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Predictive fuzzy control of an autonomous mobile robot with forecast learning function

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Abstract

This paper deals with the drive control of an autonomous mobile robot. An autonomous mobile robot is one of the intelligent robots that need abilities to recognize and to adapt to surrounding environment. We propose a new approach to meeting these needs. This approach is based on a forecast learning fuzzy control. The environment can be classified into several characteristic patterns and our robot has sets of control rules for each pattern beforehand. The robot integrates these sets into a single set using degrees of matching between the current environment and each pattern. The robot forecasts whether it will drive safely or not by prediction, by using the integrated control rules. The robot considers the results of the forecast, and then adjusts the conclusion parts of the integrated control rules in order to drive more safely in such an environment.

In this paper, to find the efficacy of our new approach, the simulation results of the drive control of the robot and the experimental results on indoor routes are shown.

Keywords: Intelligent robot; Fuzzy expert system; Fuzzy control; Predictive control; Learning algorithm

1. Introduction

Automation in factories is making steady progress, and many industrial robots are already at work there. Most robots, however, can move only in a simple pattern that they have been taught once. Recently, the need for more intelligent robots, which can recognize and adapt to their surrounding environment by themselves, are increasing more and more.

An autonomous mobile robot is one of the intelligent robots. We can define it as a robot that recognizes its environment by itself, makes a plan to adapt to this environment, and then moves to achieve this plan thus avoiding collision with obstacles. It is expected to be applied widely to many fields, such as an unmanned automated carrier in a factory or a hospital, a working robot under dangerous and severe situation, a service robot that helps housework, and so on [1–3].

Human beings can make a proper decision and take proper action with only fuzzy or insufficient information. The soft and ambiguous intelligent behavior of human can be modeled by using fuzzy

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theory. The structure of that model can be understood relatively easily. Several studies by the rule-base and conventional control has been already reported as the drive control of autonomous mobile object [11]. As applications of fuzzy theory to the drive control of autonomous mobile robot, recently, some cases were reported. One of them is a fuzzy guide control by spinning control of two motors which drive left and right wheels of robot [10] and another is the fuzzy control of speed and direction of robot using two control rule sets [4]. Each robot in these studies has an image sensor (a single CCD camera) instead of eyes and is controlled on basis of the control rules and the environment information. In guide control, the spin speeds of two motors are controlled by PID controller and the command signals to PID controller are decided by the fuzzy decision rules (i.e. a single rule set) of spin speeds of motors. In speed and direction control, the moving direction and range are decided by using two driving control rule sets (i.e. direction control rules and distance control rules) on basis of information such as distances between walls or obstacles and a robot.

As a new study, the neural-net drive control is reported [8]. Though a target is not a mobile robot, the parking control of a model car [9] and the drive control of an automobile [5, 6] have been already reported.

In this paper, we have made a fuzzy expert system for the drive control of robot, which is modeled on human motion by using fuzzy set theory. The drive control system consists of a hierarchical structure, that is a human interface, the fuzzy drive expert system, a I/O interface, and the physical units such as the motors and the camera. In this system, our purpose is to make the robot to adapt to its environment and to drive safely. Furthermore, we propose a new approach based on forecast learning and predictive fuzzy control. This method includes two new approaches. One is the predictive fuzzy drive control of the robot. Other is the improvement of some control rule sets which coped with the present environment pattern of the robot. The predictive fuzzy drive control implies a method that controls the robot not to crash into walls or obstacles on basis of the fuzzy evaluation of the future states (or the future driving location) of robot, even if the drive control rules are ill-defined. The fuzzy evaluation implies to assess the possible driving routes of the robot on basis of information whether the future location of robot is in the possible driving area or not. Our predictive control is different from other predictive control on the unfolding of possible driving area, adopting it to select a driving force (i.e. robot's driving route) and the structure of control rules. The fuzzy drive control rules are used to smoothly go through the paths. In this system, mighty driving rules may not exist on all path conditions so that the hierarchical driving rule sets for possible driving patterns are used. The adjustment of control rules also employs a new approach which is not used in any other study. That is the improvement of hierarchical control rules by using the fuzzy assessment of difference between the robot's future location estimated by roughly mathematical model of robot and the future reference position set by the possible driving area. We call this approach of improvement the forecast learning because the predicted locus of robot are taken into the improvement algorithm. By this method (i.e. the double control system) the control rule sets will be gently bettered under experience and also the control results is better in the course of time. Finally, we discuss the usefulness of fuzzy forecast learning control from experimental results.

