Power Inspection Robot Dog Inspection Line Planning and Autonomous Navigation Strategy

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Abstract: *Power inspection is crucial to ensure a stable power system. Manual inspection is time-consuming and prone to errors, so intelligent methods like machine inspection greatly improve efficiency and accuracy. However, machine inspection faces challenges in path planning due to unexpected situations. To address this, a hybrid path planning algorithm that combines improved ant colony and dynamic window methods is proposed. Implemented in a power inspection robot dog, the algorithm enhances inspection efficiency. Simulation results demonstrate its advantages in both single-task and multi-task global path planning, reducing path length, turning nodes, iterations, and running time. Local path planning experiments show successful obstacle avoidance. The practical application of the robot dog confirms its ability to navigate around basic and complex obstacles. Overall, the proposed method has good applicability to power inspection robot dog's path planning and navigation.*

Keywords: *Power inspection, a robot dog, improved ant colony algorithm, improved dynamic window method, global path planning, local path planning.*

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1. Introduction

With the continuous progress of national economy, electricity is becoming more and more important in people's daily social production activities. As the demand for electricity continues to rise, its reliability and security are becoming increasingly important concerns. Therefore, to ensure the safe and stable operation of substation, power inspection is essential. Traditional power inspection is often carried out manually, that is, staff regularly inspect the equipment of the substation [2]. This strategy relies heavily on the work experience of the inspector, which is most likely to lead to misdetection (misjudging normal equipment as faulty equipment), omission (failure to detect actual faults) or low detection efficiency, and it has been unable to meet the current social demand for stable operation of power [5]. Intelligent technology has brought new opportunities for power inspection work, with unmanned and automated inspection methods significantly improving inspection efficiency and effectively reducing the probability of false positives and false negatives. Compared to traditional inspection methods that rely on manual experience, intelligent inspection robot dogs, as an advanced technological means, have played an important role in ensuring the safe and stable operation of substations, meeting the higher requirements of modern society for power reliability and safety [7]. It inspects and monitors of power equipment and improves the quality and efficiency of inspection [15]. In addition to planning the inspection path and conducting fixed-point docking detection and data collection for all the equipment to be detected in the substation, the inspection robot dog also needs to deal with various emergencies in the substation, which has adverse effects on the accurate path planning of the robot dog [26].

Currently, the inspection route planning method for robot dogs still has great defects, which makes it difficult for robots to successfully complete the inspection task under complex terrain conditions. In view of this, this paper proposed a global path planning model based on Ant Colony Optimization (ACO) and a local path planning algorithm based on improved Dynamic Window Approach (DWA). And it is applied to the path planning process of power inspection of robot dog.

The innovation of this paper lies in the innovative combination of the Improved Ant Colony Algorithm (IACO) and DWA to construct a hybrid path planning method based on IACO-DWA, which improves the path planning performance of inspection robot dogs in complex environments from both global and local perspectives. The contribution of this study is as follows:

1) The traditional ACO is optimized to improve its shortcomings such as slow convergence speed and long search time, and a global path planning method based on IACO is proposed.
2) Optimize DWA, introduce target distance, improve its evaluation function, and form a local path planning algorithm based on DWA.
3) Combining IACO and DWA, a hybrid path planning method based on IACO-DWA is constructed.

The remainder of this paper is organized as follows: in section 2 the related work is presented, which mainly introduces the study status of robot dog and power inspection, laying a theoretical foundation for this paper. In section 3 the core research method is presented, mainly introduces the hybrid path planning method based on ACO-DWA and its application strategy in the power inspection robot dog. In section 4, the proposed method is simulated to verify its superior performance. In section 5 the summary part is presented, which summarizes the content of the full text and looks forward to the future research direction.

2. Related Work

Robot dogs have different applications in different occasions, and the functions they have can respond to different needs. Many researchers have discussed this. Shao *et al*. [25] applied four-legged robotic dogs to distance estimation for position estimation. In the experiment, the motion state of the robot dog was evaluated by the invariant extended Kalman filter, and the compensation angular velocity was introduced to optimize it, so as to determine the sensing state of the robot dog more accurately. Within the set speed range, the proposed method could enable the robot dog to better control the error of position estimation accuracy [25]. To solve the intractable problem that the number of guide dogs was lower than the actual demand, Chen and Tsui [3] and other researchers proposed to apply robot dogs to this field. Intelligent robot dogs had good motion control ability, but the four-legged design of robot dogs increased the complexity of motion control. Therefore, this paper also introduced a fuzzy control method to optimize the control performance of the four-legged robot dog. This method had strong practical value. Chen *et al*. [4] and other scholars also built an AI-based robot dog framework from the guide function of the robot dog. The framework utilized Intel UP square boards and neural computing rods to detect moving objects in the environment through a single-shot detector. The proposed model could realize the voice communication between the visually impaired and the robot dog, and could successfully process the scene information of the traffic intersection to safely guide the blind to travel. Nagy and Korondi [21] and other researchers conducted research on the behavior control module of robot dogs, and proposed a behavior transfer system to simulate the behavior pattern of dogs. The system combined iSpace's measurement system and deep learning prediction algorithms to robustly collect data and predict dog behavior patterns, respectively. The neural network in the system could analyze and measure different movement postures of dogs with high accuracy. Jim's team proposed an automated 3D reconstruction of scaffolding using robotic dogs to intelligently monitor the robustness of scaffolding in construction projects. The proposed method firstly used the robot dog scanning system to obtain the scaffold point cloud data, and then used the deep learning method to carry out 3D semantic segmentation. The proposed method showed excellent performance in the field of point cloud segmentation [13]. Hong *et al*. [10] reviewed the application status of robot dogs in the field of guide for the blind and summarized relevant views. In this paper, guide robot dogs were divided into scenario-specific and scenario-general types, and their different behavior patterns in different scenarios were summarized. This paper summarized the current limitations and laid a foundation for future research directions.

Recently, power inspection methods are becoming more intelligent, which is an effective result of many scholars' joint efforts. Nekovář *et al*. [22] proposed a new power inspection scheme and applied it to the inspection of the best transmission lines. The scheme consisted of multiple runs to provide complete coverage of a given power line. The scheme was constructed based on integer linear programming formula and combinatorial element heuristic. The proposed method could effectively detect the power line segment of the substation in the actual scenario, and had practical significance. From the perspective of UAV power inspection, Pan *et al*. [23] carried out research on its route planning. A Golden Eagle optimization model combining dual learning strategies was proposed to help UAV obtain more efficient and feasible paths during inspection. The proposed strategy enhanced the searching ability of the model and sped up the convergence rate, improving the overall optimization accuracy. The final path planning results showed that the proposed model had good path generation performance. Luo *et al*. [17] reviewed the research on UAV-based transmission line inspection. This paper discussed the origin and development of intelligent power inspection in detail, and summarized the relevant research on the process and path planning of intelligent power inspection for transmission lines. This paper summarized the challenges faced by intelligent power inspection and laid a cornerstone for future research. Zheng *et al*. [30] and other researchers explored the new mode of collaborative power inspection between drones and operational vehicles, and proposed the task assignment model and path planning strategy under this mode. K-Means algorithm and GA algorithm were applied to handle the proposed model, and the calculation results showed that the model was practical and feasible in power inspection task allocation. The

Santos *et al*. [24] team built a rope-climbing robot and applied it to the inspection of distribution lines. The model had scientific motion performance and could realize barrier-free movement on the distribution line. This motion mode was controlled by geometric motion planning method and had good potential applications in the field of power inspection. Lv *et al*. [18] believed that UAV power inspection had advantages such as high security and economic feasibility, and then put forward a UAV inspection method that considers initial task points and new task points. The method combined the Golden Eagle optimizer and the gray Wolf optimizer to realize the reasonable planning of the inspection path. The proposed hybrid inspection method had superior path planning performance and better stability.

