preplanning a collision-free path for robot navigation. On the basis of the stimulus-response behavior in bio-systems, behavior-based control[1,2] has been proposed for mobile robot navigation. Behavior-based control, however, has two significant disadvantages: Firstly, it is hard to formulate reactive behavior quantitatively. Secondly, there might be no applicable approach to coordinating conflicts and competition among different reactive behavior to achieve a good performance.

A usual approach to implementing behavior-based control is the use of artificial potential fields.[3–5] A drawback to this approach is that for formulating and coordinating reactive behavior much effort must be made to test and adjust some thresholds regarding potential fields during preprogramming. Especially, these thresholds depend heavily on environments. Another alternative[6] is to use artificial neural networks (ANNs) in behavior-based control. In the ANN approach, however, there are too many "circumstance patterns" to be trained. Dangerous driving situations are likely to occur when the robot meets with circumstance patterns that have not yet been learnt.

This paper presents a new method for behavior-based control using fuzzy logic.[7] The main idea of the present study is to improve the performance of behavior-based control for robot navigation by fuzzy logic in two ways: (1) reactive behavior is formulated by fuzzy sets and a rule base; (2) conflicts and competition among different types of reactive behavior are coordinated by fuzzy reasoning. Unlike the behavior control strategy in Ref. 1, the coordination of different sorts of reactive behavior, as proposed in this study, is performed by computing their weights rather than simply by inhibiting those with lower urgency levels.

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Consequently, unstable oscillations between different types of behavior can be avoided, and the local minimum problem in artificial potential fields which causes robots to be trapped is lessened. Since this method is orthogonal to strict geometrical computation on environments, it is more robust than the artificial potential field approach. This method also differs from the fuzzy control approaches for obstacle avoidance of a mobile robot in Refs 8–10, since perception and action units in this control strategy are integrated in one module by the use of the idea of behavior-based control, and they are directly oriented to a dynamic environment to improve real-time response and reliability.

This paper is organized as follows: Section 2 briefly reviews fuzzy logic control and behavior-based control. Section 3 presents a model for computing the distances between a mobile robot and obstacles, based on ultrasonic sensors. Section 4 proposes a fuzzy-logic-based behavior control scheme for a mobile robot. Section 5 discusses an approach to quantitatively formulating reactive behavior by using fuzzy sets and a rule base. Section 6 explains why the conflicts and competition among different types of reactive behavior can be efficiently coordinated by fuzzy reasoning. To demonstrate the effectiveness and the robustness of the proposed method, Section 7 reports a number of simulation results on robot navigation in unknown environments, such as moving obstacle avoidance in real time, decelerating on curved and narrow roads, escaping from a U-shaped object, moving towards a target, etc.

2. FUZZY LOGIC CONTROL AND BEHAVIOR-BASED CONTROL

Fuzzy logic control is based on the theory of fuzzy sets, as introduced by Zadeh.[11] A fuzzy set A in a universe of discourse X is defined by its membership function $\mu_A(x)$. For each $x \in X$, there exists a value $\mu_A(x) \in [0, 1]$ representing the degree of membership of x in X. In fuzzy logic control membership functions, assigned with linguistic variables, are used to fuzzify physical quantities. Fuzzified inputs are inferred to a fuzzy rule base. This rule base is used to characterize the relationship between fuzzy inputs and fuzzy outputs. For example, a simple fuzzy control rule relating the input v to the output u might be expressed in the *condition-action* form as follows:

If v is W Then u is Y

where W and Y are fuzzy values defined on the universes of v and u, respectively. The response of each fuzzy rule is weighted according to the degree of membership of its input conditions. The inference engine provides a set of control actions according to fuzzified inputs. Since the control actions are described in a fuzzy sense, a defuzzification method is required to transform fuzzy control actions into a crisp output value of the fuzzy logic controller. A widely used defuzzification method is the centroid method:

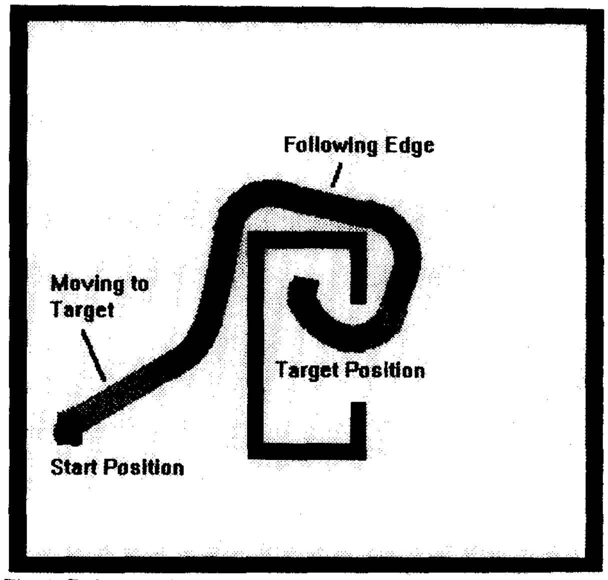

Fig. 1. Robot motion towards a target inside a U-shaped object

$$\bar{u} = \frac{\sum_{i=1}^{n} \mu_Y(c_i) * c_i}{\sum_{i=1}^{n} \mu_Y(c_i)} \tag{1}$$

where $\bar{u}$ is a crisp output value of the controller, n is the number of control rules associated with the fuzzified inputs, and c_i is the centroid of the membership function associated with each linguistic value in the output space.

Behavior-based control is based on the stimulus-response behavior in bio-systems. It is used to decompose complex robotic tasks into several reactive behaviors with simple features. An example in Fig. 1 shows that, to reach a target inside a U-shaped object, the robot has to make use of multiple simple-featured types of behavior, such as avoiding obstacles, following edges, moving towards a target, and so forth. However, the difficulties in behavior-based control arise mainly from the quantitative formulation of reactive behavior, as well as from the need for the efficient coordination and integration of conflicts and competition among different types of behavior.

