A Sensor–based Obstacle Avoidance Controller for a Mobile Robot Using Fuzzy Logic and Neural Network

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Abstract – This paper proposes a sensor–based path planning method which utilizes fuzzy logic and neural network for obstacle avoidance of a mobile robot in uncertain environments. In order to acquire the information about the environment around the mobile robot, the ultrasonic sensors mounted on the front of mobile robot are used. The neural network, whose inputs are preprocessed by ultrasonic sensor readings, informs the mobile robot of the situation of environment in which mobile robot is at the present instant. Then, according to the situation class, the fuzzy rules are fired to make a decision on the mobile robot action. This structure has a merit that the fuzzy rules for obstacle avoidance can be easily constructed for more complex environments. In addition, this method can be implemented real time since the number of fuzzy rules used to avoid the obstacles is small. The fuzzy rules are constructed based on the human reasoning and are tuned by iterative simulations. The effectiveness of the proposed avoidance method is verified by a series of simulations.

I. INTRODUCTION

Path planning is one of the most vital task in navigation of autonomous mobile robot. Path planning for mobile robot may be divided into two categories: One is the global path planning based on a priori complete information about the environment and the other is the local path planning based on sensory information in uncertain environment where the size, shape and location of obstacles are unknown. The global path planning method includes configuration space method[1], generalized Voronoi diagram[2] and potential field method[3] and is carried out in off–line manner. However, this method is not suitable for navigation in complex and dynamically changing environment where unknown obstacles may be located on a priori planned path. Thus, this method must be followed by sensor–based local path planning, so called obstacle avoidance, carried out in on–line manner.

Local path planning utilizes the information provided by sensor such as ultrasonic sensor, vision, laser range finder, proximity sensor and bumper switch. R.A.Brooks[4] applied the force–field concept to obstacle avoidance problem for mobile robot equipped with ultrasonic sensors whose readings are used to compute the resultant repulsive force. Borenstein and Koren[5] proposed the vector field histogram method for fast running mobile robot equipped with ultrasonic sensors. However, the above methods have the shortcoming that it is difficult to find the force coefficients influencing on the velocity and direction of mobile robot in cluttered environment which can not be described as a mathematical model.

In order to overcome the above problem, fuzzy logic has been employed in obstacle avoidance for mobile robot navigation. It has an advantage that it deals with the various situations without analytical model of environment. Recently, many researchers proposed the navigation algorithm using fuzzy control. Takeuchi[4] proposed the hallway following method by extracting the feature from simple hallway image. Sugeno[5] used the fuzzy control in order to make a vehicle equipped with the ultrasonic sensors move into garage space. Ishikawa[6] presented a sensor–based navigation method using the fuzzy control in an indoor environment and concentrated on constructing the efficient control knowledge base. However, in complex environment, the above method has disadvantage that it is difficult to construct the rule–base as well as time–consuming to tune the constructed rules appropriately. In addition, it takes much time to infer the mobile robot action since all the rules are used in the reasoning process.

To avoid such criticism, a sensor–based obstacle avoidance controller using fuzzy logic and neural network is proposed. While the neural network plays a role of situation classifier to judge the situation around mobile robot, the fuzzy logic plays a role of inference engine to decide the mobile robot action from the rule base associated with the classified situation. After classifying the complex environment into some primitive situations, the construction and tuning of the rules are performed with regard to each primitive situation. This avoidance controller is simulated for the wheeled mobile robot named as LCAR which has been developed in Laboratory for Control System & Automation, KAIST. As schematically shown in Fig. 1, it is equipped with twenty six ultrasonic sensors mounted on the front of mobile robot and stereo cameras mounted on the top of mobile robot besides the internal sensors for dead reckoning. The measurement range of ultrasonic sensors can be adjusted within 10m by sensor control board. In the simulation, the validity of the proposed method using fuzzy logic and neural network will be discussed. As a

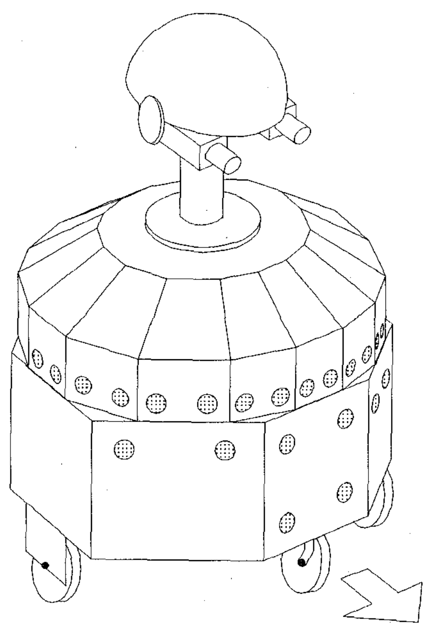

Fig. 1. The mobile robot, LCAR.

