Local path planning of mobile robot based on self-adaptive dynamic window approach

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Abstract. Dynamic Window Approach (DWA) is widely used in the local path planning of mobile robot. DWA algorithm has the advantages of simple planning algorithm and good real-time performance. However, the DWA exists unreachable target point, unreasonable path planning in the dense obstacles and it cannot ensure both speed and security. Therefore, an online parameter self-adaptive DWA algorithm is proposed to automatically adjust the weight of the objective function on the basis of the size of alternative velocity space and the distance between the mobile robot to the target point. By adapting to the dynamic changes of the environment, the optimal running speed and reasonable path of mobile robot can be obtained. The simulation verified that the mobile robot can pass through the dense obstacles area and reach the target point safely and reliably. And the problems that the robot might move around the dense obstacles and result in an unsmooth path are avoided. and the operational efficiency of the mobile robot is ensured simultaneously.

1. Introduction

Autonomous navigation is one of the core technologies of mobile robot. In the actual environment, especially in the complex environment where man and machine coexist. The robot can obtain the general map information of the environment, but it is difficult to obtain the complex information of the environment because of existence of the dynamic objects, people or other changeable factors [1]. When local map information is known, local dynamic path planning is the preferred method to realize autonomous navigation of intelligent robots [2].

In 1991, Borenstein [3] proposed the VFH(Vector field histogram) algorithm based on the histogram of Vector field in the obstacle environment or more narrow channel to find out the movement direction of the local optimal. Track is reasonable, but this method does not take into account the size of the robot, kinematics and dynamics characteristics. On this basis the paper [4] gave full consideration to the size of the robot, kinematics trajectory and dynamic performance, and put forward the improved VFH+ method. Since then, the paper [5] proposed VFH * algorithm adding the preplanning and enabled the robot to select a local optimal direction.

Almost all the algorithms cannot directly produce the optimal speed when the robot avoided the obstacles, and did not consider the physical limitation of robot. Simmons [6] proposed curvature velocity method (CVM) which described the obstacle avoidance problem as velocity space optimization problem with constraints and considered the velocity and acceleration of the robot, such as physical limitations and obstacles of environmental constraints. In the case of satisfying all constraints, optimization objective function containing three factors (speed, security and path) was established. On the basis of CVM, Fox et al. [7] proposed the more perfect dynamic window method
(DWA) giving full consideration to the physical limitation of the robot, environmental constraints, the current speed and other factors. On the basis of DWA, Seder et al. [8] combined Focused D* and DWA, effectively solving the problem of mobile obstacle avoidance. However, the DWA method still exist the following problems:

1) For complex environment, the trajectory obtained by the robot is not smooth enough [9]. In the dense area of obstacles, the robot may not choose a short path from the dense region, but bypass the dense region, resulting in the path too long.

2) When the speed weight of the DWA objective function is large, the robot will get too close to a certain obstacle when passing through a narrow channel.

Based on the above analysis, this paper improves the traditional DWA and innovatively combines fuzzy control to achieve self-adaptive adjustment of parameters, so that the mobile robot can reach the target point accurately and quickly when the number of obstacles changes dramatically.

2. Improved Dynamic Window Approach

DWA, one of the commonly used local path planning algorithm, transforms the traditional path planning which used position control to avoid obstacles into the method of using the speed control of the next cycle of the mobile robot to avoid obstacles. As shown in Figure 1, the dynamic window refers to a two-dimensional velocity space (including linear velocity and angular velocity) which is formed by sampling and simulation of the velocity of the mobile robot at the next moment. Through the simulation of multiple speeds, the alternative speed path is predicted and the speeds that may collide with obstacles in the environment are eliminated, and then an optimal speed is selected from the feasible speed space as the speed of the next movement period.