2. Robot control system

This section describes the control system of our robot.

2.1. Summary

Fig. 1 shows the structure of the robot control system. The robot (HERO 2000) takes an image in front of it by a CCD camera. The CCD camera is an eye and that image is the viewing field for the robot. The robot can recognize the environment around it by this view only. By analyzing this image, the robot recognizes walls, obstacles and so on, and then gets some information in order to navigate. Examples: that are some distances between the robot and walls or obstacle, and some

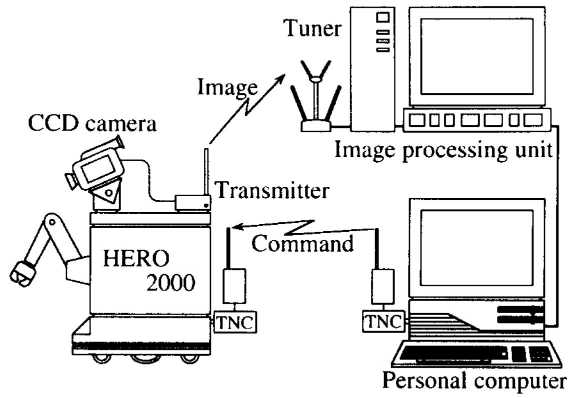


Fig. 1. Robot control units.

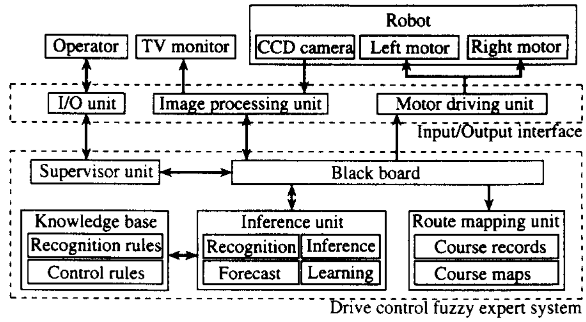


Fig. 2. Robot control system.

angles between the running direction of robot and the directions to corners, obstacle, or walls. The series of control forces to drive the robot are inferred by those information and driving control rules. The control force is the direction of movement of the robot. The direction of the robot is operated by the power wheel steering the right and left motors. The robot can move forward and back, turn spinning, and turn on circle. Although the robot has an internal micro computer, it is not enough to process large data, so a personal computer called a standalone type is used for this purpose. The data (i.e. image and commands) between the robot and the personal computer are transmitted by video transmitter and transceiver unit (as packet information), respectively, so that its sphere of activities widens.

2.2. Structure of robot control system

Our robot control system is composed of three parts, a fuzzy expert system for driving control, an input/output interface, and a robot, as shown in Fig. 2.

2.2.1. Drive fuzzy expert system

The features of our fuzzy expert system for drive control are recognition of the environment from an image taken by a CCD camera and determination of the control force to achieve an operator's driving plan by approximate reasoning. The control forces such as the change of direction of the robot and the moving distance command are obtained by drive control rules, predictive recognition rules, and an approximate reasoning of those. Those forces (or commands) include a turning left or right and a return in the corner area. The operator's driving plan is the direction and the management for targets or objects specified by the operator on each scene. This system is composed of the following units:

Inference unit. This unit plays the most important role in our robot control system. The roles of this unit are recognition of environment around a robot by the recognition rules, an inference for control forces on basis of control knowledge rule sets, the inference of safety forecasting direction for the robot by predictive recognition rules, an improvement of control rule sets by predictive learning rules, and so on.

