# Mobile Robot Path Tracking in Unknown Dynamic Environment

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***Abstract*—The paper proposes a cooperative system of fuzzy neural networks (FNN) and fuzzy logic control (FLC). And this system is used to on-line path tracking of a mobile robot in unknown dynamic environment, instead of the commonly used FLC to research on this problem. Firstly, the application of FNN based on the kinematics models of mobile robot is described in detail, moreover, it uses an improved back propagation (BP) algorithm to complete the network learning and training. Secondly, it utilizes FLC to fulfill the real-time avoiding obstacles. The simulation results show that the proposed cooperative system is effective and robust, meanwhile possesses better abilities of path tracking and real-time avoiding obstacles in unknown dynamic environment.**

***Keywords*—mobile robot, path tracking, fuzzy neural networks (FNN), unknown dynamic environment**

## I. Introduction

As an intelligent system, mobile robot that integrates many functions such as environment sensing, dynamic decision-making and planning, behavior controlling and executing, etc., can accomplish destined tasks in working environment [1]. Path tracking is one of the basic and most important problems in all kinds of researches and applications to mobile robot, is also an autonomous behavior that the mobile robot must own for accomplishing the work tasks. Especially in unknown dynamic environment, mobile robot path tracking is even a more difficult problem to solve, it requires that the mobile robot try its best not to deviate the specified path, except on the condition that robot would touch the obstacles, at this time the mobile robot has to detour its destined path, but mobile robot must return to its original path until arriving destination after it avoids the obstacles.

The traditional methods about mobile robot path tracking use linear feedback control or non-linear feedback control widely, these methods not only need accurate kinematics or dynamics models, but also design complexly, furthermore, their robustness and control effect are bad also [2]. Vector field histogram (VFH) method can control the moving direction and speed of the mobile robot, can solve the collision-free problem in unknown environments, but VFH is only a kind of local avoiding obstacles algorithm, it cannot lead the mobile robot to the goal successfully in some situations and may even result in instability. To the dynamic window approach for path planning, in which the kinematic constraints of the mobile robot are taken into account, the mobile robot can move towards the goal fast while avoiding obstacles. Although this method is applicable in many cases, the mobile robot is still susceptible to be stuck in some local minima [3]. Other methods about mobile robot path tracking are often carried out by using fuzzy inference, its advantages are that it only summarizes fuzzy rules in accordance with the knowledge in problem field, needs not establish accurate mathematic models, but the fuzzy rules can not reach in all aspects to a problem and lack generalization abilities [4]. FNN combines neural networks with fuzzy inference theory and has the advantages of both, it is a kind of networks structure based on IF-THEN fuzzy rules. FNN can not only express approximate and qualitative knowledge, but also own the abilities of learning and nonlinear expressing of neural networks. In recent years, FNN owns broad approaching characteristics, it can realize nonlinear mapping from input to output [5].

This paper utilizes FNN to realize mobile robot path tracking and to apply FLC to complete real time avoiding obstacle, at last it proves the correctness and effectualness of the method by simulation experiments. The simulation experiments also show that the cooperative system in the paper is applicable of mobile robot path planning in unknown dynamic environment.

## II. Modeling of Mobile Robot Path Tracking

This paper mainly carries out researches on a wheeled mobile robot (WMR), which is made up of two driving wheels and one caster, the caster only reacts on supporting, its effects to kinematics model may be ignored. $v, \omega$ respectively denote moving speed and rotating speed, the model of WMR is as follows:

$$\begin{bmatrix} \dot{x} \\ \dot{y} \\ \dot{\theta} \end{bmatrix} = \begin{bmatrix} \cos\theta & 0 \\ \sin\theta & 0 \\ 0 & 1 \end{bmatrix} \cdot \begin{bmatrix} v \\ \omega \end{bmatrix} \tag{1}$$