Since both the behavior-based control and fuzzy logic control can be specified to the expert system in the form of production rules, the behavior-based control can be quantitatively formulated by using fuzzy sets and fuzzy rules. For instance, a robot's wandering behavior can be described by the following *If* [*conditions*] *Then* [*actions*] statements:

If obstacles are located to the left of a robot Then the robot turns to the right

If obstacles are located to the right of a robot Then the robot turns to the left

Such statements can be quantitatively formulated by defining linguistic variables and their membership functions with ease. In addition, the problem of coordinating conflicts and competition among different types of reactive behavior can be dealt with by fuzzy reasoning. Both these points are discussed in more detail in Sections 5 and 6.

3. ULTRASONIC SENSORS

If a mobile robot moves in unknown environments to reach a specified target without collisions, sensors must be used to acquire information on the real world, as shown in Fig. 2. Fifteen ultrasonic sensors are mounted on the THMR-II robot (Tsinghua Mobile Robot II) which is a real autonomous vehicle with 1.0 m length and 0.8 m width.[12, 13] The sonar reflection from a sensor i represents the distance d_i, measured by the sensor i, between the robot and the obstacles in the real world. The ultrasonic sensors are divided into three groups to detect obstacles to the right (sensor $i=1, \ldots, 6$), front (sensor $i=7, \ldots, 9$), and left locations (sensor $i=10, \ldots, 15$). Here, the sonar data, $d_i(i=1, \ldots, 15)$, are used to compute the distances between the robot and the obstacles in the real world as follows

$$right\_obs = Min\{d_i\} \qquad i=1, \ldots, 6 \tag{2}$$

$$front\_obs = Min\{d_i\} \qquad i=7, \ldots, 9 \tag{3}$$

$$left\_obs = Min\{d_i\} \qquad i=10, \ldots, 15 \tag{4}$$

where the minimum values, *right_obs, front_obs*, and *left_obs,* which are derived from the sensor data $d_i(i=1, \ldots, 15)$, express the distances between the robot and the obstacles to the right, front, and left locations, respectively.

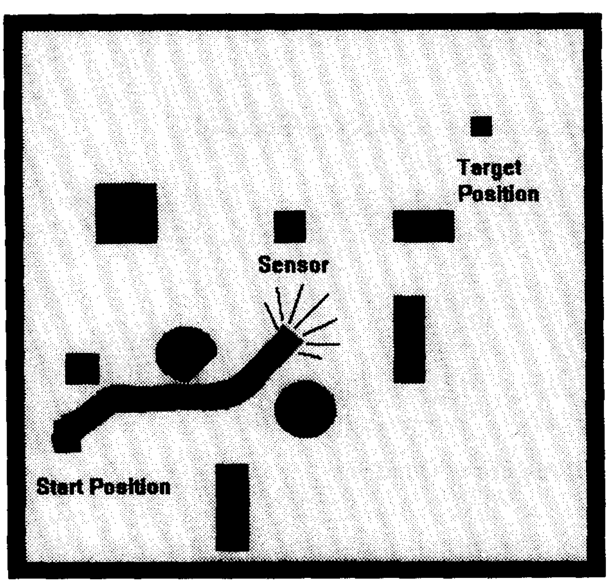

Fig. 2. Ultrasonic sensor-based robot motion.

4. CONTROL SCHEME FOR AN AUTONOMOUS MOBILE SYSTEM

The THMR-II mobile robot has two rear wheels and one front wheel. The velocities of the rear wheels are independently controlled by a motor drive unit. A fuzzy control scheme, as shown in Fig. 3(a), is proposed for the navigation of the THMR-II robot. The input signals to the control scheme are the distances *left_obs, front_obs*, and *right_obs*, between the robot and the obstacles to the left, front, and right locations and a heading angle, *head_ang*, between the robot and a specified target. When the target is located to the left of the mobile robot, *head_ang* is defined as negative, while if the target is located to the right of the mobile robot, *head_ang* is defined as positive, as shown in Fig. 3(b). In analogy to artificial potential fields, the dis-

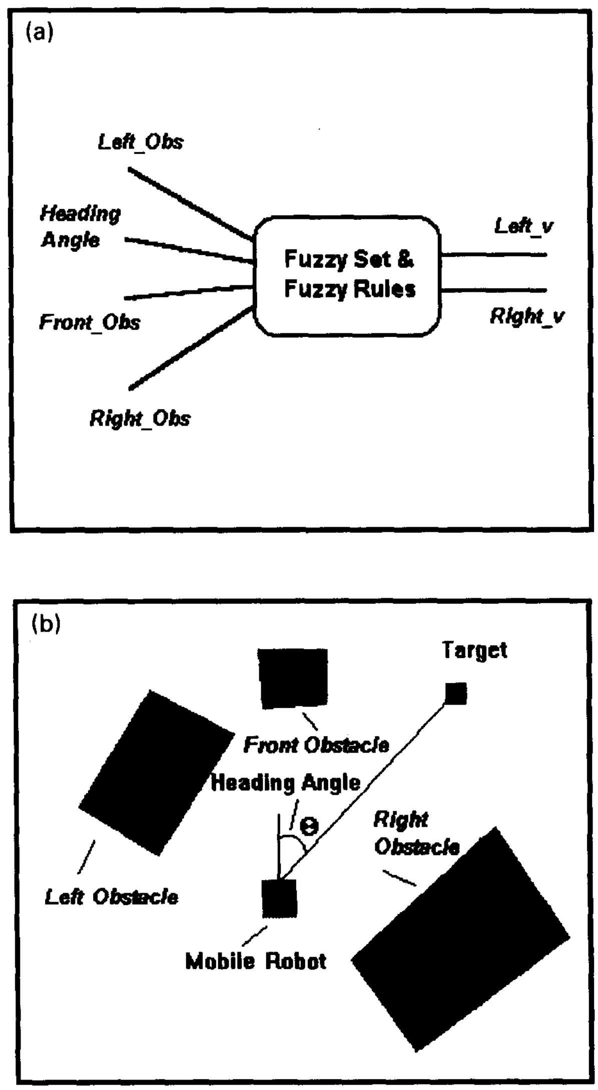

Fig. 3. (a), (b) Fuzzy-logic-based reactive behavior control scheme.