![Figure 1. Schematic of dynamic window approach.](image)

2.1. Kinematics Modeling of Mobile Robot

The mobile robot is used in this paper is a non-omnidirectional mobile robot, which can move forward, backward and rotate, but cannot move vertically. The prediction path set for mobile robot is represented by a series of circular arcs and the curves that are formed in front of the robot, as shown in Fig. 1. For the mobile distance of the mobile robot in a cycle $\Delta t$ is finite, its trajectory can be approximately regarded as a straight line. That is, the moving distance in the robot coordinate system $x$-axis coordinate system is $V_t \Delta t$. Calculate the projection distance on the X-axis and Y-axis of the world coordinate system respectively, and then the distance $\Delta x$ and $\Delta y$ of a mobile robot in the world coordinates in a cycle $\Delta t$ are expressed as:

$$\Delta x = V_t \Delta t \cos \theta_i$$

$$\Delta y = V_t \Delta t \sin \theta_i$$

(1)

(2)

So the motion model of the robot in acycle can be expressed as:

$$x = x + V_i \Delta \cos(\theta_i) = x + V_i \Delta \cos(\theta_i) - V_y \Delta \sin(\theta_i)$$

(3)
\[ y = y + V_i \Delta \sin(\theta_i) = y + V_i \Delta \cos(\theta_i) + V_i \Delta \sin(\theta_i) \] (4)

\[ \theta_i = \theta_i + w_i \Delta t \] (5)

where \(x\) is the abscissa of the mobile robot in the world coordinate system; \(y\) is the ordinate of mobile robot in the world coordinate system; \(V_i\) denotes the velocity of the mobile robot at time \(t\); \(V_s\) corresponds to the velocity along the \(x\) axis in the world coordinate system; \(V_v\) corresponds to the velocity along the \(y\) axis in the world coordinate system; \(\theta_i\) to the angle between the robot and the world coordinate \(x\) axis at the \(i\) moment; \(w_i\) is the angular velocity of the mobile robot at the \(i\) moment.

2.2. Constraint of the Speed Space
In order to simplify the calculation of the robot’s motion trajectory, the trajectory is obtained by moving at a uniform speed under the corresponding motion model from time \(t\) to time \(t + 1\).

In the two-dimensional space of velocity set \((v, w)\) (where \(v\) is the linear velocity and \(w\) is the angular velocity), the speed of the mobile robot is limited within a certain range due to the constraints of environment and robot. The constraints of the speed space include:

2.2.1. Kinematic velocity constraint
In the velocity space, the robot is limited by the maximum and minimum velocity of the motor performance and needs to meet the basic kinematic constraints:

\[ V_v = \{v \in [v_{\text{min}}, v_{\text{max}}], w \in [w_{\text{min}}, w_{\text{max}}]\} \] (6)

where \(V_v\) corresponds to the initial velocity space.

2.2.2. Dynamic velocity constraint
The maximum acceleration that the mobile robot can achieve will limit the speed, so the actual speed that the robot can achieve is:

\[ V_d = \{(v, w) | v \in [v_{c} - v_{b} \Delta t, v_{c} + v_{c} \Delta t], w \in [w_{c} - w_{b} \Delta t, w_{c} + w_{c} \Delta t]\} \] (7)

where \(V_d\) represents the feasible velocity space, \(v_c\) and \(w_c\) denote the current velocity of the robot, \(v_{b}\) and \(w_{b}\) correspond to the maximum acceleration, \(v_{c}\) and \(w_{c}\) are the maximum deceleration.

2.2.3. Speed constraint based on safe distance
In order to ensure that the mobile robot does not collide, the robot can stop at a safe distance under the condition of maximum deceleration:

\[ V_s = \{(v, w) | v \leq \left(2 \ast \text{dist}(v, w) \ast v_{b}\right)^{\frac{1}{2}}, w \leq \left(2 \ast \text{dist}(v, w) \ast w_{b}\right)^{\frac{1}{2}}\} \] (8)

where \(V_s\) denotes the safe speed space to ensure the safety of mobile robot without collision. \(\text{dist}(v, w)\) represents the shortest distance that the track of the two-dimensional space of velocity set \((v, w)\) from the obstacles.