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Therefore, the current position and posture of WMR can be gained by controlling $U = [v, \omega]^T$ . This paper designs an algorithm of mobile robot path tracking via the theorem of line between two points, depicted in Fig.1. In this diagram the WMR is moving along the line between *A* point and *B* point, the angle between path direction and heading direction is $\theta$, $\theta \in [-\pi, \pi]$. The coordinates of *A* point are $(x_a, y_a)$, that of *B* point are $(x_b, y_b)$, the current coordinates of the WMR are $P(x_p, y_p)$, so the line equation between the *A* point and *B* point is:

$$(y_a - y_b)x - (x_a - x_b)y + (x_a - x_b)y_a - (y_a - y_b)x_a = 0 \tag{2}$$

Let $d$ be the deviation distance of mobile robot from the path, then in terms of the interval formula of point to line, it can be obtained that

$$d = \frac{\left|(y_a - y_b)x_p - (x_a - x_b)y_p + (x_a - x_b)y_p - (y_a - y_b)x_a\right|}{\sqrt{(y_a - y_b)^2 + (x_a - x_b)^2}} \tag{3}$$

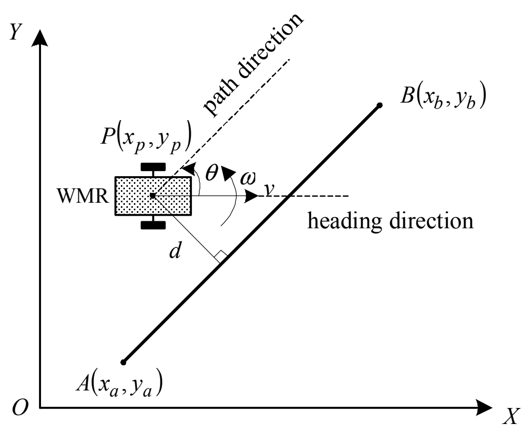


Fig.1. Mobile robot path tracking model

For the need of researching, we define that $d$ is negative if WMR is above the path, contrarily, $d$ is positive negative when WMR is below the path. $\theta$ is positive when WMR turns anticlockwise and negative when WMR turns clockwise. If the heading direction of WMR is same with its path direction, $\theta$ is zero.

The specified path that WMR will track is composed by many path points, furthermore their space length is equal.

## III. THE STRUCTURE OF FNN

According to the analysis of the mobile robot path tracking model above, we applied a typical 5 layers FNN, depicted in Fig.2, to realize robot path tracking. $d_e$ and $\theta_e$ are expected position of the robot, $d_r$ and $\theta_r$ are its practical one. Layer 1 is an input layer, which transmits the input values to next layer, the neuron number of this layer is equal to the number of the variables in the antecedents of the rules of the fuzzy logic mode1.Layer 2 shows the linguistic terms of input language variable, every neuron cell shows a kind of language variable, expresses a membership function. Let the quantities of path points be $i$, $k = 1, 2, \cdots, m_i$, where $m_i$ is number of fuzzy partition, so the total nodes of this layer are $N = \sum_{i=1}^{n} m_i$. Layer 3 and Layer 4 together show fuzzy control rules, the neurons in Layer 3 are employed to represent the front parts of the rules of the fuzzy logic mode1, they complete fuzzy **AND** operations, every node indicates a piece of rules, its relevance grade is $\alpha_j = \min\{\mu_1(i_1), \mu_2(i_2), \cdots\}$, where $i_i \in \{1, 2, \cdots, m\}$, $m$ is the total number of this layer. Layer 4 represents the rear parts of the rules, it performs fuzzy **OR** operations, the output of this layer is $\overline{\alpha}_j = \alpha_j / \sum_{i=1}^{m} \alpha_i$ . Layer 5 is the output layer of the system, namely conclusion proposition layer [6], the number of output neuron is equal to that of output variables, the function of this layer are defuzzification, the paper utilizes the method of weighted average, as $y_i = \sum_{j=1}^{m} w_{ij} \overline{\alpha}_j$ , where $w_{ij}$ represents the link weights between Layer 4 and Layer 5, its initial value is 1.

