Postprint: Research on Autonomous Navigation System for Warehouse Robots Using Improved Artificial Potential Field Method in Dynamic Environments

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Abstract

To solve the autonomous navigation problem of warehouse robots in fully dynamic environments, mathematical models for both the robot and dynamic obstacles were established based on an analysis of autonomous navigation technologies. An environmental perception platform primarily based on 2D LiDAR was constructed, and an improved Artificial Potential Field method was proposed. By simultaneously introducing relative velocity and relative acceleration factors into the traditional Artificial Potential Field method, an improved Artificial Potential Field model was obtained, enabling autonomous robot movement in fully dynamic environments. Two mobile environments were designed: an obstacle-free scenario and a scenario with multiple dynamic obstacles. Simulation verification demonstrated that applying the improved Artificial Potential Field method for path planning enables efficient avoidance of dynamic obstacles, tracking of dynamic targets, and yields smooth motion paths.

Full Text

Preamble

Research on Autonomous Navigation System of Warehousing Mobile Robot Based on Improved Artificial Potential Field Method in Dynamic Environment

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Abstract: To address the autonomous navigation challenges of warehousing robots in fully dynamic environments, this paper establishes mathematical models for both robots and dynamic obstacles, constructs an environmental perception platform primarily based on 2D LiDAR, and proposes an improved artificial potential field method. By introducing relative velocity and relative acceleration factors into the traditional artificial potential field method simultaneously, an improved artificial potential field model is developed to enable autonomous robot movement in fully dynamic environments. Two mobile environments were designed: obstacle-free and multi-dynamic obstacle scenarios. Simulation verification demonstrates that the improved artificial potential field method can efficiently avoid dynamic obstacles, track dynamic targets, and generate smooth motion paths.

Keywords: dynamic environment; autonomous navigation; artificial potential field; path planning; laser radar

0 Introduction

With the rapid development of the logistics industry, warehousing, sorting, and transportation of goods require substantial human and material resources. As the demographic dividend gradually disappears, robot participation has become a focal point of discussion, giving rise to advanced technologies such as unmanned warehouses, unmanned sorting, and unmanned delivery. Warehousing robots represent the most critical component in unmanned warehouses. These robots autonomously complete goods identification, loading, and transportation without human intervention, enabling 24-hour continuous operation that significantly reduces labor costs and improves work efficiency. For instance, Amazon employs warehousing robots in warehouses across the United States, saving nearly $10 billion annually.

Key technologies for warehousing robots have become research priorities for institutions worldwide, with autonomous navigation being the core technology. Autonomous navigation encompasses environmental perception, robot self-localization, and path planning. Environmental perception is achieved by fusing information from various sensors such as ultrasonic, infrared, LiDAR, and cameras. Robot localization can be realized through GPS, inertial systems (velocity and displacement sensors), Wi-Fi, LBS base stations, and environmental magnetic field positioning technologies. Path planning constitutes the most critical component of autonomous navigation, addressing the problem of finding an optimal or near-optimal collision-free path to target shelves in complex, dynamic environments.

Path planning requires environmental perception and self-localization information, implemented through specific planning algorithms. Over the past four decades, extensive research on path planning has yielded significant results. Commonly used path planning algorithms include artificial potential field methods, vector field methods, grid methods, ant colony algorithms, fuzzy neural networks, genetic algorithms, model predictive control, and A* algorithms. Each algorithm has its strengths and is suitable for different applications. Among these, the artificial potential field method, proposed by Khatib, is a virtual force field approach that models robot motion as movement within an artificial force field, where the target exerts attractive forces and obstacles exert repulsive forces. The resultant force controls robot motion. This algorithm is widely applied in real-time obstacle avoidance and path planning due to its simple mathematical analysis, low computational complexity, and smooth paths.