tances between the robot and the obstacles act as repulsive forces for avoiding obstacles, while a heading angle acts as an attractive force for moving to target. A significant difference between fuzzy logic and artificial potential fields is that fuzzy logic does not need strict geometrical computation on environments.[2] According to range information acquired by the sensors, some fuzzy control rules are activated by fuzzified inputs, and they are weighted by fuzzy reasoning to control the velocities of the robot's two rear wheels, denoted by *left_v* and *right_v*, respectively. The linguistic values, *far*, *med(medium)*, and *near*, are defined for *left_obs*, *front_obs* and *right_obs*. The linguistic values, *P* (*positive*), *Z* (*zero*), and *N* (*negative*), are defined for *head_ang*. The linguistic values, *fast*, *med*, and *slow*, are defined for *left_v* and *right_v*. In order to fuzzify the inputs, *right_obs*, *front_obs*, *left_obs*, and *head_ang*; and the outputs, *left_v* and *right_v*, of the control scheme, their corresponding membership functions are chosen in Fig. 4(a) and 4(b) respectively.[14] All these membership functions are triangular or trapezoidal functions which can be determined by three points; their parameters are listed in Tables 1–4.

5. FORMULATION OF REACTIVE BEHAVIOR USING FUZZY RULES

In order to fulfill a complex task in unknown environments, the mobile robot at least needs the following types of reactive behavior: (1) *Obstacle avoidance and deceleration on curved and narrow roads*; (2) *Following edges*; and (3) *Target steer*. A key issue of behavior-based control is how to formulate each reactive behavior quantitatively. For example, what is a safe distance from a wall, that the robot should keep when it moves by following the wall? Such a distance depends largely on the environment. If the robot moves in a great hall with a broad free space, this safe distance can be great. If the robot moves in a narrow corridor, this safe distance must be small. In a dynamic environment, it is

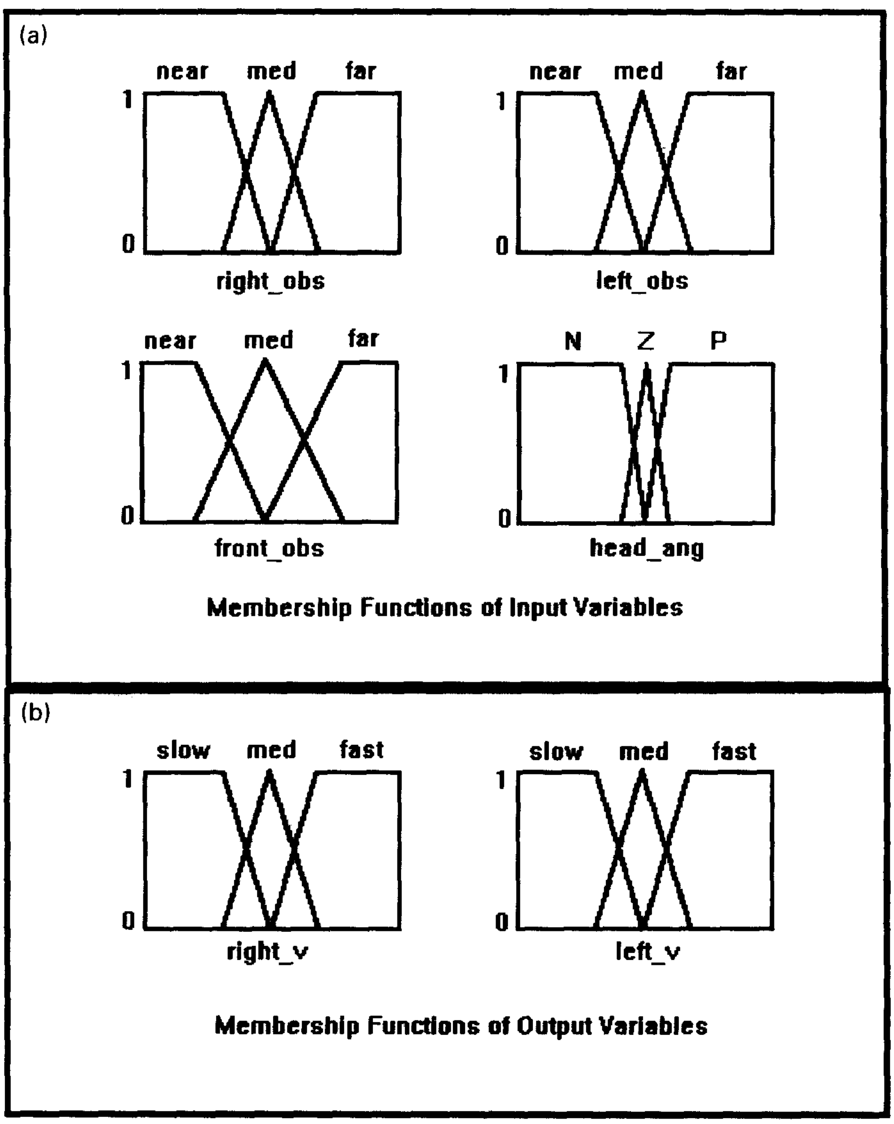

Fig. 4. (a), (b) Membership functions regarding input and output variables.

