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Neural network and fuzzy logic techniques based collision avoidance for a mobile robot

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SUMMARY

This paper is concerned with a mobile robot reactive navigation in an unknown cluttered environment based on neural network and fuzzy logic. Reactive navigation is a mapping between sensory data and commands without planning. This article's task is to provide a steering command letting a mobile robot avoid a collision with obstacles. In this paper, the authors explain how to perform a currently perceptual space partitioning for a mobile robot by the use of an ART neural network, and then, how to build a 3-dimensional fuzzy controller for mobile robot reactive navigation. The results presented, whether experimented or simulation, show that our method is well adapted to this type of problem.

KEYWORDS: Mobile robot; Obstacle avoidance; Neural networks; Fuzzy logic.

1. INTRODUCTION

Current research and development of mobile robot have attracted the attention of researchers in the areas of engineering, computer science, biology, and others. This is due to the great application potential of mobile robots. These possible applications include automatic freeway driving,[1] guidance of the blind and disabled,[2] exploration of dangerous regions & mechanical parts transfer in flexible assembly system (FAM).[3,4]

Reactive navigation[5] is a mapping between sensory data and commands, without planning. Its task is to provide a steering command letting a mobile robot reach a goal while avoiding collision with obstacles in an unknown environment. The most classical approach to the problem is called potential field method.[6] A mobile robot travels in a field of imaginary forces generated by obstacles (repulsion) and by a goal (attraction). The mapping function calculates a cumulative effect of all of those forces and chooses a locomotion command. However, this method has its inherent limitations as local minima and oscillations.[7] Another approach to the reactive navigation – occupancy grid method – is based on sensory oriented raster model of obstacles configuration. The avoidance algorithm checks the occupancy of rasters belonging to the area of the next planned movement.[8]

One of the more recent ideas in the reactive navigation research is to use fuzzy logic, already successfully applied to more general control problems.[9] It is quite convenient to incorporate an obvious part of the environmental knowledge into a fuzzy rule base. Fuzzy control systems have already demonstrated their efficiency in reactive navigation of mobile robots.[10–12] If we define the perceptual space as the space where each axis represents a group of sensors value and the command space as the space where each axis represents a command variable, a reactive navigation system is the mapping between the two spaces. For a mobile robot to navigate automatically in an unknown and clustered environment, an important factor is to identify and classify mobile robot's currently perceptual space based on multi-sensors information. In reference 11 and 12, the mobile robot's steering command is obtained based on the different directions distances between obstacles and mobile robot, that is to say, mobile robot will move toward the farest obstacle, such, mobile robot's movement could have blindness to a certain extent. In reference 10, the perceptual space identification and classification are achieved by use of fuzzy logic technique, however, the fuzzy rules number is very large, the ability of mobile robot's real-time obstacle avoidance could be reduced.

The approach that we propose deals with this problem of mobile robot obstacle avoidance in an unknown clustered environment. Our approach is first to build classifier for the perceptual space identification and classification based on an ART neural network, then to achieve mobile robot autonomous obstacle avoidance in an unknown environment by use of fuzzy logic technique. In this paper, the design of the classifier for the perceptual space identification and classification based on an ART neural network is introduced in section 2. Brief concepts of the fuzzy inference and the 3-dimension fuzzy controller for mobile robot autonomous obstacle avoidance are described in section 3. Some simulation and experiments results are shown in section 4, and conclusions appear in the last section.

2. THE PERCEPTUAL SPACE IDENTIFICATION AND CLASSIFICATION

2.1. The preprocessor of multi-sensors information

Our experimental mobile robot is a TIT-1 model mobile robot, its configuration is shown in Fig. 1. The mobile robot is equipped with a pair of front castors and a pair of rear co-axial drive wheels (see Fig. 1). Each of these drive wheels is independently driven by a DC motor which is, in turn, energized by a control voltage.

