The algorithm of obstacle avoidance based on improved fuzzy neural networks fusion for exploration vehicle

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Abstract: - In order to improve the vehicle steering stability, and avoid the obstacles fast and accurately, the fuzzy neural networks has been developed, in detail introduced this algorithm control principle. Advance control algorithm usually needs much more prior knowledge and depends on the accuracy model of process. However, fuzzy logic control technology is applied to control the plants having fuzzy, uncertainty, high-order, heavy lag without accurate mathematics model. The neural network has the advantage of self-learning, memory ability, fault-tolerant and parallel processing etc. The back propagation neural network was taken as framework, combining an improved fuzzy control algorithm, to realize the fuzzy-neural control of the exploration vehicle's navigation. It can use the improved fuzzy theory and neural networks together to form an improved fuzzy neural networks control system. So it can auto pick-up the fuzzy rule and build the subordinate function, it's self-organizing and self-learning the control knowledge which is needed for steering process and precise obstacle avoidance. The result of simulation analyses indicate that the method proposed in the paper can achieve safe and stability in steering control of obstacle avoidance of exploration vehicle.

Key-Words: - Fuzzy neural networks; obstacle avoidance; exploration vehicle; steering stability; pattern matching; path planning;

1 Introduction

For exploration vehicle operating in an unknown and changing environment, coping with uncertainty is one of the most challenging problems. Actually the EV is a wheeled mobile robot. There are several approaches proposed to solve the robot's navigation problem. Conventional control systems[1-4] are always based on mathematical models, but in many cases, a mathematical model of the control process may not exist, or may be too difficult to access. A neural network (NN) can deal with training data from which relationships can be found, although unrelated information and noise are also present. In addition, in any system, the values of variables may be within a range of states[5]. Sometimes the transition from one state to another is hard to define. The solution is to make the states "fuzzy": i.e., allow them to change gradually from one state to another. Each control method has its advantages and weaknesses. We aim to merge them, so that the advantages will be adopted while the weaknesses are eliminated. This is a mechanism by which the control system can utilize expert knowledge to solve a special problem. We know that when more than one problem-solving technique (NNs, fuzzy logic, expert systems, etc.) is used in order to solve a problem[6][8-15], the system is called a hybrid system. This allows for the synergistic combination of two techniques with more strength and less weakness than either technique alone. There are many types of hybrid system, but a combination of a data-driven learning technique (NNs) and a knowledge driven technique (the fuzzy system) will be considered here[6]. Both have high robustness and error-tolerance ability. The integration of NN and fuzzy control is called a fuzzy neural hybrid system. In fact, it is based on using a NN to simulate or optimize a fuzzy control system. Here, the neural-fuzzy hybrid is called adaptive fuzzy control based on a neural network. Its main strength is focused on a structure that is capable of extracting fuzzy knowledge by using the clustering method suggested for a NN. It is capable of optimizing fuzzy rules from sampled input–output training data. The competitive clustering method is used to train these data.

In this paper a set of PC/104 is used in the control procedure and to learn the driving knowledge to control the exploration vehicle's steering actions. The image information of guidelines is provided by three cameras on the top of exploration vehicle, after data fusion algorithm which based on fuzzy neural networks, is divided into three areas according to the distance to the exploration vehicle. While meeting with obstacle, the exploration vehicle utilizes the image information to define the shape of road and decide the position of it, and confirm the steering angle. At the same time, a fuzzy controller monitor the running results on-line, if necessary, it will modify the steering angle. The condition of the whole road is extracted to guide the exploration vehicle's steering actions in general and is used to control the driving actions in obstacle avoidance. And the nonlinear problem of fuzzy controller may be linearized by the use of describing function first. The traditional frequency domain method i.e. parameter plane, is then applied to determine the condition of stability when system has perturbed or adjustable parameters. A systematic procedure is perturbed to solve this problem. The stability problem under the effects of plant parameters and control factors are both considered here.

2 Structure of the Exploration Vehicle

The structure of the exploration includes two parts in main: one is the exploration vehicle's mechanical structure, the other is the vehicle's global control system.

2.1 Mechanical structure

An exploration vehicle for rough terrain movement has been developed using four small wheels and linkage structures. Fig.1 shows the exploration vehicle which is developed from the first EV model (equipped with 24 wheels and could turn over automatically). The experimental exploration vehicle is 0.6m×0.9m×0.8m and weights 10kg. The vehicle includes six ultrasonic sensors are arranged in front, left and right.

Fig. 1 The exploration vehicle

2.2 Control structure

Fig.2 shows the EV's global control system. The exploration vehicle we've automated using an embedded fuzzy-logic-based control system to control its speed and steering. The system's main

