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RESEARCH ARTICLE

Hybrid Path Planning Model for Multiple Robots Considering Obstacle Avoidance

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ABSTRACT To solve the problem that the single robot task execution capability is not enough to meet the whole handling task demand under complex conditions, the hybrid path planning models such as multi-robot path planning and formation cooperative control considering obstacle avoidance are studied. Firstly, for the robot global path finding problem, on the basis of the construction for a robot working environment model based on the geometric map model building method, an improved particle swarm algorithm-based global path planning model is proposed to solve the problems of low robot path planning solution efficiency and easy to fall into local optimal solutions. Secondly, for the multi-robot cooperative formation control and obstacle avoidance and inter-robot collision avoidance problems, a multi-robot formation local path planning model based on the improved artificial potential field method is constructed, a simulated annealing algorithm is introduced to optimize the traditional artificial potential field method, and a multi-robot formation control strategy, robot obstacle avoidance, and inter-robot collision avoidance methods are designed in combination with the pilot-following method to improve the robot formation path exploration The proposed method can improve the path exploration capability and handling efficiency of robot formation. Finally, the global path planning model of the robot based on the improved particle swarm algorithm is simulated and analyzed using Matlab 7.0 to verify the outstanding performance of the model in pathfinding capability. Then the local path planning model of multi-robot formation based on the improved artificial potential field is simulated and analyzed to verify the improved algorithm has good path planning as well as obstacle avoidance performance. The hybrid path planning model is applied to a real case and simulated, and the results show that the improved algorithm improves the exploration capability of the robot formation, effectively avoids obstacles, and verifies its reliability and superiority in the hybrid path planning process.

INDEX TERMS Path planning, improved particle swarm algorithm, environment modeling, artificial potential field algorithm, formation control.

I. INTRODUCTION

Industry 4.0, also known as the fourth industrial revolution, is a new era in which Cyber-Physical System (CPS), Internet of Things (IoT), and Artificial Intelligence (AI) are combined to make smart factories a reality. Since these technologies are used to connect machines, robots, and physical components, they enable the connection of machines with intelligence [1]. Robots have the advantage of being easy to operate and can be flexibly controlled and dispatched, while robots can also replace manpower to reduce material handling costs while reducing the probability of accidental risks, and have the advantages of flexible operation, reliable operation, and easy maintenance [2]–[5]. However, the focus is mainly on automation and precise repetitive tasks in manufacturing and assembly line factories, where modern robots have two main

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modes of operation compared to the traditional robots used in manufacturing: autonomous and collaborative, or multiple hybrids [6]. In the practical application of robots, the ability to operate efficiently, safely, and stably is a key factor in improving the efficiency of the entire production system, and the two most important key technologies for robots are the path planning module and the autonomous obstacle avoidance module. The meaning of the path planning problem is the process of obtaining the optimal path from the starting point to the endpoint based on the input environmental information using an efficient path planning algorithm. The meaning of autonomous obstacle avoidance is that when the robot moves along the planned path and detects the presence of static or dynamic obstacles on the route through sensors, it needs to start the corresponding obstacle avoidance algorithm so that the robot can safely and smoothly avoid the obstacles and avoid collisions leading to accidents [7], [8]. Therefore, an important factor affecting the robot's path planning and obstacle avoidance ability is its corresponding algorithm, so it is a strong necessity to design an efficient path planning and obstacle avoidance algorithm for the robot to improve its operation speed and avoid collisions.

With the huge development of the computing power of modern processors, computer vision technology has become a major application in robotics, and in [9] vision algorithms play an important role in detecting obstacles in robotic environments. The goal of path planning for mobile robots is to find collision-free paths from the starting point to the target point and to optimize them according to certain criteria. For example, sidewalk sweeping robots operate in dynamic environments [10] with moving pedestrians and objects, and the requirement for accurate execution of autonomous tasks in uncertain environments is crucial for the development of the next pair of robots [11]. Some methods are based on statistical optimization strategies such as A* [12], ant colony algorithms, and genetic algorithms. Although these methods have shown good potential, most of them may fall into an uncertain polynomial hard (np-hard) problem, which is computationally expensive for optimization methods [13]. Parallel working groups for mobile robots offer a large number of benefits compared to single robot systems. To perform a large number of various tasks with sufficient robustness, teams of robots are used instead of a single highly specialized robot [14]. In order to improve the autonomy and intelligence of the robot, most algorithms focus on improving the autonomous learning capability of the robot [15]. However, these algorithms are not widely used in practice due to several problems.

Many robotic applications require multiple robots with multiple degrees of freedom to coordinate their motions in a shared workspace. The difficulty of motion planning makes it impractical to explicitly construct such structures in a composite space of multiple robots [16]. Local path planning focuses on considering information about the robot's current local environment to give the robot good obstacle avoidance capabilities. Sensors are used to detect the robot's working environment and to obtain information about the location and nature of obstacles [17]. When moving on a planned global path, unforeseen obstacles are placed on the planned path and need to be replanned to avoid collision [18] obstacles. In 2021, Gan proposed an algorithm based on Bézier curve theory applied to robot obstacle avoidance and established a motion model for differential drive robots, and introduced a genetic algorithm to reduce the dimensionality of robot movement path coding to avoid static obstacles present in the environment and thus successfully reach the target point [19]. However, this method is not suitable for environments where many small obstacles exist. In 2021, Yao *et al.* addressed the problem of large-scale formation and formation scaling control by designing the control algorithm of the first follower based on the obtained relative position information, which makes the position between the first follower and the pilot converge to the ideal constrained position to control the scale of the whole formation in order to form an ideal formation [20]. However, when there are moving obstacles in the environment, the followers are prone to the problem of collision with each other.

In this study, a hybrid path planning model for robot formation based on an improved particle swarm algorithm and improved artificial potential field method is proposed, combining the advantages of an improved particle swarm algorithm that can quickly find the globally optimal path and the advantages of improved local obstacle avoidance method of an artificial potential field method with the robot formation control method designed in this paper, and the key contribution is to realize the path planning for cooperative control of multi-robot formation. The rest of this paper is structured as follows. First, the problems of robot path planning in industrial environments and the low transportation efficiency of robot automatic obstacle avoidance and cooperative formation control are analyzed, and the basic algorithms applied in this paper are described. The robot global path planning is modeled in Section 3. In Section 4 the improved robot local path planning algorithm is presented and modeled. In Section 5 simulation analysis is performed to simulate the robot global and local path planning respectively, showing how the proposed model is executed under different scenario maps and applying the algorithm to real cases. The conclusions of this work are drawn in the section 6. The technical route of the research in this paper is shown in Figure 1 below.

II. PROBLEM ANALYSIS AND THEORETICAL APPROACH

A. PROBLEM ANALYSIS

Transport robots are precisely multi-functional, multi-scene, multi-purpose intelligent mobile robots based on artificial intelligence-related technologies. For example, robots can replace corporate workers in high-risk handling tasks and can help medical staff transport infected medical waste, etc. In some complex conditions, the ability of a single robot to perform a task is not sufficient to meet the needs of the entire transport task, so multiple robot formations are needed

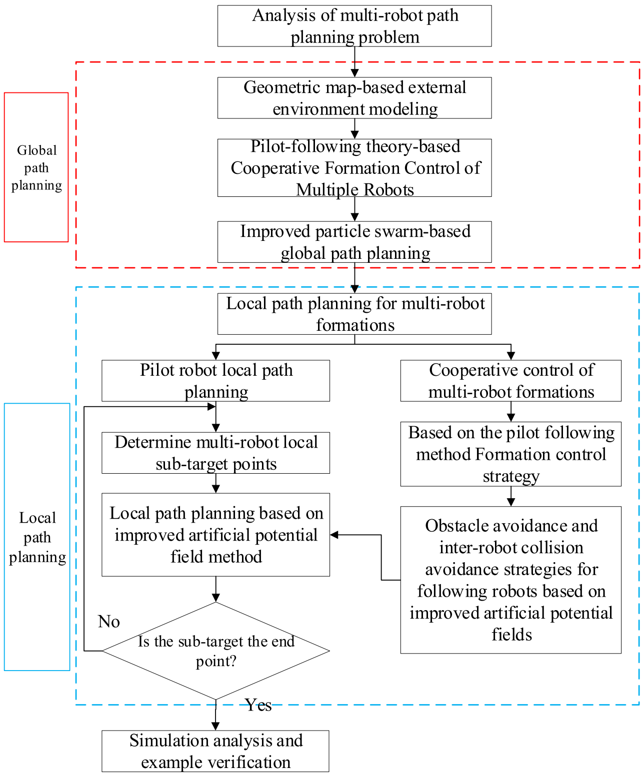

FIGURE 1. Technology roadmap.

to cooperate and work together to complete more complex transport tasks.

As the application of robots in various industries continues to expand, the transport tasks of single robots are mostly limited to the transport of small and medium-sized materials, while for large materials, such as aircraft wings and nacelles, single robots are no longer able to meet the increasingly complex work needs, and there are also many limitations of single robots, so the study of multi-robot formation cooperative transport is urgent. In modern intelligent factories, multi-robot teaming can improve the utilization rate of robots, reduce operation time, improve productivity, reduce handling costs for enterprises, and achieve the effect of robot diversification and flexibility in handling.

In production practice, robot formations may encounter dynamic or static obstacles in the process of cooperative control, and the corresponding obstacle avoidance algorithm has to be activated to avoid the obstacles to ensure the safety of transportation. In some cases, the robot has an irreplaceable role in handling large quantities, long production times, and complex working environments. With the continuous development of smart manufacturing, the concept of the smart factory comes along, and the robot has become one of the key indispensable equipment in the smart factory, so the optimization and research of the robot is of great significance to the smart factory.

In this paper, we improve the particle swarm algorithm for the shortcomings of robot path planning, propose adaptive weight change rules to improve the local search ability and global search ability of the algorithm, improve the position update formula of the particle swarm algorithm to improve the convergence accuracy of the algorithm, introduce a genetic algorithm to expand the population range, improve the possibility of the algorithm to find the optimal solution, and provide a reference for the robot global path planning problem. The algorithm can provide some reference for the global path planning problem of the robot. The basic artificial potential field method is improved to optimize the repulsive field to avoid the problem of the unreachable target, and the simulated annealing algorithm, the pilot following method, and the improved artificial potential field method are introduced to design the multi-robot formation scheme and cooperative control strategy so that the robot formation can effectively avoid obstacles and maintain a certain formation in the process of moving, which provides a theoretical reference for the cooperative control of multi-robot formation. Theoretical reference is provided for the cooperative control of multi-robot formation.

B. ENVIRONMENTAL INFORMATION MODELING

Geometric maps, also called geometric feature maps, can be described as a method of constructing a map of the environment based on geometric information (e.g., points, lines, and surfaces) of objects in the environment. The robot collects the shape, distance, size, and other features of each object in the environment through the sensors it carries and uses these features to build a map of the environment. The main feature is to simplify the objects and obstacles in the space and to enlarge the irregular objects to form a more regular figure for the subsequent path planning operation. In addition, geometric feature maps are more accurate in the local environment than topological and raster maps and can describe the environment in more detail and accurately portray the real-time environmental information.

Considering that in the actual situation, the shape, volume, contour and other factors of obstacles in the environment are not regular, so to simplify the data extraction and analysis of obstacles, the obstacles are approximately equivalent to rectangle, trapezoid, triangle and other regular shapes, as shown in Figure 2.

C. BASIC PARTICLE SWARM ALGORITHM

Particle Swarm Optimization (PSO) is a meta-heuristic global optimization algorithm proposed by Kennedy and Eberhart in 1995. The physical model on which the transition rule is based is one of the emergent collective behaviors resulting from the social interaction of a flock of birds or a school of fish. In PSO, each individual in the flock is called a particle, which represents a potential solution with two main characteristics (vectors), position and velocity.

The particle velocity and position update iterations are shown in the following equations (1)(2);

$$v_{id}^{k+1} = \omega v_{id}^{k} + c_1 \varepsilon \left(p_{id}^{k} - x_{id}^{k}\right) + c_2 \eta \left(p_{gd}^{k} - x_{gd}^{k}\right) \quad (1)$$

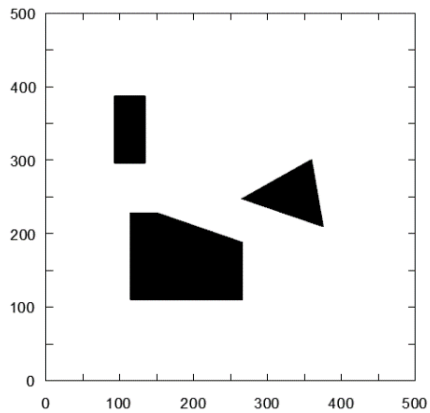

FIGURE 2. Geometric map model.

$$x_{id}^{k+1} = x_{id}^{k} + v_{id}^{k+1} \tag{2}$$

The basic particle swarm algorithm has the feature of fast convergence when solving practical problems, but there are still some limitations. Therefore, this paper will make improvements to address the shortcomings of the particle swarm algorithm in operation and solve the robot global path planning problem based on the optimized particle swarm algorithm.

