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An Improved Dynamic Window Approach Integrated Global Path Planning

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Abstract*— *Aiming at the shortcomings of dynamic windowing algorithm (DWA) into local optimal solution. This work studys a modified DWA algorithm integrated global path planning. By introducing the result of global path planning as a reference trajectory, a novel evaluation function is designed which makes the optimal trajectory be guaranteed. In addition, the work also proposes the evaluation sub-function of direction, the evaluation sub-function of smoothing speed and the evaluation sub-function of acceleration, separately, ensures the direction, smoothness and speed of movement. The algorithm is verified in mobile robot, experimental results show that the algorithm optimizes the path of mobile robot, simultaneously, the advantages of the traditional DWA, such as the practicability and continuity of motion are retained.

I. INTRODUCTION

Path planning is one of the most important branches in robotic autonomous navigation. The robot path planning problem can be described as one or more optimization targets, such as minimum work cost, shortest track length, minimum movement time, etc., Robot path planning problem can be described as finding an optimal path from the current point to the designated target point in the working environment of a robot based on one or more optimization objectives, such as the least cost, the shortest trajectory length and the least movement time, when the robot's position and posture are known[1]. The robot path planning algorithm can be divided into global path planning and local path planning according to the range of the working environment. Since the local path planning algorithm considers the motion parameters of the robot, the obstacles and the direction of the path , the local path planning problem has gradually become the focus of research in recent years.

Traditonal algorithms for local path planning include artificial potential field algorithm [2-3], histogram feature description[4], genetic algorithm [5-6], neural network method [7], fuzzy logic method [8], reinforcement learning method. [9-10]etc. The dynamic window approach (DWA) has obvious advantages in terms of feasibility and continuity of motion. The dynamic window method samples and estimates the trajectory in a feasible velocity space, and then uses the linear weighting method to give weights according to the importance degree of each target evaluation function, and comprehensively evaluates the path planning results. Relative to other local path planning algorithms. Firstly, path planning is carried out, and the idea of calculating the speed control command is easy to occur in the control period. Therefore, the DWA algorithm is more in line with the feasibility and continuity requirements of the robot motion speed.

Since the introduction of the DWA algorithm, many researchers have studied and improved it. For example, by exploring the accessible area in front of the robot motion, the relationship between the width of the feasible channel between the obstacles and the size of the robot itself is used as a new guide to construct the target. The function improves the decision-making ability of the robot to the finite-width feasible channel on the traversing path [12], proposes a new obstacle avoidance objective function by the probability that the histogram represents the trajectory collision to the obstacle, and improves the obstacle avoidance effect of the robot [13], and the DWA algorithm from the differential non-holonomic constrained robot to the fully constrained robot [14], the fuzzy control theory is used to improve the DWA algorithm to improve the performance of the robot in complex multi-dynamic obstacle environment [15], etc. To some extent, it improves the applicability of DWA. However, there are some problems in the traditional DWA-based algorithms. Specifically, the optimality, smoothness, directionality and rapidity of the robot's motion trajectory are not considered. So it is easy to appear that the motion path is not optimal, the path distance is long, the turning is too much, the motion speed fluctuates greatly, and it is easy to fall into the local optimal state, which has a great impact on the motion performance of mobile robots.

In this paper, an improved DWA algorithm based on global path planning is studied. Firstly, the global path is used as the reference item of the evaluation function, which shortens the planned path distance and avoids falling into the local optimal state, but it will cause the motion speed to fluctuate greatly. The algorithm comprehensively considers the directionality of the trajectory to be evaluated by the robot, the smoothness of the motion and the rapidity of reaching the target point, and designs a new evaluation function. The improved DWA algorithm is successfully applied to mobile robot which independently developed in laboratory. The experimental

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results show that the algorithm overcomes the problem that the traditional DWA algorithm is easy to fall into the local optimal solution, and improves the fluctuation of the direction angle of the robot during motion and improves the smoothness of the robot motion, and shorten the time the robot reaches the target point.