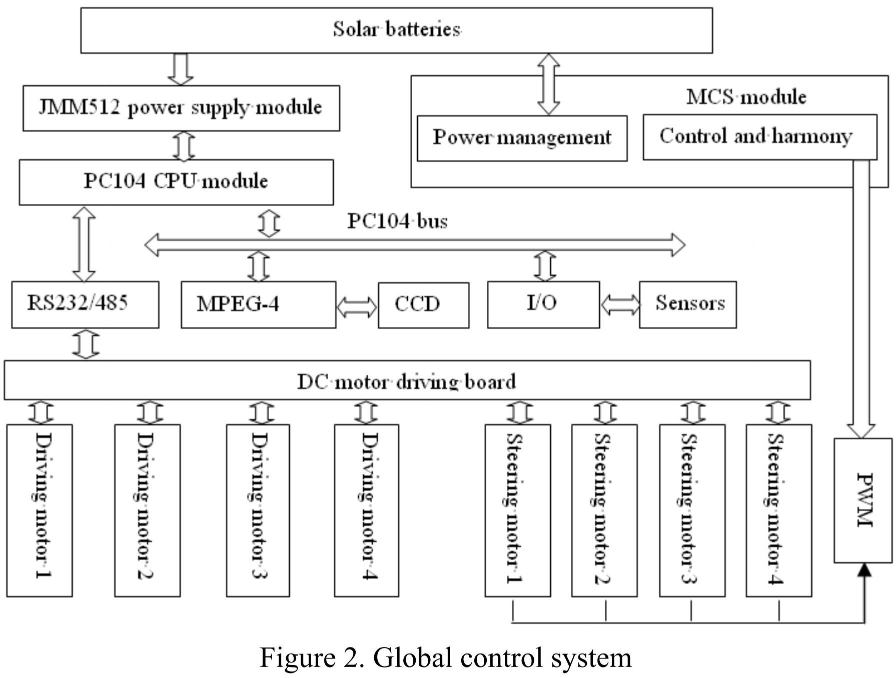


Figure 2. Global control system

sensor inputs are three CCD (charge-coupled device) color camera and GPS, and six ultrasonic sensors which setting at the EV's front, right and left. These CCD are accessorial to transmit pictures to the main computer. GPS is used to determine the goal point. The vehicle equipped with an onboard PC104 computer and a DSP; Wireless LAN support; eight DC-motors; and an analog/digital I/O card. We added a vision system in DSP connected to the control computer. The computer drives the vans using fuzzy-neuron controller: the steering (lateral) control and the speed (longitudinal) control. To automate the steering, we installed two DC servomotors in the steering wheel column. The vehicle has an electronic throttle control, so we shortened the electronic circuit to actuate the throttle using an analog output card. The brake is fully mechanical; we automated it using a pulley and two DC servomotors. We equipped the transmission with an electronic gearbox with forward and reverse selection. We automated this using a digital I/O card that sends the correct gear to the internal vehicle computer.

3 Structure of fuzzy neural networks

The fuzzy control is improved and combined with the neural networks to deal with the information of the obstacles.

3.1 Improvement of conventional fuzzy control

Conventional fuzzy controller[5] in a sampling of typical cycle operation include : sampling the measurement input; Fuzzy precision input, and expressed as Fuzzy Sets; Derivation of the output of current fuzzy controller; Finally, the fuzzy output become more precise, to control the process. Fuzzy reasoning which involves three aspects: First to calculate each current fuzzy input of the rules' conditions (IF) part of the match; then determine which of the rules are activated; finally, weighted average these activated rules results (THEN), ultimately format the control set[7].

In fuzzy control, numerical (or precision) control condition and the language inference algorithm exist incompatibilities, normally takes two interfaces link these two parts together. To simplify the process, so to strengthen the link of each part ,the text used a modified fuzzy control algorithm, The input / output of fuzzy controller are directly considered as precise volume, and the algorithm includes only two points : pattern matching and the weighted average, and then removed the multiple fuzzification and précised the process. The algorithm introduced the concept of pattern and pattern matching. Pattern includes input patterns and rules patterns, and the matching degree is expressed norm, then according to matching degree of each rule, using a weighted average algorithm to determine the output of control. Among them, IF part of pattern matching rules is to find activation unit; the THEN part of weighted average processing rules is to form the output.

3.1.1 Inputs and outputs

Supposed the controlled process is multi-variables of m inputs and m outputs. Then the fuzzy controller may be the combination of control error (E), changing rate of error (C) and the sum of errors (S).The error of the k sampling period is $e_{ci}(kT_s)$, then

$e_{ci}(kT_s) = r_i(kT_s) - y_{pi}(kT_s)$.

T_s is sampling period r and yp∈Rm is the value of supposing and the output of process. $c_c(kT_s)$ and $s_c(kT_s)$ are gained by $e_c(kT_s)$. The changing rate of error is

$$c_c(kT_s) = e_c(kT_s) - e_c[(k-1)T_s] \tag{1}$$

the sum of errors is

$$s_c(kT_s) = \sum_{i=1}^{k} e_c(iT_s) \tag{2}$$

Then three input modes of fuzzy controller could be conformed:

First: $e_{c1}, c_{c1}, e_{c2}, c_{c2}, \cdots e_{cm}, c_{cm}$

Second: $e_{c1}, s_{c1}, e_{c2}, s_{c2}, \cdots e_{cm}, s_{cm}$

Third: $e_{c1}, c_{c1}, s_{c1}, \cdots e_{cm}, c_{cm}, s_{cm}$

Each input mode is called EC、ES and ECS for short, E、C、S expresses control error, changing rate of error and the sum of errors respectively. Sampling one of the three modes as the input of fuzzy controller, expressed ui, i=1,2,…,n; the output of fuzzy controller is expressed by vk, k=1,2,…,m.