Table 1. The parameters of *left_obs* and *right_obs*

Variables	Near	Med	Far
left_obs	0.0 m	0.8 m	2.0 m
and	0.8 m	2.0 m	3.0 m
right_obs	2.0 m	3.0 m	4.0 m

hard to build an exact mathematical model for quantitatively formulating reactive behavior. Using fuzzy sets and a rule base, the quantitative formulation of reactive behavior can be well managed. In the following subsections, some fuzzy rules from the rule base are listed to explain, in principle, how these different sorts of reactive behavior are realized.

5.1. Obstacle avoidance and deceleration on curved and narrow roads

When the sonar data, acquired by the ultrasonic sensors, show that the robot is very close to obstacles or it moves on curved and narrow roads, the main reactive behavior of the robot is to reduce its speed and to make a reasonable turn for obstacle avoidance. To realize the behavior, *Obstacle avoidance and deceleration on curved and narrow roads*, the following fuzzy rules are adopted:

Rule 1: If (left_obs is near and front_obs is near and right_obs is near and head_ang is any) Then (left_v is fast and right_v is slow).

Rule 2: If (left_obs is med and front_obs is near and right_obs is near and head_ang is any) Then (left_v is slow and right_v is fast)

Rule 3: If (left_obs is near and front_obs is near and right_obs is med and head_ang is any) Then (left_v is fast and right_v is slow).

Rule 4: If (left_obs is near and front_obs is med and right_obs is near and head_ang is any) Then (left_v is med and right_v is med).

Rule 1 shows that the robot makes a right turn (right-oriented principle) for its motion when obstacles in an unknown environment are very close to the left, front, and right of the robot (assume that there exists a free space for turning the robot round). *Rules 2* and *3* show that the robot makes a left (or a right) turn when only the obstacles to the left (or the right) of the robot are not very close. *Rule 4* shows that the robot moves forward at an appropriate speed when the obstacles in the front are not very close.

5.2. Following edges

The behavior, *Following edges*, plays an important role when the robot has to escape from a U-shaped

Table 2. The parameters of *front_obs*

Variables	Near	Med	Far
front_obs	0.0 m	0.6 m	2.0 m
	0.6 m	2.0 m	3.2 m
	2.0 m	3.2 m	4.0 m

Table 3. The parameters of *head_ang*

Variables	*N*	*Z*	*P*
head_ang	−180.0°	−30.0°	0.0°
	−30.0°	0.0°	30.0°
	0.0°	30.0	180.0°

obstacle or it moves to a target located inside a room, as shown in Fig. 1. To realize this behavior, the following fuzzy rules are adopted:

Rule 5: If (left_obs is far and front_obs is far and right_obs is near and head_ang is P) Then (left_v is med and right_v is med).

Rule 6: If (left_obs is near and front_obs is far and right_obs is far and head_ang is N) Then (left_v is med and right_v is med).

Rule 7: If (left_obs is far and front_obs is med and right_obs is near and head_ang is P) Then (left_v is med and right_v is fast).

Rule 8: If (left_obs is near and front_obs is med and right_obs is far and head_ang is N) Then (left_v is fast and right_v is med).

Rules 5 and *6* show that the robot follows an edge of an obstacle when the obstacle is close to the right (or to the left) of the robot, and a specified target also is located to the right (or the left). *Rules 7* and *8* show that the robot has to make a left (or a right) turn to avoid the obstacles to the right and in the front although a specified target is located to the right (or the left). According to the distances between the robot and obstacles, the speed of the robot can be automatically controlled by the defined fuzzy sets.

5.3. Target steer

When the sonar data, acquired by the ultrasonic sensors, show that there are no obstacles around the robot, the main reactive behavior of the robot is *target steer* to move to a specified target. To realize this behavior, the following fuzzy rules are adopted:

Rule 9: If (left_obs is far and front_obs is far and right_obs is far and head_ang is Z) Then (left_v is fast and right_v is fast).

Rule 10. If (left_obs is far and front_obs is far and right_obs is far and head_ang is N) Then (left_v is slow and right_v is fast).

Rule 11: If (left_obs is far and front_obs is far and right_obs is far and head_ang is P) Then left_v is fast and right_v is slow).

Rules 9–11 show that the robot only adjusts its motion

Table 4. The parameters of *left_v* and *right_v*

Variables	Slow	Med	Fast
left_v	−0.2 m/s	−0.125 m/s	0.1 m/s
and	−0.125 m/s	0.1 m/s	0.325 m/s
right_v	0.1 m/s	0.325 m/s	0.4 m/s

direction according to the position of a specified target, and it moves towards the target at a high speed when there are no obstacles around the robot.

6. COORDINATION OF MULTIPLE REACTIVE BEHAVIOR BY FUZZY REASONING

Another key issue of behavior-based control is how to efficiently coordinate conflicts and competition among different sorts of reactive behavior to achieve a good performance. In Ref. 1, a priority strategy is used to activate a type of reactive behavior according to its urgency level. This strategy is highly contentious for robot navigation in complex environments. For example, it is difficult to determine exactly which sort of reactive behavior, *obstacle avoidance, following edges*, or *target steer*, should be fired when the robot moves through the entrance of the U-shaped object towards a target, as shown in Fig. 1. To reach the given target, in fact, all three must be efficiently integrated. The following are some deficiencies of the priority strategy noted in experiments:

(1) Much effort must be made to test and to adjust some thresholds for firing reactive behavior during preprogramming.
(2) These thresholds depend heavily on the environment, i.e. a set of thresholds, determined in a given environment, may not be suitable for other environments.
(3) Robot motion with unstable oscillations between different types of behavior may occur in some cases. This is because only one type of behavior can be activated at a given instant and two different types with neighboring priorities, e.g. *obstacle avoidance* and *target steer*, are fired in turn.