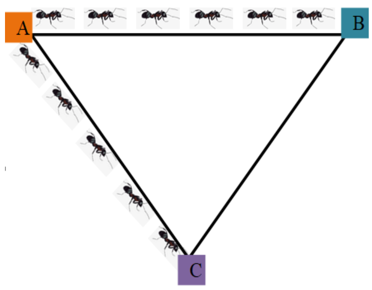
To sum up, robot dogs have great application value in many research fields, but there are only a handful of research on its path planning [29]. In addition, the current intelligent power inspection schemes are largely unmanned aerial vehicle guided intelligent inspection methods, and to the best of our knowledge, few scholars have applied robot dogs to this field. Therefore, this paper proposes a power inspection robot dog based on the hybrid path planning algorithm of IACO-DWA, aiming to obtain better path planning and appropriate navigation strategies for power inspection.

3. The ACO-DWA Robot Dog Path Planning Model

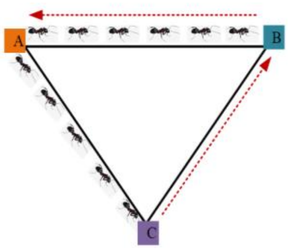
The robot dog adopts a global path planning method, aiming to find the optimal path from the starting point to the end point of the inspection area. The goal is to determine a path with the shortest length and minimum energy consumption while meeting the task requirements through the global path planning method, in order to achieve the efficiency and economy of the power inspection robot dog in performing inspection tasks. ACO has become a research hotspot in global optimization because of its good performance, more stable results, and easy integration with other algorithms. But its convergence speed is slow and the search time is long [19]. This section first improves ACO to improve its own limitations. Then, DWA strategy is introduced and its evaluation function is optimized to propose a local path planning model. Finally, the proposed ACO-DWA model is applied to the power inspection robot dog.

3.1. Global Path Planning Model Construction Based on IACO

The ACO is proposed on the basis of the behavior of ant colonies searching for food. In the process of foraging, ant colonies can find the closest distance from the nest to the food. Meanwhile, the ant population has good self-organization ability and positive feedback ability, and can automatically find a new optimization path without any external information. “Self-organization” means that the ant throws a lot of pheromones over its path as it moves. If a path has a large number of ants, then the path will accumulate more pheromones, which will attract more ants [16]. Positive feedback means that when there are more ants on a path, it accumulates more pheromones, and more ants are attracted to the path. The presence of these two mechanisms allows ants to find the best route from the nest to food. Figure 1 shows a schematic diagram of ant foraging behavior.



a) The ants feed and move on.



b) Ants return from foraging.

Figure 1. Schematic diagram of ant foraging behavior.

Figure 1 shows a schematic diagram of ants’ path selection during foraging. In Figure 1-a), ants start from nest A, randomly choose a path to reach food source B or C, and release pheromones along the path. In Figure 1-b), over time, the path with higher pheromone concentration attracts more ants, gradually forming the shortest path AB that ants preferentially choose. During this process, self-organization and positive feedback mechanisms were utilized to achieve the optimal path search from the nest to the food source. Assuming that there are ants in the population, the probability of -th ant moving from node to node at moment is shown in Equation (1).

$$p_{ij}^{k}(t)=\begin{cases}\dfrac{\left[\tau_{ij}(t)\right]^{\alpha}\cdot\left[\eta_{ij}(t)\right]^{\beta}}{\sum\limits_{k\in allowed_k}\left[\tau_{ij}(t)\right]^{\alpha}\cdot\left[\eta_{ij}(t)\right]^{\beta}} & k\in allowed_k\\ 0 & otherwise\end{cases}\tag{1}$$

In Equation (1), $\tau_{ij}(t)$ denotes the pheromone concentration on path ij and $\eta_{ij}(t)$ represents the heuristic information on path m. α denotes the heuristic factor of pheromone; β denotes the expected heuristic factor; $allowed_k$ represents the set of all viable nodes when ant k next moves. As the colony progressed, the algorithm repeated the same steps, leaving more and more pheromones in the colony. As the colony moves in different paths, the concentration of pheromone on the visited paths increases. As a result, pheromone concentrations are updated during colony movement. ACO is a heuristic algorithm based on inter-group communication, it has good stability, and will not be interfered by external factors, and can maintain good scalability in complex environment. But ACO is easy to fall into local optima. This results in long search time and slow convergence. Therefore, a dynamic stochastic method is introduced to improve the transition probability of the population, and the heuristic information of the algorithm is improved by combining the artificial potential field. The function expression of the optimized transition probability is shown in Equation (2).

$$p_{ij}^{t}(t)=\begin{cases}\arg\max\left\{\left[\tau_{ij}(t)\right]^{\alpha},\left[\eta_{ij}(t)\right]^{\beta}\right\} & g<g_0\\ \dfrac{\left[\tau_{ij}(t)\right]^{\alpha}\cdot\left[\eta_{ij}(t)\right]^{\beta}}{\sum\limits_{k\in allowed_k}\left[\tau_{ij}(t)\right]^{\alpha}\cdot\left[\eta_{ij}(t)\right]^{\beta}} & otherwise\end{cases} \tag{2}$$

In Equation (2), represents a random number between 0 and 1; represents a pre-set constant that has a large effect on the probability of transition. When the value of is large, the transfer probability is shown in Equation (3).

$$p_{ij}^{t}(t)=\arg\max\left\{\left[\tau_{ij}(t)\right]^{\alpha},\left[\eta_{ij}(t)\right]^{\beta}\right\},g<g_0 \tag{3}$$

In this case, the ant can determine its behavior based on the pheromone concentration of its chosen node and the concentration of heuristic information. However, if the search is carried out continuously in this way, the algorithm will quickly converge to a high pheromone concentration in the middle and late period, causing it to fall into local extreme values. When g_0 is small, the transition probability is shown in Equation (4).

$$g_0=1-\zeta_1\times e^{-\frac{1}{N}} \tag{4}$$

In Equation (4), represents the weight coefficient between 0 and 1, which can control; indicates the number of iterations. In Equation (4), the value of will decrease with the increase of the number of iterations, so it needs to be dynamically adjusted. By setting the value rule of, the algorithm can select nodes according to pheromone and heuristic information in the initial stage to accelerate its convergence speed. When the algorithm enters the middle and late stages, to reduce the influence of pheromone on route selection and prevent it from entering the local optimal, should be reduced.