3.1.2 The pattern of rules and inputs

Supposed there are M rules, each rule had the following structure:

IF ($U_1 = A_1^j$) AND ($U_2 = A_2^j$) …AND ($U_n = A_n^j$),

THEN ($V_1 = B_1^j$) AND ($V_2 = B_2^j$) AND ($V_n = B_n^j$),

where U_i and V_k were the ui, vk, A_i^j and B_k^j were the fuzzy subsets, $A_i^j \in \overline{U_i}$, $B_k^j \in \overline{V_k}$, $\overline{U_i V_k} \in R$. The fuzzy sets of A_i^j and B_k^j are expressed normally fuzzy sets by membership functions by $A_i^j(u_i)$: $\overline{U_i} \to [0,1]$ and $B_k^j(v_k)$: $\overline{V_k} \to [0,1]$, the membership functions could be defined as follows:

$$A_i^j(u_i) = \begin{cases} 1-(\frac{|M_{u,i}{}^j - u_i|}{\delta_{u,i}{}^j}), |M_{u,i}{}^j - u_i| \le \delta_{u,i}{}^j \\ 0 \quad , |M_{u,i}{}^j - u_i| > \delta_{u,i}{}^j \end{cases} \quad (3)$$

$$B_k^j(v_k) = \begin{cases} 1-(\frac{|M_{v,k}{}^j - v_k|}{\delta_{u,k}{}^j}), |M_{v,k}{}^j - v_k| \le \delta_{v,k}{}^j \\ 0 \quad , |M_{v,k}{}^j - v_k| > \delta_{v,k}{}^j \end{cases} \quad (4)$$

where $M_{u,i}{}^j \in \overline{U_i}$, $M_{v,k}{}^j \in \overline{V_k}$, $\delta_{u,i}{}^j$ >0, $\delta_{v,k}{}^j$ >0

Each membership function has two parameters: $M_{u,i}{}^j$ and $\delta_{u,i}{}^j$ (or $M_{v,k}{}^j$ and $\delta_{v,k}{}^j$), $M_{u,i}{}^j$ ($M_{v,k}{}^j$)is the centers of universe A_i^j (B_k^j) , $\delta_{u,i}{}^j$ ($\delta_{v,k}{}^j$)is the radius of universe A_i^j (B_k^j),so, the A_i^j and B_k^j could be expressed as:

$$A_i^j = (M_{u,i}{}^j, \delta_{u,i}{}^j),\ B_k^j = (M_{v,k}{}^j, \delta_{v,k}{}^j) \quad (5)$$

From the formula, the j rule could be expressed as

IF

($M_{u,1}{}^j, \delta_{u,1}{}^j$)… AND ($M_{u,n}{}^j, \delta_{u,n}{}^j$),

THEN

($M_{v,1}{}^j, \delta_{v,1}{}^j$)… AND ($M_{v,m}{}^j, \delta_{v,m}{}^j$),

The part of IF, input space could be expressed as

$\Omega = (\overline{U_1} \times \overline{U_2} \times \ldots \times \overline{U_n}) \in R^n$,

$M_u{}^j = (M_{u1}{}^j, M_{u2}{}^j, \ldots M_{un}{}^j) \in \Omega$

And

$\Delta_u{}^j = (\delta_{u1}{}^j, \delta_{u2}{}^j, \ldots, \delta_{un}{}^j)$,

then the part could be expressed as a sub-space $\Omega^j = \Omega$ or a hyperplane, its center and radius are M_u^j and Δ_u^j ,may be short for IF

$M\Delta_u(j), \cdots, M\Delta_u(j) = (M_u{}^j, \Delta_u{}^j)$,

The IF part of a rule and measured inputs are intituled rule model and input rule. The Ω space is divided into M sub-spaces by M rules modes. And the sub-spaces have overlapped parts along the verge of fuzzification. Supposed the measured mode as the input mode, then it is a certain point in the same space.

3.1.3 Pattern matching

For process of the control, the improved fuzzy algorithm which based on planned inference steps could appropriate control action from the current inputs and M rules, and the whole process is divided into pattern matching and the weighted average of the two parts. The first part is to deal with the IF part of the rules, and to find activation unit; Aft part is to deal with the THEN part of the activating rules. Therefore, first the current input pattern must be calculated, viz. one point of the Ω , and all rules of the pattern, viz. the matching degree of a group point in Ω .As both patterns adopted the same numerical calculation model, and in the same space from geometry, the concept of distance in matrix theory could be adopted directly to measure similarity between two patterns. The algorithm of measuring the distance as follows: Supposing the current input is

$u_0 = [u_{01}, \delta_{02}, \ldots, \delta_{0n}]$,

then the matching degree of u_0 and the j rule pattern M $\Delta_u(j)$ is $S^j \in [0,1]$,

$$S^j = 1 - D^j(u_0, M\Delta_u(j)) \quad (6)$$

Where D^j is the relative distance of u_0 and M $\Delta_u(j)$, the general methods of D^j calculation

relative ohm distance

$$D_E{}^j = \begin{cases} \frac{\|M_u{}^j - u_0\|}{\|\Delta_u{}^j\|}, \|M_u{}^j - u_0\| \le \|\Delta_u{}^j\| \\ 1 \quad , others \end{cases} \quad (7a)$$

