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RESEARCH ARTICLE

Construction of Novel Self-Adaptive Dynamic Window Approach Combined With Fuzzy Neural Network in Complex Dynamic Environments

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ABSTRACT The traditional Dynamic Window Approach (DWA) with constant weight values of the evaluation function leads to the inability of obstacle avoidance for the Automated Guided Vehicles (AGV) to perform obstacle avoidance and path planning in the complex environment. Effective avoidance of complex obstacles requires adaptive weight adjustment to address the evaluation function's challenges. This paper proposes an adaptive DWA (ADWA), which introduces neural network training on the basis of the Mamdani DWA (MDWA). Firstly, the Mamdani type fuzzy controller is designed, and then the adaptive neuro-fuzzy controller is obtained by neural network training. Then, experiments are carried out through the MATLAB simulation environment. The simulation experiment results show that the improved DWA compared to traditional DWA can make the AGV pass the obstacle environment with a better trajectory and reduce the time. The improved DWA improves the autonomous obstacle avoidance capability of AGVs, which not only perfectly fits our task requirements, but also has apparent scientific and practical significance in developing AGV autonomous obstacle avoidance technology.

INDEX TERMS Fuzzy control, dynamic window approach, neural network, automatic guided vehicle.

I. INTRODUCTION

Today's automatic guided vehicle (AGV) plays a significant role in medical evacuation and medical service support in disaster rescue. The application of the automatic guided vehicle can significantly reduce the risk of the operation and improve the operational efficiency in disaster rescue and military medical support. Especially in the complex field environment, the obstacle situation is unknown, and AGV urgently needs a reliable obstacle avoidance method. Obstacle avoidance is the critical technology for the AGV to get to the desired position [1], [2], [3], [4], [5], [6], [7], [8], [9], [10]. Autonomous obstacle avoidance is a critical issue in the field of AGV research.

Recently, different obstacle avoidance methods have been proposed by researchers for AGV autonomous obstacle avoidance. Based on the artificial potential field method for obstacle avoidance, AGV can avoid obstacles to reach the target point [11]. An autonomous obstacle avoidance framework based on a combination of sensor coupling and artificial potential field method is proposed for AGV in complex environments, in which the controller carries out obstacle avoidance by obtaining the environmental information using sensors of the AGV [12], [13], [14]. However, the artificial potential field method does not consider the kinematic performance of the AGV itself, resulting in the AGV not moving according to the planned path in the virtual environment. The dynamic window approach (DWA) is a strategy that Dieter Fox and Sebastian Thrun proposed and applied to mobile robots for obstacle avoidance in 1997 [15], [16], [17], [18], [19], [20], [21], [22], [23]. The DWA builds a preselected set of velocities based on the kinematic equations of the robot, and then the optimal speed is obtained by an evaluation function. There have been some adequate studies on DWA by researchers. A dynamic path planning method consisted of the A* algorithm and DWA by extending the number of

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explorable neighborhoods and introducing a security cost factor in the evaluation function. The security and efficiency of the dynamic path planning method are improved [24]. But its algorithm increases the obstacle avoidance time. For dynamic changes in the environment, the fuzzy control DWA automatically adjusts the weights of the objective function according to the distance from the AGV to the target point and the size of the velocity space. The problem of dangerous AGV path is avoided, but it is ineffective in complex environments [25]. Reinforcement learning is introduced in the literature [26] to enhance applicability. Reinforcement learning is used to learn the objective function weights, which can output the appropriate weights in different environments. To address the problem of insufficient evaluation functions, the literature [27] proposes an improved DWA with two additional evaluation functions to enhance the accuracy of the navigation path but with increased evaluation time.

Although the methods in the above literature can solve some of the problems of traditional DWA, some are fusions of DWA with other algorithms, which increase the complexity of the algorithms. Some do not consider the evaluation function weight value, which leads to problems such as poor obstacle avoidance path and a long time of AGV. So, this paper proposes adaptive fuzzy control DWA, which enables AGV to acquire environmental information and then adaptively output the evaluation function weight to complete autonomous obstacle avoidance efficiently. Furthermore, the proposed adaptive fuzzy control DWA not only optimizes the local obstacle avoidance path of the AGV, but also conduct the global path optimization of the AGV by automatically adjusting the angle between the AGV and the target point.

The main contributions of this paper are summarized as follows:

- We propose an adaptive DWA based on a fuzzy neural network, which aims to solve the problem of real-time and efficient obstacle avoidance for the AGV in dynamic environments.
- We use a neural network to train the input-output relationship between environmental information and the coefficients of the DWA evaluation subfunction to obtain an adaptive fuzzy control DWA. The adaptive fuzzy control DWA acquires real-time environmental information to output the corresponding coefficients.
- Our experiments demonstrate that adaptive fuzzy control DWA can achieve real-time dynamic obstacle avoidance for the AGV. Compared with the conventional DWA and the Mamdani DWA, the adaptive fuzzy control DWA has a shorter obstacle avoidance time.