In the proposed control strategy, reactive behavior is formulated by fuzzy sets and fuzzy rules, and these fuzzy rules are integrated in one rule base. The coordination of different sorts of reactive behavior can thus be easily performed by fuzzy reasoning. The following is an illustration of how this problem is dealt with by the Min–Max inference algorithm and the centroid defuzzification method in equation (1). For instance, the inputs, $left\_obs = d_1$, $front\_obs = d_2$, $right\_obs = d_3$, $head\_ang = \theta_1$, are fuzzified by their membership functions to fire fuzzy rules associated with them simultaneously. Assume that *Rule i* (see below), formulating the *obstacle avoidance* behavior, and *Rule j* (see below), formulating the *following edges* behavior, are fired according to the fuzzified inputs (in fact, many more fuzzy rules may be activated):

Rule i: If (left_obs is near and front_obs is near and right_obs is near and head_ang is N) Then (left_v is fast and right_v is slow).

Rule j: If (left_obs is near and front_obs is med and right_obs is med and head_ang is N) Then (left_v is med and right_v is med).

By fuzzy reasoning and the centroid defuzzification method, both *Rule i* and *Rule j*, related to the *obstacle avoidance* and *following edges* behavior respectively, are weighted to determine an appropriate control action, i.e. the velocities, *left_v* and *right_v*, of the robot's rear wheels, as shown in Fig. 5.

In general, the weights of *obstacle avoidance* and *target steer* depend largely on the distances between the robot and the obstacles to the left, front, and right locations; while the weight of *following edges* depends on a heading angle between the robot and a specified target. Since robot navigation is controlled by integrating all the behaviors rather than by only firing a single behavior, unstable oscillations between different types of behavior are avoided, and the local minimum problem in artificial potential fields which causes robots to be trapped is lessened.

7. SIMULATIONS

This section reports several simulation results, such as avoiding obstacles in real time, decelerating on curved and narrow roads, escaping from a U-shaped object, moving towards a target, etc. In order to demonstrate the effectiveness and the robustness of the proposed method for robot navigation in unknown environments, the parameters of given environments in the simulations, such as the positions and the shapes of obstacles, are not taken into account, and all start positions and target positions in the simulation are randomly chosen.

7.1. Moving towards a target inside a U-shaped object

Figure 1 illustrates robot motion towards a target inside a U-shaped object. Since there are no obstacles around the start position, at the start stage the robot mainly reflects the behavior, *target steer*, so that it moves towards the target at a high speed. When the robot approaches the U-shaped object, it automatically decelerates and searches for the entrance of the U-shaped object by reducing the weight of the behavior, *target steer*, and by increasing those of both *obstacle avoidance*, and *following edges*. When the robot finds the entrance by following the edges of the U-shaped object, it reaches the target at a slow speed by increasing the weights of both *obstacle avoidance* and *target steer*.

7.2. Escaping from a U-shaped object

Figure 6 shows robot motion when escaping from a U-shaped object to reach a target. In this simulation, a robot start position and a target position are located on opposite sides of the U-shaped object, i.e. the start position is located on the entrance side and the target position is located at the back. At the start stage, the robot moves towards the target at a high speed since

