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FUZZY CONTROL OF MODEL CAR

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This paper discusses fuzzy control of a model car. Fuzzy control rules are derived by modelling an expert's driving actions. Experiments are performed using a model car with a sensing unit and a micro-computer.

Keywords: Fuzzy control, Fuzzy control rules, Human operator's model, Micro-computer control, Car driving.

1. Introduction

Fuzzy control is one of the most interesting fields where fuzzy theory can be effectively applied. Recently some practical applications of fuzzy control [1–6] have been reported.

As far as fuzzy control is concerned, we can say that our main interest is now towards its applications. When we intend to apply fuzzy control to an industrial process, one of the key problems to be solved is to find fuzzy control rules. There are a number of ways to find fuzzy control rules based on:

(1) the operator's experience,
(2) the control engineer's knowledge,
(3) fuzzy modelling of the operator's control actions,
(4) fuzzy modelling of the process.

This paper discusses the fuzzy control of a model car where control rules are derived by modelling an expert's driving actions. Most of fuzzy controllers have been designed by the first and the second methods so far, Those two methods are heuristic in their natures, which are very difficult to be generalized. We face often the case where an operator cannot tell linguistically what actions he takes in such and such a situation. For instance, consider when we drive a car. We know car driving techniques by our hands and legs rather than by our brain. In fact we can easily suppose that it would be difficult to make skilful control rules based on a driver's knowledge. The first and second methods are not suitable in this control situation. Also if a process is complex, it is difficult to design a fuzzy controller even from a control engineer's point of view. In such cases it is very useful to develop a method to derive fuzzy control rules by modelling operator's control

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actions, if there is a good reason to believe that an operator does an excellent control. If it is not the case, we have to take the fourth method.

2. Preliminaries

Fuzzy control rules and reasoning method

In this study we use the following fuzzy control rules for a multi-input and single-output controller. The i-th control rule is of the form

$$\begin{aligned} R^i:\quad & x_1 \text{ is } A_1^i, x_2 \text{ is } A_2^i, \ldots, x_n \text{ is } A_n^i \\ & \rightarrow y^i = p_0^i + p_1^i x_1 + \cdots + p_n^i x_n \end{aligned} \tag{1}$$

where the A_j^i's are fuzzy variables and y^i is the output of the i-th control rule determined by a linear equation with coefficients p_j^i. The membership function of a fuzzy set A is simply written $A(x)$ and it is composed of straight lines.

When the inputs $x_1^0 - x_n^0$ are given, the truth value of the premise of the i-th rule is calculated as

$$w^i = \bigwedge_{j=1}^{n} A_j^i(x_j^0) \tag{2}$$

and the output y^0 is inferred from m rules by taking the weighted average of the y^i's:

$$y^0 = \sum_{i=1}^{m} w^i y^i \Big/ \sum_{i=1}^{m} w^i. \tag{3}$$

Identification algorithm of fuzzy control rules

Suppose that we are given input–output data $x_{1k}, x_{2k}, \ldots, x_{nk}, y_k$ taken from operator's control actions. We then have to identify

(1) the number of fuzzy partitions of the input space, for example, small, medium and big for x_1, and small and big for x_2, etc.,

(2) the membership functions of those fuzzy variables,

(3) the coefficients in the consequences of the rules the number of which is $m \times (n+1)$.

These are identified so that the output error is minimized where we mean by the output error, the difference between the output of a model and that of a process. The first problem, i.e., fuzzy partition, has no general way to be solved since it is a combinatorial problem. Engineering sense is, however, available and a heuristic search of the optimal partition is also possible. Provided that fuzzy partitions and the membership functions are given, the coefficients $p_0^i - p_n^i$ are easily identified using the output Eq. 3 so as to minimize the output error. We can use so called the stable Kalman filter. To identify the membership functions, we can use the complex method to search optimal parameters since the performance index, i.e., the output error, is nonlinear with respect to the parameters of the membership functions. Here we have to iterate the identification process of the coefficients since those depend on the membership functions in the premises. Note that each membership function is determined by two or three parameters which give the maximal grade 1 and the minimal grade 0. See [6] for the details.