The rest of the paper is organized as follows: Chapter 2 describes the basic principles of DWA. Chapter 3 analyzes the problems of traditional DWA. Chapter 4 achieves the DWA improvement. Chapter 5 conducts simulation experiments and a discussion of the results. Finally, Chapter 6 gives the conclusion of the study.

II. DYNAMIC WINDOW APPROACH

DWA can be summarized as three steps:

(1) The velocity sampling space is restricted to a specific range based on the performance limitations and environmental constraints of the AGV. A series of discrete values of velocity are then obtained based on the dynamics and kinematic properties of the AGV.
(2) The AGV kinematic equations introduce the velocities obtained in the first step and then use these velocities to simulate the trajectory of the AGV over the next period.
(3) The evaluation function evaluates these trajectories, and the trajectory with the highest score is selected as the optimal trajectory of the AGV.

A. KINEMATICS MODELING OF AGV

The basic motion structure of AGV is divided into two kinds. One is a non-omnidirectional structure, and the other is an omnidirectional structure. The main difference between these two structures is whether the main direction of motion of the AGV is restricted. The omnidirectional AGV can move in any direction, while the non-omnidirectional AGV can only move forward and backward. Since the AGV in this paper is an omnidirectional structure, the kinematic model is established for the case of AGV omnidirectional (longitudinal presence of velocity component). The motion behavior of the AGV includes straight travel, traverse, turn, and rotation. Let $x(t)$ and $y(t)$ represent the coordinates in the world coordinate system at the time. The heading angle is described by $\theta(t)$ at the time. Then (x, y, θ) represents the kinematic posture. As shown in Fig. 1, it is the AGV kinematic model.

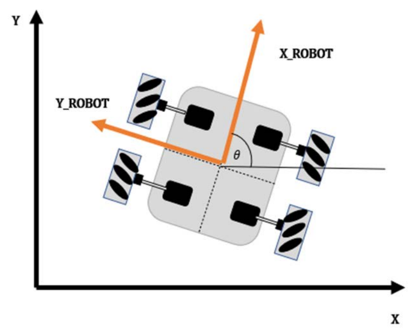


FIGURE 1. AGV kinematic model.

Let v_{xt} and v_{yt} be the lateral and longitudinal velocities of the AGV at moment t, respectively, and $\omega(t)$ be the rotational velocity. Considering the trajectory of adjacent moments as uniform linear motion, the increment of AGV's positional posture can be expressed as:

$$\begin{cases} \Delta x = v_{xt} \times \Delta t \times cos\,\theta_t - v_{yt} \times \Delta t \times sin\,\theta_t \\ \Delta y = v_{xt} \times \Delta t \times sin\,\theta_t + v_{yt} \times \Delta t \times cos\,\theta_t \\ \Delta\theta_t = \omega_t \times \Delta t \end{cases} \tag{1}$$

Therefore, the equation for calculating the positional attitude at the moment t+1 is expressed as:

$$\begin{cases} x_{t+1} = x_t + v_{xt} \times \Delta t \times \cos\theta_t - v_{yt} \times \Delta t \times \sin\theta_t \\ y_{t+1} = y_t + v_{xt} \times \Delta t \times \sin\theta_t + v_{yt} \times \Delta t \times \cos\theta_t \\ \theta_{t+1} = \theta_t + \omega_t \times \Delta t \end{cases} \tag{2}$$

B. AGV SPEED SAMPLING

Depending on the AGV and environmental factors, the speed sampling space can be limited to a reasonable range to achieve dynamic speed sampling.

(1) AGV is limited by its maximum speed and minimum speed:

$$(v, w) = v \in [v_{min}, v_{max}], w \in [w_{min}, w_{max}] \tag{3}$$

(2) AGV is limited by drive motor performance (maximum and minimum acceleration):

$$\begin{cases} v \in [v_{current} - v_b * \Delta t, v_{current} + v_a * \Delta t] \\ w \in [w_{current} - w_b * \Delta t, ws_{current} + w_a * \Delta t] \end{cases} \tag{4}$$

(3) AGV is limited by safety protection:

$$v \le \sqrt{2 * dist(v, w) * v_b}, w \le \sqrt{2 * dist(v, w) * w_b} \tag{5}$$

In the above equation, v is the linear velocity, w is the angular velocity, v_b indicates the minimum acceleration, and v_a indicates the maximum acceleration.