The feasible velocity space of mobile robot is a feasible domain formed by the interaction of three constraints:

\[ V_{R} = V_v \cap V_d \cap V_s \] (9)

where \(V_{R}\) is the dynamic window speed space of mobile robot.
2.3. Evaluation Function

In the alternative velocity space formed by mobile robot, the optimal combination of velocity angular velocity is selected through the evaluation function. Where, the evaluation function formula is:

\[ G = \sigma(\alpha \cdot \text{head}(v, w) + \beta \cdot \text{dist}(v, w) + \gamma \cdot \text{velocity}(v, w)) \]

where \(\text{head}(v, w)\) represents the direction Angle scoring function; \(\text{dist}(v, w)\) represents the nearest distance scoring function of obstacles; \(\text{velocity}(v, w)\) is speed scoring function; \(\alpha, \beta, \gamma\) are the function weight factors respectively; \(\sigma\) represents a smoothing function. The forward simulation trajectory of the mobile robot is evaluated and the trajectory with the highest score is selected as the alternative velocity.

2.3.1. Direction angle scoring function

As shown in Figure 3, \(\text{head}(v, w)\) is used to evaluate the angle \(\theta\) between the orientation and the target point when the mobile robot reaches the end of the simulated trajectory.

![Figure 2. Direction angle calculation of mobile robot.](image)

\(\text{head}(v, w)\) direction Angle scoring function adopts the value of \(180^\circ - \theta\) as the scoring standard, that is, when the included Angle \(\theta\) between the mobile robot and the target point is smaller, the direction Angle score is higher, so the direction Angle function plays a role of inspiration to the target point.

2.3.2. Obstacle distance scoring function

\(\text{dist}(v, w)\) is the shortest distance between the mobile robot and the obstacle under the current trajectory; The greater the distance between the robot and the obstacle, the safer it is, and the higher the score function is.

2.3.3. Velocity scoring function

\(\text{velocity}(v, w)\) represents a score of the current robot speed.

In the construction of evaluation function, in order to avoid too large fluctuation of data of different trajectories, which would lead to too much influence on evaluation factors of a certain trajectory, all evaluation factors need to be normalized, and the data is unified and standardized, so as to make the evaluation results more accurate. The normalized processing equation is as follows:

\[ \text{head}_{\text{normal}}(i) = \frac{\text{head}(i)}{\sum_{i=1}^{n} \text{head}(i)} \]

\[ \text{dist}_{\text{normal}}(i) = \frac{\text{dist}(i)}{\sum_{i=1}^{n} \text{dist}(i)} \]

\[ \text{velocity}_{\text{normal}}(i) = \frac{\text{velocity}(i)}{\sum_{i=1}^{n} \text{velocity}(i)} \]
where \( n \) represents the current sampling quantity of all trajectories; \( i \) represents the \( i \)th sampling trajectory of article; \( head(i) \), \( dist(i) \), \( velocity(i) \) correspond to respectively the direction angle score of the \( i \)th track, the nearest distance score of the obstacle, and the speed score ; \( head_{\text{normal}}(i) \), \( dist_{\text{normal}}(i) \), \( velocity_{\text{normal}}(i) \) are respectively the direction angle score of the \( i \)th track in article, the nearest distance score of obstacles, and the normalized results of velocity score.

By scoring and screening the simulated trajectories of mobile robot, the combination of velocity and linear velocity with the highest score \( G \) in the evaluation function is selected as the velocity of the next cycle.

The three weighting factors of the evaluation function in the original DWA are all three fixed values obtained by experience or experiment. However, different weight combinations of the three scoring functions in different environments will affect the final track score. In this way, when environment circumstance make drastic changes, it is not able to adapt to the new environment very well, and the accuracy of reaching the target decreases. Based on the above analysis, an adaptive weight adjustment method is proposed:

Combined with the fuzzy control theory, by making mobile robot to carry out local path planning sampling in the scenes with different complexity, the combined values of different weights selected from the density of obstacles in the working environment changes greatly which are established as fuzzy subsets, and then fuzzified. When implementation the improved DWA algorithm, the mobile robot samples the environment information in real time, and inputs the environment information to the fuzzy logic control, then selects the most suitable weight combination of three parameters in real time by fuzzy decision.

As shown in Figure 4, the fuzzy logic controller choose the (mimo) system, which takes the distance of the target point of the mobile robot and the size of alternative speed space as inputs respectively, and outputs the weights of three scoring functions through fuzzy decisions.