Previous research on artificial potential field methods has focused on improving the algorithm to resolve local minima and target unreachable problems. Although significant achievements have been made, most applications remain in static environments where both targets and obstacles are stationary. However, warehousing robots operate in complex, dynamic environments. First, targets may be moving. For example, in Fetch and Freight warehousing robot systems, Fetch retrieves items from shelves while Freight transports and packages them. The Fetch robot serves as a dynamic target, while Freight must dynamically follow the target. Second, obstacles can be both static and dynamic. Shelves, items, walls, and workstations in unmanned warehouses constitute static obstacles, while other operating warehousing robots and staff become dynamic obstacles.

Regarding path planning in fully dynamic environments, scholars have conducted relevant research. Reference [9] proposed an improved path planning algorithm that designs new obstacle avoidance rules based on dynamic obstacles, effectively achieving obstacle avoidance and target tracking. However, it employs uniform planning step sizes, considering only planning direction without planning force variation, resulting in non-smooth paths with large angular changes. References [10, 11] proposed an improved artificial potential field method that introduces relative velocity and relative acceleration into the attractive potential field function to solve dynamic target tracking problems, and introduces relative velocity into the repulsive potential field function to bypass dynamic obstacles. However, these methods suffer from low dynamic obstacle avoidance efficiency and long planning paths.

This paper focuses on environmental perception and path planning for warehousing robot autonomous navigation. First, a 2D LiDAR is used to construct the environmental perception system for warehousing robots, enabling real-time detection of obstacle poses around the robot. Then, based on the traditional artificial potential field method, relative position, relative velocity, and relative acceleration are introduced to improve the potential field function, thereby solving autonomous navigation problems for warehousing robots in fully dynamic environments.

1 Mathematical Models

1.1 Warehousing Robot Mathematical Model

The warehousing robot model selected in this paper is shown in Figure 1. The rear wheels are two differential drive wheels, while the front wheels are two omnidirectional wheels for support. This robot system is a typical nonholonomic system. The robot' s pose can be described by $X_r = [x_r, y_r, \theta_r]^T \in \mathbb{R}^3$, where (x_r, y_r) represents the robot' s position coordinates and θ_r represents its orientation angle.

When the robot moves with variable acceleration, the velocity relationship is:

$$\begin{cases} \dot{x}_r = v_r \cos\theta_r \\ \dot{y}_r = v_r \sin\theta_r \\ \dot{\theta}_r = \omega_r \end{cases}$$

In all expressions throughout this paper, the superscript r denotes robot-related quantities, o denotes obstacle-related quantities, and g denotes target-related quantities.

1.2 Dynamic Obstacle Mathematical Model

In unmanned warehousing environments, dynamic obstacles may include walking people, other warehousing robots, and moving shelves. Their motion states can be uniform or variable-speed linear or curvilinear motion, with random switching between motion models. The obstacle pose can be represented by $X_o = [x_o, y_o, \theta_o]^T \in \mathbb{R}^3$. In practical applications, the Euler approximation method can be used to obtain the obstacle pose change equation:

$$X_{o,n+1} = X_{o,n} + f(q_n, w_n, \theta_{o,n})\Delta t$$

Here, $q_n \in \{linear, arc\}$ represents whether the robot' s next motion state is linear or curvilinear. If $q_n = linear$, then w_n represents linear velocity; if $q_n = arc$, then w_n represents angular velocity. Different motion states exhibit certain differences.

In linear motion state:

$$f(linear, w_n, \theta_{o,n}) = \begin{bmatrix} w_n \cos\theta_{o,n} \\ w_n \sin\theta_{o,n} \\ \gamma \end{bmatrix}$$

where $\gamma = \tan\theta_{o,n}$ is the slope of linear motion, obtainable from $\theta_{o,n}$.