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result of the simulation, even in the cluttered environment, the performance of the proposed controller is satisfactory even with small number of the rules used to avoid the obstacles.

II. THE STRUCTURE OF OBSTACLE AVOIDANCE CONTROLLER

The structure of avoidance controller employed in this paper is shown in Fig. 2. This controller receives the goal configuration command $(x,y,\theta)_{com}$ from the higher level planner consisting of a global path planner and a mission planner and the present configuration $(x,y,\theta)_{robot}$ from the lower level controller. Then, this controller regenerates the immediate subgoal configuration $(x,y,\theta)_{ref}$ within the sensing area and transfers it to the lower level controller called dead reckoner. The lower level controller using the internal sensors performs the control action in order to enable the mobile to arrive at the desired position. The obstacle avoidance controller is constructed into three levels. In the first level, the relative range information is obtained by ultrasonic sensors. In the second level, the situation class of the environment, in which the mobile robot is placed, is selected. In the last level, according to the chosen class, avoidance behavior is determined based on the primitive rule base.

A. Acquisition of Environmental Information

Environment where mobile robot navigates can be classified into static and dynamic. The dynamic environment can be defined as: Obstacles can move or change their shapes, or any obstacles may not be registered in global map in the beginning. Therefore, local path planning based on sensory information is required. In this paper, eighteen ultrasonic sensors of the mounted sensors are used to understand environmental situations, for example, what types of obstacles exist in front of mobile robot or whether mobile robot can go through without colliding with obstacles. Fig. 3 shows the arrangement of ultrasonic sensors mounted on the front of mobile robot. Their technical specifications and beam pattern may be found in Polaroid[7]. They are controlled by a 8031 microcontroller communicated with PC–AT computer. Their control boards consist of a transmitter module to fire the pulses , a receiver/gain–control module to receive the attenuated echo pulses and a switching module to arbitrarily select the activation of the sensor according to the sensing mode. The block diagram of the range finder is shown in Fig. 4. Each ultrasonic sensor can be modelled as shown in the upper righthand of Fig. 3. Due to its beam opening angle α, the area covered by sensor can be approximated as a cone shape. As shown in Fig. 3, the mobile robot has five sensor suits, and each sensor suit consists of three or four sensors. The distance, d, from the center of robot frame $\{R\}$ to an obstacle detected by ith sensor and its direction, φ, can be expressed, respectively, as follows:

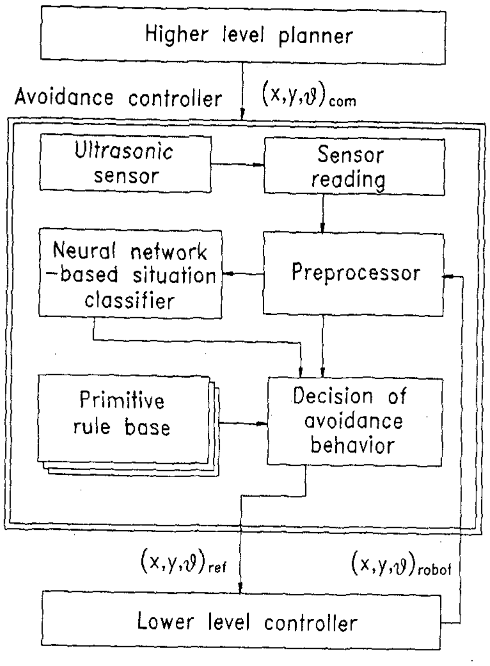

Fig. 2. The structure of avoidance controller.