II. Improved Dynamic Window Approach

A. Dynamic Window Approach

The implementation of the DWA algorithm consists of two processes: the search speed vector space and the maximization evaluation function. The algorithm limits the speed selection problem of the robot during motion to a velocity vector space (dynamic window) composed of the robot linear velocity v and the angular velocity ω, and consider the dynamic constraints and non-holonomic constraints of the robot on the velocity vector space. Several sampling points can be selected in the velocity vector space of the robot, and the trajectory can be calculated by using the kinematics model of the robot, and the trajectories can be evaluated to select the optimal trajectory. Therefore, the local path planning problem of the robot is transformed into a constrained optimization problem on the velocity vector space.

The kinematics model of the differential robot is shown in Figure 1. Where v_l and v_r represent the linear velocity of the left and right wheels of the robot, $v(t)$ and $\omega(t)$ represent the translational speed and rotational speed of the robot in the world coordinate system, respectively, and L represents distance between the left and right wheels of a robot. The following formula can be derived:

$$v(t) = \frac{(v_l(t) + v_r(t))}{2} \tag{1}$$

$$\omega(t) = \frac{(v_l(t) - v_r(t))}{L} \tag{2}$$

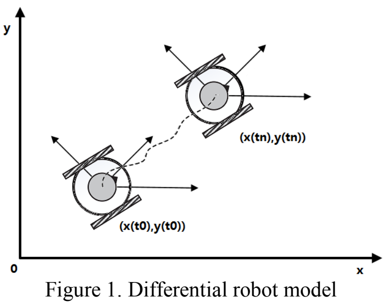


Figure 1. Differential robot model

From the above formula, the kinematic trajectory of the mobile robot can be obtained, that is, the trajectory to be evaluated. Then determine the speed vector space of the search, and define v_s as the set of all the speed vectors that the robot can reach, that is, the maximum range of the DWA algorithm search, which can be expressed by:

$$V_s = \{v \in [v_{min}, v_{max}], \omega \in [\omega_{min}, \omega_{max}]\} \tag{3}$$

Where v is the linear velocity of the robot, ω is the angular velocity of the robot, V_s is the set of all the velocity vectors that can be reached, v_{max} and v_{min} are the maximum and minimum linear velocity of the robot, and ω_{max} and ω_{min} are the maximum and minimum angular velocity of the robot.

The rectangular window centered on the current velocity vector of the robot, the velocity vector outside the window is unreachable by the robot at the next moment, so the DWA algorithm does not need to be considered in the search, thereby further reducing the velocity vector space that needs to be searched.

According to the three velocity vector sets v_s, v_a and v_d, the final search vector space of the DWA algorithm v_r can be obtained:

$$V_r = V_s \cap V_a \cap V_d \tag{4}$$

In the velocity vector space v_r, the continuous velocity vector space v_r is discretized according to the number of sampling points of the linear velocity and the angular velocity, and discrete sampling points (v, ω) are obtained. For each sampling point, the robot's kinematics model is used to simulate the trajectory of the robot in the forward simulation time. After the trajectory of the robot is obtained, the trajectories are scored by the evaluation function to select the optimal trajectory. The traditional DWA algorithm evaluation function is defined as follows:

$$\begin{aligned} \mathrm{CostFunction}(v,\omega) &= \sigma(\alpha \cdot \mathrm{heading}(v,\omega) \\ &+ \beta \cdot \mathrm{dist}(v,\omega) + \gamma \cdot \mathrm{velocity}(v,\omega)) \end{aligned} \tag{5}$$

Where $\mathrm{heading}(v,\omega)$ is the robot azimuth evaluation sub-function, $\mathrm{dist}(v,\omega)$ is the robot and obstacle distance evaluation sub-function, $\mathrm{velocity}(v,\omega)$ is the robot speed evaluation sub-function, α, β, γ are the coefficients of each evaluation sub-function. Finally, by evaluating the sampling points (v, ω) in a pair of dynamic windows v_r, the optimal speed control command at the next moment can be obtained.