Where $\|\cdot\|$ is norm,

relative hamming distance

$$D_H{}^j = \begin{cases} \frac{\sum_{i=1}^n |M_{u,i}{}^j - u_{0i}|}{\sum_{i=1}^n \delta_{u,i}{}^j}, \sum_{i=1}^n |M_{u,i}{}^j - u_{0i}| \le \sum_{i=1}^n \delta_{u,i}{}^j \\ 1 \quad , others \end{cases} \quad (7b)$$

relative max distance

$$D_M{}^j = \begin{cases} \max_{1 \le i \le n} \frac{|M_{u,i}{}^j - u_{0i}|}{\delta_{u,i}{}^j}, i |M_{u,i}{}^j - u_{0i}| \le \delta_{u,i}{}^j \\ 1 \quad , others \end{cases} \quad (7c)$$

If the u_0 and M $\Delta_u(j)$ matching completely, then $D^j = 0$, and $S^j = 1$; by contraries, if far from matching, then $S^j = 0$; others when matching incompletely, $0 < D^j < 1$, $0 < S^j < 1$.

3.1.4 Weighted average

After determine membership function, the rules can be expressed as

IF

$M\Delta_u(j)$

THEN

($M_{v,1}{}^{j},\delta_{v,1}{}^{j}$)…AND ($M_{v,m}{}^{j},\delta_{v,m}{}^{j}$),

Supposing that the same $\forall k, j, \delta_{vk}{}^{j}$. If the current input pattern u_0 and relevant rule pattern j are given, matching degree $S^j = 1$, then could deduce $v_k = M_{v,k}{}^{j}(k-1,2,...,m)$. The result satisfy the determination-making of max membership, and same to he center of gravity (COG). This could be proved supposed that the membership function is symmetrical about the center. On the other hand, if $S^j = 0$, the j rule of the system is adiaphorous to the export control; when $0 < S^j < 1$, a number of rules react on the output at the same time.

Supposing there are u_0 and P rules, after the completion of pattern matching, there are Q-matching degree if $0 < S^j < 1$, and could be expressed as $S^1, S^2, ..., S^Q$, the center of Q Group in THEN part of control rules is

$\{M_{v,1}{}^{1}, M_{v,2}{}^{1}, ..., M_{v,m}{}^{1}\}...\{M_{v,1}{}^{Q}, M_{v,2}{}^{Q}, ..., M_{v,m}{}^{Q}\}$

And can deduce vk

$$v_k = \frac{\sum_{q=1}^{Q} S^q M_{vk}{}^{q}}{\sum_{q=1}^{Q} S^q} = \sum_{q=1}^{Q} \overline{S^q} M_{vk}{}^{q} \tag{8}$$

where

$$\overline{S^q} = \frac{S^q}{\sum_{q=1}^{Q} S^q}$$

Equation (8) gives the weighted average of the THEN part of the activated rules which determined by their matching degree. Therefore, the text used only the THEN part of the central elements of the 1 max membership in activation rules, and may suppose that it is the transformation form of the determination-making of max membership.

3.2 Structure of fuzzy neural control system

According to the distance of obstacles which identified by three CCD by image processing and six ultrasonic sensors, then by using back propagation neural network as the base, and the improved fuzzy control, formed the fuzzy neural control as follows:

Define the number of control variables for the fuzzy controller, and centers for each input and output fuzzy variable. The input variable is the distance of obstacles(right middle left)、the direction and the distance of goal.

Then the variables are fuzzificated as follows:

Distance of obstacle D far (DF), near (DN)

Direction of goal Tr left (LB), left little (Ls), middle (Z), right little (RS), right (RB)

Distance of goal O ON, OFF

Outputs are the forward velocity and direction of the vehicle, fuzzyficated as follow:

Forward direction Sa left little (TL), middle(TM), right little (TR)

Forward velocity V fast (VB). Middle (VM), slow (VS)

The steering (Sa) of the exploration vehicle is fused by the environment obtained by dl, dr, dc and the information of Tr, V is fused by the information obtained by dl, dr, dc and the information of Tr, and the distance of goal.

The design of neural network as follows:

Fig. 3 shows, a layer is input, which includes three input variable: the distance of obstacles dl, dr, dc, the direction of goal Tr, the distance of goal O. The action is to transmit the inputs to the next.

B、C layer is to fuzzicate the variables, as to calculate the fuzzy function which each input belongs to. The subordinate function's algorithms of the obstacles' distance and the goal's direction are offered as follows:

$$u = \frac{1}{1+\exp[Wb_i(x - Wa_i)]} \quad DN, LB, LS \tag{9}$$

$$u = \exp[-\tfrac{1}{2}(\frac{x - Wa_i}{Wb_i})^2] \quad Z \tag{10}$$

$$u = \frac{1}{1+\exp[-Wb_i(x - Wa_i)]} \quad DF, RB, RS \tag{11}$$

where Wa_i is the weight of connection, Wb_i is universe.

The shape of fuzzy function is decided by Wa_i and Wb_i.