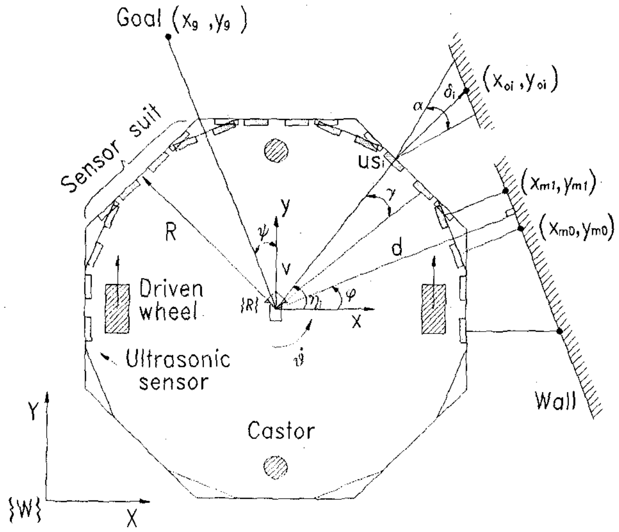

Fig. 3. The arrangement of ultrasonic sensors and coordinate frames of workspace.

$$d^2 = x_{oi}^2 + y_{oi}^2 \tag{1}$$

$$\varphi = \tan^{-1}\left(\frac{y_{oi}}{x_{oi}}\right). \tag{2}$$

The coordinates value (x_{oi}, y_{oi}) of the obstacle with respect to the robot frame $\{R\}$ is expressed as

$$x_{oi} = R\cos(\eta_i)+\delta_i\cos\{\eta_i-0.5(-1)^i(\alpha-\gamma)\} \tag{3}$$

$$y_{oi} = R\sin(\eta_i)+\delta_i\sin\{\eta_i-0.5(-1)^i(\alpha-\gamma)\} \tag{4}$$

$$\eta_i = \gamma(i-1.5) \tag{5}$$

where γ is the angle between two adjacent sensors and R is the radius of the mobile robot. It is assumed that the y–axis of the coordinate frame $\{R\}$ is aligned with the moving direction of mobile robot. In the case of a wall shaped obstacle, d and φ are

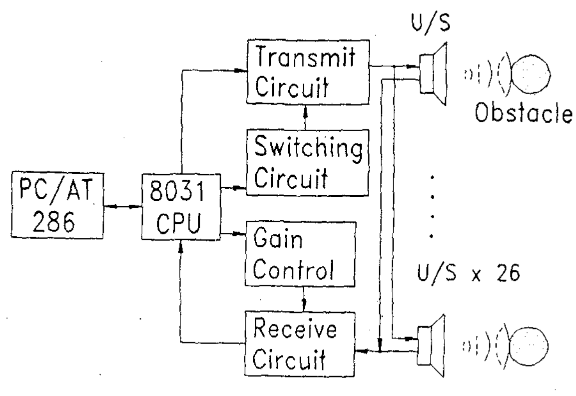

Fig. 4. The block diagram of ultrasonic range finder.

calculated as

$$d = x_{m1}\cos(\varphi) + y_{m1}\sin(\varphi) \quad (6)$$

$$\varphi = \tan^{-1}\left(\frac{x_{m1} - x_{m0}}{y_{m1} - y_{m0}}\right) \quad (7)$$

where (x_{m1}, y_{m1}) and (x_{m0}, y_{m0}) are the coordinate values representing the minimum distances from the center of the robot frame $\{R\}$ to obstacle.

B. Environment Situation Class

When the mobile robot go through the cluttered environment, a variety of environment situations may arise in front of mobile robot. To provide the most suitable avoidance behavior to the mobile robot, it is necessary to classify the various environment situations into some simple classes. The pattern of the range image formed by sensor measurements gives us the information about environment situations: whether mobile robot can go through the environment without colliding with obstacles or not and what situation takes place in front of the mobile robot. To divide the complex situation into the simple one, open space, that is, a safe path through which mobile robot can go is considered. If the open space does not exist between the two obstacles, they are merged into one obstacle. Using the open space, the cluttered environment can be divided into seven simple classes based on the range image pattern. These typical situation classes are shown in Fig. 5. The first and second classes represent the cases when the number of polygon type obstacle is one or two within sensing area. In these classes, safe paths always exist. The third and fourth class are defined as the cases when one wall type obstacle or two wall obstacles exist. The fourth class is corresponding to the hallway environment. The fifth class is the case when one obstacle is located in the center of hallway. The sixth class is corresponding to the case that the mobile robot falls into the dead alley. In this class, open space does not exist in the moving direction. The last class is corresponding to the situation in which there is no obstacle, which is the case of the open space.