In curvilinear motion state:

$$f(arc, w_n, \theta_{o,n}) = \begin{bmatrix} w_n \cos\theta_{o,n} \\ w_n \sin\theta_{o,n} \\ w_n \end{bmatrix}$$

where w_n is the arc radius during curvilinear motion. In random motion environments, w_n can also change dynamically. Simultaneously, w_n can vary dynamically, and the obstacle' s acceleration is:

$$w_{n+1} = w_n + a_o \Delta t$$

1.3 Assumptions

The autonomous navigation system for warehousing robots includes hardware and software platforms that implement robot self-localization, environmental perception, and path planning algorithms. This paper focuses on environmental perception and path planning in fully dynamic environments. To simplify analysis, the following assumptions are made:

1. The robot' s position p_r, velocity v_r, and acceleration a_r are all real-time obtainable, and the warehousing robot shape can be considered as a circle with radius R_r.
2. The target' s position p_g, velocity v_g, and acceleration a_g can be detected in real-time, and the target' s velocity satisfies $||v_g|| < v_{max}$.
3. The obstacle's position p_o, velocity v_o, and acceleration a_o can be obtained in real-time, and its shape can be considered as a circle with radius R_o.
4. Both target and obstacles are assumed to undergo uniformly accelerated motion, transitioning to uniform motion after reaching maximum speed. The mathematical model is:

$$v_{n+1} = \begin{cases} v_n + a\Delta t, & ||v_n|| < v_{max} \\ v_{max}, & ||v_n|| \geq v_{max} \end{cases}$$

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2 LiDAR-Based Environmental Perception

2.1 LiDAR Working Principle

The system input is $U_r = [v_r, \omega_r]^T \in \mathbb{R}^2$, where v_r is the robot' s instantaneous linear velocity and ω_r is the robot' s angular velocity. The input range is $U_r \in [v_{min}, v_{max}] \times [\omega_{min}, \omega_{max}]$. In practical applications, the robot' s pose changes dynamically, meaning the next pose equals the current pose plus the change within a unit time, which can be described using the Euler approximation method:

$$X_{r,n+1} = X_{r,n} + f(v_{r,n}, \omega_{r,n})\Delta t$$

where Δt is the robot planning interval, and $f(v_{r,n}, \omega_{r,n})$ is a function of linear velocity v_r and angular velocity ω_r:

$$f(v_{r,n}, \omega_{r,n}) = \begin{bmatrix} v_{r,n} \cos\theta_{r,n} \\ v_{r,n} \sin\theta_{r,n} \\ \omega_{r,n} \end{bmatrix}$$

LiDAR is a product combining traditional radar with laser technology. It emits detection signals using laser carriers toward targets, then compares the received echo signals with transmitted signals to obtain target information such as position (distance, bearing, and altitude) and motion state (velocity, pose), enabling target detection, tracking, and recognition.

The working principle for using 2D LiDAR to achieve warehousing robot autonomous navigation involves mounting the LiDAR on the robot to scan the surrounding environment in real-time, obtaining real-time distances and bearings of surrounding obstacles. This constructs an environmental map centered on the robot with the LiDAR scanning radius as the maximum area. Multiple measurements can distinguish obstacle motion poses, providing a foundation for robot path planning.

2.2 LiDAR Data Acquisition

This paper selects the RPLIDAR series LiDAR with a measurement range of 0.15-8 meters, scanning angle range of 0°-360°, maximum distance resolution of 0.5 mm, angular resolution of 0.45°, and scanning frequency of 10 Hz (10 rotations per second). Its data acquisition model is shown in Figure 2. Scanning determines the obstacle' s distance ρ_{ij} relative to the LiDAR, and the laser beam number determines the bearing ϕ_{ij}, yielding polar coordinate data points (ρ_{ij}, ϕ_{ij}) in the LiDAR-centered coordinate system.

When the LiDAR coincides with the robot' s geometric center, the LiDAR position coordinates can be represented by the robot position coordinates. If the robot's position coordinates are (x_r, y_r), then the obstacle's position coordinates are:

$$\begin{bmatrix} x_{o,ij} \\ y_{o,ij} \end{bmatrix} = \begin{bmatrix} x_r \\ y_r \end{bmatrix} + \begin{bmatrix} \rho_{ij}\cos\phi_{ij} \\ \rho_{ij}\sin\phi_{ij} \end{bmatrix}$$

where j represents the laser beam number within the same cycle and i represents the sampling time sequence.