3. Derivation of control rules

The aim of this study is to control the steering handle of a model car so that it smoothly runs through a crank-shaped course.

A computer model of a car has been made in a micro-computer to find fuzzy control rules. Man can control its steering handle, and the trajectory of the car is displayed on a monitor TV screen. The speed of the car is kept constant throughout this study. So the control input to the car is only the angle of the steering handle.

Figure 1 shows an example of the trajectories of a car on a crank-shaped course controlled by an experienced person. About 500 input–output data have been taken from eighteen trajectories. As the inputs to a human driver, four variables x_1–x_4 have been chosen as are seen in Figure 2 where

x_1 = distance from entrance of corner,
x_2 = distance from inner wall,
x_3 = direction (angle) of car,
x_4 = distance from outer wall.

The output of a driver, y, is the movement of the steering handle, i.e., the moved angle from its home position. Using the input–output data $x_{1k}, \ldots, x_{4k}$ and y_k, expert's driving actions are modelled in the form of 20 control rules. As for fuzzy partitions of the input space, we choose three fuzzy variables for x_1, two for x_2, three for x_3 and one for x_4 by observing the expert's actions.

Now we can identify the membership functions in the premises and the coefficients in the consequences. Figure 3 shows the identified membership

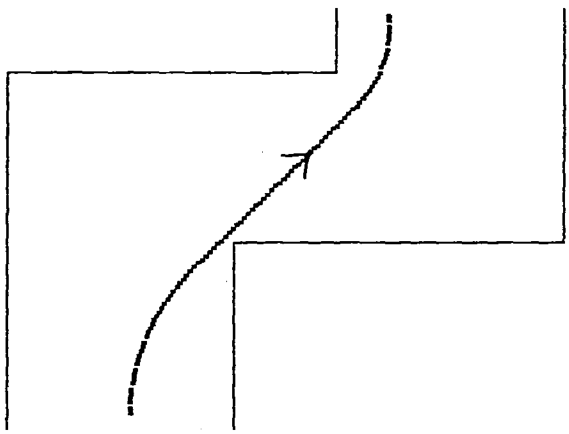

Fig. 1. Trajectory of an experienced driver's car control.

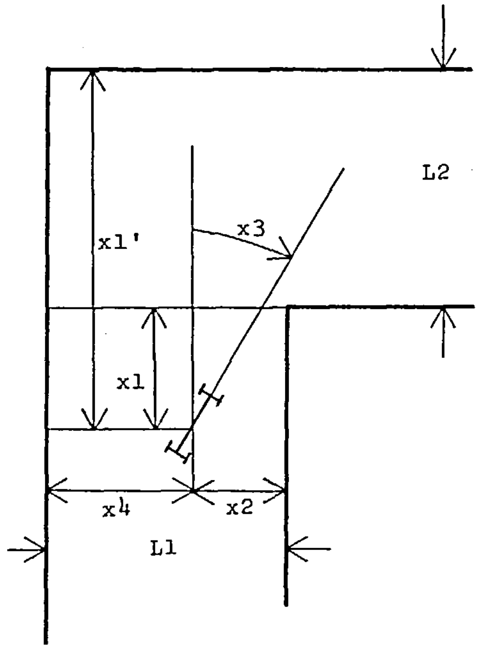

Fig. 2. Input variables to a driver.

functions associated with linguistic labels. Tables 1 and 2 show the premises of the control rules and the identified coefficients in the consequences, respectively. The rules R^1 and R^2 are for keeping the car away from the outer wall. The others are for driving it smoothly.

Now computer simulation of car driving has been done using those control rules. Figures 4a, 4b and 4c show the results of the simulation in some different situations. We can see that the derived control rules work very well.