![Figure 3. Principle of parameter adaptive adjustment.](image)

Input and output variables of fuzzy logic controller choose continuous theory domain, membership function is triangular, Target point distance as input one, Theory of domain for \([0,15\] \), Fuzzy set is \( \{Z,PS,PB\} \). The feasible velocity space as input two, Theory of domain for \([0,55\] \), Fuzzy set is \( \{Z,PS,PB\} \). The weight of the direction Angle scoring function \( \alpha \) Theory of domain for \([0,1\] \), Fuzzy set is \( \{Z,PS,PB\} \). The weight of the nearest distance scoring function \( \beta \) Theory of domain for \([0,1\] \), Fuzzy set is \( \{Z,PS,PB\} \). The weight of velocity scoring function \( \gamma \) Theory of domain for \([0,1\] \), Fuzzy set is \( \{Z,PS,PB\} \).

Mamdain type reasoning wa used for fuzzy reasoning and Barycenter method was used for fuzzy solving.
Table 1. $\alpha$ Fuzzy rule

| Input1 | Input2 |
|--------|--------|
|        | Z      | PS    | PB    |
| Z      | Z      | PS    | PS    |
| PS     | PS     | PS    | PB    |
| PB     | PB     | PB    | PB    |

Table 2. $\beta$ Fuzzy rule

| Input1 | Input2 |
|--------|--------|
|        | Z      | PS    | PB    |
| Z      | PB     | PS    | PS    |
| PS     | PB     | PS    | Z     |
| PB     | PS     | Z     | Z     |

Table 3. $\gamma$ Fuzzy rule

| Input1 | Input2 |
|--------|--------|
|        | Z      | PS    | PB    |
| Z      | PS     | PS    | PB    |
| PS     | PS     | PB    | PB    |
| PB     | PB     | PB    | PB    |

The design of fuzzy rules is based on a large number of experimental sampling results and practical experience of engineering researchers. Through experimental sampling and combined with the characteristics of DWA, the design idea of this fuzzy rule is as follows:

when the alternative speed space of mobile robot is large, and it is far from the target point, it indicates that there are fewer obstacles in the environment for the mobile robot and it is not in a hurry to avoid obstacles. At this time, the robot speed should be improved, that is, the weight combination selected should be $\alpha$ moderate, $\beta$ small and $\gamma$ large.

When the alternative speed space of mobile robot is small and far away from the target point, it indicates that the robot is in an environment with many obstacles. At this time, it is necessary to cross obstacles in priority, and the speed should be slowed down appropriately to improve the safety performance. Therefore, the weight combination of scoring function should be $\alpha$ small, $\beta$ large and $\gamma$ small.

when the alternative speed space of the mobile robot is small and it is close to the target point, it indicates that the obstacle at the position of the robot has a high density and the obstacle is near the target point. At this time, the robot should explore near the obstacle and should not use a high speed. Therefore, the weight combination of scoring function should be $\alpha$ large, $\beta$ small and $\gamma$ moderate.

when the speed of mobile robot alternative space is larger, and the distance of target is relatively close, the less mobile machine environment barriers, simple and close to the target environment, mobile robot to the target point can choose to use a faster pace, so should choose the score function of weightings for $\alpha$ larger, $\beta$ smaller, $\gamma$ larger.
According to the above design ideas of fuzzy rules, the output surface of the input $\alpha$ fuzzy rules is shown in Figure 5, the output surface of the input $\beta$ fuzzy rules is shown in Figure 6, and the output surface of the input $\gamma$ fuzzy rules is shown in Figure 7.

![Figure 4. $\alpha$ Fuzzy table output surface.](image1)

![Figure 5. $\beta$ Fuzzy table output surface.](image2)

![Figure 6. $\gamma$ Fuzzy table output surface.](image3)

3. Experimental Simulation Results and Algorithm Validation

In order to verify the effectiveness of the algorithm in this paper, Windows10 operating system, Intel(R) core(TM) i5-8400 CPU@2.80GHz and memory 8G are adopted. Based on matlab 2016a, Then simulation planning of raster maps with different number of obstacles were established. In this experiment, the starting point position of mobile robot was set as (0,0), and the target point position was set as (7,6). Specific parameters in the experiment were set as follows: the maximum speed of the mobile robot was 1m/s; the maximum angular velocity was 2rad/s; the maximum linear acceleration was 3m/s²; the maximum rotational acceleration was 4rad/s²; the velocity resolution is 5m/s, and the angular velocity resolution was 6rad/s; the time resolution was 0.1s; the forward analog orbital time was 4s.