D. GENETIC ALGORITHM

The Genetic Algorithm was proposed by Bagley. The design concept of the algorithm simulates Darwin's evolutionary theory, and the operating principle of the algorithm is highly consistent with the natural selection process of animals and plants in nature, hence the name genetic algorithm. In the process of iteration, as the number of iterations accumulates, the population quality of the algorithm will continue to improve until it evolves into the optimal population and obtains the optimal solution. The above process is similar to the principle of biological evolution, in which the good genes will be retained and inherited by the next generation, while the weakly adapted individuals will be gradually reduced to extinction. The basic operations of genetic algorithms are divided into three types, namely selection, crossover, and mutation.

Selection is the law of survival of the fittest. Individuals that are unable to adapt to changes in their environment or are not able to resist natural enemies will perish, while those that are more adaptable will survive and use these individuals to reproduce the next generation of populations, so selection can also be called Regeneration. The crossover operation refers to the exchange of the same chromosomal position of two different individuals in the selected next generation after the selection operation, which can generate new individuals to expand the population diversity. The mutation operation simulates the genetic mutation phenomenon caused by the change of living environment or climate during the reproduction process of an organism in nature, and the mutation operation can obtain new individuals to further expand the population diversity.

E. BASIC ARTIFICIAL POTENTIAL FIELD METHOD

1) PRINCIPLE OF ARTIFICIAL POTENTIAL FIELD METHOD

The artificial potential field method is a path avoidance method proposed by foreign scholar Khatib. The principle of the artificial potential field algorithm comes from the electrostatic potential field theory in physics and is obtained through the transformation of mathematical models. The principle is to abstract the process of robot movement in the actual environment as the process of displacement of an object in a force field by the action of a force. The smoothness of the paths planned by the artificial potential field method is high and safe, but there are still some limitations in the practical application. In this paper, we will analyze the causes of the problem and propose solutions to improve the artificial potential field method, to combine the improved artificial potential field method with the pilot-following method to design a cooperative control strategy for multi-robot formations, so that the robot formations can maintain a certain formation during the movement and avoid dynamic obstacles and static obstacles encountered in the movement path.

The core idea of the artificial potential field method is to abstractly describe the obstacles as well as the working environment in which the robot is located. Vision sensors are installed in the robot body to collect environmental information and perform data analysis and processing while establishing the repulsive potential field of the obstacle and the gravitational potential field of the target point, and since the robot also has a certain potential energy, the robot will move toward the target point and avoid the obstacle under the action of the superimposed potential field. It can be considered as a mass point in robot path planning. The robot path planning aims to reach the target point, which is the lowest potential energy point in the potential field distribution and has a trough shape, while the potential field generated by the obstacles in the environment has higher potential energy as the peak of the potential field distribution.

In the two-dimensional coordinate system, the whole process of robot motion in the environment can be reduced to the motion of a point, so that any position of the robot in the environment can be represented by $X \left(X = [x, y]^T\right)$.

Meanwhile, the direction of robot motion is determined by the direction of the combined field strength of the superposition of the repulsive field and the gravitational field.

The gravitational field function is obtained from equation (3).

$$U_{att} = \frac{1}{2} k \rho^m \left(X, X_g\right) \tag{3}$$

According to experience, Where $k = 15$ in the model established in this paper, X is the position coordinate of the robot in the environment, X_g is the position coordinate of the target point, $\rho(X, X_g)$ is the distance between the robot and the target point, and m is the factor of the gravitational potential field.

The basic artificial potential field method gravitational field potential distribution is shown in Figure 3.

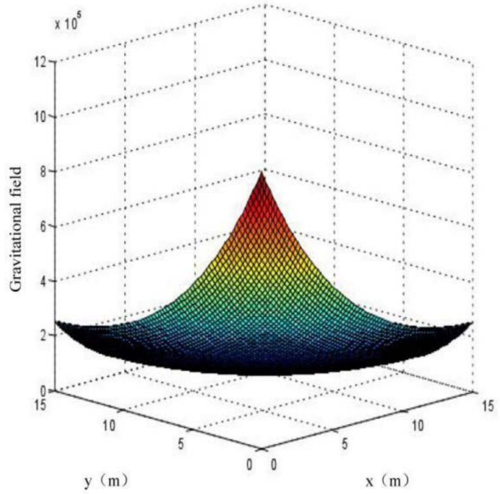

FIGURE 3. Force diagram of gravitational field.

The corresponding gravitational force F_{att} can be expressed as Equation (4).

$$F_{att} = -\nabla\left[U_{\text{att}}(X)\right] = k(X - X_g) \tag{4}$$

The repulsive field function is Equation (5).

$$U_{rep}(X) = \begin{cases} 0.5\eta\left(\dfrac{1}{\rho(X, X_{\text{i}})} - \dfrac{1}{\rho_0}\right)^2 \\ 0 \end{cases} \tag{5}$$

where η is the enhancement coefficient of proportional repulsion force. According to experience, in this paper, η is 3.7; X is the coordinate of the robot's position in the environment; X_i is the coordinate of the obstacle's position in the environment; $\rho(X, X_i)$ is the distance between the robot and the obstacle; ρ_0 is the influence distance of the obstacle in the environment; in this paper, $\rho_0 = 20$.

The repulsive potential field distribution of the basic artificial potential field method is shown in Figure 4.

Its corresponding repulsive force is Equation (6).

$$\begin{aligned} F_{\text{rep}} &= -\nabla\left[U_{\text{rep}}(X)\right] \\ &= \begin{cases} \eta\left(\dfrac{1}{\rho(X, X_i)} - \dfrac{1}{\rho_0}\right)\dfrac{1}{\rho^2(X, X_i)} \\ 0 \end{cases} \\ &\rho(X, X_i) \leq \rho_0 \\ &\rho(X, X_i) > \rho_0 \end{aligned} \tag{6}$$

The combined force on the robot is Equation (7).

$$F_t = F_{att} + F_{rep} \tag{7}$$

The distribution of the combined potential field is shown in Figure 5.

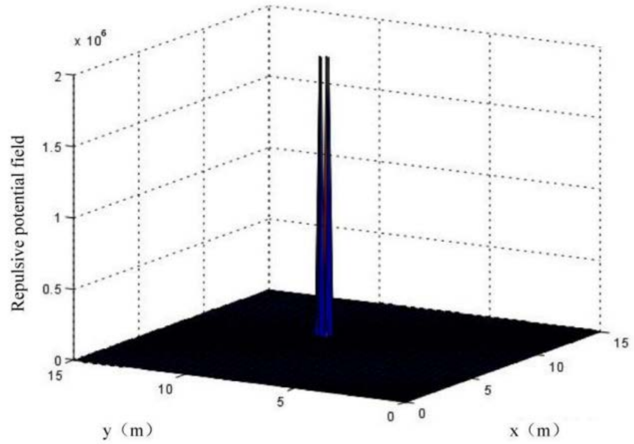

FIGURE 4. Repulsive potential field diagram.

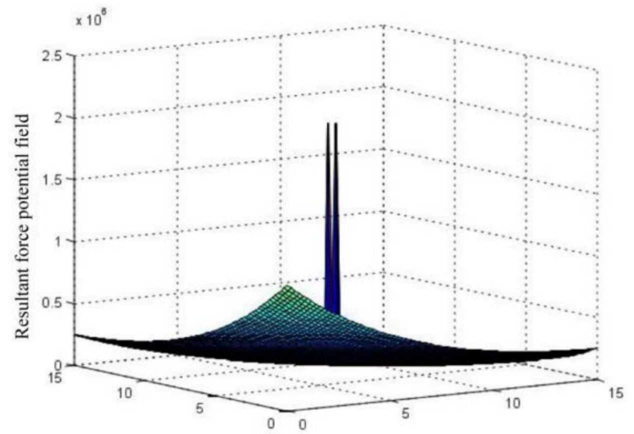

FIGURE 5. Resultant force potential field diagram.

2) DIRECTIONAL CONTROL BASED ON ARTIFICIAL POTENTIAL FIELD METHOD

In the environment, let the coordinates of the target point of the robot be $X_g = [x_g, y_g]^T$ the angle between the robot and the target point can be expressed as Equation (8).

$$\alpha = \arctan\frac{y_g - y}{x_g - x} \tag{8}$$

In addition, the attraction component of the target point to which the robot is subjected in the x and y coordinate axes directions can be expressed as Equation (9).

$$\begin{aligned} F_{att}(x) &= F_{att} \times \cos(\alpha) \\ F_{att}(y) &= F_{att} \times \sin(\alpha) \end{aligned} \tag{9}$$

Suppose, there is an obstacle in the environment that affects the path planning of the robot, denoted by $X_{01} = [x_{01}, y_{01}]^T, X_{02} = [x_{02}, y_{02}]^T, \ldots X_{0n} = [x_{0n}, y_{0n}]^T$. n Then the angle formed by the robot and the obstacle can be expressed as Equation (10).

$$\beta_{\text{n}} = \arctan\frac{\text{y}_{0n} - y}{\text{x}_{0n} - x} \tag{10}$$

The repulsive force component of the robot subjected to the n obstacle in the x and y coordinate axis directions can be expressed as Equation (11).

$$\begin{aligned} F_{\mathrm{att}}(x)_n &= F_{rep} \times \cos(\beta_n) \\ F_{\mathrm{att}}(y)_n &= F_{rep} \times \sin(\beta_n) \end{aligned} \tag{11}$$

From this, it can be seen that the angle between the direction of motion of the robot and the x-axis during the movement can be expressed as Equation (12).

$$\begin{aligned} \gamma &= \arctan\left(\frac{F(y)}{F(x)}\right) \\ &= \frac{F_{att}(y) + F_{att}(y)_1 + F_{att}(y)_2 + \cdots + F_{att}(y)_n}{F_{att}(x) + F_{att}(x)_1 + F_{att}(x)_2 + \cdots + F_{att}(x)_n} \end{aligned} \tag{12}$$

The next moving position of the robot can be expressed as Equation (13).

$$\begin{aligned} x_{k+1} &= x_k + l \times \cos\gamma \\ \mathrm{y}_{k+1} &= \mathrm{y}_k + l \times \sin\gamma \end{aligned} \tag{13}$$

where l is the moving step of the robot, x_k is the horizontal and vertical coordinate of the robot's current position, and y_k is the horizontal and vertical coordinate of the robot's next position.

From the above analysis, it is clear that the artificial potential field method has the following two advantages.

a: THE MOVING PATH IS SMOOTH

The artificial potential field method performs well in path planning for local obstacle avoidance. When the robot is moving, its surrounding environment and obstacle position information keep changing, so the size or direction of the artificial potential field force on the robot is constantly changing, which prevents the robot from suddenly changing its movement direction and moving speed, so the planned route is smoother.

b: STREAMLINED MODEL AND HIGH REAL-TIME PERFORMANCE

From the artificial potential field model, it can be seen that the model structure is concise, the robot is expressed in the form of mass points, and in the process of moving, all that is considered is the coordinates of the target point and the obstacles. In addition, there is no need for more operations, as the sensor constantly updates the detected obstacle information according to the robot's position change, and the magnitude and direction of the artificial potential field force to which the robot is subjected is also continuously updated, so the artificial potential field model can be Therefore, the artificial potential field method has high real-time performance and is well suited for local obstacle avoidance and path planning applications.

F. SIMULATED ANNEALING ALGORITHM

The simulated annealing algorithm is a metaheuristic method and is considered to be one of the first algorithms used to find the global optimum. The characteristic and advantage of this algorithm are that it accepts worse solutions than the current one with a certain probability to skip the local extremes and thus the global optimum can be searched. In this process, the residual stresses inside the material are eliminated to further stabilize the size of the material, and the grain arrangement is refined to reduce internal defects and thus improve the quality of the metal. The solution vector is randomly accepted with a certain probability, as shown in Equation (14).

$$x_i' = x_i + r \cdot v_i \cdot \frac{t}{T} \tag{14}$$

where T is the similar temperature, x_i is the vector of the current solution, x_i' is the solution when generating a small random disturbance, r is the random number on $[-1, 1]$, v_i is the step size vector with the same length as x, and t is the initial temperature.

The magnitude of the acceptance probability of the new solution is temperature dependent, as shown in equation (15).

$$P(\Delta E) = \begin{cases} 1, & \mathit{if}\ \Delta E < 0 \\ \exp -\dfrac{\Delta E}{T}, & \Delta E > 0 \end{cases} \tag{15}$$

where E is the corresponding value of the target function, and ∇E is the change in the solution of the target value.