Sampled LiDAR data inevitably contains noise points, which reduces obstacle or target detection accuracy. In practical design, raw data requires filtering. Reference [13] proposes an adaptive curvature filtering algorithm that centers on the distance ρ_{ij} measured by the LiDAR at time i on scanning line j, establishing a 3×3 data analysis window to analyze the maximum correlation of nine data points in time and space, effectively reducing noise while preserving data boundary points and retaining outliers. Reference [14] proposes a mean filtering algorithm based on elevation information flatness, which first converts LiDAR intensity information into grayscale images, then performs mean filtering on each pixel. Common LiDAR data filtering algorithms also include mathematical morphology-based filtering, slope-based filtering, TIN-based LiDAR point cloud filtering, and pseudo-scanline-based filtering algorithms. These algorithms are well-studied and easily implementable, so they are not elaborated here.

Real-time acquisition of obstacle position coordinates can determine whether obstacles are stationary or dynamic, and can calculate instantaneous velocities and accelerations of obstacles, providing data support for subsequent path planning. In unmanned warehousing systems, since dynamic obstacles are mostly other warehousing robots that possess self-localization capabilities, a wireless network system can be constructed to share pose and position information in real-time via wireless networks, thereby enabling global path planning environments. Multi-robot collaborative work in wireless networks will be addressed in future research.

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3 Improved Artificial Potential Field Method

3.1 Traditional Artificial Potential Field Method

The traditional artificial potential field method considers only distance factors between the robot and target/obstacles. The attractive potential field produced by the target is proportional to their distance—the farther from the target, the stronger the attractive potential field, and vice versa, pulling the robot toward the target. The repulsive potential field produced by obstacles is inversely proportional to their distance—the closer to an obstacle, the stronger the repulsive force, and vice versa, achieving obstacle avoidance. The mathematical relationships are:

Attractive potential field:

$$U_{att}(p) = \frac{1}{2}k_a||p_r - p_g||^2$$

Repulsive potential field:

$$U_{rep}(X) = \begin{cases} \frac{1}{2}m\left(\frac{1}{\rho} - \frac{1}{\rho_0}\right)^2, & \rho \le \rho_0 \\ 0, & \rho > \rho_0 \end{cases}$$

where k_a and m are attractive and repulsive potential field gain coefficients, respectively, $||p_r - p_g||$ is the distance between robot and target, $\rho = ||p_r - p_o||$ is the distance between robot and obstacle, and ρ_0 is the distance threshold for obstacle repulsive potential field influence—when $\rho \le \rho_0$, the robot experiences repulsive force, otherwise it does not.

Attractive and repulsive forces are obtained through negative gradients of their respective potential field functions:

$$F_{att} = -\nabla U_{att} = k_a(p_r - p_g)$$

with direction from robot to target.

$$F_{rep} = -\nabla U_{rep} = \begin{cases} m\left(\frac{1}{\rho} - \frac{1}{\rho_0}\right)\frac{1}{\rho^2}\frac{\partial \rho}{\partial p}, & \rho \leq \rho_0 \\ 0, & \rho > \rho_0 \end{cases}$$

with direction from obstacle to robot. For multiple obstacles, $F_{rep} = \sum_{i=1}^{n} F_{rep,i}$, and the final resultant force $F_{total} = F_{att} + F_{rep}$ provides direction and force for the next path planning step.

The traditional artificial potential field method is suitable for static environment path planning. However, for full dynamic warehousing applications where both targets and obstacles move randomly with changing motion forms and poses, it cannot meet planning requirements.