B. Improved Dynamic Window Approach based on global path

Combined with the DWA algorithm of global path planning, the global path is used as the reference term of the evaluation function. A new evaluation function is adopted, which comprehensively considers the distance of the generated trajectory from the global path, the distance from the local target point, and the distance from the obstacle. This algorithm improves the traditional DWA algorithm, introduces the concept of global path planning and local target points, enriches the reference terms of the evaluation function, and ensures that the robot's motion trajectory is close to the global path planned by the A*or other algorithms. Implementing a global path as a reference trajectory for local path planning.

Global path planning is introduced as the reference of local path planning. The main difference is evaluation function.

Considering the directivity of the path to be evaluated, the smoothness of robot motion and the rapidity of reaching the target point, the following evaluation function is adopted:

$$\begin{aligned}&\mathrm{costFunction}(v,\omega)=\partial\cdot \mathrm{Obs}(v,\omega)+\beta\cdot \mathrm{Pdist}(v,\omega)\\&+\gamma\cdot \mathrm{Gdist}(v,\omega)+\lambda\cdot \mathrm{DirPath}(v,\omega)+\delta\cdot \mathrm{DirGoal}(v,\omega)\\&+\eta\cdot \mathrm{SVel}(v,\omega)+\mu\cdot \mathrm{MVel}(v,\omega)\end{aligned} \tag{6}$$

Where $\mathrm{Obs}(v,\omega)$ is the distance evaluation sub-function of the robot from the obstacle, $\mathrm{Pdist}(v,\omega)$ is the distance evaluation sub-function of the robot's trajectory end point from the global path, $\mathrm{Gdist}(v,\omega)$ is the distance evaluation sub-function of the robot's trajectory end point from the local target point in the global path, $\mathrm{DirPath}(v,\omega)$ is the distance evaluation sub-function of the robot's trajectory end point from the global path's forward point. $\mathrm{DirGoal}(v,\omega)$ is the distance evaluation sub-function between the forward point of the end point of the robot trajectory and the local target point in the global path, $\mathrm{SVel}(v,\omega)$ is the smooth robot speed evaluation sub-function, $\mathrm{MVel}(v,\omega)$ is the coefficient of each evaluation sub-function to improve the robot speed evaluation sub-function and α、β、γ、λ、δ、η、μ is the coefficient of each evaluation sub-function.

(1) Global Path Distance Evaluation Subfunction

$\mathrm{Pdist}(v,\omega)$ path evaluation sub-function calculates the distance between the end point of the trajectory and the global path, and the shorter the distance, the closer the trajectory is to the global path. The global path can be obtained by using A* algorithm. The concrete formulas of the evaluation function are as follows:

$$\mathrm{Pdist}(v,\omega)=\min\sqrt{(x_{endpoint}-x_{N_p})^2+(y_{endpoint}-y_{N_p})^2} \tag{7}$$

Where $(x_{endpoint}, y_{endpoint})$ is the coordinates of the end points of the local path calculated by the kinematics model of the robot, N_p is the set of discrete points of the global path obtained by the A* algorithm, and (x_{N_p}, y_{N_p}) is the coordinates of the discrete points of the global path.

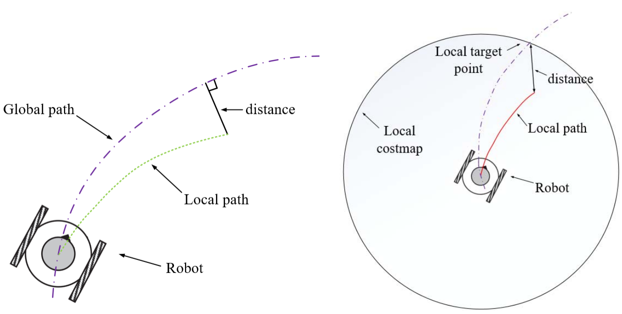


Figure 2.Schematic diagram of path evaluation sub-function and local objective evaluation sub-function

(2) Local Target Point Distance Evaluation Subfunction

$\mathrm{Gdist}(v,\omega)$ is used to evaluate the distance from the end point of the robot trajectory to the local target point, which is the last point on the global path to leave the local cost map. Local cost map can be understood as a circle within a certain distance centered on the robot, which mainly contains the information of local obstacles around the robot acquired by radar.