III. NEURAL NETWORK–BASED SITUATION CLASSIFIER

A. Structure of Neural Network

For the navigation of mobile robot in cluttered environment, it is important to know the environment situations. If the present environmental situation is recognized, it is easy to decide the avoidance action since the variables to be considered for avoidance are easily deduced from the given situation. In this study the neural network plays a role of situation classifier. The inputs of the neural network are the range images formed by 18 ultrasonic sensor readings. The network outputs identify one of the environment situations, so that the mobile robot can make appropriate decision on how to move in response to the identified environment. As shown in Fig. 6, the network used herein has one input layer, three hidden layers and one output layer. The input and output layers have 18 neurons and 7 neurons, respectively, while the hidden layers in turn have 10 neurons, 5 neurons and 12 neurons, respectively. This network is partially connected between the input layer and the second hidden layer and its remainder is fully connected. The neuron 1, 2 and 3 of the input layer are the distances from the center of mobile robot to obstacle measured by sensors belonging to the same sensor suit. Among the seven neurons in the output layer, only one neuron is activated. This activated neuron represents the environmental situation where the mobile robot is at the present instant.

B. Training the Neural Network

In order to learn the environment situation, it is important to extract the training sample patterns. In order to reduce the number of the training sample patterns, the sensing area is divided into five regions as shown in Fig. 7–(a). The regions surrounded by thick lines represent the area covered by one sensor suit. Such regions again are divided into the nine or twelve small regions by using the threshold values. The first threshold value d_{th1} represents the traversability and the value is calculated by

$$d_{th1} = R(1+\epsilon)\cot\left(\frac{\pi}{8}\right) \quad (8)$$

where R is the radius of mobile robot and ϵ is a safety factor set to 0.1. The second threshold value d_{th2} is set to the twice of the first threshold value while the d_{max} is set to the maximum range of sensors. According to those threshold values, the distances from center of mobile robot to obstacles are represented by three denoted by the integers 0, 1 and 2. In this case, total number of the input patterns required to train the neural network is 3^{18}. However, since the number of sample patterns is very large, the sample pattern is chosen based on the region covered by a sensor suit. In this case, the number of training sample patterns is 3^5. For example, as shown in Fig. 7–(b), let us consider the case when two obstacles appear within the sensing area. This environment situation belongs to the class 2. In this case, the training sample pattern is chosen as follows:
input = (2 2 2 1 1 1 1 2 2 2 2 0 0 0 0 2 2 2)
output = (0 1 0 0 0 0 0).
Thus, the neural network used as a situation classifier is trained using the 3^5 sample patterns.

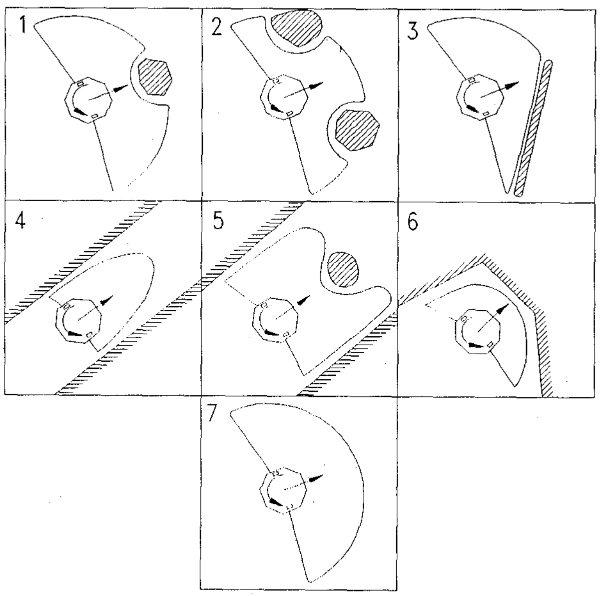

Fig. 5. The typical classes of environmental situations.

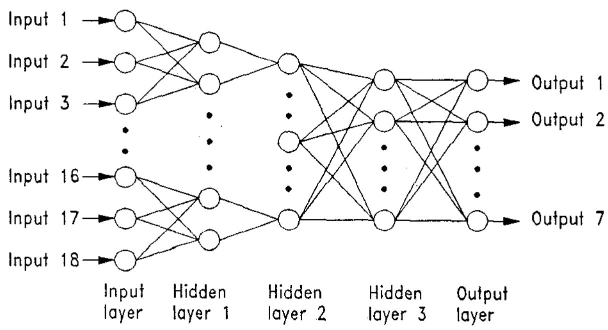

Fig. 6. The structure of the neural network used as situation classifier.