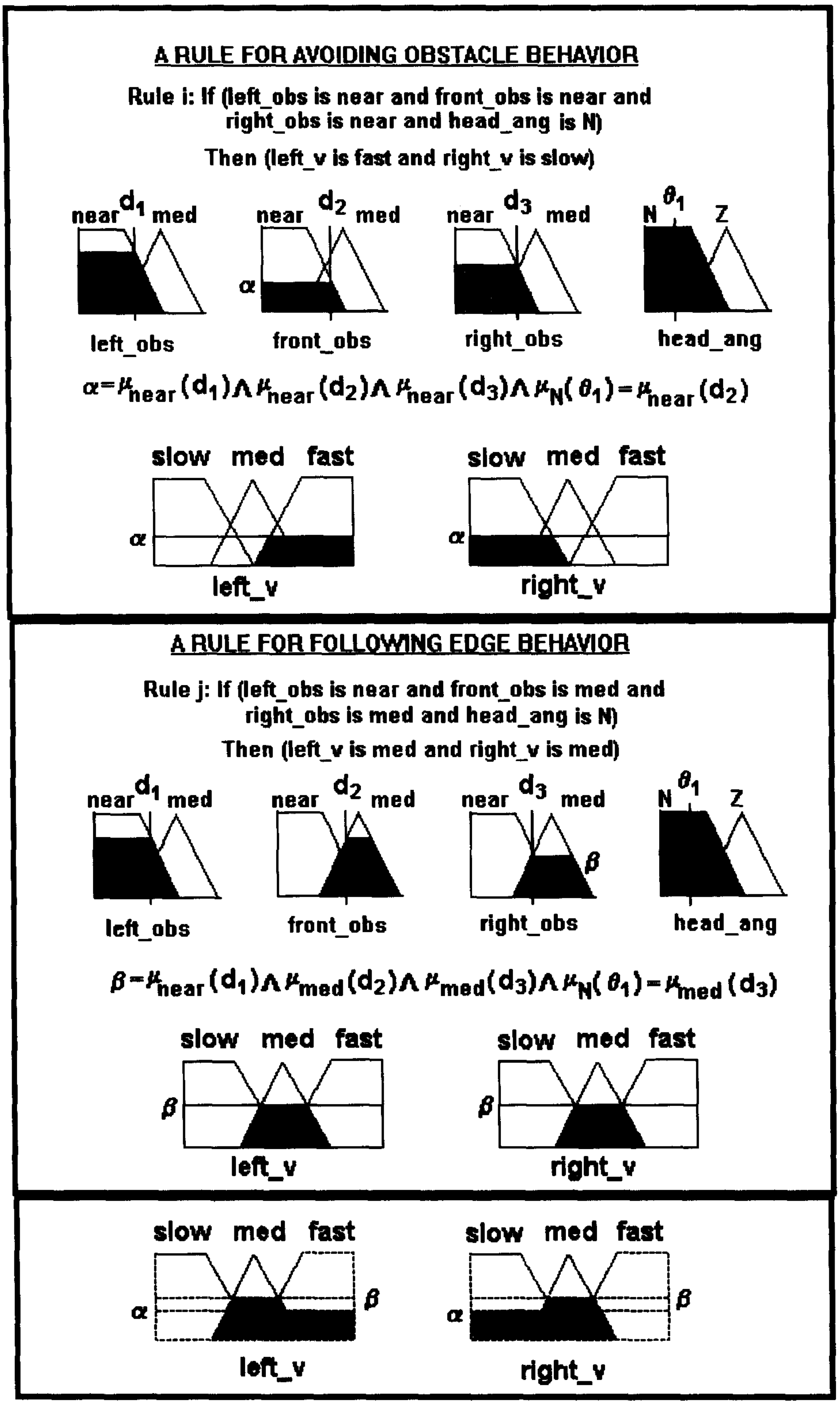

Fig. 5. Coordination of multiple reactive behavior using fuzzy reasoning.

there are no obstacles around the robot's start position. When the robot is trapped inside the U-shaped object, it moves along the edges of the U-shaped object by increasing the weight of the behavior, *following edges*, so as to escape from the U-shaped object. After the robot gets out and leaves the U-shaped object, it speeds up to move towards the target again. In this case, an artificial potential field approach may be of little use for escaping from the U-shaped object due to the local minimum.

7.3. Motion in a cluttered environment

Figure 7 shows robot motions in a cluttered environment to reach multiple targets. Several targets are

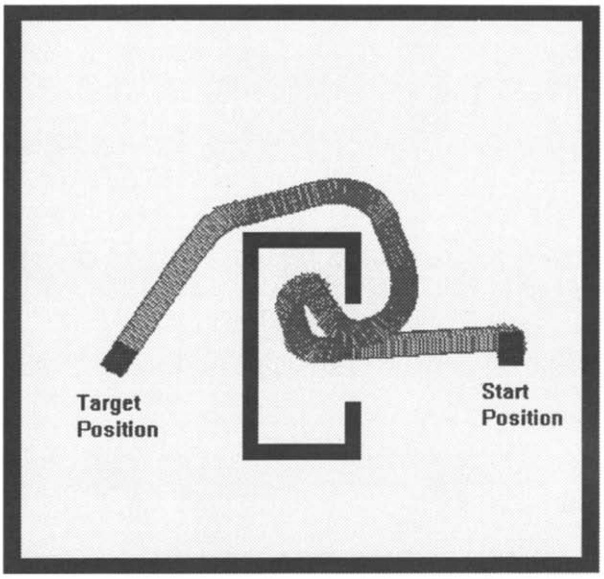

Fig. 6. Robot motion towards a target when escaping from a U-shaped object.

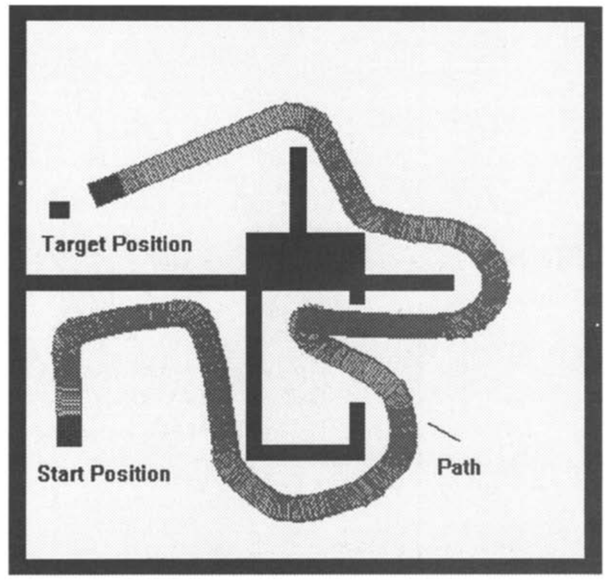

Fig. 8. Robot motion towards a target by the behavior, *following edges*.

randomly placed among different obstacle surroundings in the environment. Target 1 is located in a narrow space. Path 1 in Fig. 7 represents robot motions towards Target 1 from the start position. Path 2 in Fig. 7 represents robot motions from Target 1 to Target 2, which lies behind multiple obstacles. Path 3 represents robot motions from Target 2 to Target 3, which is placed in the region where the start position is located. It can be observed that, on the basis of the sonar data acquired by ultrasonic sensors, the robot can reach all the targets by using fuzzy reasoning to coordinate the different varieties of reactive behavior. It is noted that Path 1 does not lie between the first rectangular obstacle and the broken circular obstacle instead of going around the broken circular obstacle, i.e. this path is not optimal. The reason is that the sensor 10 (or 11), which is mounted on the left-front position of the THMR-II robot, acquires the minimum value in all the ultrasonic sensors ($i = 10, \ldots, 15$) which detect the obstacles to the left location, and this value is used as the distance between the robot and the broken circular obstacle according to equations (2)–(4), when the robot approaches the broken circular obstacle. In this case, the robot understands that this obstacle is very close to its left side, and thus the robot does not move towards the space between the first rectangular obstacle and the broken circular obstacle.

7.4. Following wall edges

Figure 8 shows a start position and a target position which are located in different rooms. Assume that a general map of the environment in Fig. 8 is not avail-

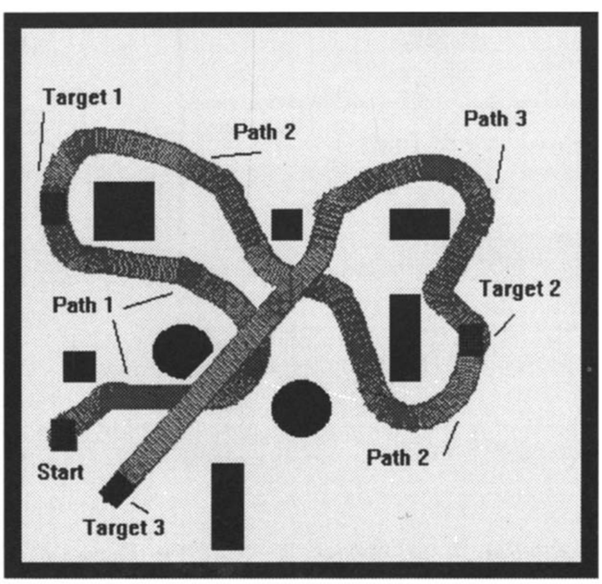

Fig. 7. Robot motion towards multiple targets in a cluttered environment.