When the algorithm has performed a certain number of iterations, the quenching temperature will gradually decrease from high to low, and this process is called the cooling phase, and the value of T is shown in equation (16).

$$T_{K+1} = T_{K\times\theta} \tag{16}$$

where T_K is the similarity temperature of iteration K, T_{K+1} is the similarity temperature of iteration $K+1$, θ is the constant controlling T decline, and $\theta \in [0.95, 0.99]$.

The simulated annealing algorithm is considered as one of the optimization methods for solving problems with multiple local extrema, so in this paper, the simulated annealing algorithm is referred to as the artificial potential field algorithm to solve the problem of falling into local extrema in robot path planning by the artificial potential field algorithm.

G. PILOT FOLLOWING METHOD THEORY

The basic principle of the pilot-following method is to set a pilot in the formation, the rest of the members as followers, in the formation movement process the pilot controls the entire formation route, followers and the pilot to maintain a certain angle and distance between the formation can control the formation.

The application of the pilot-follower method for multi-robot formation control has great advantages in terms of its simplicity and ease of implementation. Since there is only one navigator in the formation and the rest are followers, only one navigator robot needs to plan the movement route, and the other following robots can generate their own movement paths according to the navigator robot. In the multi-robot formation system, the communication topology between robots through a computer network can realize the information exchange and transmission between individual robots, and then achieve the control effect of the whole formation through mutual cooperation.

Pilot-following method according to the mutual position relationship between the pilot robot and the follower robot can be specifically divided into two categories, one is the relative distance and relative declination $(L-\varphi)$ Its principle is similar to the polar coordinates in a coordinate point through a specific distance and angle, it can determine its unique position. The second is the relative distance and relative distance $(L-L)$, similar to the plane right angle coordinate system, the distance of two directions can determine a unique point in the plane. The substantial feature of the pilot-following method is to establish a relative position relationship between the pilot and the follower to achieve the effect of controlling the whole formation, which is easy to operate in practice.

III. GLOBAL PATH PLANNING FOR ROBOTS BASED ON IMPROVED PARTICLE SWARM ALGORITHM

A. ANALYSIS OF GLOBAL PATH PLANNING PROBLEM OF ROBOT

In this paper, we will use the geometric model method to model the robot working environment as well as make improvements to the basic particle swarm algorithm. Based on the fact that the basic particle swarm algorithm is easy to fall into local minima in the process of robot pathfinding, resulting in the final searched robot movement path is not the shortest, therefore, the adaptive change strategy of inertia weight is proposed to balance the local and global seeking ability of the algorithm, and then avoid the algorithm to fall into the local optimal solution. In addition, the particle position update formula of the basic particle swarm algorithm is improved to improve the solution accuracy of the algorithm in response to the problem that the optimization accuracy of the basic particle swarm algorithm is not high. The genetic algorithm is again introduced to expand the range of feasible solutions to improve the solution quality. Finally, the improved particle swarm algorithm is applied to the global path planning of the robot and the performance of the improved particle swarm algorithm applied to the global path planning of the robot is verified by simulation experiments.

B. IMPROVED PARTICLE SWARM ALGORITHM FOR ROBOT PATH PLANNING

1) ADAPTIVE CHANGE INERTIA WEIGHTS

The size of the inertia weight ω of a particle swarm algorithm can have a strong impact on the algorithm's ability to find an optimal value and the performance of the algorithm. If the size of the ω value is reduced according to the general linear rule, it cannot be guaranteed to maintain a high level in the initial stage of the algorithm operation, which will make the algorithm easily fall into local minima. Therefore, in this paper, we design the adaptive method of ω-value to achieve the purpose of controlling the process of the algorithm, and then improve the global and local search ability of the algorithm and $\omega_{\max} = 0.9$, $\omega_{\min} = 0.2$. The specific steps are shown in Equation (17)-(21) below.

$$\omega(k) = \frac{1}{1+\exp\left(\alpha\Delta\omega(k-1)\right)} \tag{17}$$

$$\alpha = \ln\frac{1-\omega_{\max}}{\omega_{\max}} \tag{18}$$

$$\Delta\omega = \delta\times\beta \tag{19}$$

$$\delta = \frac{\omega_{\max}-\omega_{\min}}{k_{\max}} \tag{20}$$

$$\beta = \frac{V_{k-1}+V_k}{2V_{k-1}} \tag{21}$$

In equation (17), when the scale factor is introduced, the particle velocity at the last moment of flight can be adjusted adaptively;

If $\|V_{k-1}\| < \|V_k\|$, then $\beta > 1$, $\Delta\omega > \delta$, which will lead to a higher reduction of ω;

If $\|V_{k-1}\| > \|V_k\|$, then $\beta < 1$, $\Delta\omega < \delta$, which will lead to a weaker reduction of ω;

If $\Delta\omega = \delta$, the value of $\omega(k)$ decreases linearly.

In the initial stage of the iteration, if the value of ω is maintained at a high level, the search area of the algorithm can be expanded, and in the later stage of the iteration, when the value of ω decreases, the local search capability of the algorithm is improved.

Therefore, the particle velocity update equation (22) after the introduction of adaptively varying inertia weights.

$$v_{id}^{k+1} = \omega(k)\,v_{id}^{k} + c_1\varepsilon\left(p_{id}^{k}-x_{id}^{k}\right) + c_2\eta\left(p_{gd}^{k}-x_{gd}^{k}\right) \tag{22}$$

2) IMPROVEMENT OF PARTICLE POSITION UPDATE FORMULA

In the particle swarm algorithm, the particles have a better self-learning effect in the earlier stage, so the algorithm should have a larger search iteration step in the process of searching for the optimal solution at this stage, and the solution space will gradually change from large to small as the search time accumulates, so the search iteration step should be appropriately reduced to further improve the accuracy of the obtained solution. Therefore, from the above analysis, the adaptive adjustment coefficient of the tangent function is introduced into the position update formula of the basic particle swarm algorithm as shown in expression (23), and the random search factor $R \in (0, 1)$ is introduced for the better random search of particles.

$$\psi(k) = 1-\tanh\frac{k}{k_{\max}+1} \tag{23}$$

The basic particle swarm algorithm particle position update formula (24) after the introduction of the adaptive adjustment factor ψ of the tangent function.

$$x_{id}^{k+1} = \psi(k) \times R \times x_{id}^{k} + v_{id}^{k+1} \tag{24}$$

3) INTRODUCTION OF GENETIC ALGORITHMS

The improved particle swarm optimization algorithm in this paper will introduce the basic operations of the genetic algorithm to further expand the range of population as well as the population diversity to obtain the new solution set population in order to improve the solution quality.

a: SELECTION AND CROSSOVER OPERATION

Firstly, we calculate the fitness value of each individual according to the fitness formula, then we arrange the individuals in order according to the fitness value from highest to lowest, select A individuals (A is an even number), and perform the operation of two pairs of selected individuals, intercept the locally identical path information in two particles of the same pair, and perform the crossover behavior of swapping each other if there is no identical path fragment in the pair, then we will not perform the crossover behavior. However, for the offspring generation of particles obtained by the crossover operation, the position and velocity of the offspring are updated according to Equation (25)-(28) as follows.

$$child_1^k(x) = p_c \cdot parent_1^k(x) + (1 - p_c) \cdot parent_2^k(x) \tag{25}$$

$$child_2^k(x) = (1 - p_c) \cdot parent_1^k(x) + p_c \cdot parent_2^k(x) \tag{26}$$

$$child_1^k(v) = p_c \cdot parent_1^k(v) + (1 - p_c) \cdot parent_2^k(v) \tag{27}$$

$$child_2^k(v) = (1 - p_c) \cdot parent_1^k(v) + p_c \cdot parent_2^k(v) \tag{28}$$

where p_c is the random numbers on the interval [0, 1], and k is the number of iterations, $parent_1^k(x)$ is the parent generation 1 position vector, $parent_2^k(x)$ is the parent generation of 2 position vector, $parent_1^k(v)$ velocity vector is the parent generation 1, $parent_2^k(v)$ is the parent generation 2 velocity vector, $child_1^k(x)$ is 1 position vector offspring, $child_2^k(x)$ is children 2 position vector, $child_1^k(v)$ is children 1 velocity vector, $child_2^k(v)$ is children 2 velocity vector.

(2) Mutation operation

When the above crossover operation is completed, the mutation operation is performed for all $child_i^k(x)$ individuals.

$$child_i^{k+1}(x) = \begin{cases} child_i^k(x) + C_k \\ child_i^k(x) \end{cases} \tag{29}$$

where, if it is concluded by comparison that the fitness value of (a) is higher than that of (b), the result of $child_i^{k+1}(x)$ is (a) and the opposite is (b).

4) FITNESS FUNCTION

The length of the robot's movement path affects its working transportation time, so in order to complete the transportation task faster and save cost, its movement path should be as short as possible. Therefore the first objective function is established to make the robot's working moving distance the shortest, then in any iteration of the algorithm, if the distance f_1 between point $p_j(t)$ and the target point $p_j(N)$ is the minimum value, then the point is the best point.

$$f_1 = d\left(p_j(t), p_j(N)\right) \tag{30}$$

where $d(\cdot)$ is the Euclidean Metric.

The length of the shortest path traversed by the robot can be expressed as the sum of all points between the starting point $p(1)$ and the target point $p(N)$. f_1 can be expressed as Equation (31).

$$f_1 = \sum_{t=1}^{N-1} \sqrt{\left(x_{p_j(t+1)} - x_{p_j(t)}\right)^2 + \left(y_{p_j(t+1)} - y_{p_j(t)}\right)^2} \tag{31}$$

The robot cannot collide and scrape with objects in the environment during its movement, so it needs to establish a penalty function to avoid collisions and establish a second objective function f_2 as equation (32).

$$f_2 = \sum_{i=1}^{M_{\max}} \delta\alpha_i \tag{32}$$

where $M_{\max}$ is the total number of line segments of the robot's moving path when it is working, α_i is the number of intersection between i moving path segments and obstacles, and δ is the penalty factor.

The total fitness function can be expressed as equation (33).

$$fit = f_1 + f_2 \tag{33}$$

The flow of path planning for the robot using the improved particle swarm algorithm in this paper is shown in Figure 6.

IV. LOCAL PATH PLANNING FOR MULTI-ROBOT FORMATIONS BASED ON IMPROVED ARTIFICIAL POTENTIAL FIELD METHOD

A. IMPROVEMENT OF ARTIFICIAL POTENTIAL FIELD METHOD

In this section, we analyze the target unreachability problem and the local minima problem in the basic artificial potential field method for robot path planning and make improvement methods for them respectively.

1) OPTIMIZATION OF A BASIC ARTIFICIAL POTENTIAL FIELD METHOD FOR TARGET UNREACHABLE PROBLEMS

In a complex environment, dynamic or static unknown obstacles may temporarily appear around the target point, and the robot gradually moves toward the target point, approaching both the target point and the obstacles, while the magnitude of the attraction force on the robot decreases as the distance between the robot and the target point shortens according to the definition of the potential field function model, and the repulsive force on the robot gradually increases as it approaches the obstacles near the target point. This causes a deflection at the minimum of the full potential energy point, which makes the robot unable to reach the target point.

When using the artificial potential field method for path planning, information about obstacles in the environment is

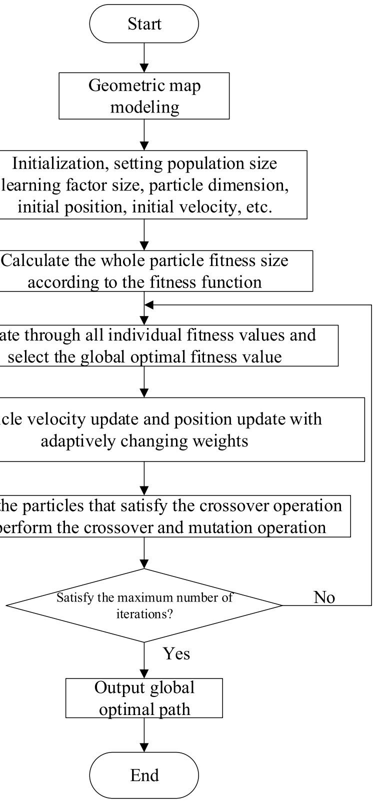

FIGURE 6. Improved particle swarm optimization robot path planning process.

collected by the sensors carried by the robot, which are used to calculate the magnitude and direction of the attractive and repulsive forces on the robot to determine the robot's next path of movement, so both play a decisive role in robot path planning.