(3) Obstacle Distance Evaluation Subfunction

$\mathrm{Obs}(v,\omega)$ is used to evaluate the distance between the robot and the obstacle, indicating the ability of the robot to avoid obstacles. The specific formulas are as follows:

$$\mathrm{Obs}(v,\omega)=\begin{cases}L\text{-}d & d>0\\ \\ -1 & d\le 0\end{cases} \tag{8}$$

Where d is the closest distance between the trajectory to be evaluated and L is the maximum limit value of the pre-set distance between the obstacles to make $L\text{-}d>0$. Once $d\le 0$, that is, there are obstacles on the trajectory to be evaluated, the trajectory will be abandoned and the speed of the trajectory will not be considered.

C. Improved Dynamic Window Approach considering direction, smoothing velocity and acceleration

The DWA algorithm combined with global path planning does not take into account the directionality of the trajectory to be evaluated, the smoothness of the motion and the rapidity of reaching the target point. In this paper, an improved DWA algorithm combined with global path planning is proposed, which takes into account the directionality of the generated trajectory, the smoothness of the robot motion and the rapidity of reaching the target point, adopts the method of adding evaluation sub-function, and puts forward direction evaluation sub-function, smoothing velocity evaluation sub-function and acceleration evaluation sub-function. It improves the smoothness of the robot's motion direction, and shortens the time.

(1) Direction evaluation subfunction

$\mathrm{DirPath}(v,\omega)$ path direction evaluation sub-function simulates a certain distance from the end point of the robot trajectory with its tangent direction forward. FPdist takes the forward point as the evaluation point to calculate the distance from the end point to the global path. The advantage of introducing this evaluation sub-function is that the influence of the direction of the end point of robot trajectory on trajectory planning is fully considered. The direction of the robot is aligned with the direction of the global path to avoid redundant turning. $\mathrm{DirPath}(v,\omega)$ is used to evaluate the distance between the forward point at the end of the robot trajectory and the local target point. The influence of the direction of the end point of the trajectory on the trajectory planning is mainly considered.

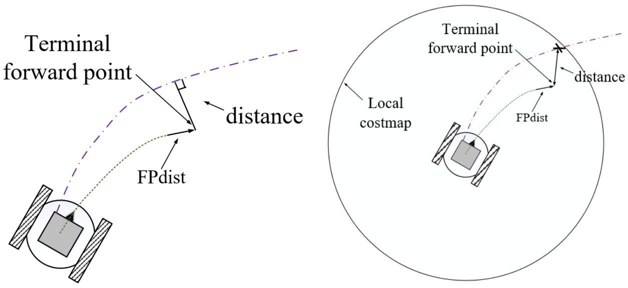


Figure 3 Schematic diagram of path direction evaluation sub-function and local target forward point evaluation sub-function

(2) Smoothing Velocity Evaluation Subfunction

$\mathrm{SVel}(v,\omega)$ is an evaluation function to increase the smoothness of motion. The closer the sampling point is to the sampling center in the velocity vector sampling space, the smaller the acceleration is in the control period, and the more stable the motion is.

$$\mathrm{SVel}(v,\omega) = a\cdot|v_c - v_t| + b\cdot|\omega_c - \omega_t| \quad (9)$$

Where v_c is the linear velocity of the robot, v_t is the linear velocity of the sampling point, ω_c is the angular velocity of the sampling space center of the velocity vector, ω_t is the angular velocity of the robot, *a* and *b* are the coefficients of each evaluation sub-function.

(3) Acceleration evaluation subfunction

$\mathrm{MVel}(v,\omega)$ is an evaluation function to improve the speed of the robot. The higher the sampling point in the velocity vector sampling space is, the higher the weight will be, which can improve the speed of the robot. Specific formulas are as follows:

$$\mathrm{MVel}(v,\omega) = \frac{v_c}{v_t} \quad (10)$$

Where v_t is the linear speed of the sampling point, v_c is the linear speed of the robot now.