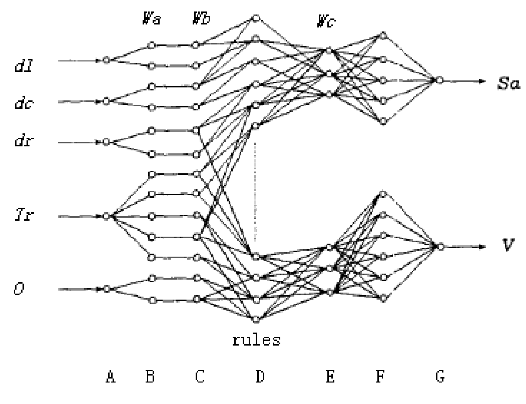


Fig. 3 The fuzzy neural network of BP

D layer is fuzzy inference; the aim is to deal with the five inputs synthetically. And it adopts 80 rules, which is connected by C，D，E.

G layer is to defuzzification, which adopted the centre-of-gravity method.

4 Simulation results and analyses [7]

In order to validate the superiority of the improved fuzzy neural network (IFNN), the performance of IFNN control has been compared to the performance of conventional control fuzzy neural network (FNN).Fig.4 shows the simulation result. From the simulation test, the IFNN is superior to FNN.

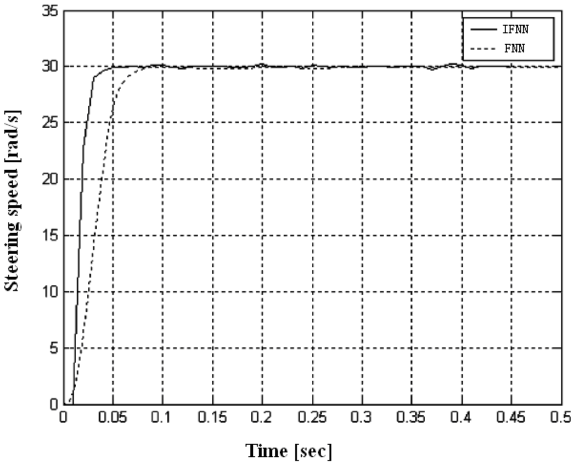


Fig. 4 The step response of improved fuzzy neural network (IFNN) control and conventional control fuzzy neural network (FNN)

The simulation program is written in MATLAB. In the condition of the behavior which running to the goal point, the relationship of the controller's input and output are simulated showing as Fig.5. When the goal point lies at the left of the EV, it will turn left; bigger angle which is apart from left, bigger turn-angle is. The same goes for the goal point lies at the right of EV. When the EV is apart from the goal point, the velocity is higher; while the goal point is nearer, the velocity is lower.

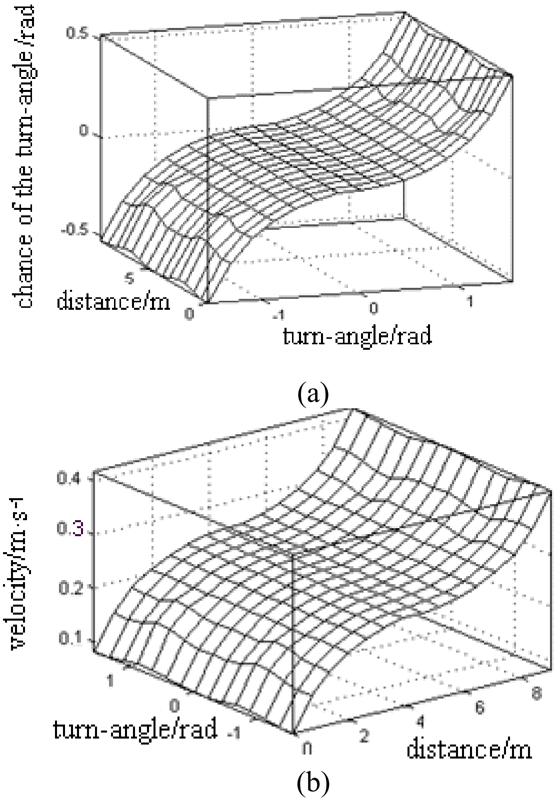
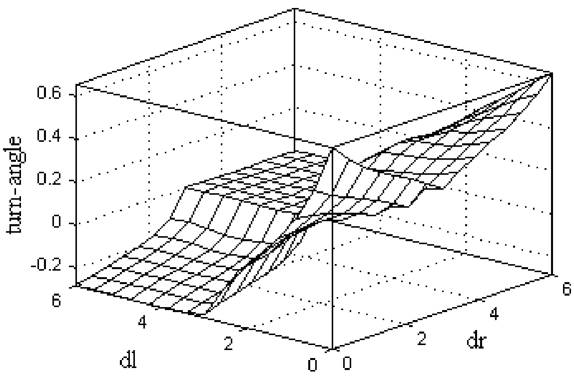
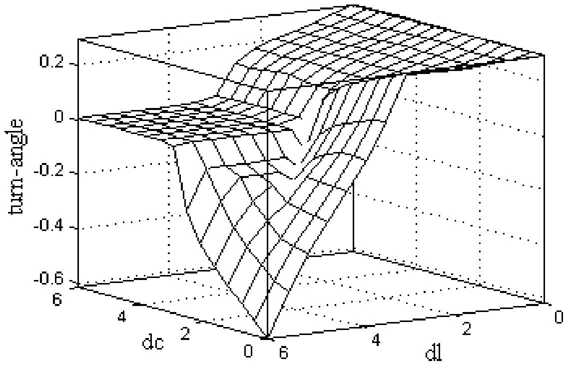


Fig.5 The relationship of the controller's input and output while running to the goal point