4. Control of model car

Since the computer simulation was successful, the authors have made a model car and tried its fuzzy control using a micro-computer. The configuration of the model car and the micro-computer for control are the following.

Body: length 40 cm, width 21 cm, weight 2 kg.

Drive force: DA motor with gear ratio 1:230.

Front wheels control: servo-motor.

Speed: 100 cm/min.

Sensor: supersonic sensor driven by a stepping motor for the measurements of distance and direction.

Micro-computer: CPU 8080 with 4K BASIC.

Figure 5a and 5b show the appearance of the model car. The fuzzy control

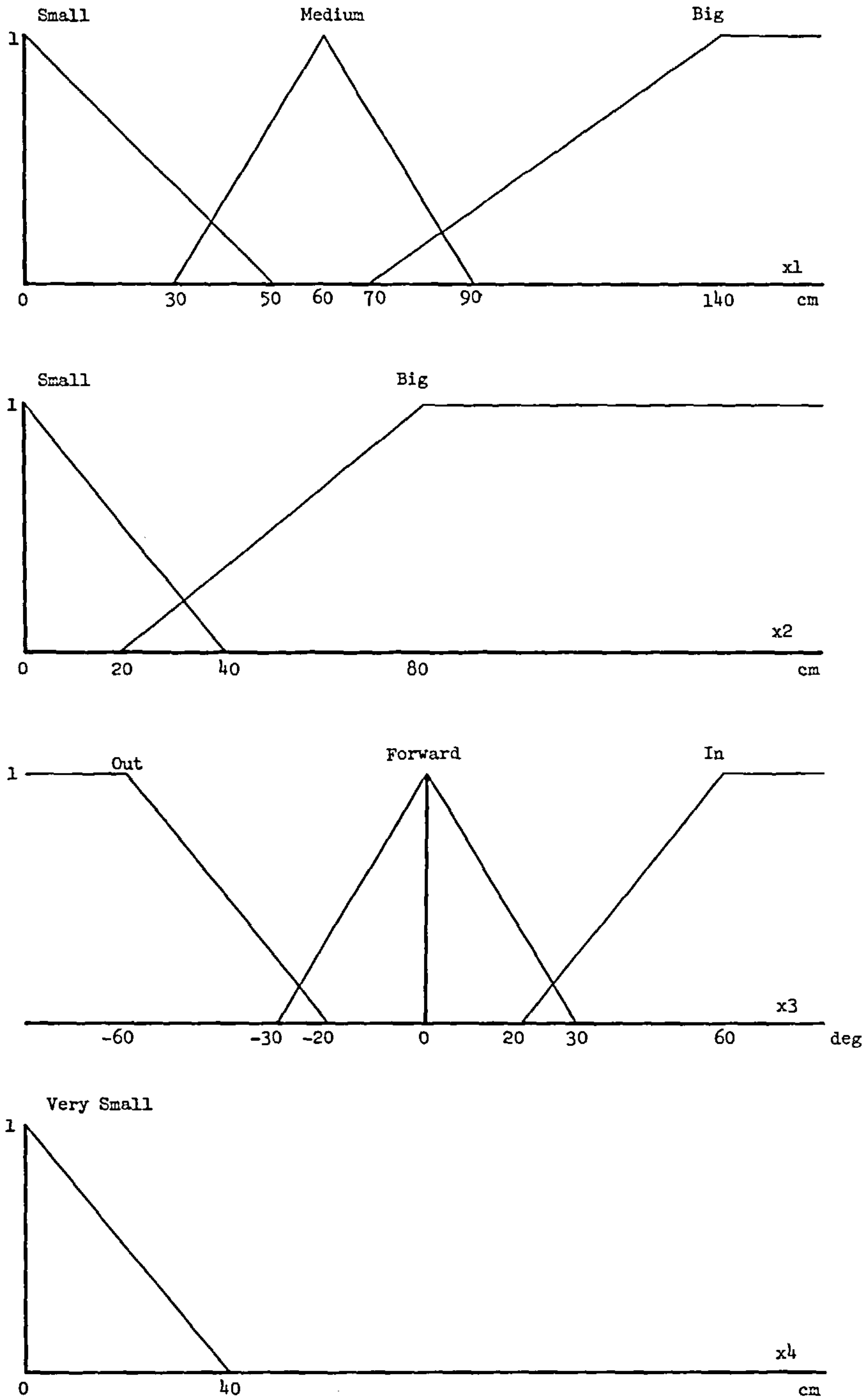

Fig. 3. Identified fuzzy variables.