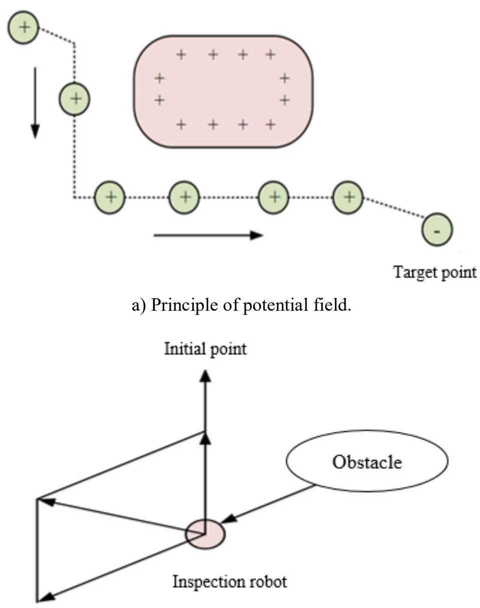
Conventional ACO can quickly and precisely find the optimal route in a simple environment, and its pseudocode is shown in Figure 2.

```
Initialize pheromone concentrations

while not termination condition:
    for each ant:
        Select path based on pheromone concentrations and heuristic information
        Deposit pheromone on path
    Update pheromone concentrations
    Update best path
```

Figure 2. Pseudo code of ACO.

However, due to the large number of target points faced by large-scale substation, the environment is more complex, and accompanied by a large number of temporary tasks, the convergence of this method is greatly challenged [14]. In the initial stage of the traditional ACO, because the choice of the direction of travel is not concentrated enough, it takes too much time to find the way and convergence is slow. To this end, the study adds the directional factor of the artificial potential field to the ACO, so that the robot dog can feel the interaction between the potential field force and the nodes in the ACO at any position. The traditional artificial potential field method combines the obstacle avoidance problem with the geometry problem, which makes the obstacle avoidance problem more concrete [6]. This method has good theoretical and practical application value, and has a great promotion effect on the research of robot obstacle avoidance. The core idea of this method is to place the inspection robot in a space full of potential to move, as shown in Figure 3. The principle is similar to the attraction between negative and positive charges in an electric field, and the repulsion between charges of the same type. In the charged state, the inspection robot avoids obstacles due to its own repulsive force.



a) Principle of potential field.

b) Artificial potential field virtual force diagram.

Figure 3. Schematic diagram of potential field action.

Figure 3 shows a schematic diagram of the improved ACO method combined with artificial potential field for path planning. The artificial potential field method borrows the basic principle of electric fields, just like how opposite charges (positive and negative charges) attract each other, and same charges (positive and positive charges or negative and negative charges) repel each other. The inspection robot has a “charge” property in this scene, so it is subject to repulsive forces from obstacles during its movement, thus avoiding obstacles and optimizing its travel path. This combination helps improve the path planning efficiency and obstacle avoidance ability of robotic dogs in complex environments. The expression of heuristic information after introducing artificial potential field is shown in Equation (5).

$$\eta_A(t) = \alpha^{F(P)\cos\theta} \tag{5}$$

In Equation (5), α is a constant greater than 1; $F(P)$ represents the force of the inspection robot dog in the artificial potential field; θ represents the Angle between the resultant force of the potential field and the direction of travel. The strength of the potential field is expressed by the heuristic factor ε, which will decrease with the increase of the number of iterations, and its function expression is shown as Equation (6).

$$\varepsilon = \frac{N_{\max} - N_i}{N_{\max}} \tag{6}$$

In Equation (6), N_{max} represents the maximum number of iterations of the algorithm; N_i indicates the current number of iterations. Therefore, the improved heuristic function is shown in Equation (7).

$$\eta_{ij}^{'}(t) = \eta_{ij}(t) \cdot \eta_A(t) \cdot \varepsilon = \frac{\alpha^{F(P)\cos\theta}}{d_{ij}} \cdot \frac{N_{\max} - N_i}{N_{\max}} \tag{7}$$

In Equation (7), d_{ij} represents the distance between the inspection robot dog moving from node i to node j. In Equation (7), when the resultant force of artificial potential field received by the robot dog is 0, it still has enlightening information, overcoming the limitation of unreachable target in the artificial potential field method. At moment t, the transfer probability of the robot dog from node i to node j is shown in Equation (8).

$$p_{ij}^{k}(t) = \begin{cases} \dfrac{\left[\tau_{ij}(t)\right]^{\alpha} \cdot \left[\eta_{ij}^{'}(t)\right]^{\beta}}{\sum\limits_{k \in allowed_k} \left[\tau_{ik}(t)\right]^{\alpha} \cdot \left[\eta_{ik}^{'}(t)\right]^{\beta}} & k \in allowed_k \\ 0 & otherwise \end{cases} \tag{8}$$

The implementation flow of IACO algorithm is shown in Figure 4. IACO first initializes the parameters and divides the ants into two groups. In the initialization phase, several ants are placed at the starting point and assigned to two groups. Each group of ants independently records their own taboo table to avoid selecting nodes that have already been visited, in order to prevent the occurrence of loops and redundant paths. During the path search process, each ant selects the next node based on the improved transition probability formula and updates its taboo table and taboo grid. At a certain moment, when two groups of ants meet, the algorithm checks whether the current coordinates of the two groups of ants match the taboo table. If they are consistent, share the path information and use the collaboration of two groups of ants to optimize the path. After each ant completes the path search, record and output the shortest path by comparing the path lengths of all ants. Two groups of ants have improved the efficiency and accuracy of path planning by combining the advantages of artificial potential field method and ACO algorithm through this collaborative search and information sharing, especially in complex environments and multitasking scenarios where the application effect is significant.

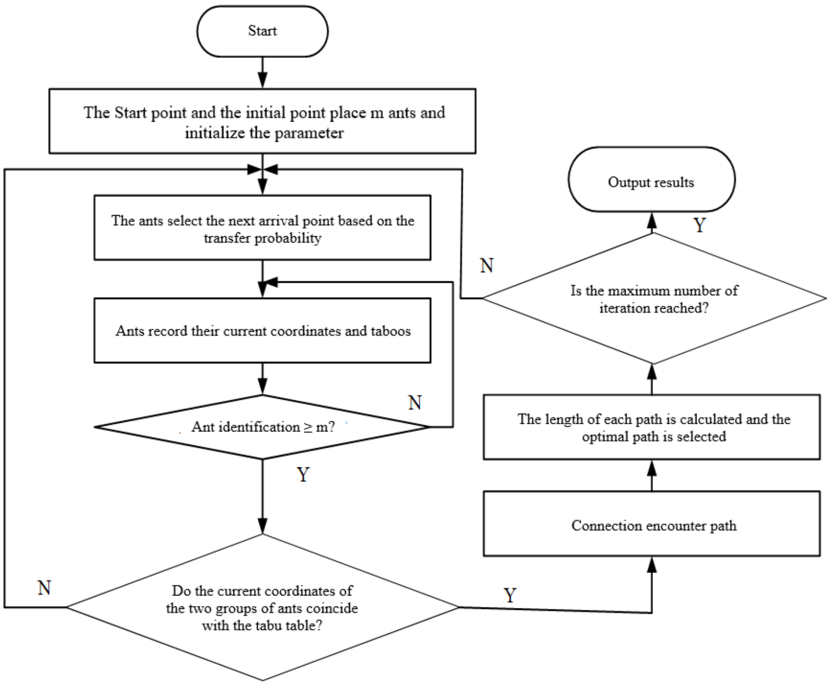
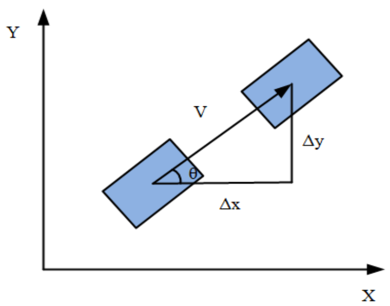