Route mapping unit. This unit has two roles. One is to record the recognized environment on the world map that the robot's locus is measured from the starting point of the robot. Another one is to record a locus of the robot on the route and a direction of robot on a branch point.

Supervisor unit. This unit synthetically manages other units to implement the driving plan.

In addition to above units, there exists the knowledge base which consists of environment recognition rules and drive control rules and a black board which handles some information from each unit.

2.2.2. Input/Output interface

This part is the interface between the drive fuzzy expert system and the external devices or the operator. This part is composed of the following units:

Image processing unit. This unit's role are to translate an analog signal to a digital image, and change it to binary value, compression, noise reduction, edge detection and so on.

Motor driving unit. This unit independently drives right and left motors according to the turning speed or the turning frequency of two motors on basis of the direction of robot and the range.

3. Driving control

This section describes the process of the drive control of our robot, that is an image processing, a predictive fuzzy control, and a forecast learning control.

3.1. Image processing [4, 7]

3.1.1. Preprocessing

Our system performs the following steps to analyze the image of environment (a sight or a scene) around the robot:

(i) Sampling and quantification (or digitizing) of that image (256 × 256 pixels, 64 grades/pixel).
(ii) Changing densities of all pixels to binary-values by using a floating threshold method.
(iii) Compressing that image into 128 × 128 pixels.
(iv) Reducing the noise of compressed values.
(v) Edge detection (generation of chain codes).

This approach is a popular way in image processing.

3.1.2. Recognition of environment around robot

Our robot has not any road map at starting point. The robot has accordingly to move in the unknown world. So the robot sees its surrounding environment through the camera image to learn about the actual world. The viewing field of the robot, however, is so narrow that he cannot see all of the surrounding environment at once. The robot

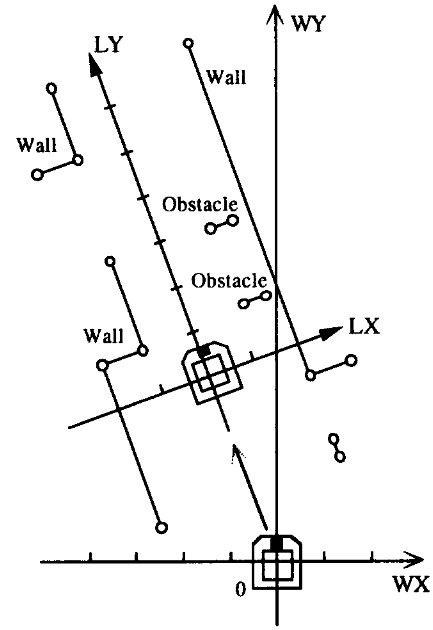


Fig. 3. Local map and world map.

records the captured images of walls and obstacles, and then creates two internal maps, a world map and a local map as shown in Fig. 3. The world map supports wide area, its origin is a starting point, while the local map supports comparatively narrow area in front of him. These maps are grown complete with repeated image capture of the environment. Now in Fig. 3, if the location of robot is indicated as (x, y) in world map and the coordinate of a object is indicated as (o_{lx}, o_{ly}) in local map or (o_{wx}, o_{wy}) in world map, the relation between the world map and the local map is formulated as follows:

$$\begin{aligned} o_{lx} &= (o_{wx} - x)\cos\theta - (o_{wy} - y)\sin\theta, \\ o_{ly} &= (o_{wx} - x)\sin\theta - (o_{wy} - y)\cos\theta, \end{aligned} \tag{1}$$

where θ is an angle between an axis in local map and that in world map.