Table 1. Fuzzy variables in premises of control rules

Rule	x_1	x_2	x_3	x_4
R^1	–	–	Out	Very small
R^2	–	–	Forward	Very small
R^3	Small	Small	Out	–
R^4	Small	Small	Forward	–
R^5	Small	Small	In	–
R^6	Small	Big	Out	–
R^7	Small	Big	Forward	–
R^8	Small	Big	In	–
R^9	Medium	Small	Out	–
R^{10}	Medium	Small	Forward	–
R^{11}	Medium	Small	In	–
R^{12}	Medium	Big	Out	–
R^{13}	Medium	Big	Forward	–
R^{14}	Medium	Big	In	–
R^{15}	Big	Small	Out	–
R^{16}	Big	Small	Forward	–
R^{17}	Big	Small	In	–
R^{18}	Big	Big	Out	–
R^{19}	Big	Big	Forward	–
R^{20}	Big	Big	In	–

Table 2. Coefficients in consequences of control rules

Rule	p_0	p_1	p_2	p_3	p_4
R^1	3.000	0.000	0.000	−0.045	−0.004
R^2	3.000	0.000	0.000	−0.030	−0.090
R^3	3.000	−0.041	0.004	0.000	0.000
R^4	0.303	−0.026	0.061	−0.050	0.000
R^5	0.000	−0.025	0.070	−0.075	0.000
R^6	3.000	−0.066	0.000	−0.034	0.000
R^7	2.990	−0.017	0.000	−0.021	0.000
R^8	1.500	0.025	0.000	−0.050	0.000
R^9	3.000	−0.017	0.005	−0.036	0.000
R^{10}	0.053	−0.038	0.080	−0.034	0.000
R^{11}	−1.220	−0.016	0.047	−0.018	0.000
R^{12}	3.000	−0.027	0.000	−0.044	0.000
R^{13}	7.000	−0.049	0.000	−0.041	0.000
R^{14}	4.000	−0.025	0.000	−0.100	0.000
R^{15}	0.370	0.000	0.000	−0.007	0.000
R^{16}	−0.900	0.000	0.034	−0.030	0.000
R^{17}	−1.500	0.000	0.005	−0.100	0.000
R^{18}	1.000	0.000	0.000	−0.013	0.000
R^{19}	0.000	0.000	0.000	−0.006	0.000
R^{20}	0.000	0.000	0.000	−0.010	0.000