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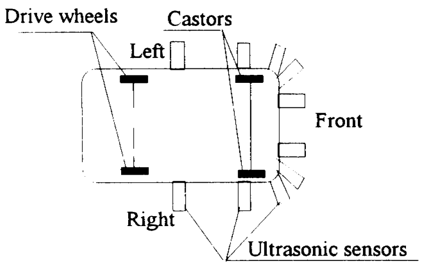

Fig. 1. The configuration of TIT-1 model mobile robot.

Initially, the robot has no information about its currently environment. An acquisition process is needed in order to obtain this information. In our TIT-1 model mobile robot, we have chosen to use a set of ultrasonic sensors to perceive the currently environment of mobile robot (see Fig. 1). During the robot movement, at every time *t,* we have some distances values available between the robot and the different obstacles. In order to improve mobile robot's real-time obstacles avoidance ability, some preprocessing is necessary to reduce the amount of data, sensors are classified into three groups: in front, on the left, and on the right. For each group, we only keep the smallest depth measure. Such, we have three inputs information for the perceptual space identification and classification.

The preprocessor also has another function, i.e. the multi-sensors information feature extraction. The feature extraction is implemented in software, which includes two functions which are (1) extract the feature value of sensors with time interval, the interval can be determined based on the robot's velocity, (2) check the extraction of features values within a short time interval, so that out-side disturbances are eliminated.

2.2. The perceptual space identification and classification based on ART neural network

The most natural approach to the perceptual space partitioning for mobile robot reactive navigation purposes seems to be one of the adaptive resonance theory methods[5]. In this paper, we chose to use an ART-2 neural network to partition a perceptual space based on three inputs information of ultrasonic sensors. The ART algorithms are relatively fast, due to competitive activation and competitive adaptation rules.

ART-2 neural network's inputs can be arbitrarily analogy vectors; it consists of the feature field F_1, the category field F_2, the two short term memory (STM) and the long term memory (LTM) between F_1 and F_2. When having the feature vectors X_i $(i = 1, \ldots, M)$ as inputs of the neural system, the feature field F_1 obtains inputs information U_i by a series of standardization operations and non-linear transformations. Then, the category field F_2 receives inputs information from the feature field F_1, that is:

$$P_i = U_i + \sum_{j=1}^{N} g(y_i)\omega_{ji},$$

where, ω_{ji} is up-bottom weight.

The input of node j in the category field F_2 is:

$$T_j = \sum_{i=1}^{M} P_i\omega_{ij}$$

where, ω_{ij} is the bottom-up weight.

The system is said to make a choice when at most one F_2 node can become active. The choice is indexed at J where

$$T_j = \max\{T_j\text{: for all } F_2 \text{ node } j\}$$

When a category choice is made at node J, $g(y_J) = d$; and $g(y_j) = 0$ for all $j \neq J$. In a choice system, the learning equations in LTM can be shown as follows:

$$\frac{d\omega_{Ji}}{dt} = d(1-d)\left[\frac{U}{1-d} - \omega_{Ji}\right]$$

$$\frac{d\omega_{iJ}}{dt} = d(1-d)\left[\frac{U_i}{1-d} - \omega_{iJ}\right]$$

If any of the vigilance constraints is violated, mismatch reset occurs in which the value of the choice function T_j is set to 0 for the duration of the input presentation. The search process repeats to select another new index J until resonance is achieved. The condition which the reset occurs in the category field F_2 is as follows:

$$\frac{\rho}{e + \|R\|} > 1$$

where, ρ is the network's vigilance parameter, $\rho \in [0, 1]$.

$$\|R\| = \left(\sum_{i=1}^{M} r_i^2\right)^{1/2}$$

$$r_i = \frac{u_i + cp_i}{e + \|U\| + \|cP\|}$$

Obviously, the higher the similarity of U with P is, the more the value of $\|R\|$ is close to 1. When $\|R\| > \rho$, no reset occurs, i.e. a new category is establish, otherwise, reset occurs in the category field F_2. The neural network utilize supervised learning mode and off-line training method.[13]

Based on the above analysis, we present the classifier architecture shown in Fig. 2.