3.2. Traditional approach

3.2.1. Basic fuzzy control

This approach is the most basic applied in many fuzzy controllers [4–6, 9, 10]. Linguistic control rules formed by IF–THEN type are employed to obtain a control action. In our robot control system, the control action guess a direction that the robot should move. The robot moves by means of the control action that are inferred by the control rules. A distance that the robot moves at a time is constant. The control rules can be classified into three cases, for a straight path, for a left turn path, and for a right turn path. The selection of these rule sets depends on the surrounding environment. The robot usually uses the control rules for a straight path. When the robot recognizes a turning point and approaches there, he changes control rules for a left turn path or a right one.

Control rules for a straight path. On a straight path, the robot has to move:
(1) following both side walls,
(2) on a center line of the path.

The robot uses four variables as follows: θ an angle of robot direction for center line, $\Delta\theta$ a change of θ, p a deviation from the center of a path; normalized $-1 \leqslant p \leqslant 1$, Δp a change of p.

The consequence of the control rule is a direction that the robot should move, defined by seven triangular membership functions. The control rules for a straight path are defined as shown in Table 1.

Control rules for a left turn. On a left turning path (as shown in Fig. 4), the robot has to turn:
(1) near the turning corner without collision,
(2) following a front wall without collision.

The robot uses four variables as follows: θ_c an angle for the turning corner, d_c a distance to the turning corner, θ_w an angle for the front wall, d_w a distance to the front wall.

The control rules for a left turn are defined as shown in Table 2.

Control rule for a right turn. A right turning path is symmetric with respect to a left one, therefore we do not describe here about it. Those rules can be easily derived.

Table 1
Control rules for a straight path

$\Delta\theta$	θ			Δp	p		
	Neg.	Zero	Pos.		Neg.	Zero	Pos.
Neg.	PB	PS	NS	Neg.	PB	PS	ZO
Zero	PM	ZO	NM	Zero	PS	ZO	NS
Pos.	PS	NS	NB	Pos.	ZO	NS	NB

NB: Negative Big, NM: Negative Medium, NS: Negative Small, PB: Positive Big, PM: Positive Medium, PS: Positive Small, ZO: Zero.

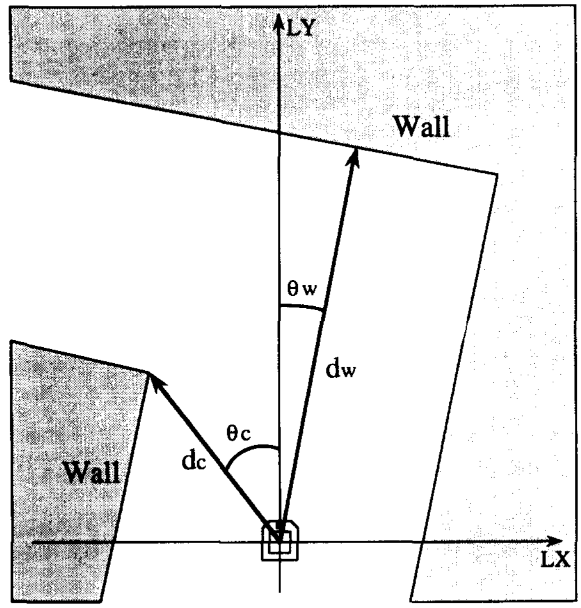


Fig. 4. Information for turn left control.

Table 2
Control rules for a left turn road

d_c	θ_c			d_w	θ_w		
	Neg.	Zero	Pos.		Neg.	Zero	Pos.
Small	NB	PM	PB	Small	NM	NB	NB
Med.	NM	PS	PM	Med.	NS	NM	NB
Big	NS	ZO	PS	Big	ZO	NS	NM

NB: Negative Big, NM: Negative Medium, NS: Negative Small, PB: Positive Big, PM: Positive Medium, PS: Positive Small, ZO: Zero.