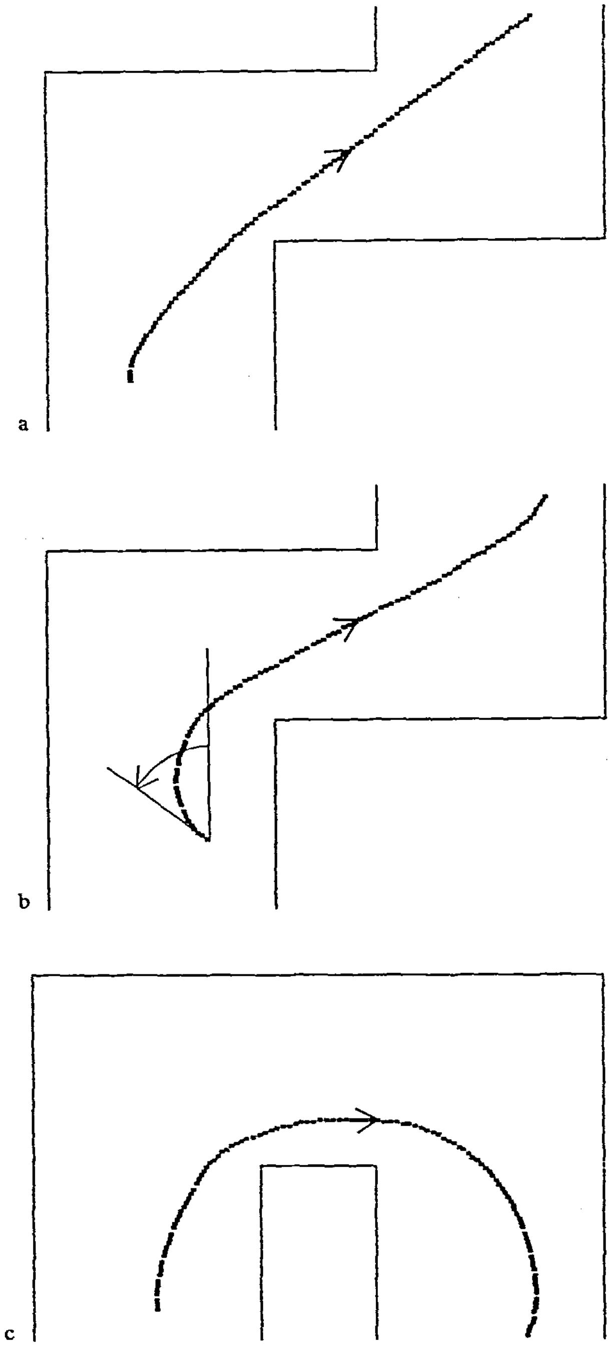

Fig. 4(a, b, c). Results of computer simulation.

algorithm is programmed in BASIC language and installed in the microcomputer. The size of the program is about 100 steps in BASIC.

In the experiments the micro-computer is not mounted on the car and is connected by a flat cable because of an electric power supply problem. We can see the cable connected to the back side of the car in Figure 5a. The other interfaces