2) REPULSION FIELD IMPROVEMENT

This paper addresses the limitations of the repulsive field function model of the basic artificial potential field method and improves it by introducing a distance factor A between the target point and the robot while adding a regulation factor B to A. The advantage of this is that the repulsive field function consists of the distance between the robot and the target point and the distance between the robot and the obstacle, and as the distance between the robot and the target point shortens, the repulsive force on the robot will gradually weaken. In turn, it solves the problem that the robot cannot approach the target point because of the obstacles around the target point. The improved repulsive potential field function is equation (34).

$$U_{rep}(X) = \begin{cases} 0.5\eta\left(\dfrac{1}{\rho(X,X_{\mathrm{i}})} - \dfrac{1}{\rho_0}\right)^2 \times \rho^{\mathrm{n}}\left(X, X_{\mathrm{g}}\right) \\ 0 \end{cases}$$
$$\rho\left(X, X_{\mathrm{i}}\right) \leq \rho_0$$
$$\rho\left(X, X_{\mathrm{i}}\right) > \rho_0 \tag{34}$$

where, according to experience, η in the model built in this paper $\eta = 3.7$, X is the coordinate of the robot's position in the environment, X_i is the coordinate of the obstacle's position in the environment, $\rho\left(X, X_i\right)$ is the distance between the robot and the obstacle, ρ_0 is the distance of the obstacle's influence in the environment, according to experience, $\rho_0 = 20$, $\rho\left(X, X_{\mathrm{g}}\right)$ is the distance factor between the target point and the robot, and n is the regulating factor greater than 0.

From the modified repulsive potential field function, the negative gradient can be found as equation (35).

$$\overline{F}_{rep}\left(X\right) = -\nabla\left[U_{rep}\left(X\right)\right] = \begin{cases} -\left(\overline{F}_{rep1} + \overline{F}_{rep2}\right) \\ 0 \end{cases}$$
$$\rho\left(X, X_0\right) \leq \rho_0$$
$$\rho\left(X, X_0\right) > \rho_0 \tag{35}$$

When the obstacle is far away from the robot and does not affect its movement path that is $\rho\left(X, X_0\right) > \rho_0$, then the robot is subjected to the repulsive force of the obstacle is 0. If $\rho\left(X, X_0\right) \leq \rho_0$, then the robot will be subjected to the repulsive force generated by the obstacle, which is composed of the following two repulsive forces as (36)-(37).

$$\overline{F}_{rep1} = \eta\left(\frac{1}{\rho\left(X, X_{\mathrm{i}}\right)} - \frac{1}{\rho_0}\right) \times \frac{\rho^n\left(X, X_g\right)}{\rho^2\left(X, X_i\right)} \tag{36}$$

$$\overline{F}_{rep2} = \frac{n}{2}\eta\left(\frac{1}{\rho\left(X, X_{\mathrm{i}}\right)} - \frac{1}{\rho_0}\right)^2 \times \rho^{n-1}\left(X, X_g\right) \tag{37}$$

Repulsion $\bar{F}_{rep1}$ is directed from the obstacle to the robot, and repulsion $\bar{F}_{rep2}$ is directed from the robot to the target point. In order to verify that the optimized repulsive potential field function model is superior to the one before optimization, the combined forces of the two and gravity are calculated respectively. The combined force $\bar{F}_{total}$ after optimization is more inclined to the target point than the combined force $\bar{F}_{total}$ before optimization.

The adjusting factor n has an important influence on the improved repulsive function, which can be divided into the following four cases according to the value range of n, as shown in Table 1 below.

According to the above analysis, introducing the distance factor $\left(X, X_g\right)$ between the target point and the robot and adding the adjusting factor n can effectively adjust the size of the repulsive force generated by the obstacles around the target point, and at the same time, the target point can always be the lowest global potential energy, thus solving the target unreachable problem.

B. BASIC ARTIFICIAL POTENTIAL FIELD METHOD FOR LOCAL MINIMUM PROBLEM OPTIMIZATION

Another limitation of the robot using the artificial potential field method for obstacle avoidance is that it is easy to fall into local minima, which is caused by the distribution of obstacles in the environment. From the above analysis of the robot into

TABLE 1. Effects of regulatory factors.

Regulatory factor n	Repulsive force function	Reach target point
$n=0$	$\overline{F}_{rep}=\overline{F}_{rep1}=F_{rep}$	NO
$0<n<1$	$\overline{F}_{rep1}=\eta\left(\frac{1}{\rho(X,X_i)}-\frac{1}{\rho_0}\right)\times\frac{\rho^n(X,X_g)}{\rho^2(X,X_i)}$ $\overline{F}_{rep2}=\frac{m}{2}\eta\left(\frac{1}{\rho(X,X_i)}-\frac{1}{\rho_0}\right)^2\times\rho^{n-1}(X,X_g)$	YES
$n=1$	$\overline{F}_{rep1}=\eta\left(\frac{1}{\rho(X,X_i)}-\frac{1}{\rho_0}\right)\times\frac{\rho(X,X_g)}{\rho_0}$ $\overline{F}_{rep2}=-\frac{\eta}{2}\left(\frac{1}{\rho(X,X_i)}-\frac{1}{\rho_0}\right)^2$	YES
$n>1$	$\rho(X,X_g)=0$	YES

the target unreachable problem, it can be seen that the robot in the process of moving by the force of attraction and repulsion, in the potential field always move towards the low potential energy, but when the robot work environment is more complex, there may be some locations in the environment where the potential energy is lower than the target point, if the robot happens to move to this location, it will cause the local minima problem.

1) LOCAL MINIMUM PROBLEM ANALYSIS

The robot is subjected to the joint action of repulsive and attractive forces in the potential field and moves from the starting point to the target point. However, there may be some special cases in the environment, i.e., the robot is subjected to zero combined force at the non-target point, and then the robot will stop moving and cannot move to the established target point, failing the path planning. A typical case where the robot falls into a local minimum is as follows.

a: CASE 1

When the obstacle is located between the robot and the target point, and the three are at the same level. In this case, if the distance between the robot and the target point is farther than the obstacle in the middle, the attraction force on the robot will be greatly increased, and the robot will likely collide with the obstacle and fail in path planning. In addition, if this situation occurs when the robot is about to reach the target point, the distance between the two is small, and the attractive force and repulsive force of the robot may be in a straight line, and the magnitude is equal and the direction is opposite, then the combined force of the robot is 0, and the robot will stop moving or make reciprocal oscillation movement, and it cannot move to the target point smoothly, failing path planning, as shown in Figure 7.

FIGURE 7. Local minimum problem of obstacles between robot and target point.

b: CASE 2

When the target point is located between the obstacle and the robot, and the three are in the same horizontal line. At this time, the robot by the target point of the gravitational force size of 0, and by the obstacles of the repulsive force size is not 0, this situation will lead to the robot towards the target point, there is the repulsive force and the attraction of the size of the opposite direction of the zero potential energy point, and then the robot can not jump out of the current position, can not reach the target point, as shown in Figure 8.

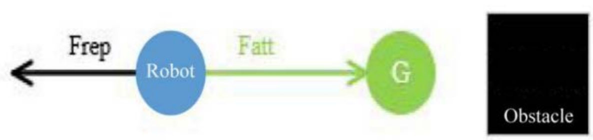

FIGURE 8. Local minimum problem with target point between obstacle and robot.

c: CASE 3

When multiple obstacles exist near the target point and constitute a channel, the robot is still in force equilibrium when the combined forces generated by the attractive force and multiple repulsive forces are exactly equal in magnitude and opposite in direction, and the robot cannot obtain the power to move, leading to a local minimal value problem, as shown in Figure 9.

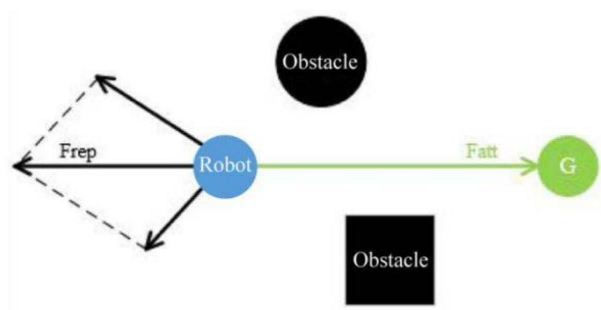

FIGURE 9. The local minimum problem of multiple obstacles forming a channel near the target point.

d: SITUATION 4

In the process of driving, the robot may encounter obstacles with a shape similar to the letter ''U'', at this time, the robot is subject to the common action of multiple obstacles. The robot will be surrounded by the ''U'' shaped obstacles and can not continue to move, and then fall into the local minimal value, as shown in Figure 10.

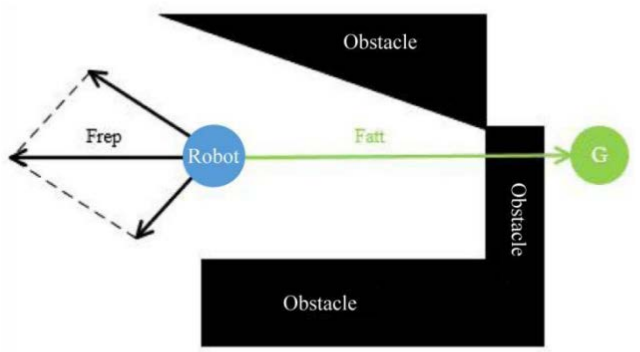

FIGURE 10. Local minimum problem of U-shaped obstacle.

2) PARTIAL MINIMAL VALUE DETECTION

In the process of path planning for robots using the basic artificial potential field method, the robot may suffer from the local minima problem, in which the robot stops moving or wanders and oscillates at a location that is not the target point.

From the operating principle of the basic artificial potential field method, it is known that the potential energy at the current position where the robot is located is used to discern whether the robot is caught in the local minima region by comparing it with the area that can be moved per unit time, in the following steps.

(1) According to the various sensors carried by the robot body to collect and fit the information of the robot and the position of obstacles in the environment, and according to the acquired information to synchronize the calculation of the potential energy of the robot's position $U(p)$, p is the robot coordinate position.

(2) From the robot's travel speed information data, we calculate the territory $R(p)$ that the robot is capable of reaching per unit time, and calculate the magnitude of the potential energy of the robot traveling to each location inside $R(p)$. p^* represents any location within the region, and $U(p^*)$ is the potential energy possessed by the robot at this point.

(3) If, when the robot is in position, the following conditions are satisfied.

$$\begin{cases} U_{att}(p) \neq 0 \\ U_{rep}(p) \neq 0 \\ U(p) \leq \min\limits_{p^* \in R(p)} U\left(p^*\right) \end{cases} \tag{38}$$

The meaning of this function is that at this moment, if the repulsive potential field and the gravitational potential field of the robot's environment are not zero, and in addition, the potential energy of the robot's reachable area is greater than or equal to the current position potential energy per unit time, then the robot can be considered to be in a local minima dilemma.

3) LOCAL MINIMAL VALUE PROBLEM OPTIMIZATION

In this paper, we propose to use a simulated annealing algorithm to jump out of the local minima position, so that the robot can move successfully to the original target point. From the principle of the artificial potential field method, it is known that the robot is moved from a high potential energy position to a low potential energy position by the joint action of the gravitational potential field and the repulsive potential field. In some complex environments, the potential energy distribution may have multiple locations A, B, C, and D, where D is the lowest potential energy location, and when the robot is trapped in a local potential energy location, it needs to use a search algorithm to continue the search to the high potential energy location to help the robot go over this potential field rise interval. When the robot is trapped to point C and cannot escape, a simulated annealing algorithm is introduced to accept the inferior solution based on a certain probability to continue the search, and once the search reaches the point, it will directly accept the superior solution to find the lowest location of the full potential energy, as shown in Figure 11.

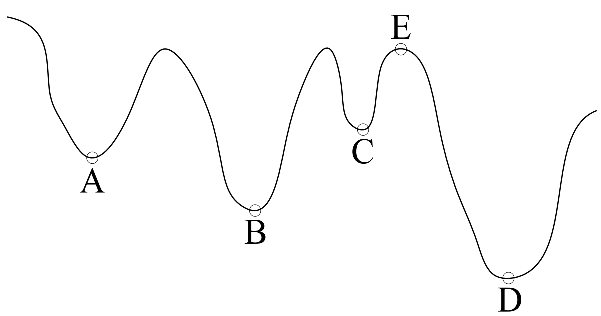

FIGURE 11. Principle of escape from local minimum.

The simulated annealing algorithm is constructed to jump out of the lowest local potential energy model as follows:

(1) Set an initial temperature T, and the initial position X for annealing operation, and set an appropriate annealing speed according to the actual situation.

(2) A uniformly distributed random disturbance term ΔX is introduced to the initial position X to obtain a new position X_i, $X_i = X + \Delta X$. Next, the value of ΔU is calculated, which means the difference between the potential field intensity $U(X_i)$ at the new position and the potential field intensity $U(X)$ at the initial position of the robot. The expression is $\Delta U = U(X_i) - U(X)$.

(3) Judge the positive and negative values of ΔU. If $\Delta U < 0$, X_i is directly accepted as the new position; if $\Delta U \geq 0$, X_i is accepted as the new position with probability

$P = exp\left(\frac{-\Delta U}{k_B T}\right)$, where k_B is Boltzmann constant and its value is 1.380649 × 10^ − 23 J/K.

(4) Judge whether the robot has successfully jumped out of the local minimum region in the potential field. If it has successfully jumped out, the operation of the algorithm can be terminated and moved to a new position X_i; otherwise, after lowering the annealing temperature T, return to Step (2) to continue the cycle of the above steps.