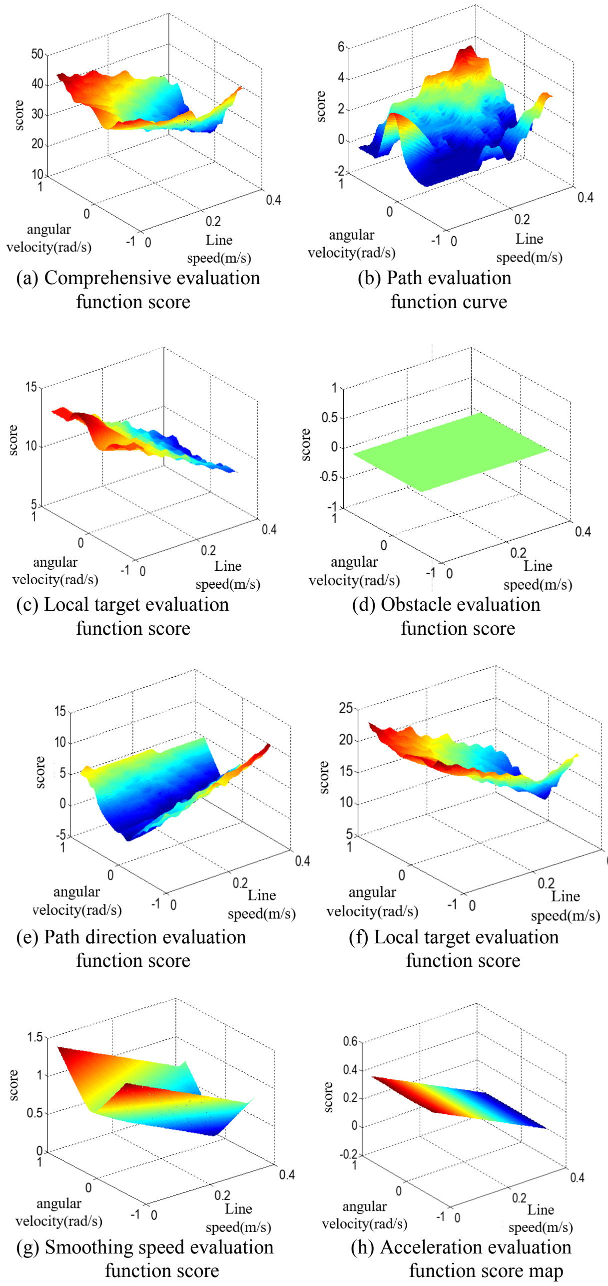
III. Experiment

In order to evaluate the directivity, smoothness and rapidity of the robot motion introduced by the improved DWA algorithm, experiments are carried out in this paper. The mobile robot based on ROS has been developed independently by our laboratory on the experimental platform.

Table 1 shows the experimental parameters of the path planning algorithm for mobile robots based on improved DWA. The maximum acceleration and deceleration limits are selected according to the maximum endurance of the motor. Fig. 4 is a three-dimensional topological diagram of each evaluation function of the robot, where the speed of the robot is $(v,\omega)=[0.378947, 0.110526]$ and the dynamic window of the robot is $V_r=\{(v,\omega)\,|\,v\in[0,0.4]\wedge\omega\in[-0.5895,0.8105]\}$. In the process of motion, 20 sampling points are set for linear velocity and angular velocity, and the three-dimensional graph of evaluation function is drawn by interpolation algorithm as shown in figure 4. The evaluation function is executed at the speed with the smallest score value.