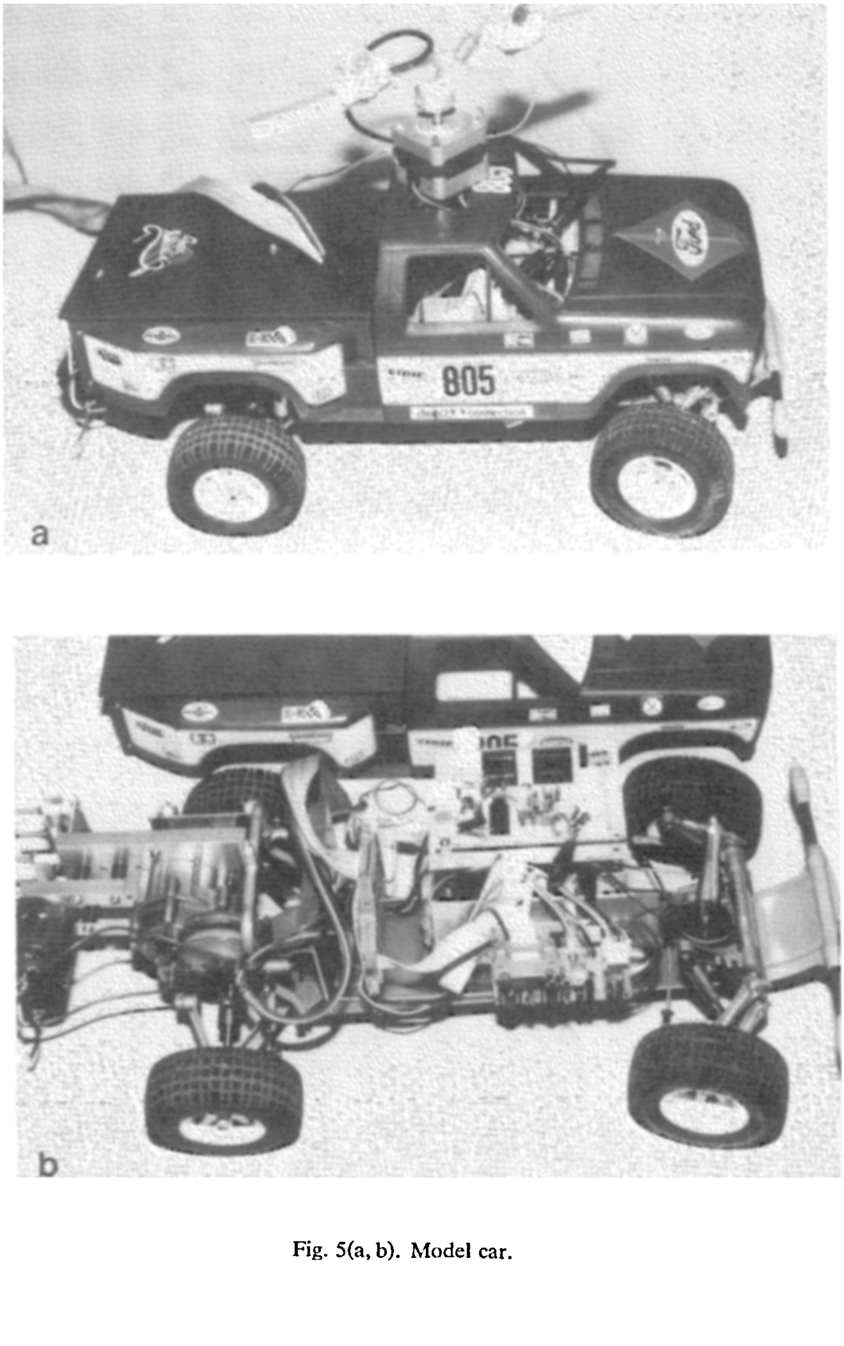

Fig. 5(a, b). Model car.

for the inputs and outputs of the micro-computer are mounted on the car as are seen in Figure 5b.

We shall now look at the sensing devices.

Measurement of distance

A sensor is made by using a 40 KHz supersonic transducer. It can measure distance by counting the time difference between the time of emitting supersonic wave and that of receiving its echo reflected by the outer or inner wall. For the purpose of the measurements the wall is placed along the driving course. The sensor can measure at most 2 meters' distance. Its resolution is about 2 cm.

Measurement of direction

The supersonic sensor is rotated just like a radar by a stepping motor. We can see the sensing unit on the roof of the car in Figure 5a. When the sensing unit is put on the position in parallel with the wall, it can receive supersonic echo. Since a supersonic wave has a good directivity, the direction of the car can be measured by counting the number of pulses put into a stepping motor between the home position of the sensing unit and the position where it can catch the echo. The stepping motor is rotated by 3.6° with 1 pulse. The resolution of the sensor is 7.2°.

Control of front wheels

A servomotor is used to control the front wheels. The output of the fuzzy controller is transmitted to a servomotor through a D/A converter. The resolution of this control is about 0.86° bit. When the rotation angle of the front wheels is 1°, the change of the direction of the car is about 1/60° after 1 sec run. Therefore the universe of discourse for fuzzy variables has to be adjusted by considering the above mentioned fact and also the real situation of the driving course. However the problem is quite simple because it is merely the modification of controller's gain factors.

Experiments

Fuzzy control experimnts have been performed on a test course with 1 meter width. Figure 6a–6d show the trajectories of the model car in some different situations. As we can see, the car can run very smoothly through a crank-shaped course. However it has occasionally failed because of sensing error.

5. Conclusions

It has been found that the way to derive fuzzy control rules from an experienced operator's control actions is very useful to design a fuzzy controller. The authors are now applying this sort of fuzzy control to put a car into a garage, where the speed of a car has to be also controlled.