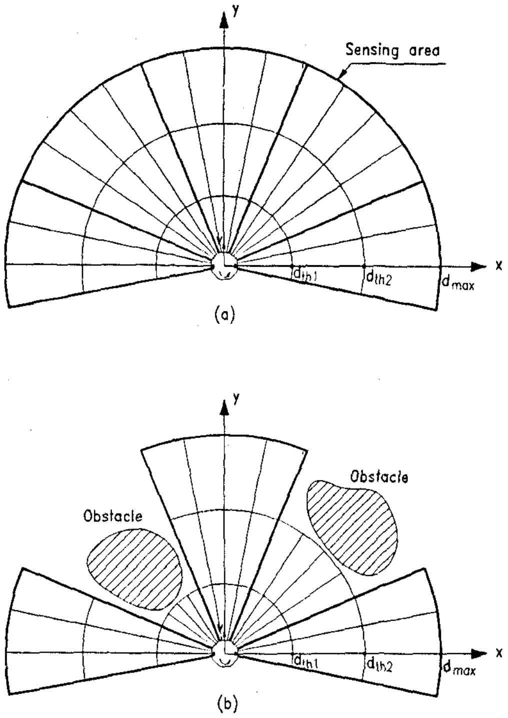

Fig. 7. An example of training sample pattern.
(b) An example of class 2. (a) The divided sensing area.

IV. OBSTACLE AVOIDANCE USING FUZZY LOGIC

Our goal is to design the avoidance controller which emulates the obstacle avoidance behavior using the fuzzy control. Design proceeds in the following sequence; (1) fuzzification of the input–output variables, (2) rule base construction, (3) reasoning process and (4) defuzzification of output variables.

A. Fuzzification of the Input–output Variables

The goal of obstacle avoidance is to make the mobile robot arrive at destination point without colliding with unknown obstacles. In order to accomplish this effectively, we must control the mobile robot motion in consideration of the obstacle position (x_o,y_o) and mobile robot configuration (x,y,θ) with respect to the world coordinate frame $\{W\}$ shown in Fig. 3. The motion of the mobile robot can be realized by the control of its steering angle θ and velocity v, respectively. Thus, we choose the input variables as d_i, φ_i and ψ and the output variables as incremental steering angle $\Delta\theta$ and velocity v. The subscript, i, denotes the number of the detected obstacles. The variables d_i and φ_i are calculated by equations (1) and (2) in the cases of class 1 and class 2. In the cases of class 3 and class 4, they are calculated by equations (6) and (7). The ψ is the angle between heading direction of mobile robot and the direction of goal position and is defined as follows:

$$\psi = \tan^{-1}\left(\frac{y_g-y}{x_g-x}\right) - \frac{\pi}{2} \qquad (9)$$

where (x_g,y_g) is the coordinates of the goal position with respect to the frame $\{W\}$. The input variables d_i, φ_i and ψ are expressed by linguistic fuzzy set values (VN,NR,FR), (NB,NS,ZZ,PS,PB) and (NB,NS,ZZ,PS,PB) respectively while output variable v and $\Delta\theta$ are expressed by linguistic fuzzy set values (ZZ,PS,PM,PB) and (NB,NM,NS,ZZ,PS,PM,PB) respectively. The linguistic terms have the following meanings:

VN: *very nearest*	NR: *near*
FR: *far*	NB: *negative big*
NM: *negative medium*	NS: *negative small*
ZZ: *zero*	PS: *positive small*
PM: *positive medium*	PB: *positive big.*

Fuzzy subsets contain elements with degree of membership. Fuzzy membership function $\mu_d(\cdot)$ of fuzzy set, d, assigns a real number between 0 to 1 to every element in the universe of discourse. This membership value indicates the degree to which the element belongs to the fuzzy set. The membership functions of the fuzzy set defined for avoidance are shown in Fig. 8. Although fuzzy membership function can have various shapes depending on the designer's preference, trapezoidal and triangular shapes are chosen to simplify the computation.

B. Rule Base Construction

The obstacle avoidance rules are constructed based on human reasoning. Since the complex environment is classified into some simple situations, it is easy to construct a primitive rule base associated with each situation. In order to construct the rule bases effectively, let us consider the important factors associated with each class.

1) Class 1: the case with one obstacle.
In this case, the important parameters to be taken into account for avoidance are the position of an obstacle. Thus, the fuzzy variables to be used in the rule construction are d, φ and ψ. In this class, two open spaces always exist.

2) Class 2: the case with two obstacles.
The parameters to be taken into account for avoidance in this case are the positions of obstacles. Thus the fuzzy variables to be used in the rule construction are d_i, $\varphi_i(i=1,2)$ and ψ. Where the index 1 denotes the position and orientation of the mobile robot relative to the nearest obstacle while the index 2 denotes those relative to the second nearest one.