Experiment 1: Experiment results with different weights in the same environment
In the experiment, as shown in Figure 7, the weight combination were $\alpha =0.1, \beta =0.8, \gamma =0.4$. The robot approached the target point (7,6) after crossing the obstacle in the dense area, but does not reach the target point, instead, it bypassed the target point and fallen into a loop. The experimental results shows that the mobile robot can cross the dense obstacle space but fail to reach the target point. The reason why the target point cannot reached is that the direction angle scoring function is not instructive enough for the low weight of the target point.

As shown in Figure 8, the weight combination were $\alpha =0.5, \beta =0.8, \gamma =0.4$. The mobile robot was blocked by obstacles and cannot avoid obstacles when it reached the position (3.5,3.5). The
experiment shows that the direction angle scoring function of mobile robot has a large weight, and the exploration performance of robot declines and the target cannot be reached.

As shown in Figure 9, the weight combination were $\alpha = 0.15, \beta = 0.3, \gamma = 0.6$. The mobile robot successfully reached the target point. Experimental result shows that the mobile robot can reach the target point under this weight combination, which means that the path planning can be realized under the appropriate weight combination by using dynamic window.

As shown in Figure 10, the initial weight combination of the improved DWA was set to be the same as that shown in Figure 7 and Figure 8. The mobile robot crossed the dense obstacles and successfully reached the target point. The mobile robot can accurately reach the target position by identifying the environment information, adjusting the parameters in real time and selecting the combination of the most parameters.

| Table 4. Path Planing Time |
|----------------------------|
| Time(s)                     |
| 1  | 2  | 3  | 4  | 5  |
| traditional DWA         | 22.65 | 22.49 | 22.22 | 22.18 | 22.71 |
| adaptive DWA            | 23.01 | 22.53 | 22.01 | 22.10 | 23.01 |

As shown in Table 4, after multiple tests and comparisons, the improved DWA can effectively improve the environmental adaptability while ensuring the time efficiency of arrival.

Experiment 2: The results of the improved algorithm in different environments

As shown in Figure 11, after multiple tests and comparisons, the improved DWA can effectively improve the environmental adaptability while ensuring the time efficiency of arrival.
Figure 12. Simple environment algorithm validation.

The improved algorithm was applied to the simulation environment with different complexities, and it had been verified by simulation experiments in Figure 11 and Figure 12 for many times. Using the improved self-adaptive DWA, when the density of the obstacle environment changes greatly or few obstacles in the environment, the mobile robot can ensure to reach the target point safely and efficiently.

4. Conclusion
Aimed at solving the problems of the traditional DWA that it cannot ensure both speed and security, self-adaptive DWA is proposed in this paper. Through establishing the fuzzy dynamic window, the mobile robot can identify the environment, and then calculate the alternative speed space and acquire the distance of the target, and finally choose the most optimal weighting parameters combination that is made a strategic decision by fuzzy controller, so as to ensure that the mobile robot can arrive at the target point accurately and safely.

Through a different weight of experiments in the same environment in the Experiment 1, the experimental results show that the traditional DWA algorithm will have the problem that the target cannot be reached. After a large number of experiments, the experimental time to reach the target point can be 22.18s at least. The robot using the method of adaptive dynamic window approach to set the initial weight that as the inaccessible weight combination (such as $\alpha = 0.1, \beta = 0.8, \gamma = 0.4$) can successfully bypass obstacles and reach the target spending 22.01s. It is verified that the improved algorithm has strong stability and high accuracy, and can still ensure the efficiency of mobile robot.

Under the changing environment in the Experiment 2, the adaptive DWA algorithm can cross the environment with the dramatically changes density of obstacle by the density of obstacles taking 120.37s and cross a simple environment taking 18.03s. The experimental results show that the mobile robot can still reach the target point with both safety and speed, and ensure the adaptability and accuracy with the environment transformation. Compared with traditional DWA, the improved algorithm in this paper is obviously better.

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