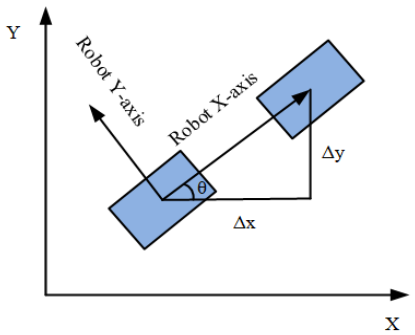
Figure 4. Implementation flow of IACO algorithm.

3.2. Local Path Planning Model Based on Dynamic Window Method

The DWA is a method to control the human motion behavior of a machine, which can produce smooth, continuous motion trajectories, enabling the robot to travel safely in complex environments. The basic idea of DWA is to obtain the motion trajectory of the velocity in the future period of time by calculating multiple velocity sample sets [12]. Then, by comparing the obtained motion trajectories, the best one is selected and the patrol robot is driven forward at the corresponding speed [8]. DWA algorithm is widely used in robot control because of its high real-time performance and low computational cost. In this paper, the evaluation function of DWA is improved, the target distance is introduced into it, and the local path planning is carried out by improving DWA. It is assumed that the inspection robot can only move forward and turn, but cannot move in all directions. In two adjacent time units, the inspection robot does not travel a long distance. The trajectory can be approximated as a straight line, and then the distance can be projected to the *X* and *Y* axes respectively [28]. Figure 5 shows the motion track diagram of the inspection robot dog under the simple model and the complex model.



a) Simple model diagram.



b) Complex model diagram.

Figure 5. Motion track diagram of the inspection robot dog.

Assume a scenario in which t+1 is relative to t, the relative displacement of the inspection robot dog is shown in Equations (9) and (10).

$$\Delta x = v\,\Delta t\cos(\theta t) \tag{9}$$

In Equation (9), Δx represents the displacement of the inspection robot dog in the horizontal direction within the time increment Δt; v is the speed of the inspection robot dog; cos(θt) is the cosine value corresponding to the movement direction angle θ of the inspection robot dog. Equation (10) represents the vertical displacement of the inspection robot dog within the time increment Δt.

$$\Delta y = v\,\Delta t\sin(\theta t) \qquad (10$$

In Equation (10), sin(θt) is the sine value corresponding to the motion direction angle θ of the inspection robot dog. The movement trajectory of the inspection dog over a period of time is shown in Equations (11) to (13). Equation (11) represents the horizontal coordinate position of the inspection robot dog at time t.

$$x = x_0 + v\Delta t\cos(\theta t) \tag{11}$$

In Equation (11), x_0 represents the horizontal coordinate position of the inspection robot dog at the initial time t_0. Equation (12) represents the vertical coordinate position of the inspection robot dog at time t.

$$y = y_0 + v\Delta t\sin(\theta t) \tag{12}$$

In Equation (12), y_0 represents the vertical coordinate position of the inspection robot dog at the initial time t_0. Equation (13) represents the direction angle of motion of the inspection robot dog at time t.

$$\theta t = \theta t_0 + \omega\Delta t \tag{13}$$

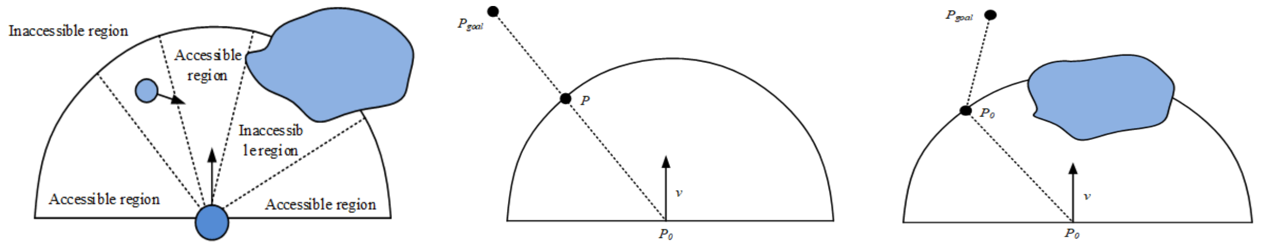
In Equation (13), θt_0 is the direction angle of motion of the inspection robot dog at the initial time t_0. In complex scenes, the robot dog not only has speed on the *X*-axis, but also has speed on the *Y*-axis. At this point, the distance of the robot dog on the *Y*-axis needs to be decomposed into the coordinate system and superimposed to obtain the final trajectory. After that, speed sampling is needed to prevent the robot dog from colliding with obstacles. In addition, evaluation function also plays an important role in DWA, and its function is expressed as Equation (14).

$$G(v,w) = \sigma(\alpha heading(v,w) + \beta dist(v,w) + \gamma velocity(v,w)) \tag{14}$$

In Equation (14), *heading*(v,w) represents the azimuth evaluation; (A *dist*(v,w)) Indicates a gap evaluation; *velocity*(v,w) stands for speed evaluation. The combination of the three enables the inspection robot dog to effectively avoid obstacles and move forward at a faster speed during the working process. But when the robot dog approaches the target, the Angle becomes larger, which causes the robot to wobble and be unstable. If the angle between the two is small, the robot dog will travel at a higher linear speed. However, when the robot dog approaches the destination, it slows down so that it can dock at the destination. To sum up, the evaluation function is improved, as shown in Equation (15).

$$G(v,w) = \sigma(\alpha Gdist(v,w) + \beta dist(v,w) + \gamma velocity(v,w)) \tag{15}$$

In Equation (15), G*dist*(v,w) denotes the distance between the end of the trajectory corresponding to velocity (v, w) and the target point. The workspace of a robot dog often encounters many unknown difficulties. In its local planning, the real-time detection of the environment is often achieved through the method of rolling Windows, so that the robot dog can avoid obstacles encountered in the complex environment [20]. In the resulting scrolling window, the current position of the robot dog is seen as the center of the window. The distance that can be detected is taken as the window radius, so that the robot dog constantly moves towards the sub-target in the window when moving. Then, with the help of these sensors, the robot dog continuously updates the area it is in through its perception of the surrounding environment and moves towards the area it is in. If the robot dog correctly selects part of the target, it can achieve the target well; otherwise, there is a risk of collision with obstacles. Under different circumstances, the robot dog's selection strategies for local subtargets are shown in Figure 6.



a) Feasible regional division. b) Select the subheading punctuation when accessible. c) Select Subitem punctuation if there are obstacles.

Figure 6. Robot dog's selection strategy for local subtargets.