3) Class 3 and 4: the cases with one or two wall type obstacles.
In these cases, the avoidance actions differ from those of the class 1 and 2. The avoidance action is to move parallel to the wall while maintaining the safe distance.

4) Class 5: the case with one obstacle in the hallway.

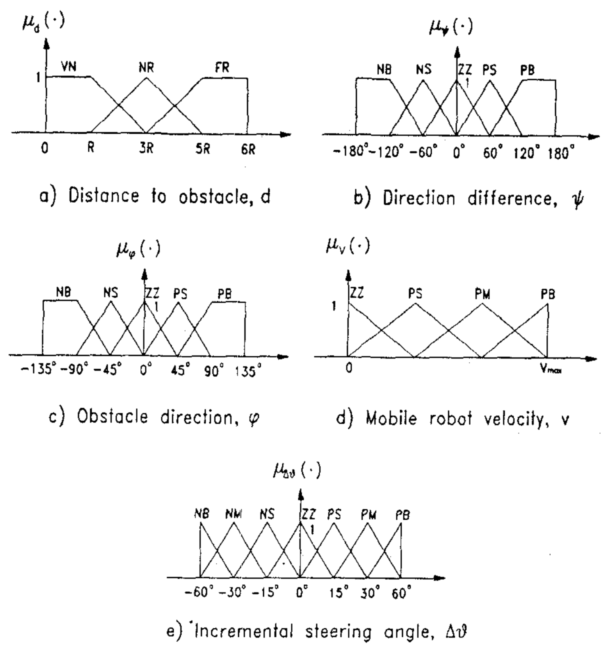

Fig. 8. The membership functions of fuzzy variables.

In this case, the rules are combined with those of the class 1 and 4. The parameters used in the rule base construction are d_i, $\varphi_i(i=1,2,3)$ and ψ.

5) *Class 6*: the case with dead alley.
In this case, avoidance action is to follow the boundary of the obstacle until the mobile robot arrives at imaginary goal position while maintaining the safe distance from obstacle. The imaginary goal position is determined by storing the dead alley position. The straight path is planed between the stored dead alley position and goal position. The imaginary goal position lies on the planned path. If the mobile robot arrives at the imaginary position, the situation class 6 is disabled.

6) *Class 7*: the case with no obstacle in the sensing area.
In this case, the mobile robot can move at maximum velocity or maximum steering angle toward the goal position.

When these factors are taken into consideration in constructing the rule base, the rules for obstacle avoidance take the form by using IF–THEN statements:

$$^{j}R_k\text{: IF } (\psi = \Psi_k) \text{ AND } (d_i = D_{ik}) \text{ AND } (\phi_i = \Phi_{ik}),$$
$$\text{THEN } (v = V_k) \text{ OR } (\Delta\theta = \Delta\Theta_k)$$

where $^{j}R_k$ denotes the kth rule of the rule base associated with the jth situation class and Ψ_k, D_{ik}, Φ_{ik}, V_k and $\Delta\Theta_k$ are the fuzzy subsets defined in the universe of dicourse X_ψ, X_{d_i}, X_{φ_i}, X_v and $X_{\Delta\Theta_j}$. This rule $^{j}R_k$ can be decomposed of $^{j}R_k(v)$ and $^{j}R_k(\Delta\theta)$. The rule base for the jth situation class is regarded as the fuzzy relation which produces relation matrices in four dimensions and given by

$$^{j}R_k(v) = \Psi_k \times D_{ik} \times \Phi_{ik} \times V_k \tag{10}$$

$$^{j}R_k(\Delta\theta) = \Psi_k \times D_{ik} \times \Phi_{ik} \times \Delta\Theta_k \tag{11}$$

For the avoidance algorithm made up of such rules, overall relation $^{j}R(v)$ and $^{j}R(\Delta\theta)$ are calculated by taking $\bigcup_k (^{j}R_k(v))$ and $\bigcup_k (^{j}R_k(\Delta\theta))$, respectively. The $^{j}R(v)$ and $^{j}R(\Delta\theta)$ are the matrices consisting of the membership values $\mu_{^{j}R(v)}$ and $\mu_{^{j}R(\Delta\theta)}$, respectively and given by

$$\mu_{^{j}R(v)}(\psi, d_i, \varphi_i, v) = \bigcup_k \{ \mu_{\Psi_k}(\psi) \cap \mu_{D_{ik}}(d_i) \cap \mu_{\Phi_k}(\varphi_i) \cap \mu_{V_k}(v) \} \tag{12}$$

$$\mu_{^{j}R(\Delta\theta)}(\psi, d_i, \varphi_i, \Delta\theta) = \bigcup_k \{ \mu_{\Psi_k}(\psi) \cap \mu_{D_{ik}}(d_i) \cap \mu_{\Phi_k}(\varphi_i) \cap \mu_{\Delta\Theta_k}(\Delta\theta) \}. \tag{13}$$