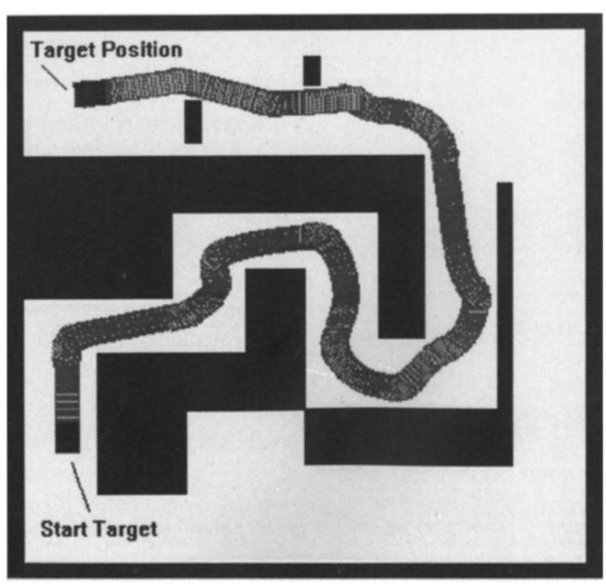

Fig. 9. Robot motion at lower speed on curved and narrow roads.

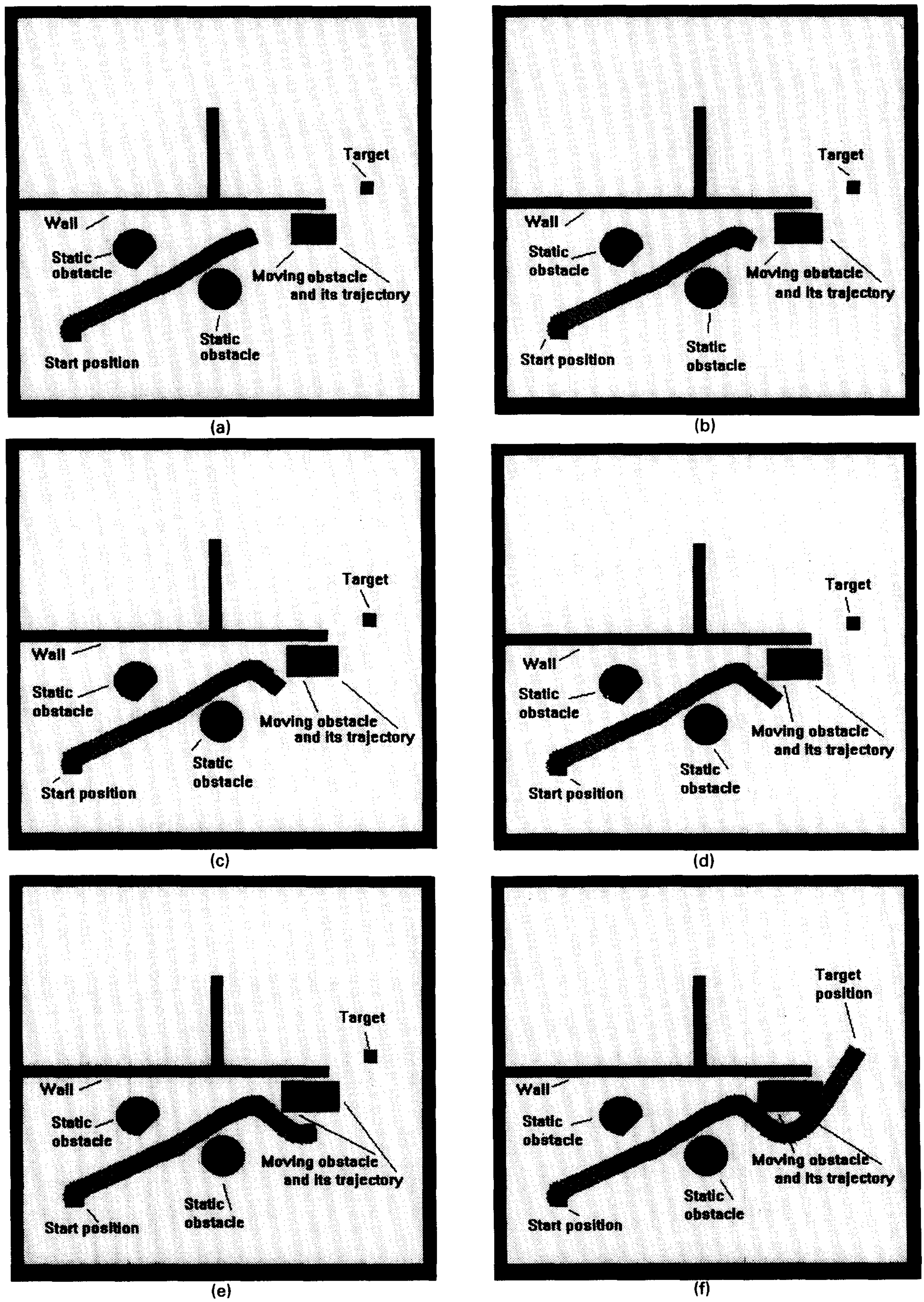

Fig. 10. (a)–(f) Robot motion when avoiding a moving obstacle.

able. At the start stage, therefore, the robot moves directly towards the target according to the heading angle between the robot's current position and the target. Since the right-oriented principle is implemented in the fuzzy navigation algorithm, the robot turns to the right by using the behavior, *following edges*, when it "hits" a wall. After getting out of this room, the robot is trapped inside a U-shaped object by moving towards the target and then escapes from the U-shaped object by following its wall. When the robot reaches the room where the target is located, it moves towards the target by the behavior, *target steer*.

