Fuzzy Control for Optimal Navigation of A Mobile Robot

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Abstract: This paper aims to investigate the navigation control of a mobile robot in a confined environment. Steering angle becomes control variable which is computed from the fuzzy control rules. The identification method proposed in this paper presents the fuzzy control rules obtained through modelling of the driving actions of human operator. The feasibility of the proposed method is evaluated through the application of the identified fuzzy control rules to the navigation control of a mobile robot which follows the center of a corridor.

1. INTRODUCTION

In recent years many efforts have been devoted to the problem of navigation of a mobile robot based on fuzzy logic control[9,10]. An attempt to derive the fuzzy sets and control rules is to model the driving actions of an expert. Given a set of input and output data obtained from the expert's control actions, the identification of fuzzy rules, which includes the determination of the fuzzy partitioning numbers of input variables and the optimal parameters of the membership functions is carried out.

A new identification method of the fuzzy control rules is presented in this paper. The identification is classified into the decision of the number of fuzzy implications and the decision of the parameters which constitute the fuzzy implications. The number of the membership functions of each input variable is determined by soft c-means clustering. The number of fuzzy rules is determined by the multiplication of the cluster numbers of each input variable. The identification of parameters is carried out utilizing genetic algorithms which without additional parameters for running, display an excellent robustness in complex optimization problems. The identified fuzzy control rules are applied to the navigation of a mobile robot which follows the center of a corridor in a confined environment.

2. SYSTEM CONFIGURATION

The hardware configuration, system performance , and system characteristics for the control of the mobile robot used in the present study is described.

2.1. Hardware Configuration

Hardware configuration for the control of a mobile robot is shown in Fig. 1, where IBM PC AT(i80386) is employed as a main controller with ultrasonic sensor, and vehicle module and sensor data acqusition module are only utilized in the study.

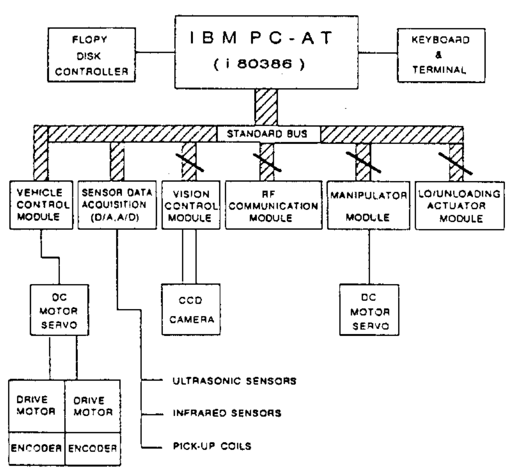


Fig. 1. Hardware configuration for the control of a mobile robot

The system block diagram for the navigation control of a mobile robot is shown in Fig. 2, in which the main controller of a mobile robot combines the range data from ultrsonic sensors to calculate the position and the orientation of the mobile robot, and determines the new steering angle to go. To perform this task effectively, the controller are supplemented by vehicle control module and sensor control module.

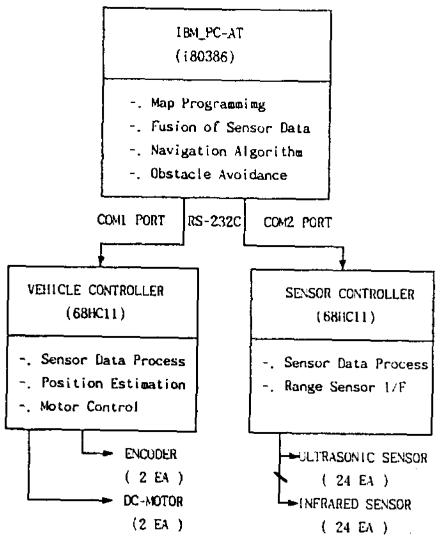


Fig. 2. System block diagram for the navigation control

2.2 System Structure and Its Characteristics

The geometry of the mobile robot used is shown in Fig. 3, and its main characteristics are as follows: the robot has a 0.28(m) height, a 0.75(m) length, and a 0.7(m) width. The reference point is located in the center of 4 free wheels. Maximum velocity is 1(m/s), and maximum acceration $1(m/s^2)$. The steering angle is controlled by the difference between velocities of the two driving wheels. Sampling time is 0.14(sec). All these characteistics are specified in the LABMATE made by TRC corporation. It receives the increments in the steering angle, the constant velocity 0.3(m/s), and the turning speed 0.2(m/s) as inputs to this experiment. The appearance of the mobile robot is shown in Fig. 4.