During training, the attentional vigilance parameter is set at its higher value to ensure a high resolution of the resulting category. When the network is presented with a feature vector for the first time, it is encoded in LTM through modification of the LTM connection weights. A node is allocated in the category field F_2 to represent the pattern. The parameters associated with the feature vector now get assigned to this allocated F_2 node. On presentation of subsequent feature vectors, the network's

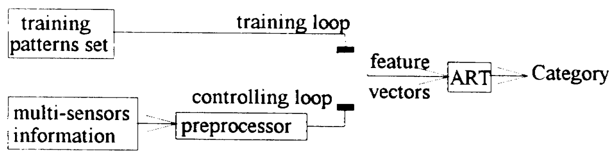

Fig. 2. The block diagram of the classifier.

orienting subsystem first determines closeness of match between the pattern currently imposed on the network and any of the patterns that have previously been seen. If the current pattern happens to be closely matched to the one the network has already seen, it is clustered into the same category. The vigilance parameter helps to control the fineness of classification desired. After completion of training, the top down and the bottom up connection weights of the network are saved into the computer memory. When the network is introduced in the control loop, identification and classification proceeds almost instantly. Search for the category associated with the right parameter is achieved by dynamically altering the attentional vigilance parameter until an "optimal vigilance" is found.

The various types of actual environment which are perceived by mobile robot must be covered by the categories which are partitioned by the classifier based on multi-sensors information, which means that at least one category must have a non-zero activation for each perceptual space. The key is that the training patterns set should store all the feature of possible perceptual space based on sensors distribution. Considering the sensors distribution on the TIT-1 model mobile robot shown in Fig. 1, with the simple obstacle description we have (three sensor groups), we can classify the perceptual space as 8 categories shown in Fig. 3. By use of this paper's classifier shown in Fig. 2, the mobile robot can achieve the identification and partitioning on the currently perceptual space, and then classify the currently perceptual space as one of these 8 categories.

3. THE 3-DIMENSION FUZZY CONTROLLER

Based on our controlling demands, the fuzzy controller has three controlling inputs, that are the category of the perceptual space, the smallest distance between mobile robot and a category of the perceptual space and mobile robot's velocity, two controlling outputs, that are the mobile robot's steering orientation and its acceleration.

3.1. Fuzzification of exact input variables

Now, we build a linguistic database to describe the input values. Since the categories of the perceptual space are 8 finite values T_i^0 $(i = 1, 2, \ldots, 8)$, we define T_i^0 as fuzzy inputs T, so, its membership value is 1 if $x = T_i^0$ and 0 if $x \neq T_i^0$. We define D^0 and V^0 as the exact distance and velocity inputs to fuzzy controller respectively. Then we analyzed the requirements of the controller for mobile robot obstacles avoidance, the real intervals of D^0 and V^0 are limited to $[-4, 4]$ and $[-3, 3]$ respectively. We denote D and V as fuzzy distance and fuzzy velocity variables within the discussion universal $[-4, 4]$ and $[-3, 3]$ respectively, the linguistic labels D_j of fuzzy distance D are VN(very near), N(near), M(medium), F(far) and VF(very far), the linguistic labels V_k of fuzzy velocity V are NSV(negative slow velocity), SV(slow velocity), MV(medium velocity) and HV(high velocity).

U and W are denoted as fuzzy steering orientation and fuzzy acceleration variables within the discussion universal $[-8, 8]$ and $[-4, 4]$ respectively, their linguistic labels are LVL(left very large), LL(left large), LM(left medium), LS(left small), ZO(zero), RS(right small), RM(right medium), RL(right large), RVL(right very large), and QD(quickly deceleration), SD(slow deceleration), Z(zero), SA(slow acceleration), QA(quickly acceleration), respectively.