TABLE I. EXPERIMENTAL PARAMETER TABLE

Parameter name	Value	Parameter name	Value
$v_{\max}$	0.4m/s	$v_{\min}$	0m/s
$\omega_{\max}$	3rad / s	$\omega_{\min}$	0rad / s
$\dot{v}_a$	$2\mathrm{m/s^2}$	$\dot{v}_b$	$-2\mathrm{m/s^2}$
$\dot{\omega}_a$	$3.5\mathrm{rad/s^2}$	$\dot{\omega}_b$	$-3.5\mathrm{rad/s^2}$
Δt	0.2s		



(a) Comprehensive evaluation function score
(b) Path evaluation function curve
(c) Local target evaluation function score
(d) Obstacle evaluation function score
(e) Path direction evaluation function score
(f) Local target evaluation function score
(g) Smoothing speed evaluation function score
(h) Acceleration evaluation function score map

Figure 4 Evaluation function

Fig. 4 (a) is a comprehensive evaluation function score chart. The lowest sampling point is [0.4, 0.147368], which is the execution speed command selected for this sampling. Its score is 18.0789. Fig. 4 (b) is a path evaluation function. The closer the trajectory generated by the sampling point velocity is to the reference path, the lower the score is, and the stronger the ability to follow the reference trajectory is. Figure 4 (c) is a local target evaluation function. The closer the trajectory generated by sampling points is to the local target point, the lower the score is, and the closer the trajectory is to the local target point. Fig. 4 (d) is an obstacle evaluation function, with a score of 0, indicating that the trajectory generated at that time does not collide with the obstacle. Fig. 4 (e) is the path direction evaluation function. The closer the forward point of the trajectory to be evaluated is, the lower the score is. It shows that the better the alignment effect of the reference trajectory is. Fig. 4 (f) is a scoring diagram of the local target direction evaluation function. It is the distance from the forward point of the end point of the trajectory generated by the sampling point to the local target point. The better the orientation of the robot, the closer the distance from the local target point. Fig. 4 (g) is a smooth speed evaluation function score chart. The lower the score is near the current speed of the robot in the sampling center to ensure the smoothness of its motion. Fig. 4 (h) is an acceleration evaluation function. The larger the linear velocity, the lower the score, the faster the robot can move and the faster the robot can be.

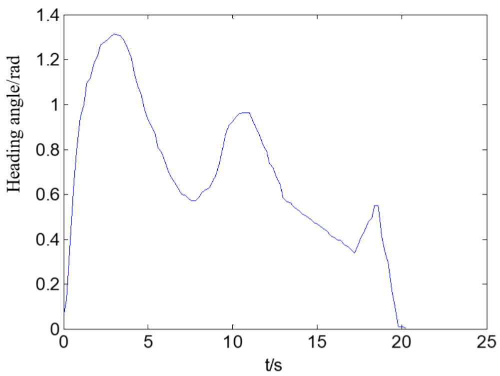


Fig. 5 Direction angle of robot based on DWA algorithm combined with global path planning

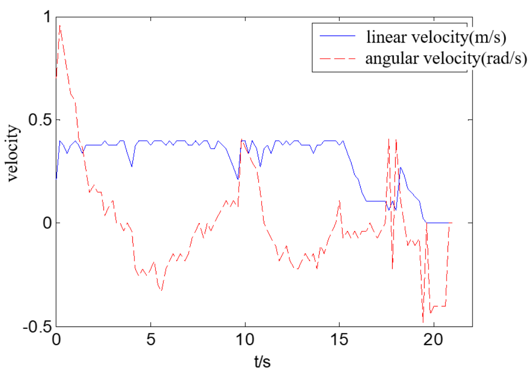


Figure 6 Line and angular velocity based on DWA algorithms with global path planning

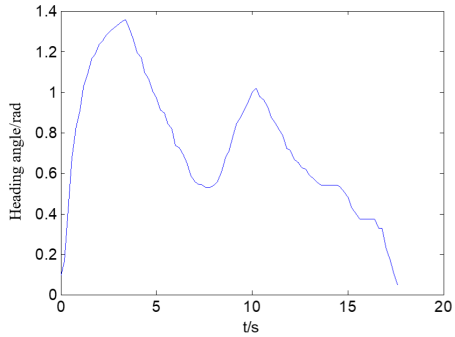


Figure 7 Adding the heading angle curve of the orientation evaluation function of the robot