4) IMPROVE THE PROCESS OF ARTIFICIAL POTENTIAL FIELD METHOD

The above paper addresses the problem of target unreachability and the problem of falling into local minima when applying the basic artificial potential field method to robot path planning, and the improved artificial potential field method flow is shown in Figure 12.

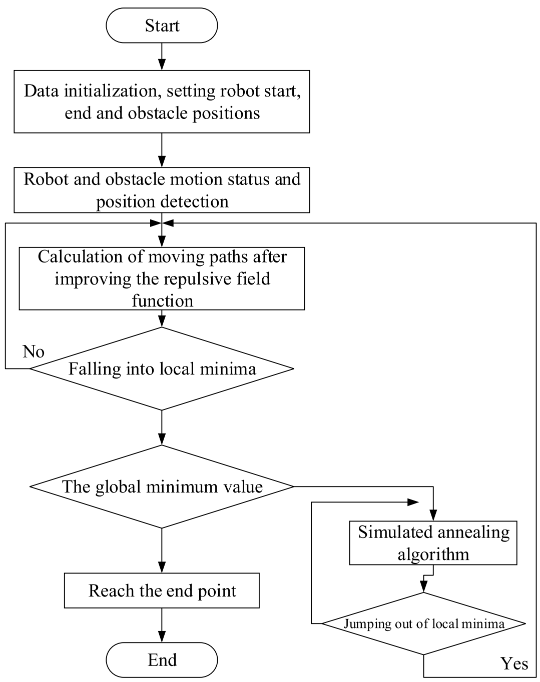

FIGURE 12. Improved process of artificial potential field method.

Step 1: The parameters of the improved artificial potential field method were initialized, including the proportional gravity enhancement coefficient k, the proportional repulsion enhancement coefficient η, the obstacle influence distance ρ_0, and the starting and ending positions of the robot were set.

Step 2: The sensor carried by the robot is used to detect the motion state and position of the robot and obstacles.

Step 3: The potential field function of the improved repulsive force field is used to plan the moving path of the robot.

Step 4: Judge whether the robot has fallen into the local minimum position. If not, return to Step 3 to search for the moving path. If it has fallen into the local minimum, judge whether it is the global minimum.

Step 5: Determine whether it is the global minimum. If it is the global minimum, the robot will reach the established target point and complete the path planning task. If it is not the global minimum, the simulated annealing algorithm introduced in this paper will be used to jump out of the local minimum and return to Step 3.

C. MULTIROBOT FORMATION CONTROL AND OBSTACLE AVOIDANCE BASED ON IMPROVED ARTIFICIAL POTENTIAL FIELD METHOD

1) PILOT ROBOT ARTIFICIAL POTENTIAL FIELD DESIGN

When there is an obstacle in the environment, the pilot robot gradually moves toward the target point and avoids the obstacles it encounters along the way under the joint action of the repulsive potential field generated by the obstacle and the attractive potential field generated by the target point. The pilot robot gravitational potential field function can be defined as follows.

$$U_{att} = \frac{1}{2} k \rho^2 \left(X, X_g\right) \tag{39}$$

In this paper, $k = 15$, X is the position of the pilot in the map, X_g is the position of the target point, and $\rho\left(X, X_g\right)$ is the distance between the pilot robot and the target point.

The Navigator robot is subject to attraction F_{att} provided by the target point as follows.

$$F_{att} = -\nabla\left[U_{att}(X)\right] = k\left(X, X_g\right) \tag{40}$$

The Pilot robot repulsive field function can be defined as shown below.

$$U_{rep}(X) = \begin{cases} 0.5\eta(\frac{1}{\rho(X, x_i)} - \frac{1}{\rho_0})^2 \rho^n(X, X_g) \\ 0 \end{cases}$$
$$\begin{cases} \rho\left(X, X_i\right) \leq \rho_0 \\ \rho\left(X, X_i\right) > \rho_0 \end{cases} \tag{41}$$

where η is the proportional gain coefficient, $\eta = 3.7$ in this paper, X is the coordinate of the robot's position in the environment, X_i is the coordinate of the obstacle's position in the environment, ρ_0 is the influence distance of the obstacle in the environment, $\rho_0 = 100$ in this model, n is the adjusting factor greater than 0, $n = 3$ in this paper.

The repulsive force of the navigator in the potential field by the obstacle F_{rep}:

$$F_{rep}(X) = -\nabla\left[U_{rep}(X)\right] \tag{42}$$

$$\nabla\left[U_{rep}(X)\right] = \begin{cases} -(F_{rep1} + F_{rep2}) \\ 0 \end{cases}$$
$$\begin{cases} \rho\left(X, X_i\right) \leq \rho_0 \\ \rho\left(X, X_i\right) > \rho_0 \end{cases} \tag{43}$$

$$F_{rep1} = \eta\left(\frac{1}{\rho\left(X, X_i\right)} - \frac{1}{\rho_0}\right) \times \frac{\rho^n\left(X, X_g\right)}{\rho^2\left(X, X_i\right)} \tag{44}$$

$$F_{rep2} = \frac{n}{2}\eta\left(\frac{1}{\rho\left(X, X_i\right)} - \frac{1}{\rho_0}\right)^2 \times \rho^{n-1}\left(X, X_g\right) \tag{45}$$

2) DESIGN OF ROBOT FORMATION CONTROL BASED ON ARTIFICIAL POTENTIAL FIELD METHOD

Each following robot will be affected by the potential field generated by the pilot robot, and maintain a certain range of relative distance l and angle φ. Therefore, the potential field generated by the pilot robot should be a combination of two parts, the first part is $U_{i,j}^{l}$, the potential field can adjust the relative distance l between each following robot and the pilot robot so that it is controlled in a certain range, the second part is $U_{i,j}^{\varphi}$, the role of the potential field is to control the angle between each following robot and the pilot robot.

Where $U_{i,j}^{l}$ can be expressed as follows.

$$U_{i,j}^{l} = A\left(\frac{(L^d)^2}{\|r_{ij}\|^2} + \log\|r_{ij}\|^2\right) \tag{46}$$

where i is the pilot robot, j is the follower robot, r_{ij} is the distance between them, L^d is the expected distance between them, A is the gain coefficient, $A = 0.5$ according to experience in this paper.

The potential field force function for the relative distance l between the pilot robot and the following robot can be expressed as follows.

$$\nabla U_{ij}^{l} = \frac{\partial U_{ij}^{l}}{\partial r_{ij}} A\left(-\frac{2L^d}{\|r_{ij}\|^3} + \frac{2}{\|r_{ij}\|}\right) \tag{47}$$

The potential field function $U_{i,j}^{\varphi}$ is expressed as the following equation.

$$U_{i,j}^{\varphi} = B\left(\frac{(\Phi^d)^2}{\|\varphi_{ij}\|^2} + \log\|\varphi_{ij}\|^2\right) \tag{48}$$

where φ_{ij} is the actual relative Angle between the pilot robot and the follower, Φ^d is the expected Angle between them, and B is the gain coefficient. According to experience, $B = 0.5$.

The potential field force function with respect to the relative angle φ between the pilot robot and the following robot can be expressed as follows.

$$\nabla U_{ij}^{\varphi} = \frac{\partial U_{ij}^{\varphi}}{\partial \varphi_{ij}} B\left(-\frac{2\Phi^d}{\|\varphi_{ij}\|^3} + \frac{2}{\|\varphi_{ij}\|}\right) \tag{49}$$

It follows that the total potential field function that can control the entire multi-robot formation is modeled by the following equation.

$$\begin{aligned} U_{ij}^{l\varphi} &= U_{i,j}^{l} + U_{ij}^{\varphi} \\ &= A\left(\frac{(L^d)^2}{\|r_{ij}\|^2} + \log\|r_{ij}\|^2\right) + B\left(\frac{(\Phi^d)^2}{\|\varphi_{ij}\|^2} + \log\|\varphi_{ij}\|^2\right) \end{aligned} \tag{50}$$

Then the total potential field force function for the whole multi-robot formation is modeled by the following equation.

$$\begin{aligned} F_{ij}^{l\varphi} &= \nabla U_{ij}^{l\varphi} \\ &= A\left(-\frac{2L^d}{\|r_{ij}\|^3} + \frac{2}{\|r_{ij}\|}\right) + B\left(-\frac{2\Phi^d}{\|\varphi_{ij}\|^3} + \frac{2}{\|\varphi_{ij}\|}\right) \end{aligned} \tag{51}$$

According to the artificial potential field function model constructed above for the pilot robot and its following robots, the relative distance A and relative angle B can be adjusted according to the requirements of the actual task to prevent the robots in the robot formation from being too scattered during the movement and thus maintain a certain formation, as shown in Figure 13.

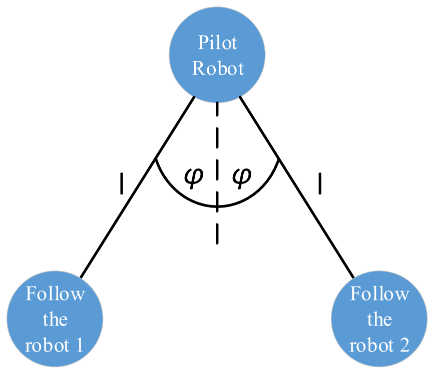

FIGURE 13. **Schematic diagram of robot formation control.**

3) DESIGN OF OBSTACLE AVOIDANCE STRATEGY FOR FOLLOWED ROBOTS

When the robot formation encounters an obstacle during the movement, the follower robot will recognize the obstacle within the visual range, and then adjust the relative angle between itself and the pilot robot and keep the relative distance constant to avoid the obstacle, as shown in Figure 14.

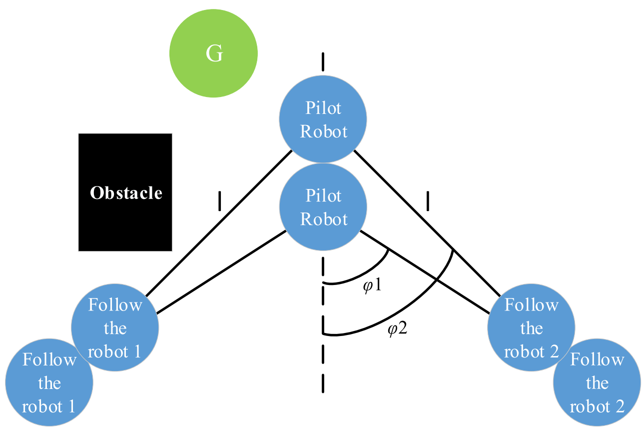

FIGURE 14. **Follower robots obstacle avoidance process diagram.**

Due to the active obstacle avoidance strategy, the length of the distance between the follower robot and the obstacles it can recognize has an impact on the relative angle between the follower robot and the navigator robot and is therefore defined as follows.

$$\varphi = \begin{cases} \Phi^d & \rho \geq \rho_0 \\ \Phi^d \times \dfrac{\log(20\rho)}{\log(20\rho_0)} & \rho < \rho_0 \end{cases} \tag{52}$$

As the value of ρ gradually increases, the size of φ also gradually expands. When ρ increases to ρ_0, the expected Angle Φ^d between the follower robot and the pilot robot will be maintained. On the contrary, when ρ gradually shrinks from ρ_0, the follower robot will gradually narrow its relative angle with the pilot robot, thus avoiding obstacles.

V. HYBRID PATH PLANNING DESIGN FOR MULTI-ROBOT FORMATIONS CONSIDERING OBSTACLE AVOIDANCE

The improved particle swarm optimization (IPSO) algorithm proposed in this paper has good performance in the global path planning of robots with known environmental information and can find the best moving path for a robot in a short time. However, in the actual working environment, since the working environment is not all known, there may be some temporary stacked obstacles blocking the robot's moving path, resulting in the failure of path planning or even the possibility of collision with obstacles. Therefore, when using a single IPSO algorithm to plan the robot's moving path, there are certain limitations in a complex working environment, and it may not be able to complete the assigned moving task.

The improved artificial potential field method proposed in this paper has good application effects in the local path planning of the robot, so that the robot can avoid static or moving obstacles in the process of moving. However, the artificial potential field method is a kind of local path planning algorithm. In the local obstacle avoidance range, it has unique advantages, but also some limitations. The artificial potential field method cannot efficiently control the overall working environment, resulting in low efficiency in path planning and the easy failure of path planning. At present, robots are widely used in enterprise storage or logistics workshops, where they can replace manpower to carry goods efficiently. However, in the process of performing some complex handling tasks, the handling capacity of a single robot cannot meet the task needs, and multiple robots must be relied on to cooperate to complete the handling task. Therefore, it is necessary to study the formation of multi-robot formation and cooperative control technology.