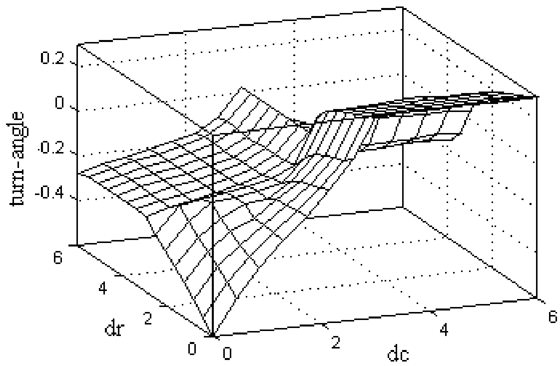
In the condition of obstacle avoidance behavior, the relationship of controller's output and inputs are simulated, and the results indicate that EV always move to the direction which apart from the obstacles according to Fig.6(a)-(c). The velocity of the EV is increasing with the farther distance between the EV and the obstacle according to Fig.6(d)-(f). From these figures, the controller is satisfied to the practical status.



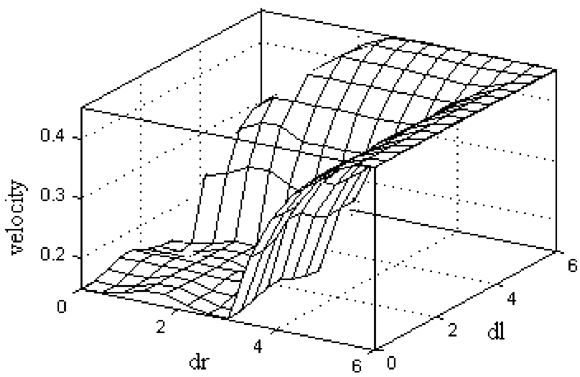
(a)The relationship between turn-angle and dr\dl



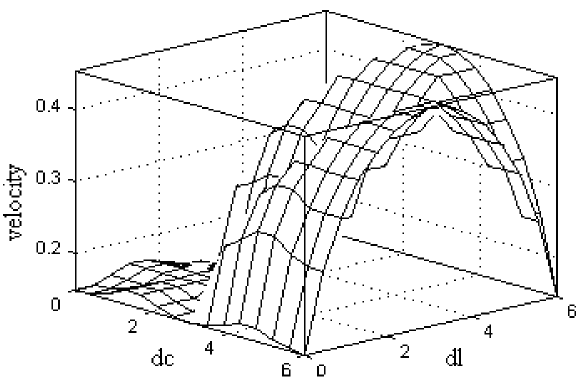
(b)The relationship between turn-angle and dc\dl



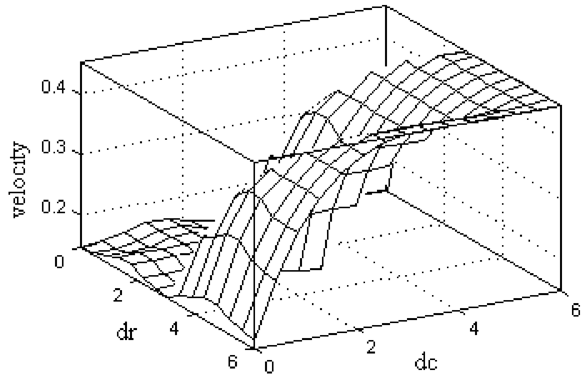
(c)The relationship between turn-angle and dr\dc



(d)The relationship between velocity and dr\dl



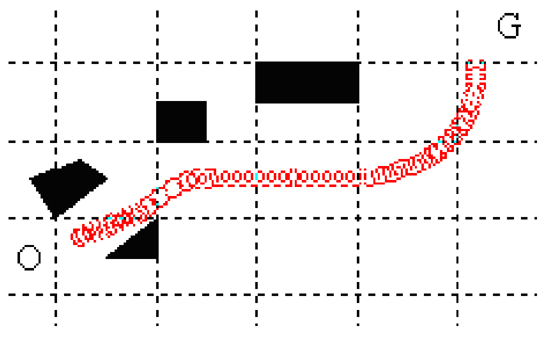
(e)The relationship between velocity and dc\dl



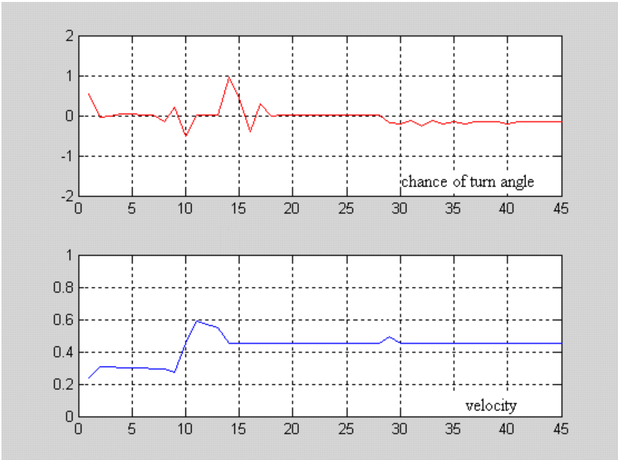
(e)The relationship between velocity and dr\dc