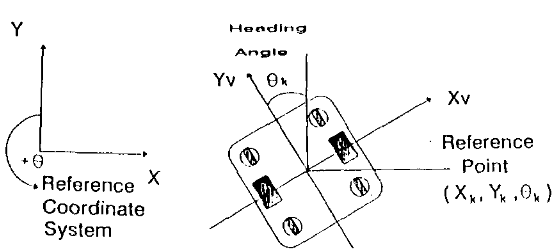


Fig. 3. Geometry of the mobile robot

Fig. 4. Appearance of the mobile robot

The arrangement of ultrasonic sensors to measure the distances from the left and right walls is shown in Fig. 5, where the sensors, S0, S9, Sa, and S10 are only utilized in the navigation control.

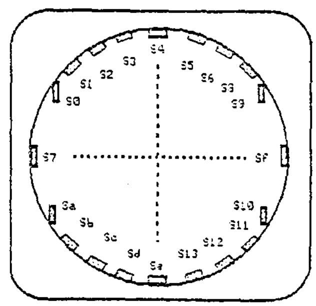


Fig. 5. Arrangement of the ultrasonic sensors

3. FUZZY CONTROL

Recently, a new approach of fuzzy logic has been utilized to control the navigation of a mobile robot. One method to derive the fuzzy sets and control rules is to model the driving actions of experts. Given a set of input-output data obtained from the expert's control actions, the membership functions of those fuzzy variables and the parameters which define the consequents of fuzzy implications are identified by the proposed method in this paper. The problem to solve is thus to move a mobile robot to follow freely the center of corridor in a confined area.

3.1. Fuzzy Control for Navigation

Fuzzy control model for the mobile robot to follow the center of a corridor is shown in Fig. 6, where at every sampling interval, the distances, r1, r2, l1, and l2 to the left and the right walls are measured, and the orientation of the mobile robot is calculated by means of the measured distances.

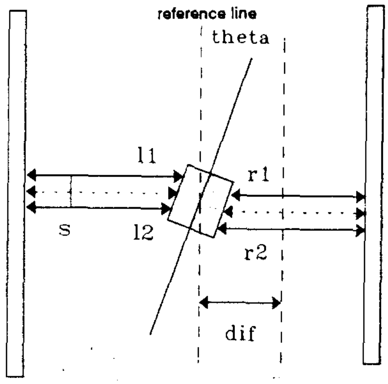


Fig. 6. Model to follow the center of a corridor

The fuzzy controller inferences the new steering angle from the orientation of the mobile robot and the difference between the distances to the left and right walls, and the mobile robot is moved with the new steering angle. The block diagram of the fuzzy controller is shown in Fig. 7.

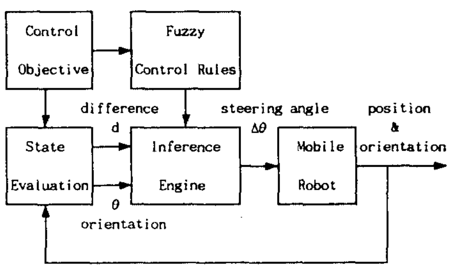


Fig. 7. Block diagram of the fuzzy controller

3.2. Identification of Fuzzy Control Rules

Format of the fuzzy implications and reasoning algorithms used are as follows:

R^1: If x_1 is Small and x_2 is Big, then $y_1 = w_1 \cdot a_1 + b_1$

R^2: If x_1 is Big and x_2 is Medium, then $y_2 = w_2 \cdot a_2 + b_2$

where $w_1 = \mu_{Small}(x_1^{\circ}) \cdot \mu_{Big}(x_1^{\circ})$, and

$w_2 = \mu_{Big}(x_1^{\circ}) \cdot \mu_{Medium}(x_1^{\circ})$

The output inferred from above two implications is as follow

$$y^* = \frac{w_1 \cdot (w_1 \cdot a_1 + b_1) + w_2 \cdot (w_2 \cdot a_2 + b_2)}{w_1 + w_2}$$

The identification of the fuzzy control rules of the above format may be classified into two steps. One step is the identification of structure which corresponds to the determination of fuzzy partitioning of input space and the shape of membership function of fuzzy variables. Another step is the identification of parameters which corresponds to the determination of parameters defining the membership functions and the coefficients in the consequents. Schematic diagram of the identification procedure is shown in Fig. 8.