During the inspection process, the robot dog constantly collects environmental information and updates the window map in real time. If the window detects an obstacle, the analysis predicts its motion state. Through the calculation of linear prediction model, the trajectory of obstacle and its next driving position are obtained. The robot can avoid static obstacles by constantly updating subpoints in the scrolling window. For dynamic obstacles, its trajectory will be predicted and whether it will collide with it will be judged. If a collision is possible, the driving trajectory needs to be adjusted.

3.3. Power Inspection Strategy of Robot Dog Based on Hybrid Algorithm Path Planning Model of IACO-DWA

The four-legged robot dog is a class of four-legged based, four-legged robots that have higher smoothness and greater flexibility than the average one-legged or two-legged robot. Compared with other six-legged and eight-legged multi-legged robots, four-legged robot dogs can move their legs freely [11, 27]. In this paper, the ACO-DWA algorithm was installed in the robot dog to carry out more efficient path planning to successfully complete the power inspection task. Figure 7 shows the movement of a four-legged bionic robot dog.

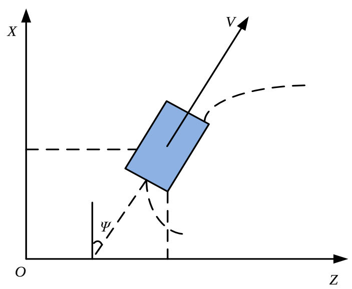


Figure 7. Motion diagram of four-legged robot dog.

According to the kinematic relation, the relation shown in Equation (16) can be obtained.

$$\begin{bmatrix} x \\ z \\ \psi \end{bmatrix} = \begin{bmatrix} \cos\psi \\ -\sin\psi \\ 0 \end{bmatrix} v + \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} \psi' \tag{16}$$

In Equation (16), (x, z) represents the plane coordinates of the center of mass of the four-legged robot dog; v denotes the speed of advance; ψ denotes the yaw Angle of motion; ψ' represents yaw angular velocity. According to the kinematic relationship shown in Equation (16), the motion control system of the robot dog can be regarded as A system in which the input $u(v,\psi')$ controls the state quantity $\phi(z,\psi)$. Each node on the planned path should satisfy the equation of Equation (17).

$$\begin{aligned} \phi_r &= [x_r, z_r, \psi_r] \\ u_r &= [v_r, \psi_r'] \end{aligned} \tag{17}$$

In Equation (17), r represents the reference value of the planned path. The error function of the robot dog can be obtained from Equations (16) and (17), as shown in Equation (18) [1, 9].

$$\phi'(k+1) = A_{k,t}\phi'(k) + B_{kt}u'(k) \tag{18}$$

In Equation (18), k denotes the number of iterations; A, B denotes the Taylor expansion for each state point of the robot dog. The route planning algorithm of the electrical inspection robot dog designed in this paper can not only ensure that the electrical inspection robot can carry out inspection stably, but also enable the electrical inspection robot to recognize and sense the direction of the inspection path, so as to comprehensively realize the inspection path planning of the inspection task. When the robot dog performs power inspection, it first adopts the IACO algorithm for global path planning, that is, it plans the specific path that the power inspection robot needs to inspect. After determining the inspection area and inspection obstacles, the electric inspection robot dog can initially plan its obstacle avoidance path. In this route planning, the inspection routes with obstacles will be dropped, but if all routes have obstacles, the obstacle avoidance function of the electric inspection robot dog needs to be turned on. In this paper, DWA sliding window mode was adopted to drive the power inspection robot dog to avoid obstacles and complete patrol tasks smoothly, as shown in Figure 8. The overall operation process of the path planning model of the power inspection robot dog with IACO-DWA.

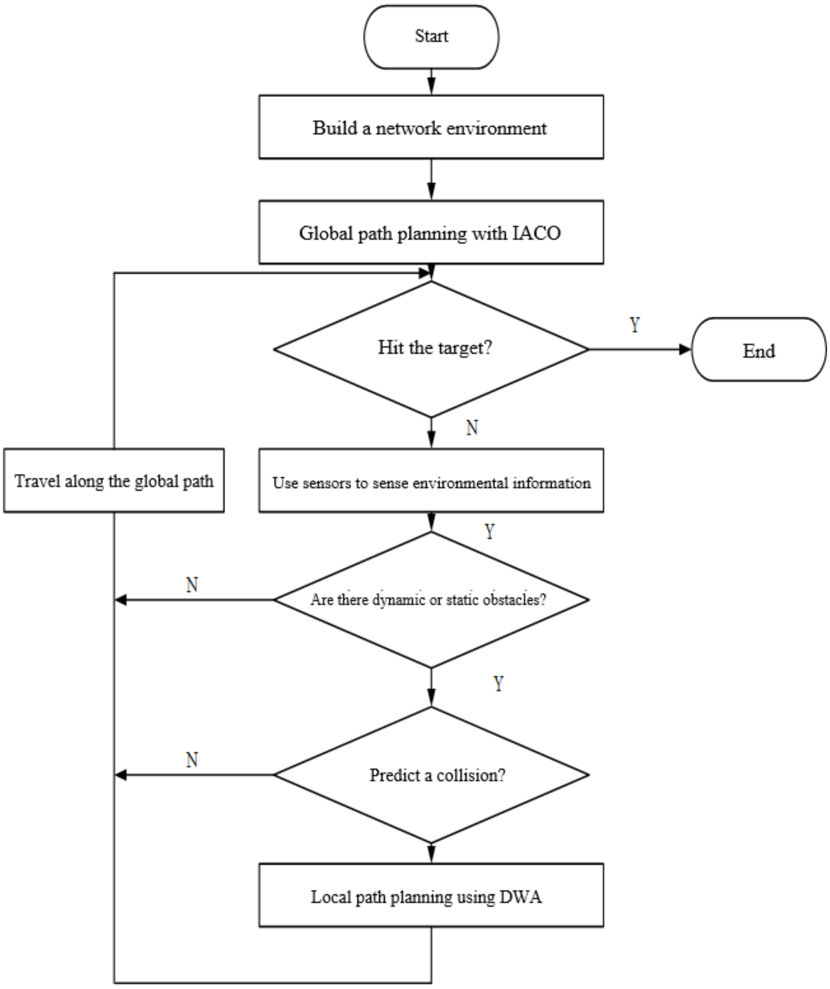


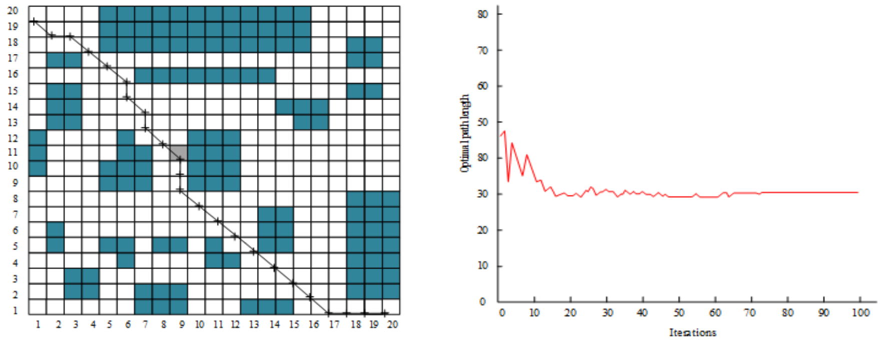
Figure 8. Overall operation flow of the path planning model of the power inspection robot dog with ACO-DWA.