The AGV velocity set needs to satisfy three constraints, which can plan a collision-free and possible trajectory combination. Then all the velocities are substituted into the evaluation function, and the optimal trajectory is selected as the next moment AGV trajectory.

C. EVALUATION FUNCTION

In order to select the speed of the final execution trajectory from the trajectory, the evaluation function is as follows:

$$\begin{aligned} G(v, w) = \sigma [&\alpha \times heading(v, w) + \beta \times dist(v, w) \\ &+ \gamma \times velocity(v, w)] \end{aligned} \tag{6}$$

Heading(v, w) measures the angular difference θ between the AGV orientation angle and the target orientation angle at the end of the trajectory during the simulation period driven by the selected sampling speed.

Dist(v, w) represents the minimum distance between the AGV and the obstacle on a simulated trajectory. The smaller the distance, the more likely the AGV will collide with the obstacle.

Velocity(v, w) is the forward speed of the AGV, which is used to evaluate the speed of the AGV during its travel to the target point.

The α, β, γ are the coefficients of evaluation sub-functions, representing the weight of each evaluation sub-function in the evaluation function. The α affects the angle between the AGV and target direction. The β affects the distance between the AGV and obstacle. The β is the most important for obstacle avoidance. In the obstacle avoidance, when the β is larger, the distance of the AGV from the obstacle is larger. When the β is smaller, the distance of the AGV from the obstacle is smaller. The γ affects the speed of the AGV. The α, β, γ jointly affect the evaluation function to achieve obstacle avoidance of the AGV.

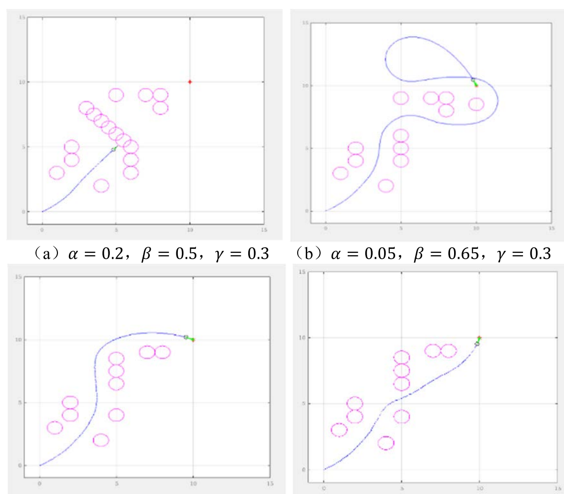
The evaluation function needs to be normalized to ensure that the three metrics have a combined effect on the algorithm and prevent the evaluation function from becoming discontinuous due to the high rating of one metric. The calculation formula is as follows:

$$\begin{cases} normal_{heading(i)} = \dfrac{heading(i)}{\sum_{i=1}^{n} heading(i)} \\ normal_{dist(i)} = \dfrac{dist(i)}{\sum_{i=1}^{n} dist(i)} \\ normal_{velocity(i)} = \dfrac{velocity(i)}{\sum_{i=1}^{n} velocity(i)} \end{cases} \tag{7}$$

where: i is the current trajectory to be evaluated, n is the number of combinations of linear and angular velocities that satisfy the velocity constraint at the time of velocity sampling.

III. PROBLEMS OF TRADITIONAL DWA

By analyzing the literature [28], [29], [30], [31], [32], [33], [34], [35], AGV using conventional DWA can complete obstacle avoidance and reach the target point in a facile environment. However, the AGV usually works in complex and variable environments. As the density of obstacles increases, the success rate of conventional DWA in finding a path decreases. In order to analyze the effect of conventional DWA on obstacle avoidance in different environments, this paper conducted a simulation experiment of obstacle avoidance for the AGV using the conventional DWA through MATLAB. As shown in Fig. 2, it is the result of the simulation experiment.



(a) $\alpha = 0.2$, $\beta = 0.5$, $\gamma = 0.3$ (b) $\alpha = 0.05$, $\beta = 0.65$, $\gamma = 0.3$

(c) $\alpha = 0.05$, $\beta = 0.65$, $\gamma = 0.3$ (d) $\alpha = 0.2$, $\beta = 0.5$, $\gamma = 0.3$

FIGURE 2. Results of conventional DWA simulation experiments.

The combination of evaluation function weights shown in Fig. 2(a) leads to the inability of the AGV to complete obstacle avoidance for straight-line obstacles. The combination of evaluation function weights shown in Fig. 2(b) leads to redundant rotation of the AGV near the target point. The different evaluation function weight combinations shown in Fig. 2 (c, d) lead to different paths and times for the AGV to reach the target point under the same obstacle environment. The above simulation experimental results show that the evaluation function weights α, β, γ are critical factors in determine the performance of the DWA obstacle avoidance. There are problems with AGV stopping in front of obstacles, redundant rotation near the target point, and poor AGV obstacle avoidance paths because of the constant evaluation function weight. Therefore, the evaluation function weights α, β, γ need to be adaptively outputted with the environment to achieve autonomous obstacle avoidance for AGV.