C. Reasoning Process

Avoidance action v and $\Delta\theta$ are determined by utilizing the input data obtained from the sensors and inferring the primitive rule base. The inference mechanism uses the minimum–maximum operation and each output action v and $\Delta\theta$ are calculated by

$$\mu_V(v) = \bigcup_{(\Psi, D_i, \Phi_i)} \{ \mu_{^{j}R(v)}(\psi, d_i, \varphi_i, v) \cap \mu_\Psi(\psi) \cap \mu_{D_i}(d_i) \cap \mu_{\Phi_i}(\varphi_i) \} \tag{14}$$

$$\mu_{\Delta\Theta}(\Delta\theta) = \bigcup_{(\Psi, D_i, \Phi_i)} \{ \mu_{^{j}R(\Delta\Theta)}(\psi, d_i, \varphi_i, \Delta\theta) \cap \mu_\Psi(\psi) \cap \mu_{D_i}(d_i) \cap \mu_{\Phi_i}(\varphi_i) \} \tag{15}$$

The above relations define the fuzzy subset V and $\Delta\Theta$ representing the velocity and incremental steering angle of the mobile robot,respectively.

D. Defuzzification of Output Variables

In order to determine the crisp output action $\bar{v}$ and $\Delta\bar{\theta}$ from the fuzzy subsets V and $\Delta\Theta$, defuzzification process is required. The defuzzification is performed by using the method of the center of gravity and the outputs are expressed by

$$\bar{v} = \Big(\sum_{m=1}^{p} \mu_V(v_m) \cdot v_m\Big) / \Big(\sum_{m=1}^{p} \mu_V(v_m)\Big) \tag{16}$$

$$\Delta\bar{\theta} = \Big(\sum_{m=1}^{q} \mu_{\Delta\Theta}(\Delta\theta_m) \cdot \Delta\theta_m\Big) / \Big(\sum_{m=1}^{q} \mu_{\Delta\Theta}(\Delta\theta_m)\Big) \tag{17}$$

where p and q denote the number of the linguistic fuzzy subsets for V and $\Delta\Theta$, respectively.

V. SIMULATION

As an illustration of the foregoing process, a series of simulations were made using an arbitrary constructed environment composing of ten obstacles. In such an environment, seven classes of the situations classified by neural network arose. It was assumed that the radius of mobile robot is 0.25m and the size of environment is 40mx40m. The measurement range of sensor was assumed to be six times the radius of mobile robot. The maximum robot speed was assumed to be 30cm/sec. Using the rule bases constructed in the previous section, the avoidance action were inferred. Fig. 9 shows the avoidance action when the rule bases are used. As shown in the figure, the mobile robot fails to avoid the obstacles without collision. In this example, environment situations classified by neural network arise in the order of the situation class 2, 3, 4, 5, 2, 1 and 4. As shown in the figure, in order to make the mobile robot have the avoidance action suitable for the class 1, rule base must be tuned. The result after tuning the rule base of class 1 is shown in Fig. 10. The figure shows a satisfactory avoidance action, but avoidance action associated with hallway environment is unsatisfactory in terms of the path smoothness and navigation time. Again, rule base associated with hallway environment is tuned by the same procedure used in situation class 1. Fig. 11 shows the result of the improved avoidance action. When different start and goal position is given, avoidance action using the rule base tuned in the above is illustrated in Fig. 12. Fig. 13 shows the mobile robot action in case of the dead alley. In this example, the mobile robot follows the boundary of obstacle while maintaining a safe distance from obstacle.

VI. CONCLUDING REMARK

A sensor–based obstacle avoidance suitable for the cluttered environment has been presented. The avoidance method uses the neural network to recognize the environmental situation in which the mobile robot is at the present instant and the fuzzy logic to infer the avoidance action from a rule base associated with the recognized situation. This approach is effective in that the construction and tuning of rules can be easily realized. Since the avoidance action is inferred from the rule base associated with the present situation rather than the whole rule bases, the number of rules employed in the reasoning process is small. Therefore, the method can be implemented in the real–time obstacle avoidance for mobile robot. In further study, the strategies to learn the environment situation in learning–by–observation manner and to tune the rules autonomously should be considered.