4. Experimental Results

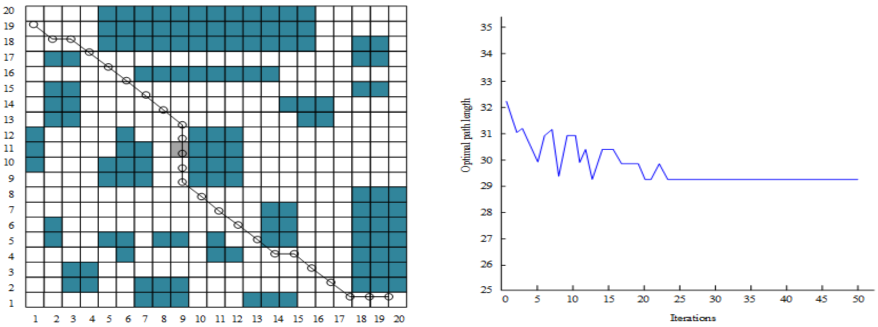
In this section, the performance of the proposed model is verified. Firstly, the effect of global path planning and local path planning based on IACO-DWA model is analyzed. In the second section, the practical application effect of the electric power inspection robot dog based on IACO-DWA is tested.

4.1. Effect Analysis of Global Path Planning and Local Path Planning of IACO-DWA Model

In this paper, the effect of global path planning and local path planning of IACO-DWA is analyzed. This paper is based on the grid diagram of substation environment, and the simulation experiment is carried out on MATLAB software. This paper takes single-task point path planning and multi-task point path planning as examples to simulate the global path planning of traditional ACO and IACO. The simulation starting point coordinates set by the research are (0, 20), the end point coordinates are (20, 0), and the first task point coordinates are (9, 11). Figure 9 shows the simulation results of the two algorithms under a single point task. In the figure, under the same environment and inspection conditions, the IACO algorithm has been improved in terms of turning nodes, iteration times and optimal path length. The number of ACO iterations is 63 and the optimal path length is 30.209. The number of iterations of IACO is 24, and the optimal path length is 29.194. Compared with ACO, the path length, number of turning nodes, number of iterations and running time of IACO are reduced by 3.4%, 22.19%, 61.9% and 15.59% respectively. Therefore, the enhanced algorithm has a great improvement in convergence speed and convergence speed.

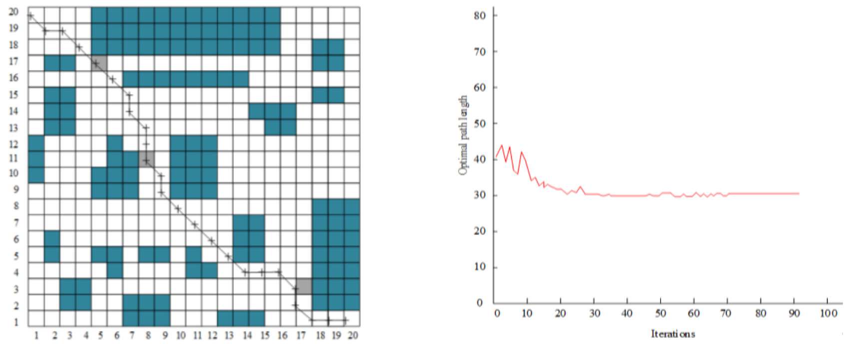


a) ACO single-task point path planning result.

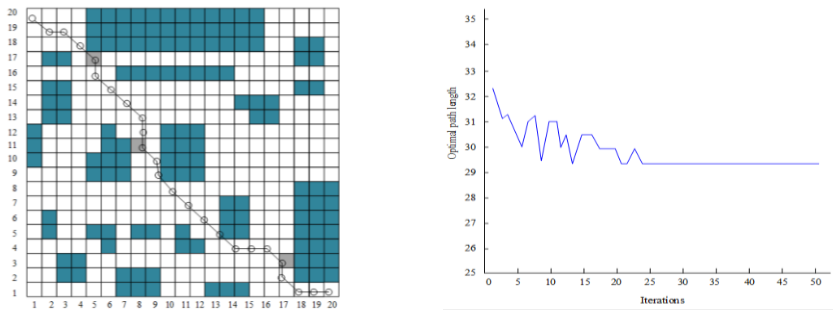


b) IACO single-task point path planning result.

Figure 9. Simulation results of the two algorithms under a single point task.



a) ACO multi-task point path planning results.



b) IACO multitask point path planning results.

Figure 10. Simulation results of the two algorithms under multi-task.

Substations generally require multiple inspection task points, and this paper simulates the process in the secondary simulation. Figure 10 shows the simulation results of the two algorithms under the multi-point task. In addition to setting the starting point coordinate (0, 20) and the end point coordinate (20, 0), the experiment also set three task points (5, 17), (7, 11) and (17, 3), as shown in the gray grid in the figure. In the figure, in the same case, when the ACO algorithm has carried out 60 times, the algorithm still has a small oscillation, and its optimal search path is 30. The number of IACO iterations is 23, and the optimal path length is 30.087. Compared with the ACO algorithm, the optimization path of IACO algorithm is increased by 0.6%, while the number of steering nodes is reduced by 7.1%, the number of iterations is reduced by 61.7%, and the running time of the program is reduced by 16.8%. This method has a great improvement in iteration times, turning nodes and running speed. Therefore, IACO algorithm has great advantages in convergence speed and path planning.

Table 1 shows the comparison of specific simulation results between two IACO and another commonly used

Improved Particle Swarm Optimization (IPSO) algorithm at single task point and multi-task point. From the data shown in the table, it is not difficult to infer that IACO has advantages. The main reason is that a dynamic random parameter is added to the selection probability of IACO, which can increase the concentration of pheromone in the early stage and accelerate the convergence of the algorithm. Meanwhile, the influence of pheromone concentration on search results is reduced during and after the search process, so that the search process will not enter the local extreme value. In addition, by introducing the artificial potential field into the heuristic information, the convergence of the algorithm is accelerated and the global path optimization efficiency is improved.

Table 1. Simulation results of the two algorithms at single task point and multiple task point.

Model	Single task				Multitask			
	Path length	Turning node	Iterations	Running time	Path length	Turning node	Iterations	Running time
IACO	29.194	7	24	34.71	30.087	14	23	35.37
IPSO	31.214	9	56	44.12	31.487	16	58	41.25
Variation	-6.47%	-22.22%	-57.14%	-21.33%	-4.45%	-12.50%	-60.34%	-14.25%

Next, the performance of the ACO-DWA algorithm in local path planning is analyzed. The experiment is also carried out on MATLAB software based on raster map. In this paper, the improved DWA was simulated using several different types of obstacles. First, set the starting coordinates to (0, 0) and the ending coordinates to (10, 10). Figure 11 shows the simulation results of DWA under various obstacles. Among them, A and B are static obstacles. In Figure 11, when the robot dog reaches (1, 1.5), the dynamic obstacle O1 with (2, 5) as the initial coordinate is detected. The robot dog moves in a straight line along x=2, towards the negative half axis of the *Y-axis*, and the moving step is 2. Based on the prediction of the trajectory of the obstacle, the robot dog determined that there was a possibility of collision with O1, so it took a waiting strategy. In Figure 11-b), after passing the detected obstacle O1, the robot dog travels along its original path towards the local subpoint. Dynamic obstacle O2 is added to Figure 11-c), the robot dog makes trajectory prediction for it, believes that inevitable collision will occur, and uses the improved DWA to re-plan the travel route. After bypassing the O2, return to the original route. In Figure 11-d), a dynamic obstacle O3 is added, which will collide with O3 after the analysis and prediction of the robot dog. With the correction of the DWA, the robot dog plans the route and finally reaches the destination. Thus, the feasibility of DWA can be verified.