The membership function of every fuzzy subset of input and output fuzzy variables D, V, U, and W is:

$$\mu(x) = \exp\left[-\left(\frac{x-a}{\sigma}\right)^2\right]$$

where, σ is a important parameter which affects the

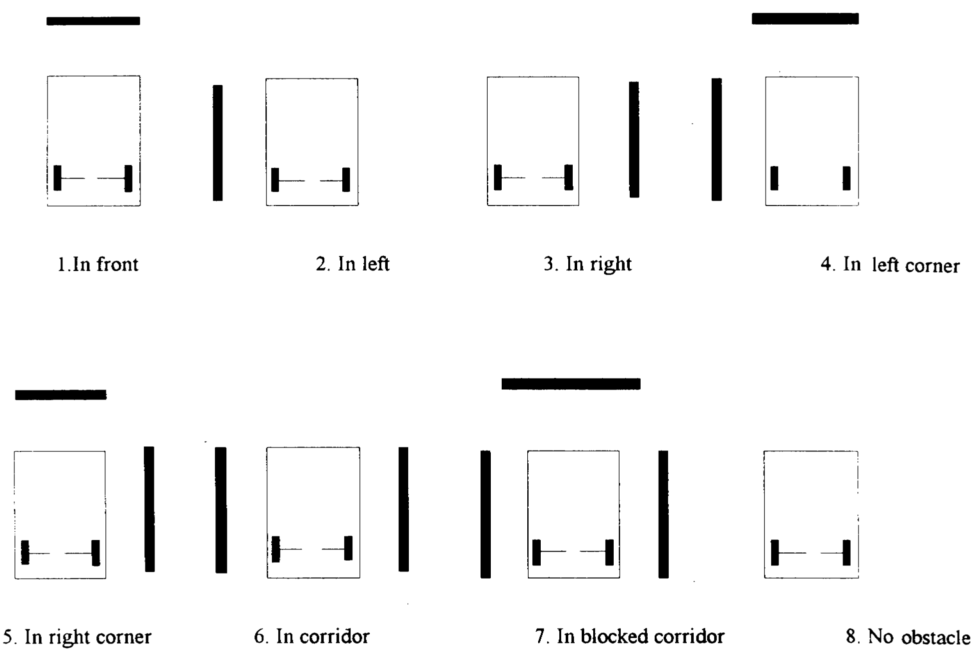

Fig. 3. The 8 categories of the perceptual space.

property of fuzzy controller. Tuning the value of σ means adjusting the shape of the membership functions of the all linguistic sets. There is no theory on how to do that manually. It must be done through experiments. After many experiments, we obtain the optimum value for our mobile robot.

3.2. Fuzzy inference

For our application, based on the fuzzy subsets of each fuzzy variables as above, the number of fuzzy controlling rules is 160, that is;

if (T is T_i and D is D_j and V is V_k)

then (U is U_{ijk} and W is W_{ijk})

where, $i = 1, \; 2, \ldots, 8, \; j = 1, 2, \ldots, 5, \; k = 1, 2, \ldots, 4$. These rules can also be written as follows:

if (T is T_i and D is D_j and V is V_k) then V is U_{ijk}

and

if (T is T_i and D is D_j and V is V_k) then W is W_{ijk}

Then their fuzzy relations are, respectively:

$$R^U_{ijk} = (T_i \times D_j \times V_k \times U_{ijk})$$

and

$$R^W_{ijk} = (T_i \times D_j \times V_k \times W_{ijk})$$

The total fuzzy relations are, respectively:

$$R^U = \bigcup_{i,j,k} (T_i \times D_j \times V_k \times U_{ijk})$$

and

$$R^W = \bigcup_{i,j,k} (T_i \times D_j \times V_k \times W_{ijk})$$

The membership functions of fuzzy relations are:

$$\mu_{R^U}(t, d, v, u) = \bigvee_{i=1,j=1,k=1}^{i=8,j=5,k=4} \mu_{T_i}(t) \wedge \mu_{D_j}(d) \wedge \mu_{V_k}(v) \wedge \mu_{U_{ijk}}(u)$$

and

$$\mu_{R^W}(t, d, v, w) = \bigvee_{i=1,j=1,k=1}^{i=8,j=5,k=4} \mu_{T_i}(t) \wedge \mu_{D_j}(d) \mu_{V_k}(v) \wedge \mu_{W_{ijk}}(w)$$

where, $t \in T, \; d \in D, \; v \in V, \; u \in U, \; w \in W$.