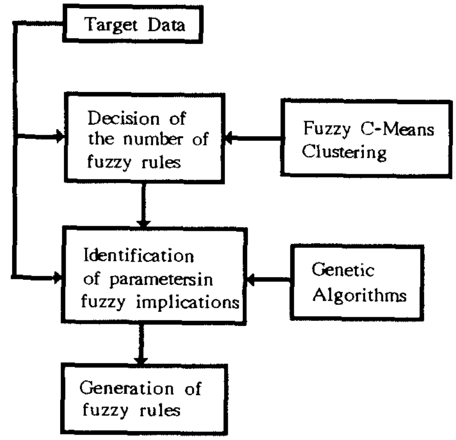


Fig. 8. Schematic diagram of the identification procedure

The identification of structure is carried out by means of SCM(Soft C-Means) clustering. Our purpose is to find the optimal or sub-optimal numbers of clusters to describe effectively the relation of each input-output value of a system. For the brevity, we consider a system composed of two inputs, x_1 and x_2, and one output, y. If the optimal or sub-optimal cluster numbers, x_1-y and x_2-y, are c_1 and c_2, respectively, the optimal number of fuzzy implications is determined by the multiplication of c_1 and c_2. The validity of partitioning is evaluated by index S[8]. The appropriate values of clusters are determined at low values of S[8].

SCM Clustering Algorithm

The soft c-means(SCM) clustering algorithm produces a fuzzy c-partition of the data set $X=(X_1, X_2, \ldots, X_n)$. The basic steps of the algorithm used in this paper are given as follows[1]:

Step 1

Calculate the c cluster centers $\{v_i^{(p)}\}$ with $U^{(p-1)}$ and the formula for the ith cluster center.

$$v_{iL}^{(p)} = \frac{\sum_{k=1}^{n} (\mu_{ik})^m X_{kl}}{\sum_{k=1}^{n} (\mu_{ik})^m}, \quad L = 1, \ldots, d \qquad (1)$$

Step 2

Update $U^{(p)}$ for k = 1 to n.

① Calculate I_k and I_k'.

$I_k = \{i \mid 1 \le i \le c,\ D_{ik} = \| X_k - V_i \| = 0\}$

$I_k' = \{1, 2, \ldots, c\} - I_k$

② For data item k, comput new membership values.

i) If $I_k = 0$, $\mu_{ik} = D_{ik}^{2/(1-m)}$, $\mu_{ik} < \alpha \rightarrow \mu_{ik} = 0$

$$\mu_{ik} = \mu_{ik} / \sum_{i=1}^{c} \mu_{ik} \qquad (2)$$

ii) If $I_k' \neq 0$, $\mu_{ik} = 0$ for $i \in I_k'$, and $\sum_{i \in I_k} \mu_{ik} = 1$.

Step 3

$$J_m^{(p)} = \sum_{k=1}^{n} \sum_{i=1}^{c} (\mu_{ik})^m D_{ik}^2$$

Repeat until $| J_m^{(p)} - J_m^{(p-1)} | < \varepsilon$.

The identification of parameters which define the membership functions of the premise and the coefficients of the consequent is carried out by means of genetic algorithms which display an excellent robustness in the complex optimization problems.

Genetic Algorithms

Genetic algorithms are iterative adaptive general purpose search strategies based on the prinples of natural population genetics and natural selection. A simple genetic algorithms which yields good results in many practical problems is composed of three operators: reproduction, crossover and mutation. Reproduction is a process in which individual strings are copied according to the fitness values which we want to maximize. Copying strings according to their fitness values means that strings with a higher value have a higher probability of contributing one more offstring in the next generation. After reproduction, simple crossover may proceed in two steps: Fitst, members of the newly reproduced strings in the mating pool are mated at random. Second, each pair of strings is selected uniformly at random between 1 and string length less than one, L-1. Two new strings are created by swapping all characters between position k+1 and L inclusively. Mutation is a secondary operator whose use guarantees that the probability of searching a particular sub-region of the solution is never zero. These operators are simplicity itself, involving nothing more complex than random number generation, string copying, and partial string exchanging; yet, despite their simplicity, the resulting search performance is wide-ranging and impressive due to implicit parallelism of genetic algorithms.

In many problems, the objective is stated as the minimization of some cost function rather than the maximization of some utility or profit. In the parameter identification, our purpose is to minimize the cost function, eq.(3) which is defined as the average of squared errors between target output data and inferred output data.

$$E = \frac{1}{n} \cdot \sum_{i=1}^{n} (y_i^o - y_i^*)2 \qquad (3)$$

where n is the total number of data, y_i^o target output value, y_i^* output inferred from fuzzy implications. With genetic algorithms, we use to the following cost to fitness transformation:

Fitness function, $f = 1.0/E$ (4)

4. SIMULATION & EXPERIMENT

The feasibility of the proposed approach is then evaluated through the application of the identified fuzzy control rules to have the mobile robot follow the center of a corridor in a confined area.