Let *D* represent the fuzzy variable of *d* and *Theta* represent the fuzzy variable of $\theta$. *D and Theta* are divided five fuzzy subset $\{NB, NS, ZO, PS, PB\}$ . $v$ has three fuzzy subset $\{STOP, SLOW, FAST\}$ , and $\omega$ has five fuzzy subset $\{NB, NS, ZO, PS, PB\}$. The fuzzy inference rules of $\omega$ are given in Table I, and the fuzzy inference rules of $v$ are displayed as:

If $\omega$ is *NS* or $\omega$ is *PS* then $v$ is *SLOW*
If $\omega$ is *NF* or $\omega$ is *PF* then $v$ is *STOP*
If $\omega$ is *ZO* then $v$ is *FAST*

TABLE I. FUZZY INFERENCE RULES of $\omega$

| *D* / *Theta* | *NB* | *NS* | *ZO* | *PS* | *PB* |
|---|---|---|---|---|---|
| ***NB*** | *ZO* | *NS* | *NF* | *NF* | *NF* |
| ***BS*** | *PS* | *ZO* | *NS* | *NF* | *NF* |
| ***ZO*** | *PF* | *PS* | *ZO* | *NS* | *NF* |
| ***PS*** | *PF* | *PF* | *PS* | *ZO* | *NS* |
| ***PB*** | *PF* | *PF* | *PF* | *PS* | *ZO* |

The membership function used in the paper is Gauss function, as:

$$\mu(x_i) = \exp\left[-\frac{(x_i - c_{ij})^2}{\delta_{ij}^{\ 2}}\right] \tag{4}$$

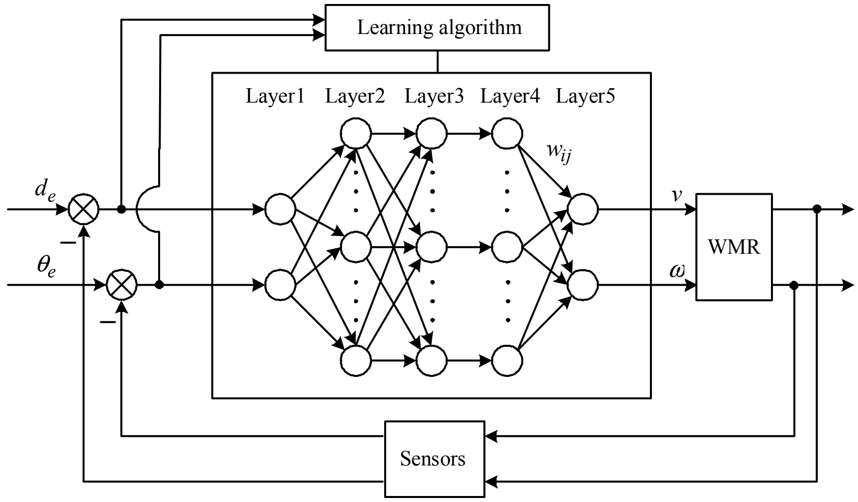


Fig.2. FNN block diagram of mobile robot path tracking

Where $c_{ij}$ and $\delta_{ij}$ are the center and width of the Gauss membership function. From the structure of FNN shown in Fig.2, the $c_{ij}$ and $\delta_{ij}$ are adjusted by networks training and self-learning, so the $w_{ij}$, which initial value is random. Finally, it makes the errors between practical value and expected value minimal, that is to say the tracking of mobile robot is more exact.

## IV. NETWORKS LEARNING ALGORITHM

In FNN, the parameters of $c_{ij}$, $\delta_{ij}$ and $w_{ij}$ are needed to be confirmed. This paper uses improved BP algorithm with an additive momentum item to train the networks. According to rules learning and by using gradient descending algorithm, it makes total mean square deviation minimum between practical value and expected value minimal through adjusting weight and threshold [6]. The modified iteration formula of the weight value of this improved BP algorithm can be described as:

$$\Delta X^{K+1} = M \cdot \Delta X^{K} + (1-M) \cdot \varepsilon \cdot \nabla f\left(X^{K}\right) \qquad (5)$$

Where $K$ is training times, $M$ is momentum item, generally its value is about 0.95. $\nabla f\left(X^{K}\right)$ is the gradient of object function, $\varepsilon$ is learning step length. Because in BP algorithm the error function descend toward negative gradient direction, the modified formula of $k$ layer networks weight value may be described as

$$\Delta w_i^{\ k} = -\varepsilon \cdot \frac{\partial E}{\partial w_i^{\ k}} \qquad (6)$$

Let error function be $E = (V - P)^2 / 2$, where $V$ is an expected signal, and $P$ is a practical output one, so when adding momentum item, it obtains

$$\Delta w_{ij}^{\ k}(t+1) = M \cdot \Delta w_{ij}^{\ k}(t) + (1-M) \cdot \varepsilon \cdot \frac{\partial E}{\partial w_{ij}^{\ k}} \qquad (7)$$

Then $w_{ij}(t+1) = \Delta w_{ij} + w_{ij}(t)$, similarly $\Delta c_{ij}$ and $\Delta \delta_{ij}$ are deduced.