Fig.6 The relationship of controller's input and output

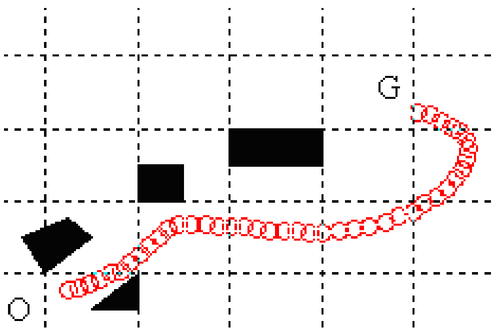
After simulation, the method has good effect. In Fig.7,"O"is the original point and "G" is the goal point. In the face of different obstacles, the The results of Fig.7 (a) and (b) show that the fuzzy controllers perfectly mimic human driving behavior in driving and route tracking, as well as in more complex environment Fig.7(c) and (d), such adaptive cruise control, avoid obstacles and arrive at the goal successfully. Fig.7 (e) and (f) are at idem. Fuzzy control's flexibility let us integrate a host of sensorial information to achieve our results. To improve and further this work, we plan to use CCD sensors for pedestrian detection, obstacle avoidance. We'll also integrate new wireless communication systems that include vehicle-to-human, and vehicle-to-infrastructure. Finally, we're planning to use exploration vehicle that address some existing GPS positioning problems and improve location accuracy.



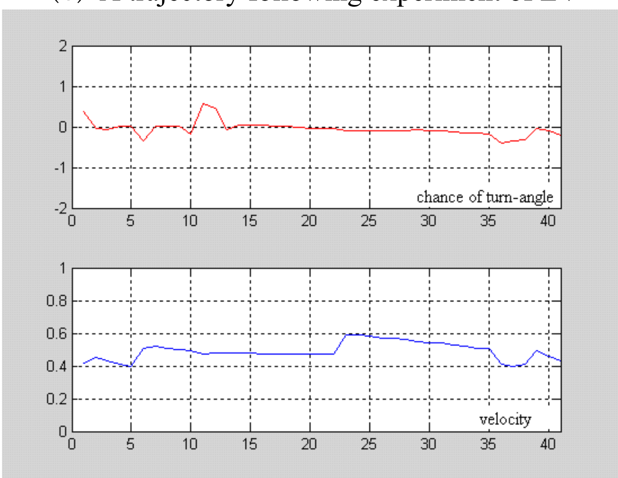
(a) A trajectory following experiment of EV



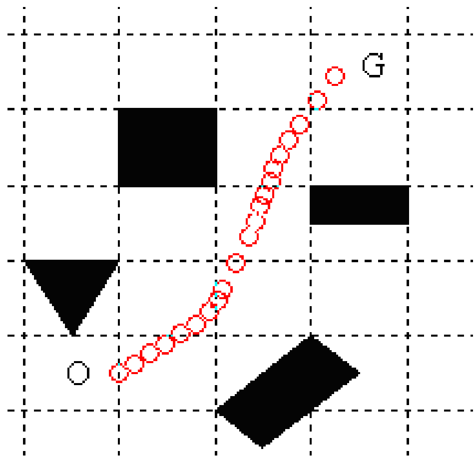
(b)The curve of turn-angle and velocity



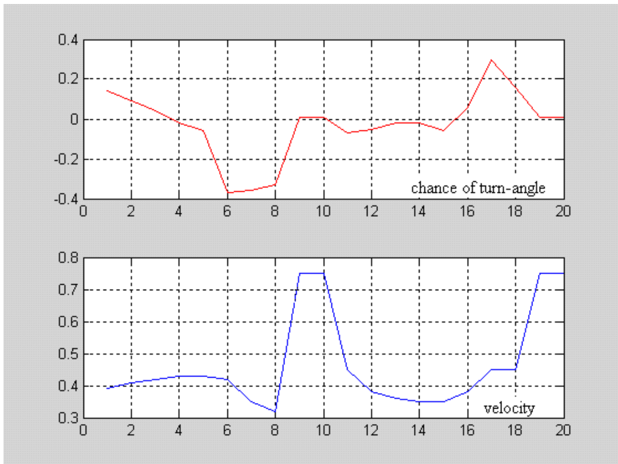
(c) A trajectory following experiment of EV



(d) The curve of turn-angle and velocity



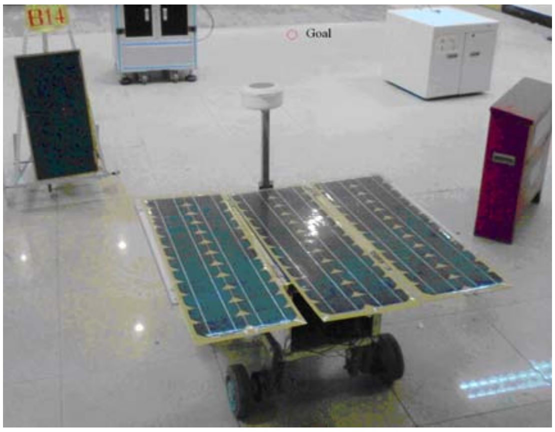
(e) A trajectory following experiment of EV