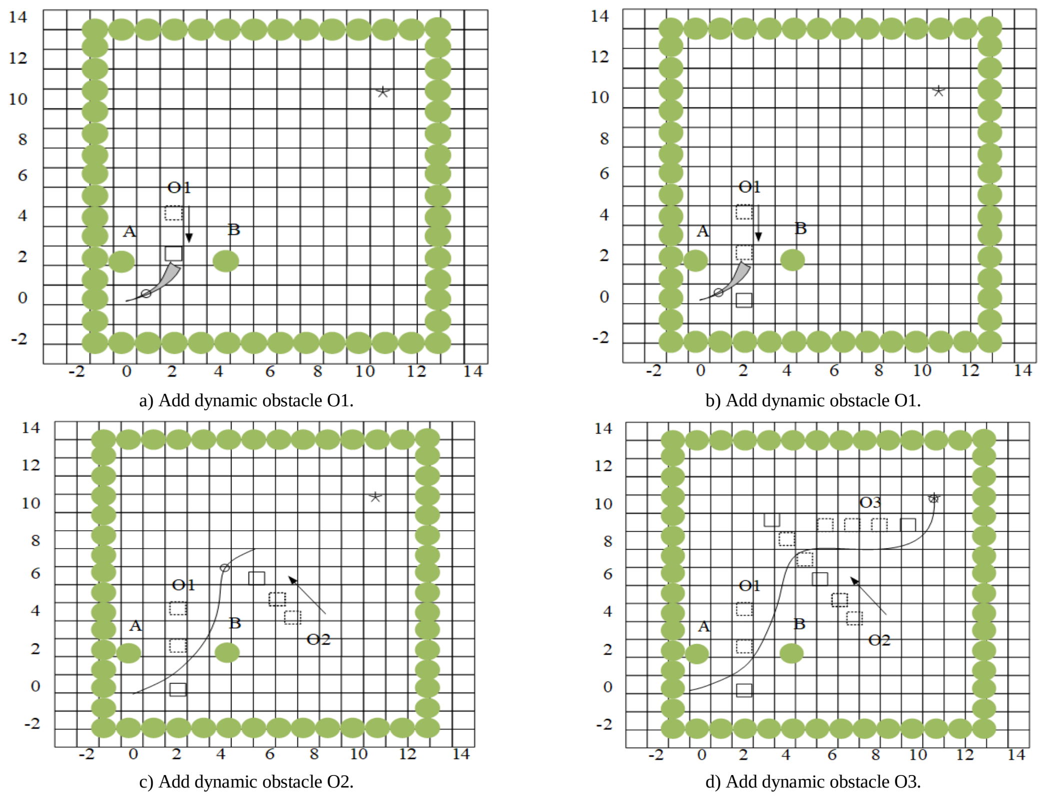
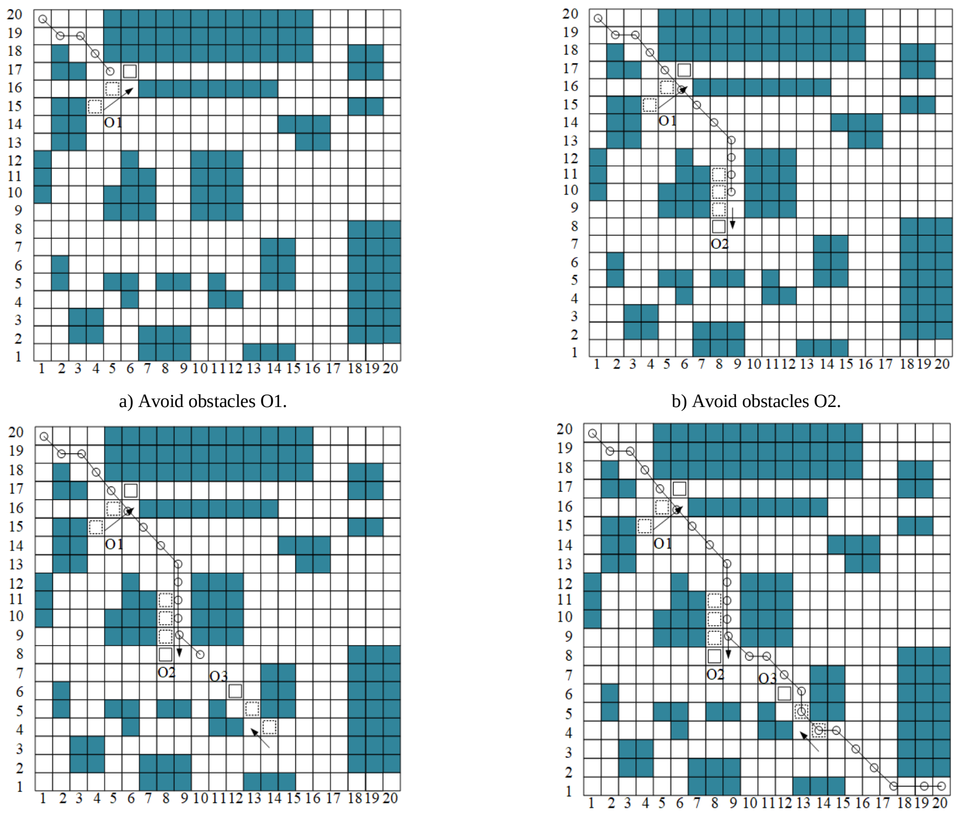


Figure 11. Simulation results of DWA under various obstacles.

After comparing and analyzing the performance of IACO and DWA algorithms, the experiment is selected to verify the hybrid path planning model of IACO-DWA. Also in MATLAB software, the hybrid algorithm is simulated. Based on the simulation experiment of single task point inspection conducted by IACO, different dynamic obstacles are added. When the robot dog walks along the globally optimized route, it uses its multiple sensors to continuously collect information about the surrounding environment, and constantly updates the map in the rolling window. In Figure 12, at (5, 16), the robot dog finds dynamic obstacle O1. At this point, the robot dog predicts its movement path according to the rolling window, and determines that there will be a side collision. In this case, the robot dog chooses to stay for a period of time according to the local path planning strategy. After O1 passes, continue on the best route. In Figure 12-b), when the robot dog is at (9, 13), dynamic obstacle O2 is detected. At this point, the robot dog will predict the movement of O2 through the rolling window, determine that there will be no collision, and then continue to move forward in the current state. In Figure 12-c) and Figure 12-d), O3 is detected in the window when the robot dog runs to (10, 8). Based on its trajectory, the robot dog determines that a collision is inevitable. At this point, the robot dog uses the improved DWA to re-plan the route. After avoiding O3, the robot dog returns to its globally optimal path and continues on its way. Figure 12-d) shows the globally optimal path planned for the site. In the process of robot traveling, the improved DWA algorithm can make real-time prediction and analysis of the robot's dynamic obstacles and moving trajectory, and return to the original optimal path after completing the local path planning. Therefore, the feasibility and accuracy of the hybrid algorithm in this paper can be verified.



a) Avoid obstacles O1. b) Avoid obstacles O2.

c) Avoid obstacles O3. d) Avoid obstacles O4.