When there are fuzzy inputs T, D, and V, based on fuzzy inference rules, the fuzzy control outputs U and W are obtained as follows:

$$V = (T \times D \times V) \circ R^U$$

and

$$W = (T \times D \times V) \circ R^W$$

Their membership functions are respectively:

$$\mu_U(u) = \bigvee_{t,d,v} \mu_{R^U}(t, d, v, u) \wedge \mu_T(t) \wedge \mu_D(d) \wedge \mu_V(v)$$

and

$$\mu_W(w) = \bigvee_{t,d,v} \mu_{R^W}(t, d, v, w) \wedge \mu_T(t) \wedge \mu_D(d) \wedge \mu_V(v)$$

3.3. Defuzzification

The final result must be translated into a number to be sent to the mobile robot. There are many such techniques. One of the solutions called *mean of maximum,* computes the mean of all the points which will maximize the membership function. One of the drawbacks is that it does not take much into account the shape of the curve. Another frequently used solution is the *Center of Area Method.* The exact steering orientation U^O and acceleration W^O are given by the formula:

$$U^0 = \frac{\sum_{i=1}^{9} u_i \mu_U(u_i)}{\sum_{i=1}^{9} \mu_U(u_i)}$$

$$W^0 = \frac{\sum_{i=1}^{5} w_i \mu_W(w_i)}{\sum_{i=1}^{5} \mu_W(w_i)}$$

3.4. The fuzzy controller for obstacles avoidance

Based on the analysis as above, we have designed the three dimensions fuzzy controller for the mobile robot obstacles avoidance in an unknown environment; its architecture is shown in Fig. 4.

By use of this paper's fuzzy controller as shown in Fig. 4, our mobile robot can achieve transmission safely and quickly in an unknown environment; its controlling process is:

Firstly, the two block of the classifier and the calculating the nearest depth obtain the multi-sensors information which come from the measuring depths between the mobile robot and obstacles in the currently space. The multi-sensors information is the feature vectors which represent and reflect the currently perceptual space.

Then, based on the feature vectors of the currently perceptual space, the classifier partitions the currently perceptual space as one of the space categories shown in Fig. 3, and the nearest distance between mobile robot and obstacles in the currently environment is obtained. At the same time, we also obtain the currently velocity of mobile robot by use of the feedback device.

Finally, we obtain the crisp control outputs (steering orientation and its acceleration) through fuzzification, fuzzy inference and defuzzification on the three crisp inputs (the category, the nearest distance and the velocity), these crisp control outputs are used to control the mobile robot.

4. EXPERIMENTS

To assess the performance of this paper's collision avoidance method and system experiments were conducted using the TIT-1 mobile robot in an indoor unknown environment. Four types of experiments were run to test the mobile collision avoidance system in situations likely to be encountered indoors. These experiments include: (i) traverse through the straight

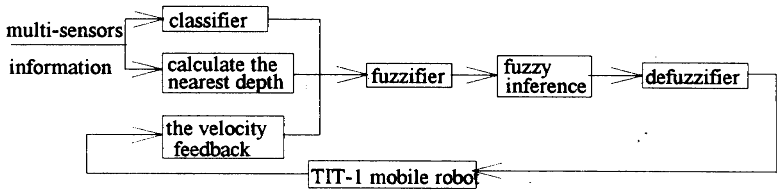

Fig. 4. The block diagram of the 3-dimension fuzzy controller.

corridor and then make a 90-degree turn, (ii) head-on approach towards obstacles, (iii) partially blocked hallways with free space on one side of the obstacle, and (iv) avoid some arbitrarily position obstacles. Each of these scenarios and avoiding obstacle procedures is depicted in Fig. 5(a)–(d) respectively. From Fig. 5, we can see that the robot has a little of oscillation because there is the lack of steering angle feedback, and we also can easily see from Fig. 5(d), the robot always avoided collision but its behavior effected a tendency to wander about in the environment. This can be attributed to the fact that the robot was not provided with a particular goal. Experiments show that the robot can safely and quickly traverse an unknown environment.