The appropriate numbers of clusters which cprrespond to those of fuzzy partitioning of input spaces are selected with reference to the validity measure graphs for fuzzy partitioning shown in Fig. 10 and 11. In these figures, the graphs show that the suitable cluster numbers to describe effectively the relation between difference between distances to left and right wall and new steering angle, and orientation and new steering angle, are 3 or 4, respectively. Although the best numbers in the two grahps are 4 in the view of the clustering, the numbers, 3 are selected for the two cases in order to minimize the number of fuzzy implications.

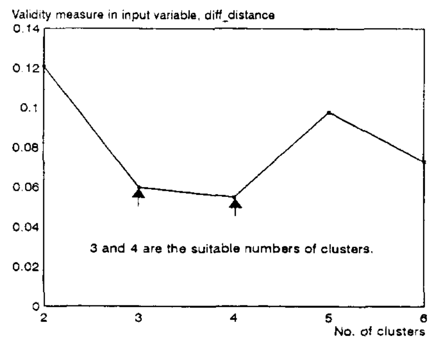


Fig. 10. Graph for the decision of cluster number in diff_distance and new steering angle

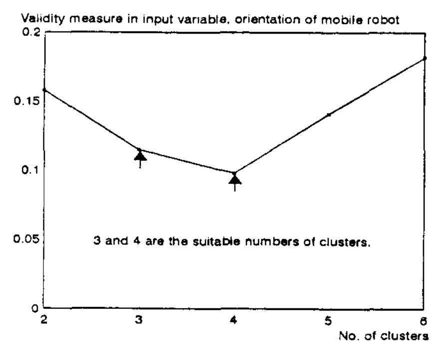


Fig. 11. Graph for the decision of cluster number in orientation and new steering angle

For the determined clusters, membership values are calculated by the clustering, and they are depicted in Fig. 12 and 13 and labeled as Positive, Zero, Negative, respectively.

To eliminate the ripples of the membership functions shown in Fig. 12 and 13, we transformed them into trapezoidal and triangular forms as shown in Fig. 14, in which the parameter p_1, p_2, ..., p_6, and a_1, b_2, ..., a_9, b_9 are identified by using of GAs.

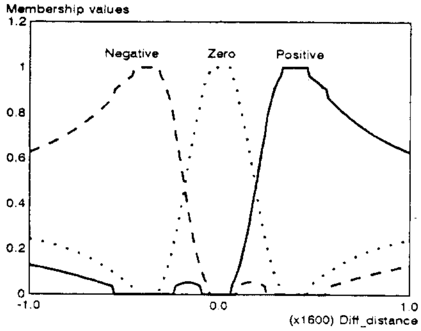


Fig. 12. Membership functions of diff_distance obtained by the clustering

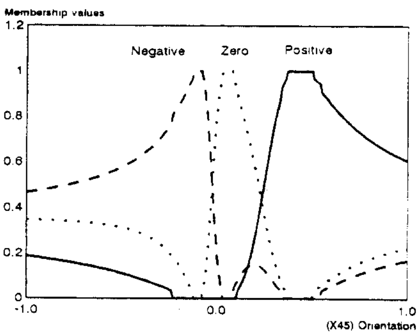
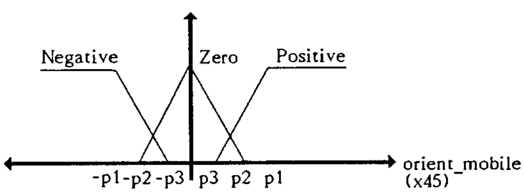
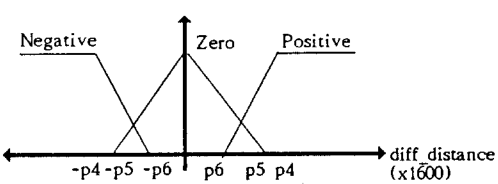


Fig. 13. Membership functions of orientation obtained by the clustering

Initial parameters for GAs are as follows:

Population size	50
Length of individuals	10
Crossover rate	0.6
Mutation rate	0.033