3.2.2. *Predictive fuzzy control*

It is a question for the basic fuzzy control whether the control rules are well defined or not. The ill-defined control rules give an unsuitable control action. If our robot uses an unsuitable control action,the robot will move to an unexpected direction and may come into collision with a wall or an obstacle. To avoid a collision, it is necessary that the robot makes sure safety.

There is a fuzzy control that forecasts a control effect on basis of a mathematical model or a fuzzy model of object (i.e. a driving model) [7]. It properly controls a motion of robot by using the forecasted information. This approach is also called a predictive fuzzy control and has been applied to a subway in Sendai [12]. Using this approach, the robot forecasts a safe action. First, the robot picks out a possible driving area as shown in Fig. 5(b) from the local map. Note that NB, NM, ... , PB are fuzzy labels as shown in Fig. 5(c) and the driving distances, as examples, PS and ZE imply turning right about 90 cm on the circle locus of inside wheel at radius 270 cm and go forward about 120 cm, respectively. Next, the robot simulates possible courses on the area, and then finds out a range of the control action that the robot can move safely. It is called a possible range (or available direction) and it is shown in Fig. 5(d).

When the control action inferred by the integrated control rule set is within the possible range, the navigation is safe; otherwise, it is not. Therefore, the robot uses the nearest control action from the inferred one in the possible range as shown in Fig. 6. Now, the examples of control rules are shown in

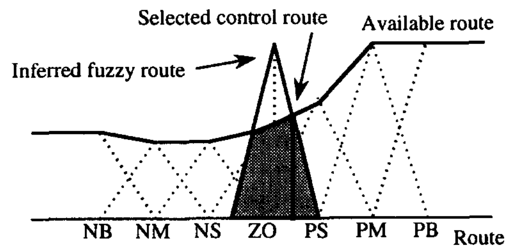
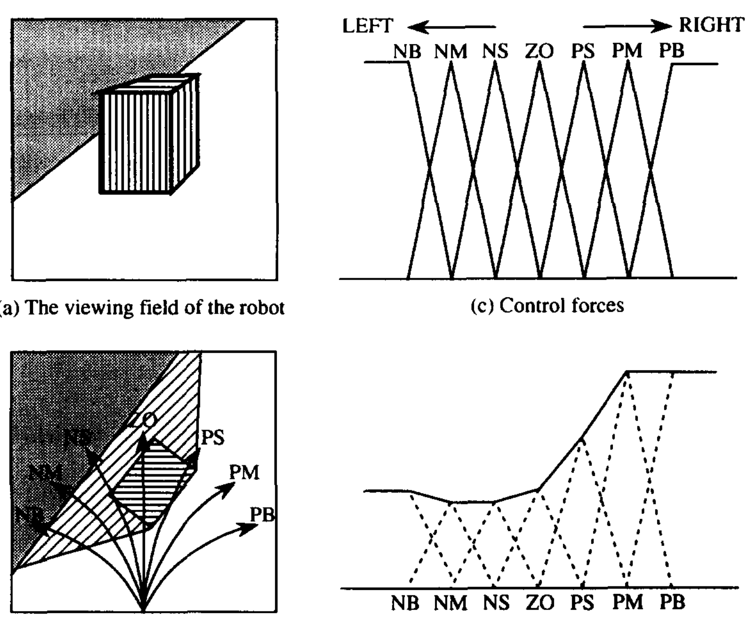


Fig. 6. Decision of the control action.



(a) The viewing field of the robot

(c) Control forces

(b) Simulation on a possible driving area

(d) Possible range

Fig. 5. Possible driving area: (a) the viewing field of the robot; (b) simulation on a possible driving area; (c) control actions; (d) possible range.

Tables 1 and 2. The control rule set used in reality is integrated by the weights ω. (see Section 3.3) from the control rules for environment patterns surrounding the robot.