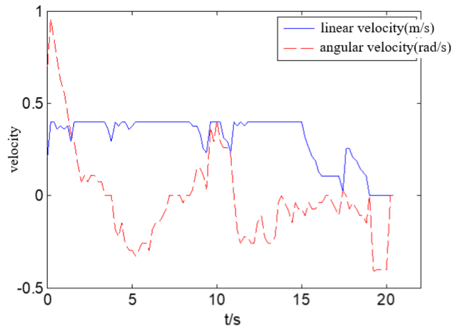


Figure 8 Velocity Curve with Smoothing Angular Velocity Evaluation Function

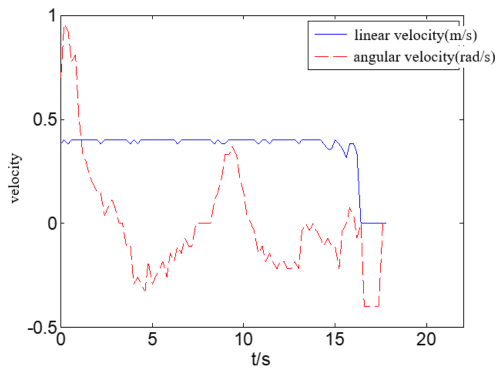


Figure 9 Adding acceleration evaluation function

Then, the DWA algorithm robot experiment combined with global path planning is carried out, and the course angle curve, linear velocity and angular velocity curve of the robot are obtained, as shown in Figs. 5 and 6.Then, the experiment of adding the orientation evaluation function of the robot is carried out, and the change curve of the course angle is drawn, as shown in Fig. 7. Thirdly, the experiment of adding smoothing velocity evaluation function is carried out, and the curve of velocity change is drawn, as shown in Figure 8. Finally, the acceleration evaluation function experiment is added, and the improved linear and angular velocity curves of the robot are obtained, as shown in Figure 9.Fig. 5 shows an increase in heading angle at about 18 seconds. In Figure 7, the orientation evaluation sub-function of the robot is added. Because the direction of the planned trajectory is considered, the adjustment of the steering angle is avoided, the redundant steering is reduced and the performance of the algorithm is optimized. Fig. 6 is a linear velocity and angular velocity curve of DWA algorithm combined with global path planning. From the graph, it can be seen that the fluctuation of linear velocity and angular velocity of the robot is very obvious, and the robot runs unsteadily. From the comparison between Figure 6 and Figure 8, it can be concluded that smoothing speed evaluation function is added to make the change of motion speed more smoothly. The fluctuation of velocity in Figure 6 is very obvious, especially the fluctuation of angular velocity between 16 seconds and 18 seconds in Figure 6, while the velocity curve in Figure 8 is much smoother, which makes the robot run more smoothly. From the comparison of Fig. 6 and Fig. 9, it can be concluded that the acceleration evaluation function is added to improve the running speed of the robot. From the comparison of the two graphs, it can be concluded that the linear velocity of the robot in Figure 9 is almost at the maximum. With the increase of acceleration evaluation function, the time of reaching the target point of the robot is shortened from 19.4 s to 16.2 s, the average speed is increased from 0.3013 m/s to 0.3579 m/s, the time is shortened by 16.5%, and the average speed is increased by 18.7%, which improves the running speed of the robot.

IV. CONCLUSION

The improved DWA algorithm based on global path planning is studied in this paper. A new evaluation function is designed. The global path planning is used as the reference of DWA evaluation function. It can give the robot motion reference at any time. It not only guarantees the stability of the robot motion position, but also guarantees the stability of the robot direction. At the same time, the direction evaluation sub-function, smoothing speed evaluation sub-function and acceleration evaluation sub-function are proposed, which fully considers the direction stability and speed smoothness of the robot motion, and improves the rapidity of the robot to reach the target point. The algorithm has been applied to practical mobile robots. The experimental results show that the algorithm can optimize the path of the robot, avoid falling into the problem of local optimum, and improve the direction, smoothness and rapidity of the robot motion.

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