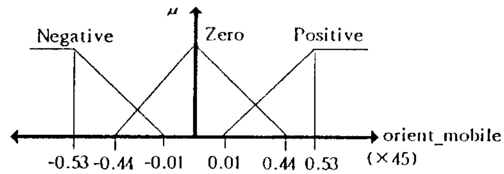


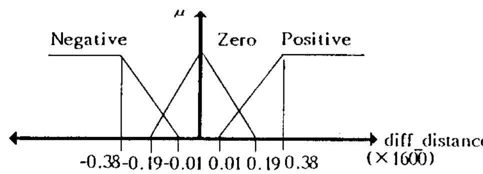


If diff_dist is Negative & orient_mobile is Negative
then $y_1 = a_1 \cdot w_1 + b_1$
If diff_dist is Negative & orient_mobile is Zero
then $y_2 = a_2 \cdot w_2 + b_2$
If diff_dist is Negative & orient_mobile is Positive
then $y_3 = a_3 \cdot w_3 + b_3$
If diff_dist is Zero & orient_mobile is Negative
then $y_4 = a_4 \cdot w_4 + b_4$
If diff_dist is Zero & orient_mobile is Zero
then $y_5 = a_5 \cdot w_5 + b_5$
If diff_dist is Zero & orient_mobile is Positive
then $y_6 = a_6 \cdot w_6 + b_6$
If diff_dist is Positive & orient_mobile is Negative
then $y_7 = a_7 \cdot w_7 + b_7$
If diff_dist is Positive & orient_mobile is Zero
then $y_8 = a_8 \cdot w_8 + b_8$
If diff_dist is Positive & orient_mobile is Positive
then $y_9 = a_9 \cdot w_9 + b_9$

Fig. 14. Fuzzy control rules with identified structure

The fuzzy control rules identified from the expert's control actions is shown in Fig. 15.





If diff_dist is Negative & orient_mobile is Negative
then $y_1 = -1.265 \cdot w_1 + 52.034$
If diff_dist is Negative & orient_mobile is Zero
then $y_2 = -6.050 \cdot w_2 + 26.440$
If diff_dist is Negative & orient_mobile is Positive
then $y_3 = 9.500 \cdot w_3 - 9.066$
If diff_dist is Zero & orient_mobile is Negative
then $y_4 = 0.114 \cdot w_4 + 14.819$
If diff_dist is Zero & orient_mobile is Zero
then $y_5 = -0.568 \cdot w_5 + 0.568$
If diff_dist is Zero & orient_mobile is Positive
then $y_6 = -2.335 \cdot w_6 - 13.785$
If diff_dist is Positive & orient_mobile is Negative
then $y_7 = -5.985 \cdot w_7 + 8.061$
If diff_dist is Positive & orient_mobile is Zero
then $y_8 = 5.449 \cdot w_8 - 26.018$
If diff_dist is Positive & orient_mobile is Positive
then $y_9 = 3.473 \cdot w_9 - 53.904$

Fig. 15. The fuzzy control rules for the navigation

The navigation trajectory of the mobile robot controlled by the identified fuzzy control rules is displayed in Fig. 16.

5. CONCLUSION

A high degree of autonomy in the mobile robot behavior for following the center of a corridor in a confined environment is reached by means of fuzzy control rules which model the control strategies of human drivers. It can be improved by adding the routine to avoid obstacles in front of the mobile robot and complementary sensory system, such as vision. The robot shows flexsible and robust behavior facing quite different situations and recovering from unexpected inputs in spite of the scarce information intially available.

6. REFERENCE

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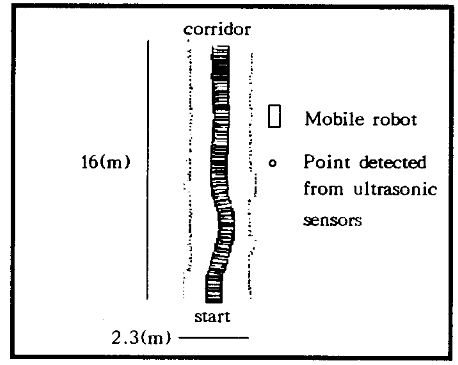
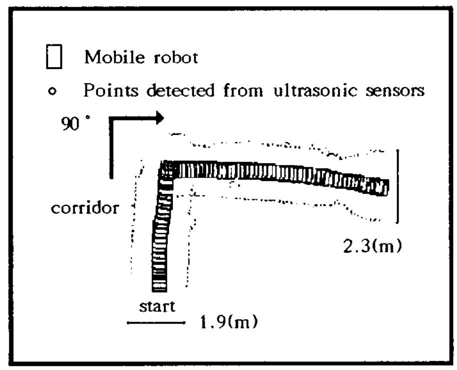


(a) " | " typed corridor



(b) " ┌" typed corridor

Fig. 16. The navigation trajectory of the mobile robot