3.2.1 Improved Attractive Potential Field Function and Force

When the target is a moving picking robot, the warehousing robot must not only match the target' s position but also maintain identical velocity and motion trends, meaning relative velocity and relative acceleration between robot and target should be zero. Traditional attractive potential field functions cannot satisfy this requirement and need improvement.

To address the need for warehousing robots to maintain the same motion trends as targets in terms of velocity and acceleration, relative velocity and relative acceleration factors are introduced into the traditional attractive potential field function [15, 16], as shown in equation (13):

$$U_{att}(p, v, a) = \frac{1}{2}k_p||p_r - p_g||^2 + \frac{1}{2}k_v||v_r - v_g||^2 + \frac{1}{2}k_a||a_r - a_g||^2$$

where k_p, k_v, and k_a are positive constant factors, and p_r, v_r, a_r and p_g, v_g, a_g represent the position, velocity, and acceleration of robot and target, respectively. $||p_r - p_g||$ is the geometric distance between robot and target, $||v_r - v_g||$ is the magnitude of relative velocity, and $||a_r - a_g||$ is the magnitude of relative acceleration.

As shown in equation (13), the attractive potential field function becomes zero only when all three terms—relative position, relative velocity, and relative acceleration between robot and target—are simultaneously zero; otherwise, it continues to provide attractive force to the warehousing robot.

The attractive force function can be obtained through the negative gradient of the attractive potential field function, derived as in equation (14):

$$F_{att}(p, v, a) = -\nabla U_{att}(p, v, a) = -\frac{\partial U_{att}}{\partial p} - \frac{\partial U_{att}}{\partial v} - \frac{\partial U_{att}}{\partial a}$$

The first term represents position attractive force:

$$F_{att,p} = -\frac{\partial U_{att}}{\partial p} = -k_p(p_r - p_g)$$

with direction from robot to target.

The second term represents velocity attractive force:

$$F_{att,v} = -\frac{\partial U_{att}}{\partial v} = -k_v(v_r - v_g)$$

with direction along the difference vector between target velocity vector and robot velocity vector.

The third term represents acceleration attractive force:

$$F_{att,a} = -\frac{\partial U_{att}}{\partial a} = -k_a(a_r - a_g)$$

with direction along the difference vector between target acceleration vector and robot acceleration vector.

Thus, the total attractive force on the robot is:

$$F_{att} = F_{att,p} + F_{att,v} + F_{att,a}$$

To facilitate analysis of the relationship between introduced velocity components and position, a coordinate transformation can be performed by introducing a homogeneous transformation matrix to obtain the robot’ s coordinate transformation between old and new coordinate systems, as shown in equation (23). The attractive force calculation process and vector relationships are illustrated in Figure 3 [Figure 3: see original paper].

3.2.2 Improved Repulsive Potential Field Function and Repulsive Force

In fully dynamic environments where obstacles are also in motion, similar to the improved attractive potential field function, relative velocity and relative acceleration factors are introduced into the repulsive potential field function [17], as shown in equation (19):

$$U_{rep}(p,v,a) = \begin{cases} \frac{1}{2}m_p\left(\frac{1}{\rho} - \frac{1}{\rho_0}\right)^2 + \frac{1}{2}m_v||v_r - v_o||^2\cos\alpha + \frac{1}{2}m_a||a_r - a_o||^2\cos\beta, & \rho \le \rho_0 \text{ and } \alpha,\beta \in [-\frac{\pi}{2},\frac{\pi}{2}] \\ 0, & \rho > \rho_0 \text{ or } \alpha,\beta \notin [-\frac{\pi}{2},\frac{\pi}{2}] \end{cases}$$

where m_p, m_v, and m_a are positive constant factors, and v_o and a_o are obstacle velocity and acceleration, respectively. $||v_r - v_o||$ is the relative speed between robot and obstacle, and $||a_r - a_o||$ is the relative acceleration magnitude. α and β are the angles between the robot’ s relative velocity vector and relative acceleration vector with respect to the obstacle and the relative position vector. The improved repulsive potential field function introduces components of relative velocity and relative acceleration along the line connecting robot and obstacle. The relationships among various repulsive potential fields are shown in Figure 4 [Figure 4: see original paper].