Analysis by the above knowable, single algorithm in the complex environment is unable to play its some advantages, and multi-robot cooperation can meet the demand for higher handling. Therefore, this paper proposes a multi-robot formation work environment information known to the global path planning and the environment of the unknown local path planning mixed path planning method of combining. In addition, the formation of multiple robots can keep a certain formation, avoid temporary obstacles in the environment during driving, and ensure that there is no collision between each robot.

The hybrid path planning for robot formation can be divided into two parts, firstly, the robot formation control method proposed in this paper is used to construct a multi-robot formation, and secondly, the IPSO algorithm proposed in this paper is used to plan a moving path for the navigator robot from the starting point to the endpoint, based on this path, a local path is obtained by using the improved artificial potential field method proposed in this paper to Avoid static or dynamic obstacles that appear in the process, the follower robot will follow the path of the pilot robot to move, and will adjust the angle between each other to avoid obstacles encountered, as well as to avoid collision between each other, until the movement to the endpoint, to complete the task of handling, the algorithms and methods mentioned above are described and studied in detail in the previous paper, so we will study how to design a The hybrid path planning algorithm for robot formation will be investigated in the following steps, The flow of hybrid path planning algorithm is shown in Figure 15.

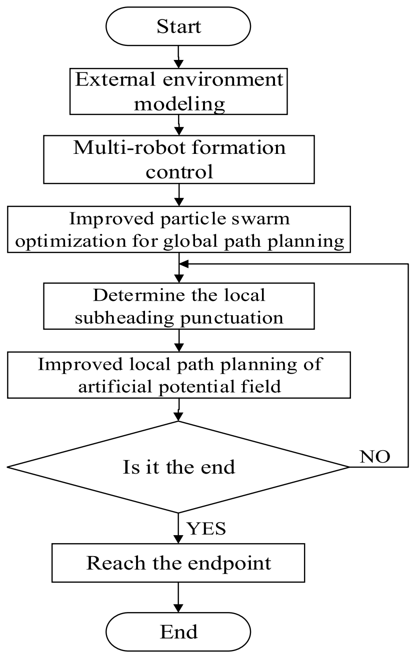

FIGURE 15. **Hybrid path planning algorithm flow.**

Step 1: Global static environmental information is collected using sensors and radar devices carried by the robot formations themselves and human-aided measurements, and a geometric model is applied to construct an environmental map.

Step 2: Formation control of multiple robots using the robot formation control method based on the pilot-following method and the artificial potential field method proposed in this paper.

Step 3: Use the improved particle swarm algorithm for global path planning to find an optimal path from the starting point to the target point.

Step 4: Iterate through the global optimal path generated by Step 3 and identify each inflection point in the global optimal path.

Step 5: At the same time, from the beginning of each inflection point, the pilot robot will apply the improved posterior potential field method for local path planning, while the follower robot will follow the path of the pilot robot and maintain a certain distance and angle with it, and the whole multi-robot formation will maintain a certain formation, and in the process of moving the whole robot formation, it will actively avoid the encountered The entire multi-robot formation will maintain a certain formation, and during the movement of the entire formation, it will actively avoid obstacles and avoid collision between robots.

Step 6: Judge whether the current local path planning sub-target point is the original target point, if not then the robot formation reaches the sub-target point, return to step 4, the next sub-target point is the original target point continue to apply the improved artificial potential field method for path planning if the sub-target point is the original target point then complete the robot formation path planning task.

VI. SIMULATION ANALYSIS

A. SIMULATION ANALYSIS OF ROBOT GLOBAL PATH PLANNING BASED ON IMPROVED PARTICLE SWARM ALGORITHM

To verify that the improved particle swarm algorithm proposed in this paper has strong optimization performance, the basic particle swarm algorithm (Particle Swarm Optimization, PSO), the population variation-based particle swarm algorithm (Mutation Particle Swarm Optimization, MPSO) and the improved particle swarm algorithm (Improved Particle Swarm Optimization, IPSO) in this paper are selected to conduct simulation comparison experiments and analysis in two maps with different complexity. Improved Particle Swarm Optimization (IPSO) in two maps with different complexity to carry out simulation comparison experiments and analysis.

Keeping the population size and the number of iterations of the above algorithm the same, $n = 50$; $k_{\max} = 200$. In the standard PSO algorithm, c_1 and c_2 affect the importance of individual particle experience and population experience, respectively, both of which have an important influence on the particle search process, so the values of both are generally set to the same value i.e., $c_1 = c_2 = 1.5$. In the standard PSO algorithm with MPSO $\omega = 0.5$, while In this paper, we will use the proposed adaptive variation weights to automatically adjust the value of ω. The refined search coefficient δ in MPSO is 0.056 and the variation threshold p_t is taken as 0.8.

Figure 16, Figure 17, and Figure 18 show the search results of the movement path planning for the robot using the PSO algorithm, MPSO algorithm, and IPSO algorithm proposed in this paper in Environment Map.

From Figure 16, Figure 17, and Figure 18, it can be seen that when the basic PSO algorithm is applied to the robot for path planning in map environment 1, the length of the moving path is longer than the other two algorithms, which proves that the PSO algorithm is caught in local extremes in the process of pathfinding and does not search for the global optimal solution or a solution closer to the global optimal solution, and the moving path is too long, causing The robot's travel time and energy consumption are too long, which indicates that the basic PSO algorithm is not outstanding in terms

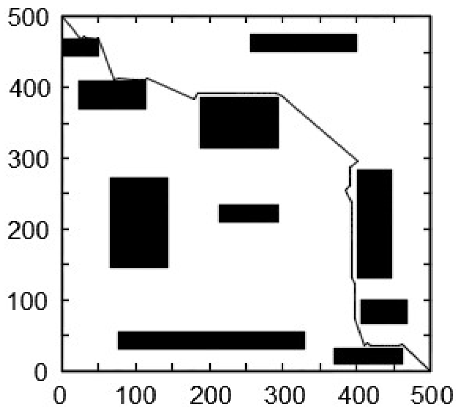

FIGURE 16. PSO algorithm path planning in 500 × 500 map environment 1.

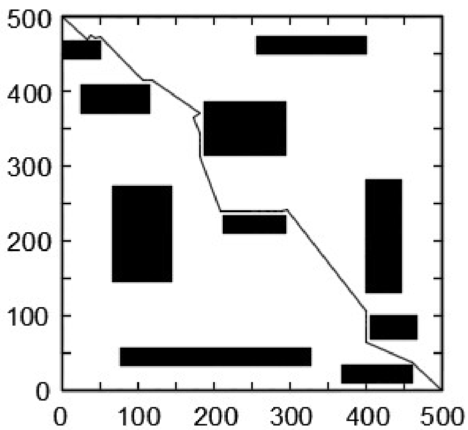

FIGURE 17. MPSO algorithm path planning in 500 × 500 map environment.

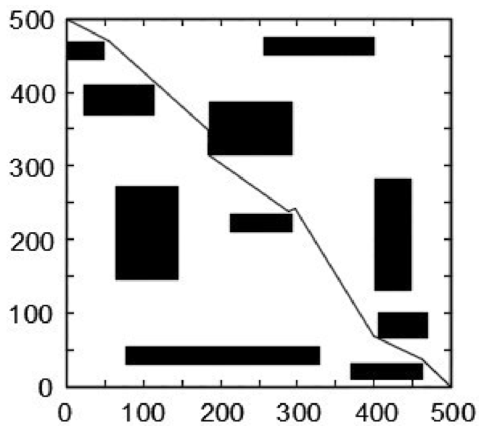

FIGURE 18. IPSO algorithm path planning in 500 × 500 map environment.

of its ability to find the optimal solution and needs to be improved and optimized. When the MPSO algorithm is used to plan the robot's path, the length of the path is slightly shorter than that of the basic PSO algorithm, and the overall pathfinding ability of this algorithm is stronger than that of the basic PSO algorithm. When the IPSO algorithm is applied to pathfinding, the quality of the paths obtained is much better than the other two algorithms, and the paths obtained using the IPSO algorithm are much smaller than those obtained by the basic PSO algorithm in terms of the length of the moving paths. It shows that the IPSO algorithm proposed in this paper has good performance in robot pathfinding.

The iterative convergence curves of the algorithms when using the above three algorithms for path planning of the robot in the same map environment respectively are shown in Figure 19.

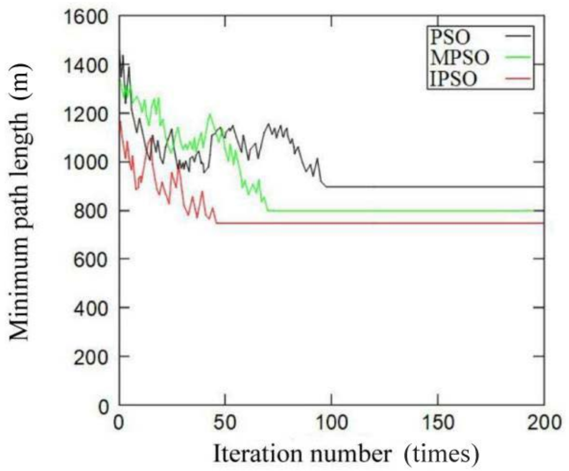

FIGURE 19. Iterative curves of three algorithms in environment 1.

From Figure 19, it can be seen that the convergence curve obtained by applying the basic PSO algorithm to the robot path planning problem has more iterations and the shortest robot path when the curve converges compared with the MPSO algorithm and the IPSO algorithm proposed in this paper, which proves that the basic PSO algorithm has some limitations in solving the robot path planning problem. The convergence curve of the MPSO algorithm has a certain degree of advantage over the basic PSO algorithm, and the number of iterations used for convergence is less than that of the basic PSO algorithm, and the length of the shortest robot path is shorter than that of the basic PSO algorithm, which proves that the robot path planning performance of the MPSO algorithm is somewhat improved compared with that of the basic PSO algorithm. It is proved that the robot path planning performance of the MPSO algorithm is improved to a certain extent compared with that of the basic PSO algorithm. The iteration curve of the algorithm obtained by applying the IPSO algorithm proposed in this paper to robot path planning has the least number of algorithm iterations when converging, and the shortest moving path of the robot is also the shortest among the three, so the IPSO algorithm proposed in this paper has a strong robot pathfinding ability. More detailed comparison results and data of the three algorithm simulation experiments are shown in Table 2.

TABLE 2. Comparison of simulation results of three PSO in environment one.

	Shortest path length/cm	Running time /s	Optimal number of iterations
PSO	892.13	5.4	97
MPSO	801.54	3.8	70
IPSO	737.31	2.5	46

As can be seen from Table 2, the shortest path length, the running time and the optimal number of iterations for convergence of the IPSO algorithm are better than those of the PSO and MPSO algorithms when the IPSO algorithm is applied to the robot for path planning. In addition, the search efficiency of the IPSO algorithm is 52.6% and 34.3% higher than that of the PSO and MPSO algorithms, respectively. The search time of the IPSO algorithm is 53.7% and 34.2% shorter than that of the MPSO algorithm and PSO algorithm. Therefore, the IPSO algorithm proposed in this paper has strong robot path-finding performance.

To verify the path planning capability of the improved particle swarm algorithm in more complex situations in this paper, the PSO algorithm, MPSO algorithm, and the IPSO algorithm proposed in this paper were used to plan the mobile path of the robot in the map environment II with higher complexity, as shown in Figure 20, Figure 21 and Figure 22.

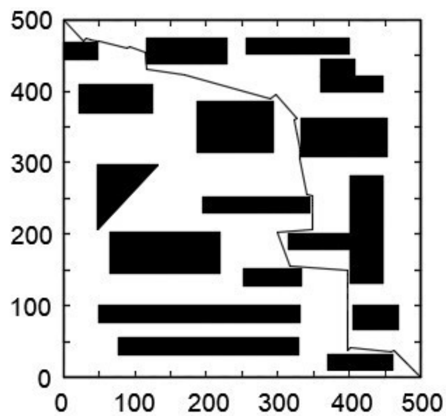

FIGURE 20. PSO algorithm path planning in 500 × 500 map environment 2.

From Figure 20, Figure 21, and Figure 22, it can be seen that when the basic PSO algorithm is used for path planning of the robot in Map 2, the length of the mobile path obtained is still the longest among the three algorithms, and the algorithm falls into local extremes in the process of finding the optimal value and does not search for the vicinity of the global optimal solution, indicating that the pathfinding ability of the basic

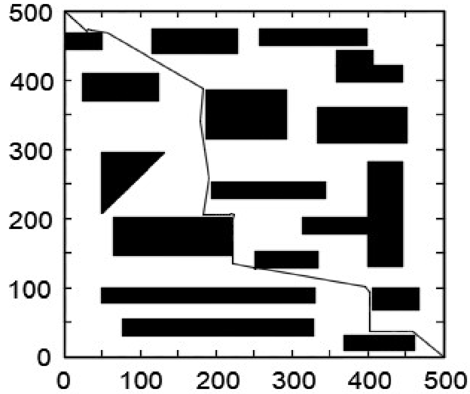

FIGURE 21. MPSO algorithm path planning in 500 × 500 map environment.