IV. DWA IMPROVEMENT

This paper proposes an improved DWA, which combines the traditional DWA with the fuzzy theory. Through the fuzzy theory, the DWA adaptively outputs the weight coefficient of the evaluation function with the environment. To obtain the training data for the Adaptive-Network-Based Fuzzy Inference System (ANFIS), it is first necessary to design the Mandani-type fuzzy controller to avoid obstacles effectively. Then the evaluation function weight data of the AGV obstacle avoidance process is extracted and used to train the fuzzy neural network [36].

A. MANDANI-TYPE FUZZY CONTROLLER

1) FUZZIFICATION

In the evaluation function, α is mainly related to the distance between the AGV and the target point and the angle, and β and γ are mainly influenced by the distance between the AGV and the obstacle. According to the study context, there are three inputs:

(1) The distance D_O between the AGV and the obstacle with the theory of domain for [0,10m] describe in vague language as {near (N), middle (M), far (F)}.
(2) The distance D_t between AGV and the target point with the theory of domain for [0,70m] describe in vague language as {near (N), middle (M), far (F)}.
(3) The angle θ between the AGV direction and the target point with the theory of domain for [0°,180°] describe in vague language as {small (S), medium (M), large (L)}.

The affiliation functions of D_O, D_t, and θ use trapezoidal and Gaussian functions. As shown in Fig. 3, this is a diagram of their affiliation functions.

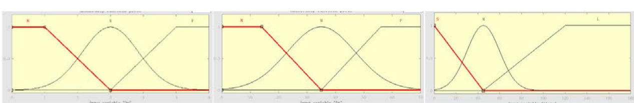


FIGURE 3. D_O, D_t, θ **affiliation functions diagram.**

There are three output parameters: heading weight α theory of domain for [0,0.4]. The obstacle avoidance weight β and the velocity weight γ theory of domain for [0,1]. The descriptive fuzzy language is {XS (very small), S (small), M (medium), L (large), XL (very large)}. Affiliation functions α, β, γ are Gaussian functions. As shown in Fig. 4, it is their affiliation function.

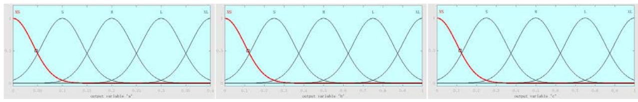


FIGURE 4. α, β, γ **affiliation functions diagram.**

2) FUZZY RULE

The formulation of fuzzy rules is the core step to complete fuzzy control. Based on the principle of DWA and considering the practical application of DWA to outdoor AGV path planning, five rules are used according to fuzzy rule design principles as follows:

(1) When the D_t is large, the D_O is large, and the θ is small, the AGV gives priority to fast forward toward the target position and is not in a hurry to avoid obstacles. So it is determined that the α is smaller, the β is smaller, and the γ is larger.
(2) When the D_t is large, the D_O is large, and the θ is large, the AGV gives priority to adjusting the heading and turning to the direction of the target position without rushing to avoid the obstacle. So it is determined that the α is larger, the β is smaller, and the γ is moderate.
(3) When the D_t is small and the θ is large, the AGV needs to adjust the heading to the direction of the target position and reduce the forward speed. So it is determined that the α is larger, the β is smaller, and the γ is smaller.
(4) When the D_O is small, the AGV must prioritize obstacle avoidance, reduce the travel speed, and explore near the obstacle to avoid collision accidents. So it is determined that the α is smaller, the β is larger, and the γ is smaller.
(5) Regardless of any situation, when close to an obstacle, the AGV must prioritize obstacle avoidance and then consider the impact of the D_t and the θ.

As shown in Table 1, it is a Mamdani-type fuzzy rule design.

According to the design of the above fuzzy rules, there are four representative fuzzy rule surfaces, as shown in Fig. 5.

As shown in Fig. 5, it can be found that the fuzzy rule surface is not smooth, and the evaluation function weight output is jumpy. The parameters and rules of the Mamdani-type fuzzy controller cannot be modified after they are determined, and the adaptability is poor. The path planning effect will be defectively facing a complex and changing environment. Therefore, the ANFIS is applied to solve the above problems.

B. ANFIS FUZZY CONTROLLER

1) ANFIS PRINCIPLE

ANFIS is a fuzzy inference system based on the Takagi-Sugeno model. The learning mechanism of the neural

TABLE 1. Mamdani-type fuzzy rule.