7.5. Decelerating on curved and narrow roads

Figure 9 shows robot navigation on curved and narrow roads. The robot departs from its start position and automatically decelerates when it approaches the first 90° turn. Then it turns to the right and moves into a very narrow road at a slow speed. At the following 90° bends, the robot automatically makes reasonable turns to keep on the road. When the robot gets on the road where the target is located, it moves to the target using obstacle avoidance.

7.6. Moving obstacle avoidance

Figure 10(a–f) shows the graphical simulations of robot motion when avoiding a moving obstacle in a dynamic environment. This example is used to illustrate how a car driving on a road avoids another car moving in the opposite direction. Assume that the speed of the moving obstacle is lower than that of the mobile robot. In this simulation, a moving obstacle is set nearby the target. This moving obstacle moves along a wall and blocks the path of the robot's motion towards the target in Fig. 10(a). When the robot perceives, by sonar data, that the obstacle is moving towards it, and there is a wall on its left side, it only pays attention to avoiding this obstacle by making a right turn, as shown in Fig. 10(b–d). After the robot goes round the moving obstacle, it moves directly towards the target, as in Fig. 10(e–f).

8. CONCLUSIONS

Using behavior-based control, a complex task can be easily described by several simple behaviors. However, difficulties arise from the quantitative formulation of reactive behavior as well as from the need for the efficient coordination and integration of conflicts and competition among different types of reactive behavior. Fuzzy logic provides an efficient method for representing knowledge with uncertainty. It is generally difficult, though, to determine adequate fuzzy rules when fuzzy logic control is applied to a complex task.

This study combines the advantages of both fuzzy logic control and behavior-based control to compensate for their deficiencies. Stimulus-response behavior is used to analyze, and to decompose a complex task. Fuzzy rules and fuzzy reasoning are used to formulate each type of reactive behavior, using simple features, and to coordinate the conflicts and competition among multiple simple-featured varieties of behavior. The determination of fuzzy rules for each simple-featured type of behavior is thus made easier.

This navigation algorithm has better reliability and real-time response since perception and action units are integrated in one module, and they are directly oriented to a dynamic environment. The simulation results show that the proposed method, using ultrasonic sensors, can be applied to robot navigation in complex and unknown environments by efficiently coordinating multiple types of reactive behavior, such as *obstacle avoidance and deceleration on curved and narrow roads*, *following edges*, and *target steer*.

The robot may not reach a target when the robot is navigated within a maze-like environment, or when an entrance (or an exit) of a U-shaped object is narrower than 1.5 times the robot width. There are two reasons: firstly, a general map of the environments is not yet being used. Secondly, equations (2)–(4) for computing the distances between the robot and the obstacles are unable to reflect the shape of the obstacles. In order to improve navigation performance further, the present study is being extended to implement a vision system for determining some subgoals and building a local map, since the proposed method is suitable for multi-sensor fusion and integration.[15]

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REFERENCES

1. Brooks R. A. A robust layered control system for a mobile robot. *IEEE J. Robot. Automation* **RA-2**, 14–23 (1986).
2. Arkin R. C. and Murphy R. R. Autonomous navigation in a manufacturing environment. *IEEE Trans. Robot. Automation* **RA-6**, 445–454 (1990).
3. Krogh B. H. A generalized potential field approach to obstacle avoidance control. SME-RI Technical Paper MS84-484 (1984).
4. Khatib O. Real-time obstacle avoidance for manipulators and automobile robots. *Int. J. Robot. Res.* **5**, 90–98 (1986).
5. Wang T. and Zhang B. Time-varying potential field based 'perception-action' behaviors of mobile robot. *Proceedings of the IEEE International Conference on Robotics and Automation*, pp. 2549–2554 (1992).
6. Berns K., Dillmann R. and Hofsteller R. An application of a backpropagation network for the control of a tracking behavior. *Proceedings of the IEEE International Conference on Robotics and Automation*, pp. 2426–2431 (1991).
7. Li W. Fuzzy logic based perception-action behavior control of a mobile robot in uncertain environments. *Proceedings of IEEE World Congress on Computational Intelligence FUZZ-IEEE '94*, pp. 1626–1631 (1994).
8. Sugeno M. and Nishida M. Fuzzy control of model car. *Fuzzy Sets Syst.* **16**, 103–113 (1985).
9. Takeuchi T., Nagai Y. and Enomoto N. Fuzzy control of a mobile robot for obstacle avoidance. *Information Sci.* **45**, 231–248 (1988).

10. Maeda M., Maeda Y. and Murakami S. Fuzzy drive control of an autonomous mobile robot. *Fuzzy Sets Syst.* **39**, 195–204 (1991).
11. Zadeh L. A. Fuzzy sets. *Information and Control.* **8**, 338–353 (1965).
12. Li W. and He K. Z. Sensor-based robot navigation in uncertain environments using fuzzy logic. *Proceedings of the 1994 ASME International Computers in Engineering Conference.* In press.
13. Ai H. Z. Research on autonomous system for mobile robots. Ph.D. thesis, Department of Computer Science and Technology, Tsinghua University, Beijing, P.R. China (1991).
14. Li W. Perception-action behavior control of a mobile robot in uncertain environments using fuzzy logic. *Proceedings of IEEE/RSJ International Conference on Intelligent Robots and Systems.* In press.
15. Li W. Fuzzy logic based robot navigation in uncertain environments by multisensor integration. *Proceedings of 1994 IEEE International Conference on Multisensor Fusion and Integration for Intelligent Systems.* In press.

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