Thus, the robot always gets a safe control action and moves safely on the paths. This approach (our predictive control) takes an average between the basic fuzzy control and other predictive control. Now our predictive control in this case is inferred by following rules:

If TR is NB and robot is IN then ER is NB
If TR is NB and robot is OUT then ER is not NB
If TR is NM and robot is IN then ER is NM
If TR is NM and robot is OUT then ER is not NM
If TR is PB and robot is IN then ER is PB
If TR is PB and robot is OUT then ER is not PB (2)

where

TR	the tentative route
ER	the enforceable route
IN	it means that the robot is *in* the possible area in the future
OUT	it means that the robot is *out* of the possible area
NB	negative big (a very left side)
not NB	complement of negative big (not a very left side)
NM	negative medium (a left side)
not NM	complement of negative medium (not a left side)
PB	positive big (a very right side)
not PB	complement of positive big (not a very right side)

and the possible area implies the range which the robot possibly takes for the avoidance control (i.e. those are possible routes).

Note that the mathematical model of the robot used in this paper has been already formulated by a reference paper [10]. The rules integrated in Section 3.3. are used for the control.

3.3. Forecast learning fuzzy control [7]

3.3.1. Proposition

According to a predictive fuzzy control, our robot can get a safe control action. But it is not always suitable, because we cannot precisely define the control rules that adapt to all of the environment around the robot. The robot will get a poor control action as long as he uses ill-defined control rules. To solve this problem, we propose a new approach based on forecast learning fuzzy control, and apply it to the robot control system. This approach adds the learning function to a predictive fuzzy control.

The forecast fuzzy learning control is performed in the following steps:

(i) Pre-defined control rule sets for some environment patterns are ready.
(ii) During the drive control, the environment around a robot is acquired and the future position (state) is guessed.
(iii) By the evaluation of the forecasted state, the control rule sets which matched the present environment pattern are improved.
(iv) After that the robot is controlled by the improved rule sets.

In this way some control rule sets will be smoothly bettered under experience and the control results in the course of time. The conventional algorithm for the improvement of rules uses the past and present data. The future states of the robot, which are forecasted by the mathematical model, are used in this paper, therefore the predictive control was employed. The usage of the future state means that a forecast learning reflects to the control action after this. That is to immediately get a control effect by using control rules after learning. Also, we employ a forecast learning control and a predictive control to increase the reliability of control performance, that is the fitness of control rules and the precision of the model for the robot.

Note that the mathematical model of the robot is very important, and its precision is needed on a suitable degree to identify the tendency of the robot's action.

3.3.2. Learning algorithm

This section describes the learning function for the rule improvement.

Pattern classification. The possible range takes various shapes according to environmental changes and is composed of several characteristic patterns. In our approach, the possible range is divided into three patterns such as (1) the left side, (2) the center, and (3) the right side on a road as shown in Fig. 7(a), and then the robot prepares a set of control rules for each pattern beforehand (i.e. rule sets (1)–(3) as shown in Fig. 7(d)). Note that these control rules do not have to be suitable. Other patterns except the above three patterns are also considered in this paper.

Rule selection. The robot forecasts its surrounding environment (see Fig. 7(b)) in our approach. The sets of control rules for each pattern are integrated into a set with degrees of agreement (i.e. ω. in Fig. 7(c)) between a current environment and each divided pattern (see Fig. 7(a)). Fig. 7(d) shows this approach. The robot infers a control action by using these integrated control rules. To make sure safety, the robot can forecast a control effect by this action under the virtual control simulation. Thus, using a rule selection mechanism, the robot always gets a safe control action and moves safely.