## V. BEHAVIOR DESIGN OF MOBILE ROBOT AVOIDING OBSTACLES

It is well known that a behavior of avoiding obstacles is necessary for a mobile robot. When dynamic environment information indicate that the mobile robot is approaching to an obstacles, it adopt the first mission being avoiding obstacles. For achieving the information in unknown environment in time, it assumes that sensors assembled on the mobile robot are at least divided into three groups, these sensors are separately used to percept left obstacle, right obstacle and front obstacle of the mobile robot. Fig.3 depicts a sketch map of mobile robot avoiding obstacles. It can apply IF-THEN rules to realize avoiding obstacles easily, so we do not introduce them detailedly in the paper, such as in [7]. At the meantime, for the sake of mobile robot fulfilling the task of path tracking better, it require that the priority of the avoiding obstacles behavior must precede that of the path tracking behavior. If mobile robot still needs other more behaviors to finish a task of path tracking, these behaviors are only combined based on the priority of each elementary behavior to form a certain path tracking combination behavior.

However, one important point to be noted is that if mobile robot only own these two behaviors, it would not judge whether the mobile robot reach the target position or not. And if mobile robot is tracking a path which is composed with many path points, it must know when it reaches a path point. This problem can be solved by adding a target detecting behavior, which is used to check whether it has reached the target point, to the mobile robot.

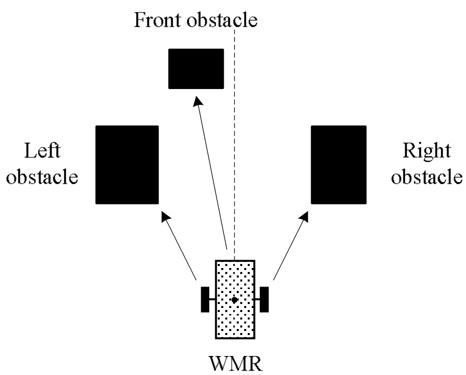



Fig.3. Sketch map of avoiding obstacles

## VI. SIMULATION EXPERIMENTS AND ANALYSIS

In simulation experiments, learning step length $\varepsilon$ is 0.05, start position of mobile robot may be set arbitrarily. The amounts and positions of static obstacles and positions of moving obstacles are set by simulation program randomly, the directions and speeds of the moving obstacles are also random. During computer simulations, let the speed of the moving obstacles can't exceed the moving speed of mobile robot, this is because if the obstacles moved too fast, the mobile robot could not avoid the obstacles and would lead to collide with each other. At the same time, the direction variations of the moving obstacles are also needed to limit, to prevent it changing acutely.

A case of experimental results is shown in Fig.4. In the circumstance of mobile robot, there are not moving obstacles, solid line is an expected tracking trajectory and dotted line is an actual motion path of the mobile robot, the mobile robot tracking error curve is given in Fig.5. We can clearly see from these two pictures that mobile robot move fast to the specified path at the beginning, when meets the obstacles, it detours and returns to that specified path exactly and rapidly.

Fig.6 shows the experimental results in dynamic environment, a specified path to be tracked by mobile robot is a line between start point and end point, mobile robot is denoted by a black solid circle and the hollow circle is its moving trajectory, an obstacle is moving toward the path and will block the way of mobile robot immediately, this can be seen from Fig.6 (a), when mobile robot detects this obstacle, it right-turn sharply, shown in Fig.6 (b) and Fig.6 (c), then after mobile robot avoids the obstacle, it returns that original path till the end point, shown in Fig.6 (d). The tracking error curve is shown in Fig.7.