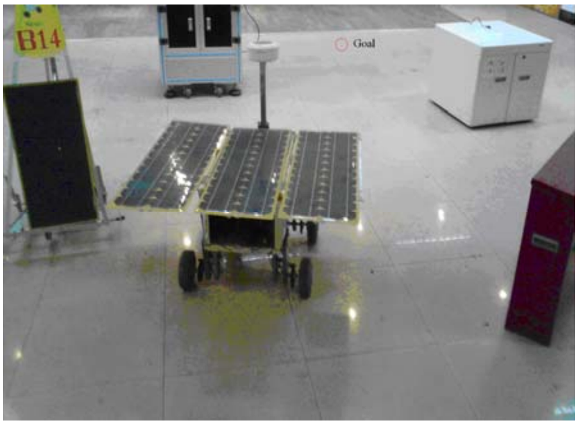
(f) The curve of turn-angle and velocity
Fig.7 Avoidance of obstacles: experiments with exploration vehicle

5 Experiment verification

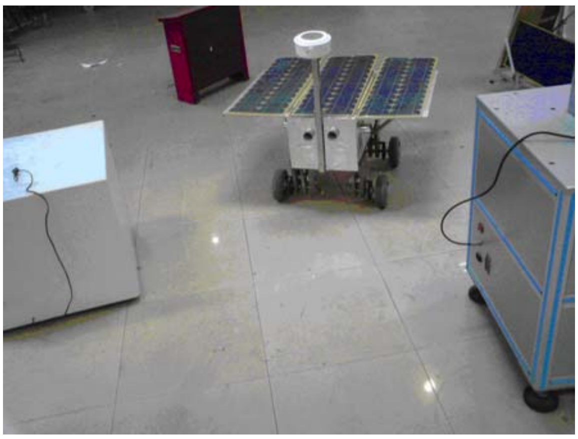
In this experiment, the navigation system solved several trap situations that occurred because the structure of the surroundings was modified. Fig. 6a–f shows the vehicle moving along a passage to reach the goal. Firstly the vehicle met the red box and the triangle obstacle, after data fusion, the vehicle selected to avoid the nearly obstacle-red box (Fig.8(a),(b)). Next, there was the triangle obstacle left in the front of the vehicle, and the white box in the right. Rapidly, the sensor perceived the change and was integrated in the grid(Fig.8(c),(d)). At last, the planning module computed the course towards the exit and arrive at the goal(Fig.8(e)). The vehicle succeeded in avoiding the obstacles by graded fuzzy-neural based multi-sensor fusion method. The experiment took 200s and the average speed was 0.153m/s.



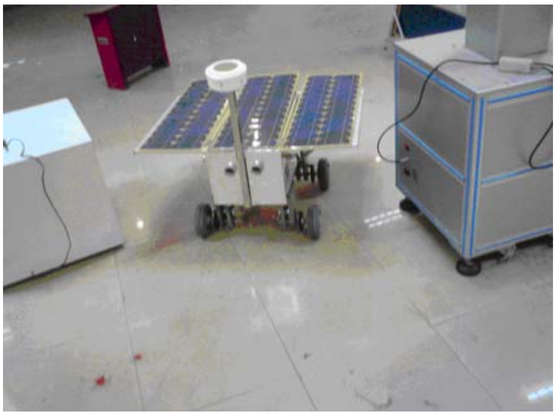
(a)The EV moving from the original point



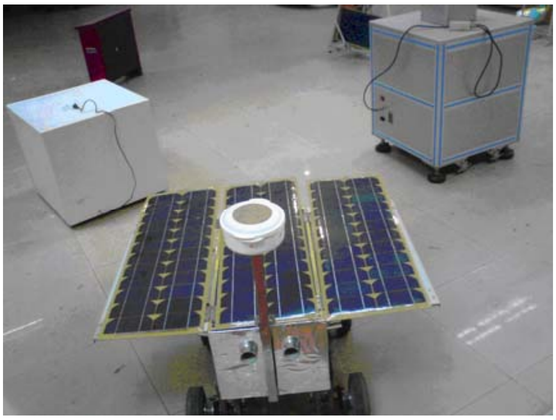
(b)Select to avoid the red box and the triangle obstacle



(c)Facing obstacles of the white box and the blue box



(d)Select to avoid the obstacles



(e)Arrive at the goal point

Fig. 8 Experiment: in this experiment, the vehicle avoided four successive trap situations dynamically created by a human. (a–e) Some snapshots of the motion.

6 Conclusion

In this paper, a new fuzzy neuron controller based on FNN and its application to the exploration vehicle control was discussed. Unlike conventional neural network control or fuzzy control, the presented controller does not require a lengthy learning (or training) or a large number of training data in advance. The control scheme uses on-line learning (inner learning) that is fast enough to realize real-time control.

The new algorithm is entirely based on sensor data which results in a purely sensor-based navigation system for mobile robots. As a result, it inherits the main advantage that the robot can navigate safely in a dynamic environment with easy reaction in real-time to obstacles detected by sensors. Simulation results also show that the controller is robust with respect to initial fuzzy rules and performs well for untrained trajectories. The algorithm is able to continue satisfactory of steering control in obstacle avoidance and goal-seeking behavior. The experimental results show the efficiency and effectiveness of the improved algorithm. However, it suffers from the common drawback that the robot does not how if the path it is following is an optimal one, or that it may fail to reach the goal even if a path to the goal exists. Work is in progress to incorporate an intelligent path-planning algorithm in the navigation system.

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