Numbers	Input			Output		
	Do	*Dt*	*θ*	*α*	*β*	*γ*
1	N	N	S	XS	XL	XS
2	N	N	M	S	XL	XS
3	N	N	L	S	XL	XS
4	N	M	S	XS	XL	S
5	N	M	M	S	XL	S
6	N	M	L	M	XL	S
7	N	F	S	XS	L	S
8	N	F	M	S	L	S
9	N	F	L	M	L	S
10	M	N	S	S	M	S
11	M	N	M	M	M	S
12	M	N	L	L	M	S
13	M	M	S	S	M	M
14	M	M	M	M	M	M
15	M	M	L	L	M	M
16	M	F	S	XS	M	M
17	M	F	M	S	M	M
18	M	F	L	M	M	M
19	F	N	S	S	XS	M
20	F	N	M	M	M	M
21	F	N	L	L	XS	M
22	F	M	S	S	S	XL
23	F	M	M	L	S	L
24	F	M	L	XL	S	M
25	F	F	S	S	XS	XL
26	F	F	M	L	XS	L
27	F	F	L	XL	XS	M

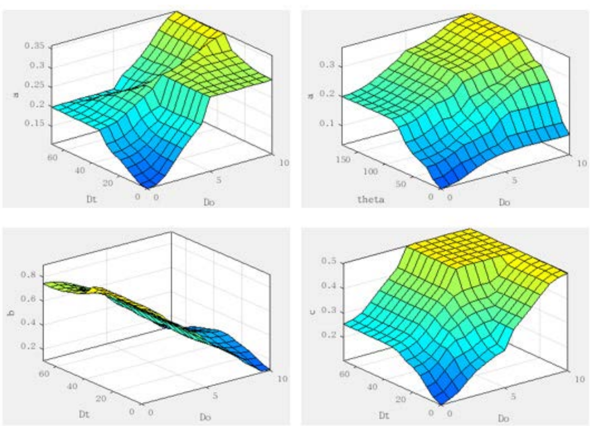


FIGURE 5. Fuzzy rule surfaces.

network is used to automatically extract rules from the input and output sample data to form the ANFIS controller. As shown in Fig. 6, it is a typical ANFIS system architecture [37].

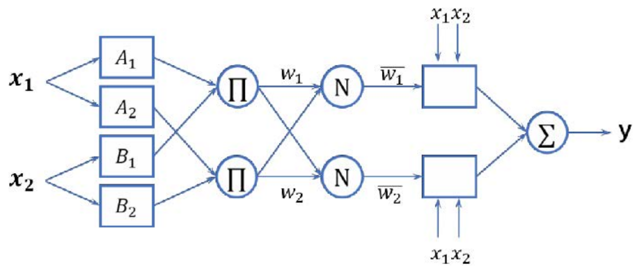


FIGURE 6. ANFIS system architecture.

2) ANFIS DESIGN

A training dataset was built from a Mamdani-type fuzzy controller and trained in Neuro-Fuzzy Designer of Matlab2018a. The experimental environment is the Ubuntu18.04 operating system based on the Pytorch framework. CPU: Intel Core I9-10900K, GPU: NVIDIA RTX 3090, 24GB.

The dataset was imported into Neuro-Fuzzy Designer. The input parameters are D_O, D_t, θ. The output parameters are α, β, γ. The Generate FIS is set to Grid partition, the affiliation function is set to gaussmf, the output function is set to constant, the Optim Method is set to hybrid, the Error Tolerance is set to 0.005, and the Epochs is set to 500. The training process is shown in Fig. 7 below. The fuzzy neural network structure is shown in Figure 8. Because Neuro-Fuzzy Designer can only perform single output training, the output results α, β, γ are obtained by training three times.

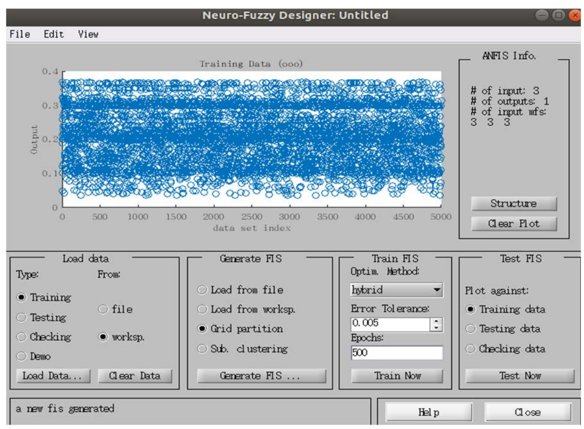


FIGURE 7. ANFIS training process.

The pairs of input variable of the training fuzzy affiliation functions compared with the original affiliation functions are shown in Figure 9. The pairs of output of the training fuzzy rule surfaces compared with the original rule surfaces are shown in Figure 10.