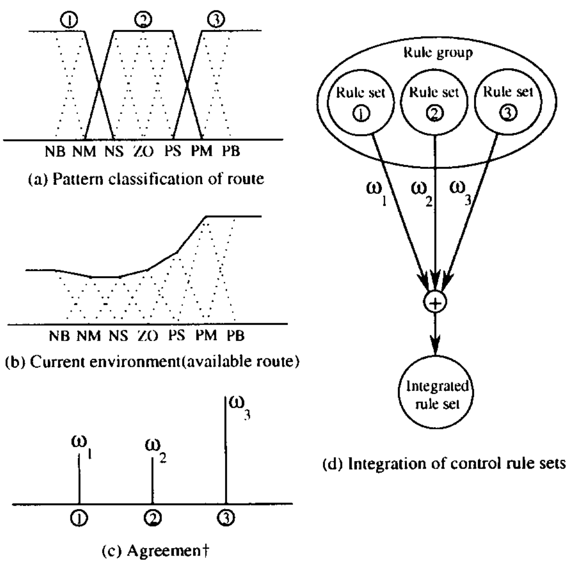


Fig. 7. Selection of rule set for drive control: (a) pattern classification of route; (b) current environment (available route); (c) degrees of agreement; (d) integration of control rule sets.

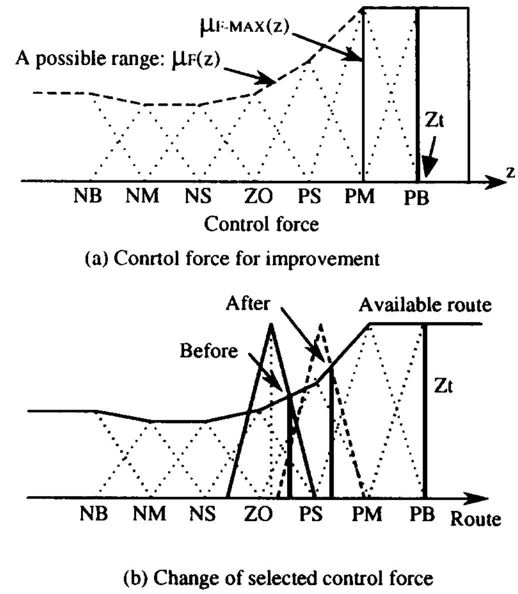


Fig. 8. Correction of control action, Z_t: (a) control action for improvement; (b) change of selected control action.

Rule correction. A correction of control action, Z_t is defined as the safest control action in the possible range shown in Fig. 8(a) and is given as the following equation:

$$z_t = \frac{\int z \cdot \mu_{F-\mathrm{Max}}(z)\,\mathrm{d}z}{\int \mu_{F-\mathrm{Max}}(z)\,\mathrm{d}z}, \tag{3}$$

where Z is universe of discourse of control action (a possible direction of the robot):
$z \in Z$,

$$\mu_{F-\mathrm{Max}}(z) = \begin{cases} \mu_F(z), & \mu_F(z) \geqslant \mu_F(y) \\ 0, & \text{other} \end{cases} \quad (\text{for } \forall y \in Z), \tag{4}$$

where μ_F is a membership function for a movable range.

To shorten a gap between the correction of control action and the inferred control action (see Fig. 8(b)), the robot corrects the results of the integrated control rules that have great influence in the inference of control action. A correction satisfies the following equation:

$$Z^{*\prime} = \begin{cases} Z^* + \alpha(Z_t - Z^*) \\ (1-\alpha)Z^* + \alpha Z_t \end{cases} \quad (\alpha \in [0,1]), \tag{5}$$

where Z^* is an inferred control action before correction, $Z^{*\prime}$ is an inferred control action after correction, Z_t is a correction of control action and α is a parameter of correction.

If α equals zero, the correction will be null. If α equals unit, an inferred control action will equal a correction of control action in one time correction. The robot puts the corrected control rules back into knowledge base for each divided pattern and uses an inferred control action after correction (Fig. 8(b)). Repeating this process, the robot learns the suitable control rules for each divided pattern. As a consideration we do not recommend that one takes "α equals unit", because the possible range (i.e. a mathematical model of robot) is not completely faithful. When α closes unit, the mathematical model of robot is more reliable than the control rules. While if α closes zero, the control rules are more reliable than that of the robot.