The negative gradient functions of the potential field with respect to velocity and acceleration can be obtained as in equations (28) and (29). From equations (25)-(29), the repulsive force function is:

$$F_{rep} = F_{rep,p} + F_{rep,v} + F_{rep,a}$$

To facilitate analysis of the relationship between introduced relative velocity components and position, the coordinate system can be translated and rotated. First, move the coordinate origin to the obstacle center, then rotate the X-axis to the direction of the obstacle' s velocity relative to the robot, establishing a new Cartesian coordinate system. In this coordinate system, the robot' s position coordinates are transformed as shown in equation (24). Figure 5 [Figure 5: see original paper] illustrates the repulsive function calculation process and relationships among various functions.

As shown in Figure 5, the improved repulsive function adds two additional repulsive forces, $F_{rep,v}$ and $F_{rep,a}$, to the traditional position-based repulsive force, enhancing obstacle repulsion. Simultaneously, in the direction perpendicular to the position repulsive force, two additional forces $F'_{rep,v}$ and $F'_{rep,a}$ are added, providing the robot with obstacle circumvention capability.

Finally, the resultant force of F_{att} and F_{rep} provides the next planning direction and force for the robot:

$$F_{total} = F_{att} + F_{rep}$$

4 Simulation and Results Analysis

To verify the feasibility of the improved artificial potential field method in warehousing robot path planning, MATLAB R2016a was used to conduct simulation experiments for target tracking in both obstacle-free and obstacle-present scenarios.

4.1 Algorithm Description

To address path planning for warehousing robots in dynamic environments, this paper focuses on introducing relative velocity and relative acceleration between the robot and target/obstacles into the potential field function, yielding improved attractive and repulsive force functions. The algorithm implementation first requires obtaining position, velocity, and acceleration information of the robot, target, and obstacles. Second, the attractive force from the target to the robot is calculated. Third, it determines whether the robot is within the obstacle repulsive force range; if so, the corresponding repulsive force value is calculated, otherwise the repulsive force is zero. Finally, the resultant force on the robot is computed to calculate the robot' s acceleration and velocity for the next step, ultimately achieving target tracking motion. The specific flow is shown in Figure 6 [Figure 6: see original paper].

4.2 Target Tracking Without Obstacles

First, target tracking experiments can be conducted based on the improved attractive function in an obstacle-free environment to adjust relevant parameters in the attractive function and select appropriate values. Simulation parameters are shown in Table 1 .

Table 1 Simulation parameters without obstacles

Simulation Parameter Name & Symbol	Value (Unit)
Simulation environment area s	30 (m^2)
Target initial position p_g	(5,27) (m)
Target initial velocity v_g	(0.3, -0.3) (m/s)
Target initial acceleration a_g	(0.2, -0.4) (m/s^2)
Robot initial position p_r	(3,15) (m)
Robot initial velocity v_r	(0,0) (m/s)
Robot initial acceleration a_r	(0,0) (m/s^2)
Robot mass m	10 (Kg)
Planning time Δt	0.3 (s)
Maximum moving speed v_{max}	3 (m/s)

Through multiple experiments in the same environment, adjusting the three parameters k_p, k_v, and k_a yields different tracking effects. Some achieve fast response time but exhibit excessive oscillation, increasing tracking path overhead, as shown in Figure 7 [Figure 7: see original paper]. Others show smooth tracking but slow response, requiring long tracking time, as shown in Figure 8 [Figure 8: see original paper].

A trade-off exists among response speed, stability, and accuracy during target tracking. Parameter selection requires compromise consideration. When $k_p = 4$, $k_v = 5$, and $k_a = 2$, the robot tracks the target at $T = 6$s and maintains the same motion state as the target. The path planning is shown in Figure 9 [Figure 9: see original paper], demonstrating the most ideal tracking effect.