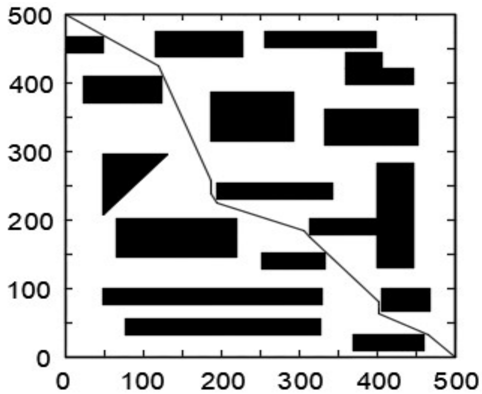

FIGURE 22. IPSO algorithm path planning in 500 × 500 map environment.

PSO algorithm is not outstanding. In addition, when the path planning is performed using the MPSO algorithm, the mobile path length of its robot is shorter than that using the basic PSO algorithm, indicating that its path quality is higher than that of the mobile path obtained by the MPSO algorithm. However, the mobile path obtained by using the IPSO algorithm proposed in this paper is the shortest among the three, which proves that the IPSO algorithm proposed in this paper has a stronger path-finding ability compared with the other two algorithms.

The convergence curves of the algorithm iterations for path planning using the three algorithms in Environment II are shown in Figure 23.

It can be seen from Figure 23 that the convergence speed of the iterative curve of the basic PSO algorithm is the slowest, and the shortest moving path of the robot obtained by the convergence is the longest among the three algorithms. Although the MPSO algorithm with the shortest path length in the convergence speed than the basic PSO algorithm was promoted, the proposed IPSO algorithm has a faster convergence rate compared with that, and the minimum path length is shorter, showing that the proposed IPSO algorithm for robot path planning optimization ability is more outstanding. The comparison results and data of the three algorithms are shown in Table 3.

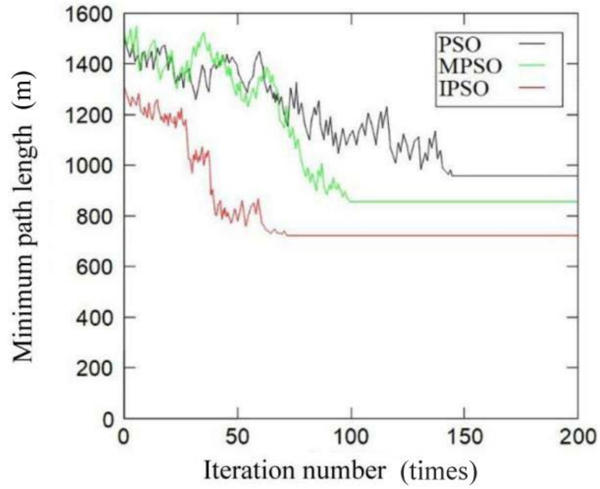

FIGURE 23. Iterative curve of three algorithms in environment 2.

TABLE 3. Comparison of simulation results of three PSO in environment two.

	Shortest path length/cm	Running time /s	Optimal number of iterations
PSO	968.91	9.2	144
MPSO	874.03	7.1	99
IPSO	753.03	4.9	72

As can be seen from Table 3, the robot pathfinding performance of the IPSO algorithm proposed in this paper is the best among the three algorithms, in which the mobile path length is 22.2% and 13.9% shorter than that of the applied PSO and MPSO algorithms, respectively, and the algorithm running time is 46.7% and 31.0% less than that of the applied PSO and MPSO algorithms, respectively, and the mobile The path search efficiency is 50% and 31.3% higher than that of the PSO and MPSO algorithms, respectively. Therefore, the IPSO algorithm proposed in this paper has good results when applied to robot path planning.

B. SIMULATION ANALYSIS OF LOCAL PATH PLANNING FOR MULTI-ROBOT FORMATIONS BASED ON IMPROVED ARTIFICIAL POTENTIAL FIELD METHOD

1) SIMULATION ANALYSIS OF SINGLE ROBOT FORMATION CONTROL AND OBSTACLE AVOIDANCE

Based on the improvement strategy and the process of algorithm simulation proposed for the problems of the basic artificial potential field method, two different working environments are configured under 2.20-GHz PC, 8GB RAM, Windows 10, 64-bit operating system environment using MATLAB 2018a software, and dynamic obstacles as well as static obstacles are added to them at the same time to conduct simulation comparison tests to verify the effectiveness of the

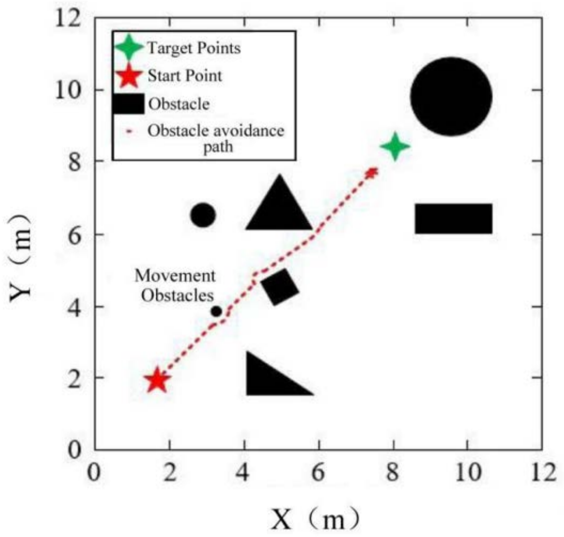

FIGURE 24. Path planning of basic artificial potential field method in environment 1.

improved artificial potential field method proposed in this paper.

(1) In Environment 1, the basic artificial potential field method and the improved artificial potential field method of this paper are used to plan the robot's moving path respectively, and the simulation results are shown in Figure 24 and Figure 25.

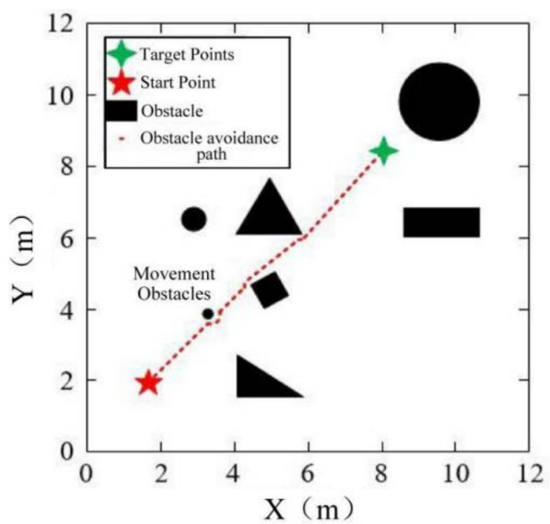

FIGURE 25. Improved artificial potential field method for path planning in environment 1.

As can be seen from Figure 24, the basic artificial potential field method was used to plan the robot movement path in the environment 1. In the initial stage, the robot successfully evaded the moving obstacles when it detected them and successfully avoided the encountered obstacles, however, the target unreachability problem occurred at the upcoming end point and produced an oscillating wandering movement, resulting in the path planning failure.

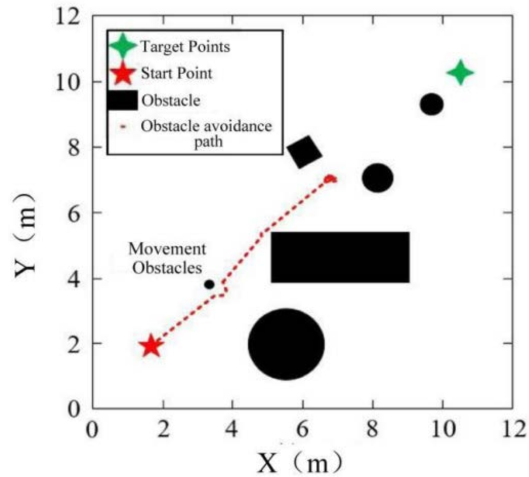

FIGURE 26. Path planning of basic artificial potential field method in environment 2.

In Figure 25, when the improved artificial potential field method is used to plan the robot's moving path, it also successfully avoids the moving obstacles in the initial stage and smoothly avoids the obstacles on the moving path, in addition, no target unreachability problem occurs during this period, and it successfully moves to the target point, which proves that the improved artificial potential field method proposed in this paper has good obstacle avoidance and path planning performance, and can effectively avoid dynamic and static obstacles.

(2) To further verify the improvement effect of the basic artificial potential field method, the results of the robot path planning by applying the basic artificial potential field method and the improved artificial potential field method in Environment 2 are shown in Figure 26 and Figure 27.

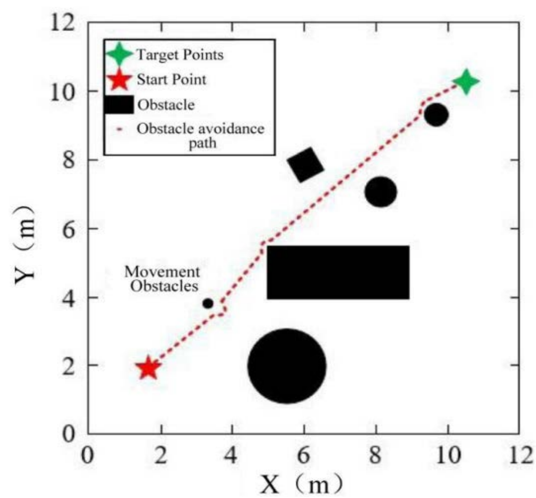

FIGURE 27. Improved artificial potential field method for path planning in environment 2.

As can be seen from Figure 26, in environment 2, the basic artificial potential field method was used to plan the robot's moving path, and when the robot recognized the moving obstacle, it successfully avoided it, however, when the robot continued to move, it fell into the local minima and could not continue to move toward the target point, leading to the failure of path planning. As shown in Figure 27, the improved artificial potential field method introduced by the simulated annealing algorithm in this paper successfully avoids the local minima and enables the robot to move smoothly to the target point. Therefore, the improved artificial potential field method proposed in this paper has good path planning and obstacle avoidance performance.

In the environment, the improved particle swarm optimization algorithm, the improved artificial potential field method and the hybrid path planning algorithm proposed in this paper are respectively applied to conduct path planning simulation experiments for a single robot. The results are shown in Figure 28, Figure 29 and Figure 30.

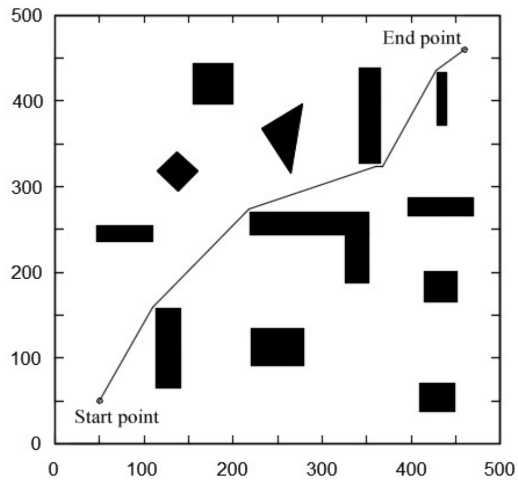

FIGURE 28. Improved particle swarm optimization for path planning in 500 × 500 map.

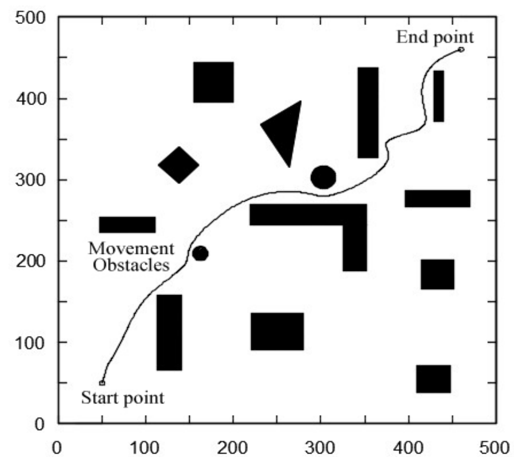

FIGURE 29. Improved artificial potential field method path planning in 500 × 500 map.

Figure 28 shows that temporary obstacles in the environment can be ignored by using improved PSO to mobile robot path planning. The improved particle swarm algorithm can

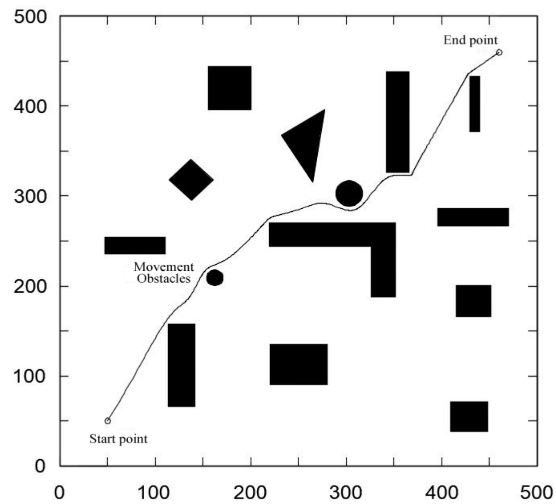

FIGURE 30. Hybrid algorithm path planning in 500 × 500 map.

search for a very high quality mobile path from start to finish, and the path to the turning point is relatively smooth, but if the robot follows this path, there will be a collision with temporary obstacles in the environment, resulting in the occurrence of danger.