Note that this algorithm, which only corrects the consequent of rule, is employed to briefly train the rule.

4. Experimental results

We made a simulation for the autonomous mobile robot and made simulations on drive control with it. After that, actual experiments were made on a straight path with two obstacles. One of purposes is to drive the robot on the center line of the path. Figs. 9(a)–(c) show the experimental results. There are three cases, a basic fuzzy control, a predictive fuzzy control and a forecast learning fuzzy control (i.e. the predictive fuzzy control with a forecast learning function). The direction of the robot on initial condition is slightly left in all the cases.

In case of the basic fuzzy control (a), the robot achieved the control objectives, but ran into collision with an obstacle. In other cases (b) and (c), the robot avoided collision. In case of the forecast learning fuzzy control (c), by comparison with case of the predictive fuzzy control (b), the robot reached the center of the road earlier and avoided the obstacles keeping a safe distance. If the robot did not have the purpose to drive on the center line, the result of the predictive fuzzy control (b) could be a good one. On the standpoints such as reliability, controllability, and dynamical response, it is found that the forecast-learning fuzzy control is best. From these results, a safe driving of the robot will be implemented on many path-patterns by this algorithm.

Note that a value α equals 0.6 in Fig. 9(c). Although a result which was stimulated at $\alpha = 1.0$ is not shown here, the driving of the robot was snaky like motion as control result.

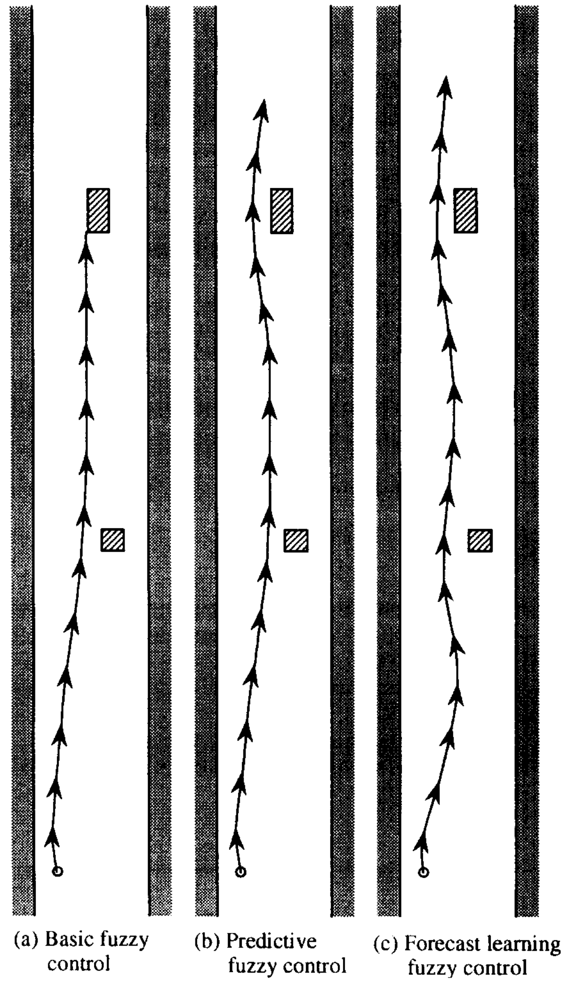


Fig. 9. Experimental results: (a) basic fuzzy control; (b) forecast fuzzy control; (c) forecast learning fuzzy control.

5. Conclusion

We proposed a new approach based on forecast learning fuzzy control and applied it to the drive control system of the autonomous mobile robot. The features of this approach are a classification of the surrounding environment into several patterns, a correction of the control rules for each pattern by itself, and an adaptation to the surrounding environment. From the experimental results, we could find the efficacy of our new approach.

The future problems are full recognition of objects, the improvement of an image processing unit, and an application to other areas.

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