4.3 Target Tracking With Obstacles

Based on the dynamic target environment, three dynamic obstacles are randomly set to verify the warehousing robot’ s capability for obstacle avoidance and target tracking in dynamic environments. Specific simulation parameters are shown in Table 2 .

Table 2 Simulation parameters with obstacle conditions

Simulation Parameter Name & Symbol	Value (Unit)
Target initial position p_g	(5,27) (m)

Simulation Parameter Name & Symbol	Value (Unit)
Target initial velocity v_g	(0.4, -0.4) (m/s)
Target initial acceleration a_g	(0.4, -0.2) (m/s^2)
Robot initial velocity v_r	(0,0) (m/s)
Robot initial acceleration a_r	(0,0) (m/s^2)
Obstacle 1 initial position p_{o1}	(0.5,15) (m)
Obstacle 1 initial velocity v_{o1}	(2.5, -2) (m/s)
Obstacle 1 initial acceleration a_{o1}	(-0.1, 0.15) (m/s^2)
Obstacle 2 initial position p_{o2}	(13,21) (m)
Obstacle 2 initial velocity v_{o2}	(-3, -1) (m/s)
Obstacle 2 initial acceleration a_{o2}	(0.6, 0.05) (m/s^2)
Obstacle 3 initial position p_{o3}	(8.5,14) (m)
Obstacle 3 initial velocity v_{o3}	(1,2) (m/s)
Obstacle 3 initial acceleration a_{o3}	(-0.2, -0.2) (m/s^2)
Robot mass m	10 (Kg)
Planning time Δt	0.3 (s)
Maximum moving speed v_{max}	5 (m/s)
Attractive proportional coefficients (k_p, k_v, k_a)	(2,5,1)
Repulsive proportional coefficients (m_p, m_v, m_a)	(4,4,3)

Under the combined action of attractive and repulsive forces, the warehousing robot avoids obstacles while tracking the target. The specific process is shown in Figures 10 [Figure 10: see original paper] through 16 [Figure 16: see original paper].

The simulation results show that at $t = 1.8$s, the robot enters the influence range of Obstacle 1 and avoids it by $t = 2.1$s while continuing to track the target. At $t = 3.3$s, the robot enters Obstacle 2' s influence range and avoids it by $t = 3.9$s. At $t = 6$s, the robot encounters Obstacle 3, avoids it by $t = 6.6$s, and continues tracking the target. At $t = 13$s, the robot reaches the same position as the target and maintains identical velocity and acceleration for continued motion. The simulation results verify that the improved artificial potential field method effectively solves warehousing robot path planning problems in fully dynamic environments with high tracking efficiency and smooth paths.

4.4 Comparison With Other Algorithms

To further verify the superiority of this algorithm, the simulation environment from reference [16] was used for comparative experiments, with results shown in Figure 17(b) [Figure 17: see original paper]. Figure 17(a) shows the simulation results from reference [16], while Figure 17(b) shows the results of this algorithm. The comparison reveals that at $t = 10$s, this algorithm has already achieved synchronized motion with the target, with a smoother trajectory. Therefore, this algorithm demonstrates greater advantages in dynamic obstacle avoidance and dynamic target tracking.

5 Conclusion

This paper first analyzed the working principles of warehousing robot autonomous navigation, presented mathematical models for robots and obstacles, constructed an environmental perception platform based on 2D LiDAR, and proposed an improved artificial potential field method that enables warehousing robots to autonomously navigate in fully dynamic environments. By introducing the robot’ s relative position, velocity, and acceleration with respect to targets and obstacles into the traditional potential field function, simulation verification demonstrates that warehousing robots can not only effectively avoid dynamic obstacles but also precisely track target robots, laying a solid foundation for future application in real unmanned warehousing environments.

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