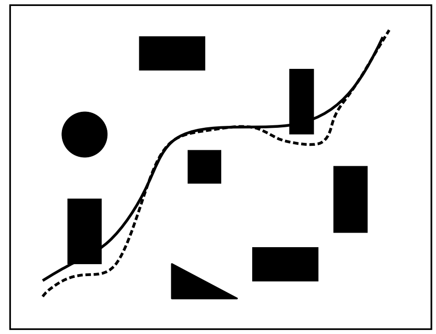


Fig.4. Simulation results without moving obstacles

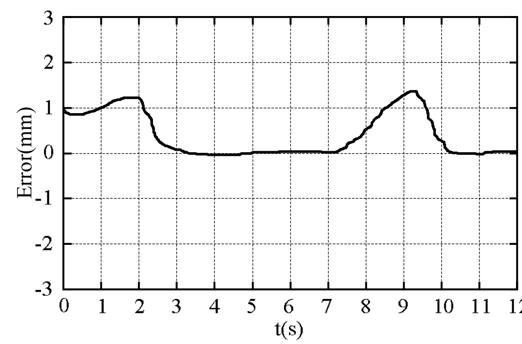
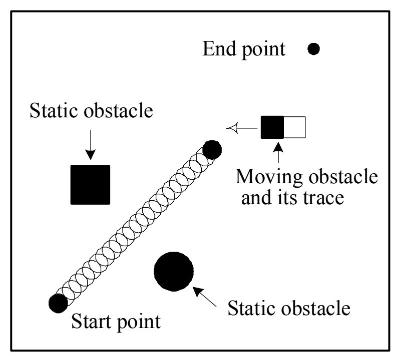
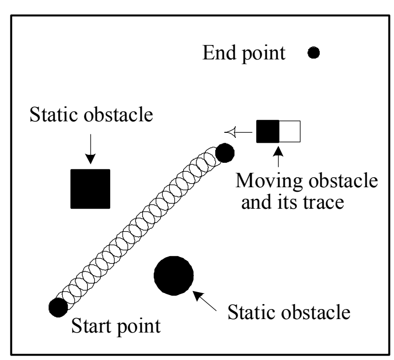


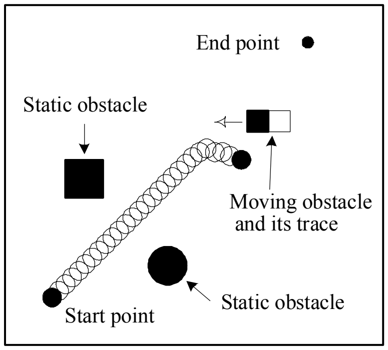

Fig.5. Error curves of path tracking



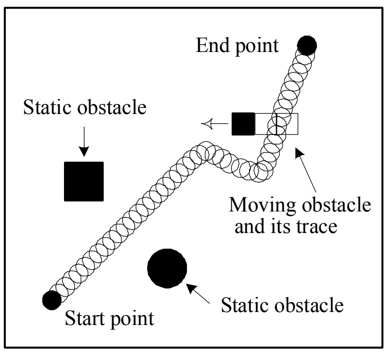

(a)




(b)




(c)




(d)

Fig.6. Processes of mobile robot avoids collision with a moving obstacle

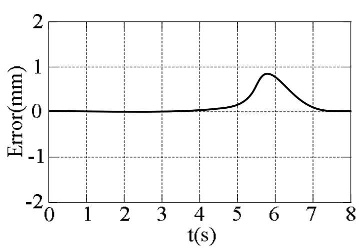



Fig.7. Error curves of path tracking

## VII. Conclusion

Instead of only adopting conventional FLC, a cooperative system constructed by FNN and FLC is presented in the paper, which is used to realize on-line path tracking for a mobile robot in unknown dynamic environment. Theory analysis and experimental results show that this method can effectively improve the abilities of mobile robot path tracking in unknown dynamic environment and finish the tasks successfully. It also can be seen that the combination of FNN and FLC appears to be a good adapted ability, it is easy to expand functions and enhance intelligent levels of mobile robot. From the safety and practical situation point of view, future work will be focused on the further studies in real unknown complicated environment based on this method proposed in this paper.

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