As shown in Fig. 9, the Mamdani-type separation of each region is expected, which does not have good applicability. In contrast, the affiliation function obtained by ANFIS training is reasonable, and its distribution is consistent with the actual environment of DWA obstacle avoidance. As shown in Fig. 10, the Mamdani-type output surface plot has apparent

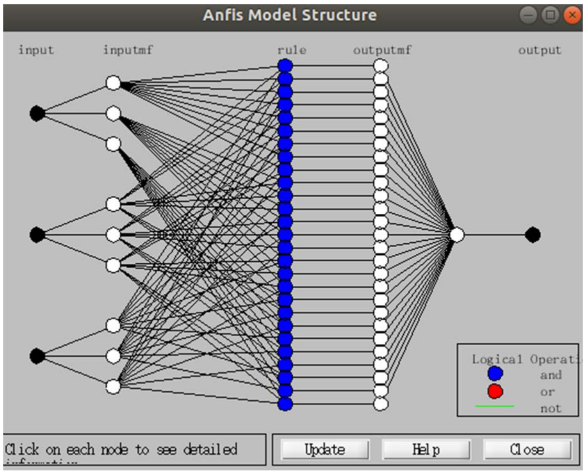
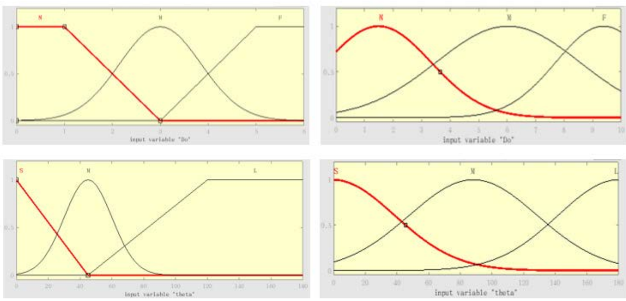
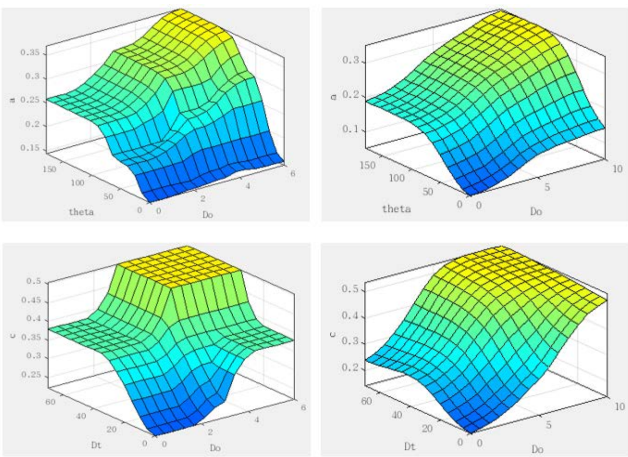


FIGURE 8. Fuzzy neural network structure.



(a) before training (b) after training

FIGURE 9. Comparison of affiliation functions.



(a) before training (b) after training

FIGURE 10. Comparison of fuzzy regular surfaces.

steps change, which indicates that the output jumps more and is not conducive to AGV obstacle avoidance. Contrarily, the output surface after ANFIS training is smooth and achieves an adaptive output of evaluation function weights.

V. RESULTS AND DISCUSSION

The MDWA means the combination of the Mamdani and the DWA. The ADWA means the combination of the ANFIS and the DWA. The DWA, MDWA, and ADWA are tested respectively in the simulation environment. According to the outdoor work of AGV, this paper designs four different kinds of obstacle environment maps, i.e. conventional static obstacle environment, complex static obstacle environment, simple dynamic obstacle environment and fusion obstacle environment. Simulation experiments were performed five times for each algorithm. As shown in Table 2, it is AGV kinematic model parameters.

TABLE 2. AGV kinematic model parameters.

$v(\min)$	$v(\max)$	$\Delta v/\Delta t$	$\omega(\min)$	$\omega(\max)$	$\Delta\omega/\Delta t$
$0m/s$	$3m/s$	$1m/s^2$	$0rad/s$	$2rad/s$	$1rad/s^2$

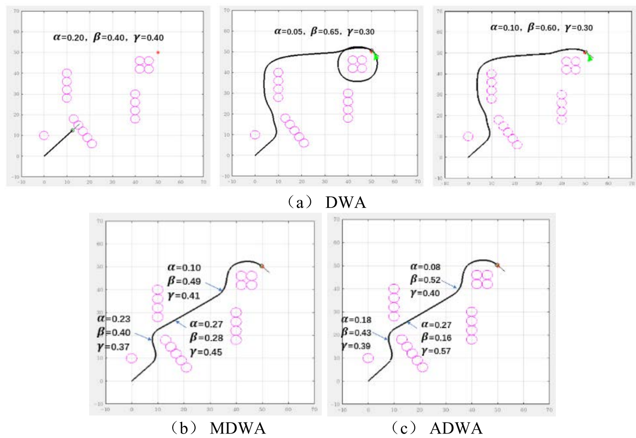


FIGURE 11. Simulation path in conventional obstacle environment.