5. CONCLUSION

Trial runs of the robot in an indoor unknown environment demonstrated that the robot was capable of rudimentary collision avoidance limited by the lack of steering angle feedback. By use of the perceptual space identification method presented in this paper, the robot can quickly and accurately identify and partition the currently perceptual space based on three groups sensors information. Then, taking the category of the perceptual space, the nearest distance between the robot and obstacles and the traversing velocity of the robot as inputs, we designed a three–dimensions fuzzy controller, and achieved a collision-free traversing of the mobile robot in an unknown environment.

Fuzzy logic control has proved to be a satisfactory control strategy for the mobile robot collision avoidance problem.[10–12] But, if a mobile robot achieves the identification and partitioning on the perceptual space and then obstacles avoidance by only using fuzzy control theory, the number of fuzzy rules will be very large and the real-time performance of the controller will be poor. This paper utilizes a neural network technique to identify and partition the space and then utilizes a fuzzy logic technique to establish a fuzzy controller for obstacle avoidance. Thus, this paper's method overcomes these disadvantages.

Further research on this topic should include an investigation of utilizing position feedback. Such feedback would permit straight line drive capability and much smoother path traversal. The sensor arrangement and quality should also be improved.

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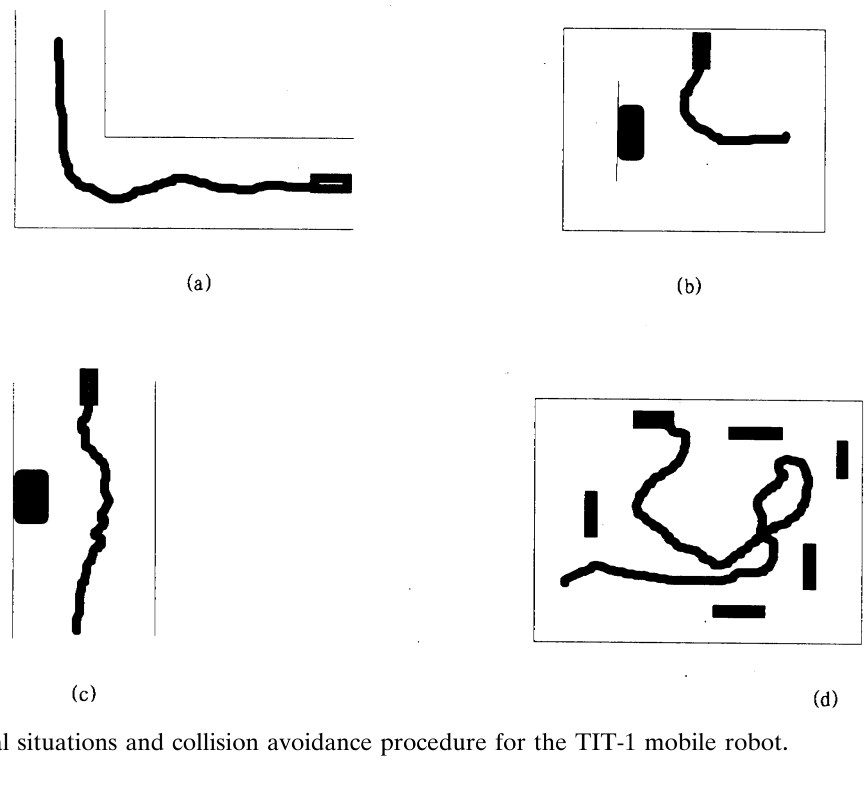

Fig. 5. Four experimental situations and collision avoidance procedure for the TIT-1 mobile robot.

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