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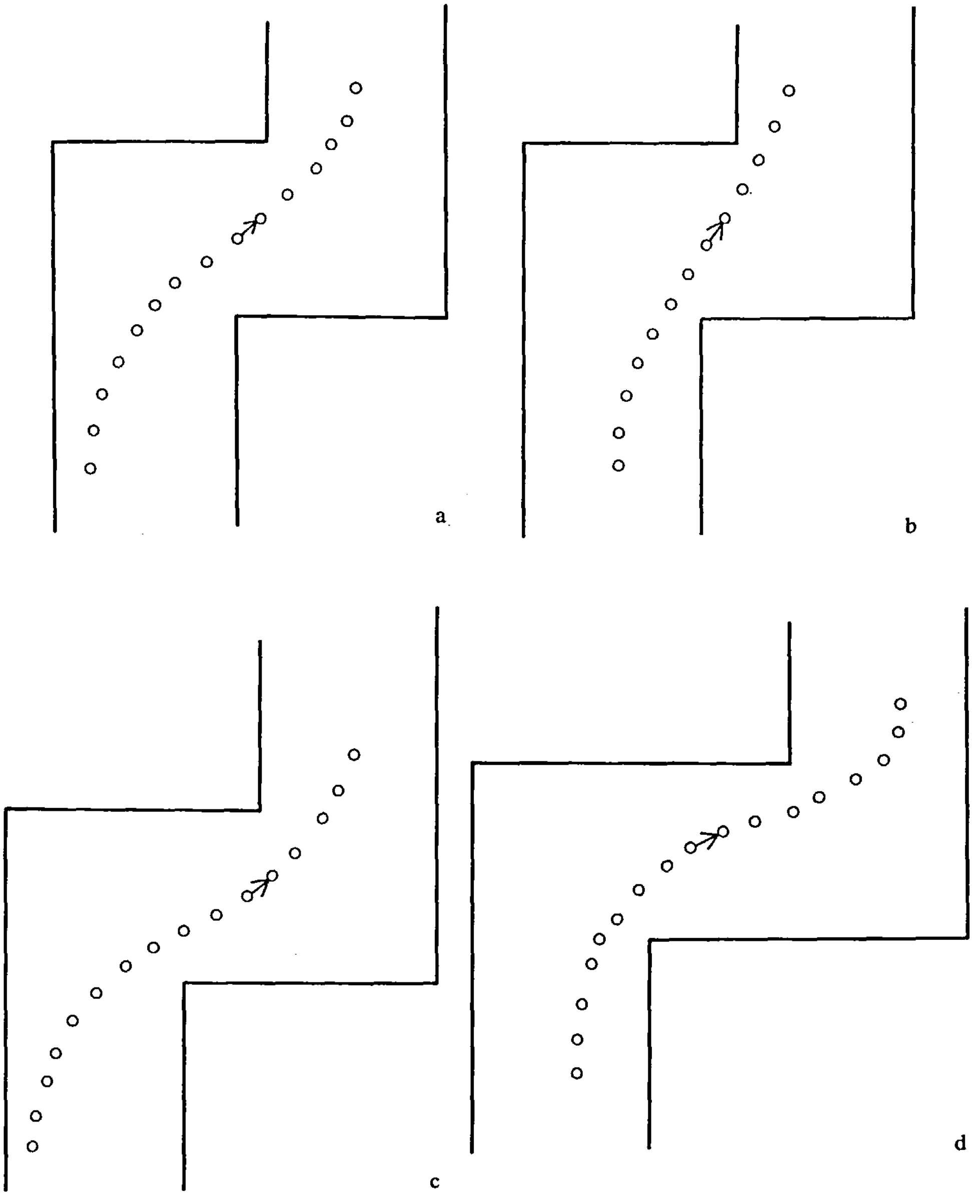

Fig. 6(a, b, c, d). Results of fuzzy control of model car.

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