A. CONVENTIONAL STATIC OBSTACLE ENVIRONMENT

The conventional static obstacle environment map is set up for the customary obstacle conditions in the outdoor environment. The DWA evaluation function weights are set, as shown in Fig. 11(a). The initial evaluation function weights for MDWA and ADWA are assigned to $\alpha = 0.1, \beta = 0.5, \gamma = 0.4$. As shown in Fig. 11(b, c), it is the simulation experimental path planning results. As shown in Table 3, it is five simulation experimental time.

TABLE 3. Simulation time in conventional obstacle environment.

Algorithm	Number 1	2	3	4	5	Average time
DWA	Unsuccessful	Rotate	106.14s	108.55s	107.32s	107.34s
MDWA	91.36s	92.47s	91.20s	93.51s	92.76s	92.26s
ADWA	87.80s	87.53s	86.39s	87.31s	85.98s	87.00s

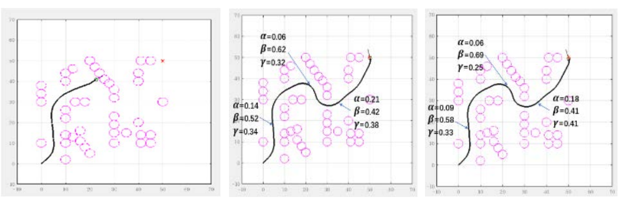
It can be found through the simulation experiment. When the initial evaluation function weights are set to $\alpha = 0.2, \beta = 0.4, \gamma = 0.4$, the AGV stops in front of the obstacle and cannot complete obstacle avoidance. When the initial evaluation function weights were changed to $\alpha = 0.05, \beta = 0.65, \gamma = 0.3$, the AGV made a non-essential rotation near the target point. When the initial evaluation function weights were modified to $\alpha = 0.1, \beta = 0.6, \gamma = 0.3$, the AGV reached the target point. The above three cases illustrate that different evaluation function weight settings can lead to different obstacle avoidance paths of the AGV. However, regardless of setting the initial evaluation function weights, MDWA and ADWA can achieve path planning, and the trajectories are the same. It indicates that the improved DWA can adaptively output the evaluation function weights to achieve autonomous obstacle avoidance of the AGV. From Table 4, we can see that the improved DWA avoidance time is much smaller than DWA. The simulation time of ADWA is slightly shorter than MDWA. The reason is that the α is smaller, β is larger, and γ is larger of ADWA than MDWA in the first avoidance. During the linear motion of AGV, the γ of ADWA is larger. Therefore, the AGV motion time is reduced, and thus the total path planning time ADWA is smaller than MDWA.

TABLE 4. Simulation time in complex obstacle environment.

Algorithm	Number 1	2	3	4	5	Average time
MDWA	145.73s	143.69s	146.50s	145.81s	143.07s	144.96s
ADWA	139.20s	137.54s	137.82s	138.69s	139.15s	138.48s

B. COMPLEX STATIC OBSTACLE ENVIRONMENT

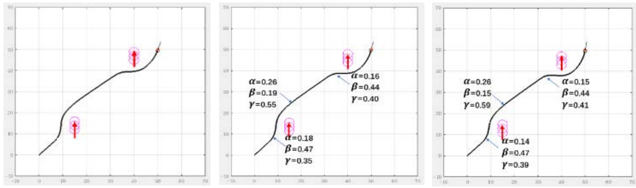
The complex static obstacle environment map is set up for the more complex obstacle environments featuring the outdoor environment. The initial evaluation function weights are set to $\alpha = 0.1, \beta = 0.5, \gamma = 0.4$. As shown in Fig. 12, it is the simulation experimental path planning results. As shown in Table 4, it is five simulation experimental time.



(a) DWA (b) MDWA (c) ADWA

FIGURE 12. Simulation path in complex obstacle environment.

It is found that DWA cannot complete the obstacle avoidance task by simulation experiments. However, both MDWA and ADWA can complete the obstacle avoidance task well, and the path planning trajectory is almost the same. But the simulation time of ADWA is shorter than that of MDWA. Because the evaluation function weight of ADWA output obtained by neural network training is more reasonable, more adaptable to the complex obstacle environment, and enables the AGV to pass the obstacle quickly while ensuring safety.