In Figure 29, adopting the improved artificial potential field method for robot path planning operation, can effectively avoid the environmental obstacles existing in the interim, making it to the target, but the overall path length is compared with using an improved particle swarm algorithm to get the moving path longer and bending. This increases the working time and reduces work efficiency.

In Figure 30, this paper designed a mixture of path planning algorithms for robot path planning. Fusion can effectively improve the particle swarm algorithm and the improved artificial potential field method. The advantages of the guarantee of the shorter path from start to finish at the same time can effectively avoid the environment map's temporary obstacles. Therefore, the hybrid path planning algorithm proposed in this paper has excellent performance.

2) SIMULATION ANALYSIS OF MULTI-ROBOT FORMATION CONTROL AND OBSTACLE AVOIDANCE

Following the algorithm and parameter settings designed in the previous section, a rectangular map with a map size of 500 × 500 is created using MATLAB 2018a software in a 2.20-GHz PC, 8 GB RAM, Windows 10, 64-bit operating system environment. The starting coordinates of the leader robot 1 are set to (60, 60) and the ending coordinates are set to (450, 450). The starting coordinates of the follower robot 2 are (0, 60) and the starting coordinates of the follower robot 3 are (60, 0) with $L^d = 60$m and $\Phi^d = \pi/4$. The simulation results are shown in Figure 31.

In Figure 31, the three robots start moving from the starting point and encounter obstacles in motion on the moving path of robot 2. By adjusting the angle between itself and the

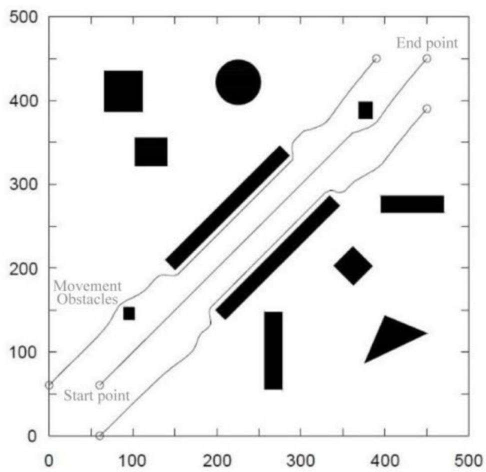

FIGURE 31. Robot formation obstacle avoidance simulation in 500 × 500 map.

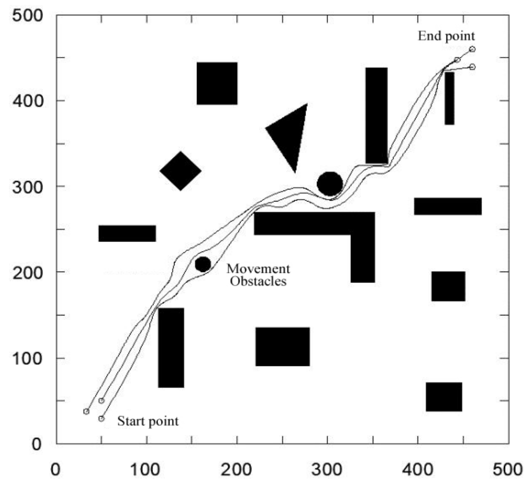

FIGURE 32. Hybrid algorithm for robot formation path planning in 500 × 500 map.

navigator robot 1, the obstacle avoidance operation is completed, demonstrating the effectiveness of the active obstacle avoidance strategy of the follower robot. Robot 3 was also deflected by an angle due to the need to maintain the formation of the robot formation. After robot 2 successfully avoided the obstacle, the robot formation re-tended to maintain the L^d and Φ^d movements. Subsequently, the robot formation was driven into a channel with obstacles on both sides of the moving path, and the follower robot 2 and the follower robot 3 again adjusted the angle between themselves and the navigator robot 1, and the three robots successfully drove into the narrow channel. When the three robots pass the narrow passage smoothly, the follower robot 2 and the follower robot 3 adjust the angle between themselves and the navigator robot 1, and the robot formation re-tends to maintain the L^d and Φ^d movements. When pilot robot 1 encountered an obstacle, its position deviated from the established trajectory and changed significantly when the pilot robot 1 performed the obstacle avoidance operation, and the angle of the moving direction of the follower robot 2 and the follower robot 3 was adjusted accordingly to maintain the formation. When the navigator robot 1 successfully avoided the obstacle, it continued to move toward the endpoint. Finally, the pilot robot successfully reached the endpoint, and the two follower robots reached the designated position with the position state of $L^d = 60$m and $\Phi^d = \pi/4$, which verified the effectiveness of the obstacle avoidance strategy.

In the same environment, the simulation experiment and analysis of the hybrid algorithm for multi-robot formation control and path planning are carried out. The robot in the middle is the pilot, and the follower robot 1 and follower robot 2 are located on the left and right sides of the pilot respectively. The path planning simulation of the entire robot formation is shown in Figure 32.

In Figure 32, the hybrid path planning algorithm proposed in this paper is combined with the cooperative control method of robot formation based on the improved artificial potential field method and the piloting and following method. The robot formation can smoothly travel from the starting point to the end point and avoid dynamic and static obstacles that occasionally appear on the road.

In the initial stage, the robot 2 encountered obstacles, so the robot 2 adjusted itself and the relative angle and distance between the leading robot and the following robot in order to achieve the purpose of avoiding obstacles. The robot formation in order to maintain the whole fleet formation, the follower robot 2 also made the same adjustment, achieving the goal of keeping the formation relatively stable.

When the formation is successful in avoiding the obstacles, it will return to the original formation when it passes the circle in front of the pilot robot. The obstacle avoidance robot and two follower robots, in order to maintain the stability of the formation, also make the corresponding adjustments when avoiding the obstacles and tending to the original mobile robot formation.

When the robot formation moved to the middle of the map, it adjusted the relative angle and distance between itself and the pilot robot in order to avoid the obstacle, successfully avoiding the obstacle, and the follower robot also made a corresponding adjustment. Finally, the robot formation successfully moved to the target point and kept the same formation as the starting point, which proved the effectiveness of the robot formation hybrid path planning algorithm designed in this paper.

C. CASE VALIDATION ANALYSIS

Company A is a machinery and equipment manufacturer headquartered in a coastal city in eastern China. The company's products include transmission equipment and mechanical components, which are widely used in various machinery and equipment, such as industrial robots, medical machinery, industrial machine tools, cranes, and so on. While the company's scale and business scope are expanding, company A

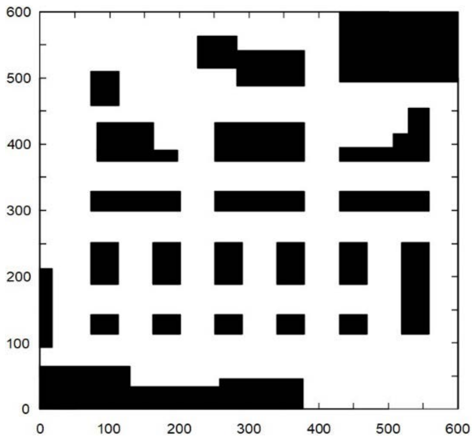

FIGURE 33. Warehouse map modeling of a company in 600 × 600 map.

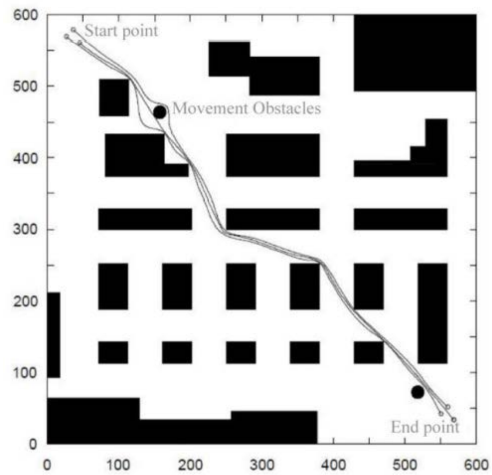

FIGURE 34. Hybrid algorithm robot formation path planning in 600 × 600 map.

is also gradually promoting the application of digitalization and automation technology in all aspects of the company's production and logistics, transforming from a traditional machinery and equipment manufacturer to a fully intelligent manufacturing enterprise.

Company A's internal warehouse is an important part of the company's production and logistics, and there are a lot of production materials and finished products transportation. Most of the products in the warehouse transportation process are using the manual operation of handling machines to complete the task, not to achieve intelligent handling resulting in the handling path is not the shortest and causing a waste of time. In addition, there are some serious safety hazards in the actual work of workers, which may cut against other equipment in the warehouse. Therefore, to improve the efficiency of the company's internal warehouse operation and avoid the occurrence of danger, the company's senior management decided to use intelligent robots to replace manual work.

This section uses the geometric model map modeling method to model the map of the company's warehouse, set obstacles, and configure environmental information according to the layout of this warehouse and the location and size of mechanical equipment, shelves, and other equipment in the warehouse, as shown in Figure 33.

To verify the practical application performance of the formation control method and path planning method for multi-robot formations, a robot formation consisting of three robots is set up and its starting position and end position are set using the robot formation method proposed in this paper. The starting position of the pilot robot is (45, 560) and the ending position is (568, 33), the starting position of the follower robot 1 is (26, 569), and the starting position of the follower robot 2 is (36, 579), where the black object is a known obstacle and the black circular object is a temporary obstacle. The multi-robot formation control and hybrid path planning method proposed in this chapter is used to construct multi-robot formations and perform path planning, and the simulation results are shown in Figure 34.

As can be seen from Figure 34, when the hybrid path planning algorithm proposed in this paper is applied to the robot for path planning in the warehouse of company A, it moves smoothly from the starting point to the target point, and can effectively avoid the static obstacles and dynamic obstacles encountered in the driving process, and ensures that the moving path is shorter and the moving path is smoother, which fully reflects the superiority of the hybrid path planning algorithm and ensures the, Therefore, the hybrid path planning algorithm proposed in this paper has certain feasibility and effectiveness when applied to the path planning of multi-robot formation.

VII. CONCLUSION

Based on the in-depth analysis of the current situation of robot, autonomous obstacle avoidance, formation and cooperative control and path planning research at home and abroad, this paper designs a hybrid path planning model of robot formation based on improved particle swarm algorithm and improved artificial potential field method, and shows through simulation experimental results that while avoiding obstacles, it can effectively keep the robot formation in a certain formation and improve transportation efficiency. The research conclusions are as follows.

(1) To improve the search capability of the basic particle swarm algorithm applied to robot global path planning, adaptive change weight rules are proposed to expand the search range of the algorithm while improving the local search capability of the algorithm; in addition, improvements are made to the particle position update formula of the particle swarm algorithm, and genetic algorithms are introduced to expand the population range and improve the possibility of the algorithm to find the optimal solution. The simulation results prove the superiority and effectiveness of the improved particle swarm algorithm.

(2) The repulsive field of the basic artificial potential field method is optimized for the unreachable target problem of

the basic artificial potential field method for robot local path planning, and the simulated annealing algorithm is introduced for the problem that the basic artificial potential field method is easy to fall into the local minima in some cases to jump out of the local minima position and make the robot drive to the target point smoothly. To verify the superiority of the improved basic artificial potential field method for robot path planning, simulation comparison experiments are conducted in two different maps, and the results show that the improved artificial potential field method has stronger path planning performance.

(3) The artificial potential field function of the pilot robot, the artificial potential field function of the follower robot, the control scheme of the robot formation, the obstacle avoidance strategy of the follower robot, and the collision avoidance strategy among the follower robots are designed based on the improved artificial potential field method and the pilot-follower method, so that the robot formation can effectively avoid the obstacles and maintain a certain formation during the moving process.

(4) Construct a multi-robot formation using the robot formation control method proposed in this paper, and then use the improved particle swarm algorithm proposed in this paper to plan a moving path for the navigator robot from the starting point to the target point, and the navigator robot applies the improved artificial potential field method for path planning, and the followers will move according to the trajectory of the navigator robot, and the whole robot formation will avoid the obstacles encountered in the process The whole robot formation will avoid the obstacles encountered in the process, and prevent the collision between robots while maintaining a certain formation. From the simulation results, it can be seen that the proposed cooperative control path planning algorithm for robot formation has good performance.

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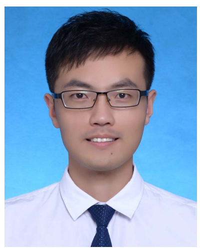

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