Figure 12. Effect of hybrid path planning based on ACO-DWA.

4.2. Practical Application Effect of Electric Power Inspection Robot Dog based on ACO-DWA

Through the above analysis and design, the obstacle avoidance path planning method of electric inspection robot dog based on IACO-DWA is designed. To test its actual working performance, this paper uses the obstacle-avoiding path planning Method (Method 1) based on GPS navigation technology and the obstacle-avoiding path planning Method (Method 2) based on carrier-free communication technology to complete a comparative experiment. To enhance the reliability of the experimental results, a kind of inspection robot dog named HKD09 is used in this paper. The driving device, motor and other accessories of this series of inspection robot dogs work very well and will not cause interruption of the test. In the test, the trajectory of the robot dog was detected, including five basic inspection actions, such as straight line, turn, backward and translation. To ensure the difficulty of the test, the study combines 20 basic obstacles with 10 complex obstacles, and carries out random mixing on the inspection test route of the inspection robot. Before the experiment, three inspection robot dogs are entered into three obstacle avoidance path planning methods for electric inspection robot dogs. Meanwhile, the patrol task is sent to the power inspection robot dog. The test ends when all the inspection robot dogs arrive at the inspection task exit.

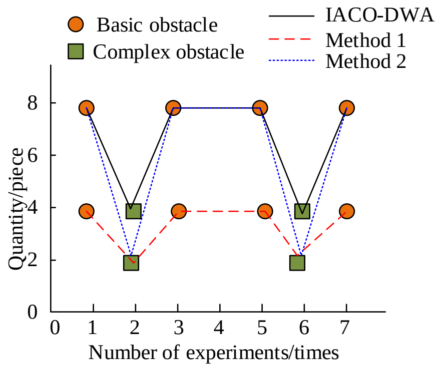
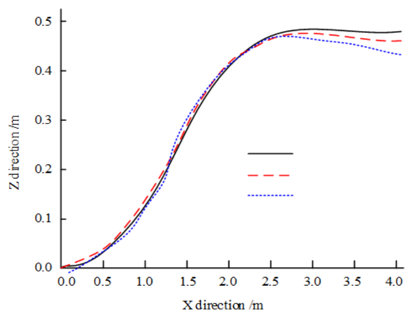


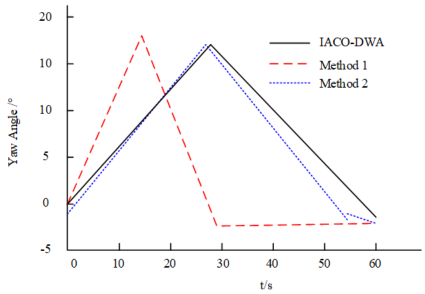
Figure 13. Test results of the number of obstacles avoided by the inspection robot dog.

Figure 13 illustrates the test results of the number of obstacles avoided by the inspection robot dog. The three kinds of electric inspection robot dogs can avoid basic obstacles, but the obstacle avoidance data are different. The obstacle avoidance path planning method of power inspection robot dog based on ACO-DWA can successfully avoid 9 basic obstacles and 5 complex obstacles. Method 1 can avoid 5 basic obstacles and 3 complex obstacles; Method 2 can successfully avoid 7 basic obstacles and 2 complex obstacles. The obstacle avoidance path planning method of the robot dog based on IACO-DWA successfully avoids all the basic obstacles, mainly because the IACO-DWA can effectively ensure that the robot dog's behavior fluctuations do not touch the obstacles during inspection.

Figure 14 shows the changes in the moving tracks of the three types of robot dogs at different reference speeds. At different reference speeds, the three types of robot dogs can track the reference track very well, and the error is within the predetermined range. Compared to Method 1 and Method 2, the IKO-DWA robot dog has easier steering and is able to track the track and yaw Angle well.



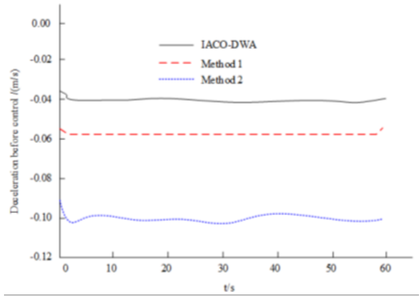
a) Trajectory changes.



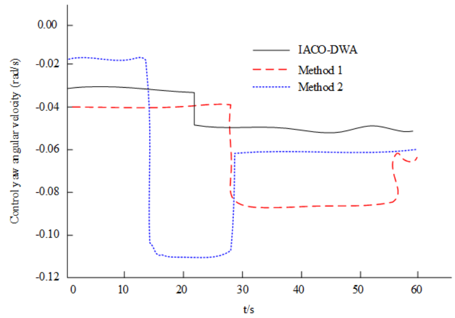
b) Yaw angle change.

Figure 14. Changes of moving tracks of three kinds of robot dogs at different reference speeds.

Figure 15 shows the changes of forward speed and yaw angular speed of the three robot dogs at different reference speeds. Among them, the robot dog can track the forward and lateral movement of the target very well, and the tracking error is within the predetermined allowable range. Compared with Method 1 and Method 2, the control amount of the robot dog implemented with IACO-DWA changes more smoothly. This is mainly because, based on the ACO-DWA, the robot dog can achieve steering more easily.



a) Changes in the speed of advance.



b) Yaw angular velocity change.

Figure 15. Control changes of three kinds of robot dogs.

5. Conclusions

Aiming at the situation that electric robot dogs often face unexpected situations during inspection, a hybrid path planning model based on IACO-DWA is constructed in this paper. Relevant simulation experiments are carried out for ACO, IACO, DWA and ACO-DWA. The results of global path planning under single task show that the path length, number of turn nodes, number of iterations and running time of IACO are reduced by 3.4%, 22.19%, 61.9% and 15.59%, respectively. The results of global path planning under multi-task show that although the optimized path of IACO is increased by 0.6% compared with ACO, the steering node, the number of iterations and the running time are reduced by 7.1%, 61.7% and 16.8%, respectively. The comparison results between IACO and IPSO also verify the superiority of IACO. The path length, the number of turning nodes, the number of iterations and the running time of IPSO are higher than that of IACO. Local path planning results indicate that the constructed model can effectively avoid obstacles. The practical application results of the power inspection robot dog show that compared with Method 1 and Method 2, the ACO-DWA can successfully avoid 9 basic obstacles and 5 complex obstacles. Therefore, the proposed method has good applicability to the path planning and navigation strategy of the power inspection robot dog. There are still some limitations in this paper, that is, the influence of factors such as the battery life of the robot dog is not considered, which can be improved in future research.

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