(a) DWA (b) MDWA (c) ADWA

FIGURE 13. Simulation path in simple dynamic obstacle environment.

C. SIMPLE DYNAMIC OBSTACLE ENVIRONMENT

Obstacle avoidance performance experiments are conducted for conditions where dynamic obstacles exist in the environment. This environment map sets two dynamic obstacles. The first obstacle moves from position the (15,0) parallel to the Y-axis at a speed of 1m/s. The second obstacle moves from position the (40,0) parallel to the Y-axis at a speed of 1m/s. The initial evaluation function weights are set to $\alpha = 0.1, \beta = 0.5, \gamma = 0.4$. As shown in Fig. 13, it is the simulation experimental path planning results. As shown in Table 5, it is five simulation experimental time.

TABLE 5. Simulation time in simple dynamic obstacle environment.

Algorithm	Number 1	2	3	4	5	Average time
DWA	52.31s	51.38s	52.59s	51.86s	51.91s	52.01s
MDWA	50.01s	50.52s	50.45s	50.34s	50.40s	50.34s
ADWA	49.50s	49.57s	49.82s	49.49s	49.72s	49.62s

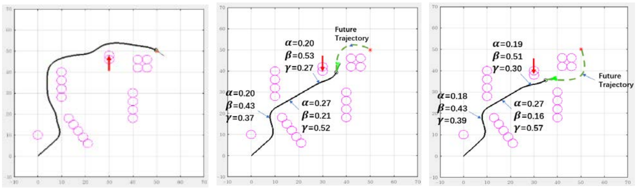
The simulation results show that the three algorithms can make the AGV complete obstacle avoidance and reach the target position. The improved DWA simulation time is shorter, so the improved DWA can quickly make the AGV complete obstacle avoidance. The simulation time of ADWA is slightly shorter than MDWA because ANFIS outputs more reasonable evaluation function weights, which demonstrated that the ADWA can weigh between the obstacle avoidance weight and speed weight during obstacle avoidance, and then output a larger speed weight when there is no obstacle.

D. FUSION OBSTACLE ENVIRONMENT

The fusion obstacle environment adds a dynamic obstacle in the conventional static obstacle environment map. The dynamic obstacle moves reciprocally from position the (30,30) to position the (30,50) at a speed of 1m/s. The initial evaluation function weights are set to $\alpha = 0.1, \beta = 0.5, \gamma = 0.4$. As shown in Fig. 14, it is the simulation experimental path planning results. As shown in Table 6, it is five simulation experimental time.

TABLE 6. Simulation time in fusion obstacle environment.

Algorithm	Number 1	2	3	4	5	Average time
DWA	112.47s	111.72s	113.61s	111.90s	112.35s	112.41s
MDWA	97.14s	97.50s	96.45s	96.91s	97.03s	97.00s
ADWA	92.54s	92.93s	93.11s	92.48s	92.66s	92.74s



(a) DWA (b) MDWA (c) ADWA

FIGURE 14. Simulation path in fusion obstacle environment.

From the simulation experiment results, it is shown that the DWA can complete the obstacle avoidance task, but the planning path is poor and the AGV motion time increase. The improved DWA including the MDWA and the ADWA can complete the trajectory planning. The average simulation time of ADWA is 4.26s less than that of MDWA because the combination of evaluation function weights output from ANFIS makes the AGV movement faster.

Based on the above simulation experiments, it can be concluded that both the DWA and improved DWA can achieve obstacle avoidance in the conventional static environment. However, the DWA cannot complete obstacle avoidance in a complex obstacle environment, while improved DWA can complete obstacle avoidance, and the ADWA simulation times are shorter than the MDWA in a complex static obstacle environment. The effectiveness and superiority of the improved DWA are verified by the experimental simulation results well verify.

VI. CONCLUSION

This paper proposes an improved DWA with adaptive output evaluation function weights to address the problems of stopping in front of obstacles, rotating near the target point, and poor obstacle avoidance path when AGV uses traditional DWA for obstacle avoidance. Firstly, the environmental information is fuzzified. The input parameters are the distance between AGV and obstacle, the distance between AGV and target point, and the angle between AGV heading and target point. The output quantities are the evaluation function weights. Then, the fuzzy controller is designed based on the fuzzy theory. The Mamdani type controller fuzzy rule surface step change is evident, while the ANFIS fuzzy rule surface is relatively smooth. Finally, from the simulation experiments in different obstacle environments, it is found that the improved DWA can adaptively output the evaluation function weights. However, the ADWA enables the AGV to complete autonomous obstacle avoidance better, and the simulation time is shorter than the MDWA. The experimental results also show that ADWA has better environmental adaptability and obstacle avoidance performance in an unknown environment. The research results will benefit the development of the AGV autonomous obstacle avoidance technology.

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