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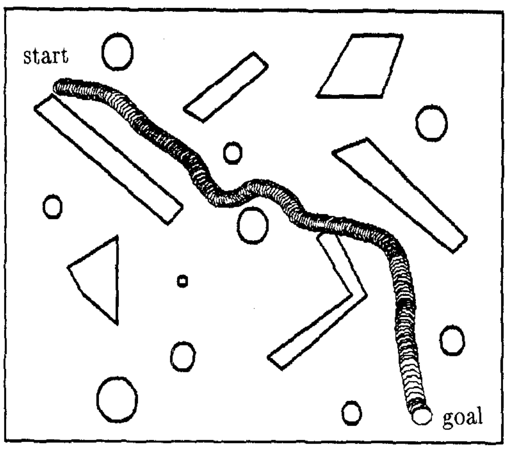

Fig. 9. The failure case of obstacle avoidance.

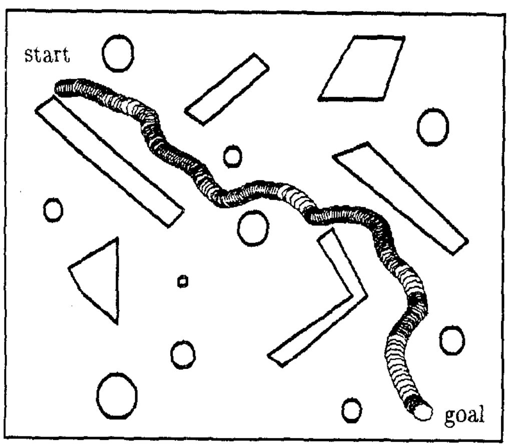

Fig. 10. The successful case of obstacle avoidance.

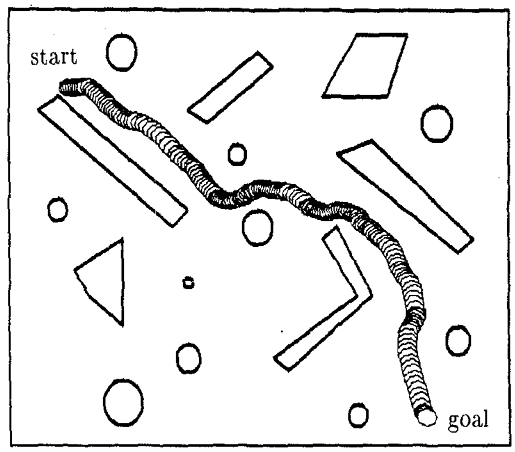

Fig. 11. An obstacle Avoidance using the more improved rules.

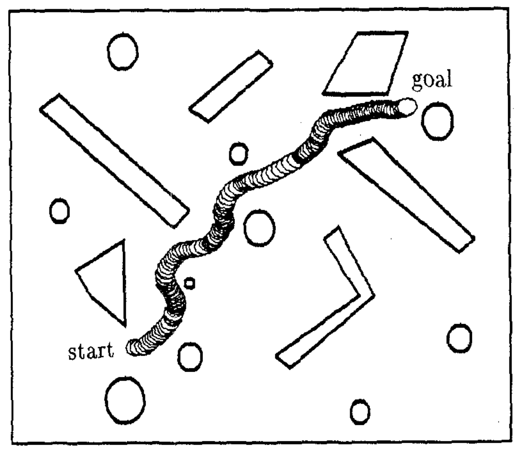

Fig. 12. An example for different start and goal position.

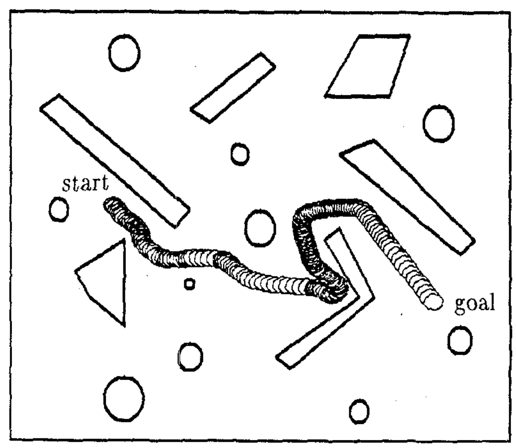

Fig. 13. Obstacle avoidance in case of the dead alley.