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RESEARCH ARTICLE

Path Planning of Inspection Robot Based on Improved Intelligent Water Drop Algorithm

XUHUI ZHANG, YING JI, CHUNYANG WANG, (Member, IEEE), HAIJUN LIN, AND YUEQIANG WANG

School of Measurement and Communication Engineering, Harbin University of Science and Technology, Harbin 150080, China

Corresponding authors: Xuhui Zhang (zxh_99ok@163.com) and Chunyang Wang (wangchunyang.work@outlook.com)

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ABSTRACT In response to the limitations observed in the Intelligent Water Droplet (IWD) algorithm for path planning, including its weak problem-solving capability and susceptibility to local optimization, this paper presents an enhanced Intelligent Water Droplet algorithm. The improved algorithm incorporates the distance factor between nodes and the target point into the original algorithm's path probability, enhancing its problem-solving prowess and expediting algorithmic convergence. Simultaneously, a roulette-based probability selection method is introduced to circumvent local optimization during the solution process. Additionally, the algorithm is coupled with the Floyd algorithm to refine the planned path, reducing the number of inflection points to align with the motion characteristics of the inspection robot. Simulation results underscore the effectiveness of the enhanced Intelligent Water Droplet algorithm in mitigating the impact of local optimization in path planning. In comparison to the original IWD algorithm, the optimized path exhibits a 17.42% reduction in length, a 58.3% decrease in the minimum number of iterations required for path convergence, and a 36.3% reduction in the number of path inflection points. Furthermore, the total path length is decreased by 7.7% following path optimization via the Floyd algorithm.

INDEX TERMS Path planning, intelligent water drop algorithm, local optimality, Floyd.

I. INTRODUCTION

Since the advent of mobile robots, researchers have focused their efforts on enhancing navigation control and optimizing path planning [1], [2]. Path planning [3] encompasses the calculation of the route from the initial state to the destination state, guided by specific criteria within a known or unknown environment. This process can be divided into global path planning, based on pre-existing complete information, and local path planning, which relies on sensor data. For inspection robots operating in complex environments, the efficacy of global path planning plays a pivotal role in determining the efficiency and orderliness of inspection tasks [4].

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The main movement mode of inspection robots mainly wheeled movement, characterized by its fast speed and high efficiency. However, wheeled robots are burdened by a disadvantage: they exhibit suboptimal turning efficiency. These robots must decelerate before making turns and then accelerate once they negotiate the corner. This not only results in energy loss but also prolongs the time required for the robot to complete its tasks. Hence, when devising a path for an inspection robot, it becomes imperative to minimize the number of inflection points in order to ensure the seamless operation of the robot.

Presently, path-planning algorithms can be categorized into two primary groups: traditional and intelligent algorithms. Standard algorithms encompass the artificial potential field method [5], fuzzy logic algorithms [6], heuristic search algorithms [7], and others. Intelligent algorithms, on the other hand, primarily include genetic and swarm intelligence algorithms [8]. While these algorithms excel at charting optimal paths in specific environments, they do present certain challenges. The artificial potential field method is susceptible to local optima and may struggle to reach the target. Fuzzy logic algorithms face difficulties in the induction and online adjustment of fuzzy rules, resulting in poor adaptability. The Heuristic A* algorithm [9] involves substantial computation for each node, leading to extended processing times that diminish its search efficiency with increasing node count. Genetic algorithms [10] exhibit subpar real-time performance. In contrast, swarm intelligence algorithms represent a novel class of bionic algorithms that combine probabilistic selection with heuristic search, offering superior self-organization and robustness.

In order to enhance the path planning capabilities of inspection robots, reduce planning time to enhance timeliness, and minimize the number of inflection points for smoother robot operation, this paper introduces several enhancements to the traditional intelligent water drop algorithm. These improvements encompass the incorporation of distance factors relative to the target node in probability selection, the refinement of local and global sediment quantity updates, and path smoothing through the integration of the Floyd algorithm. As evident from the course planning results, the improved algorithm yields shorter path lengths and effectively mitigates local optimal solution disruptions caused by grid barriers, rendering the path planning process more rational and efficient.

II. INTELLIGENT WATER DROP ALGORITHM

The Intelligent Water Drops Algorithm [17] (IWD) is a group intelligence algorithm proposed by Hamed Shah Hosseini, which simulates the principle of water droplets interacting with sediment to form a water flow path when they move [18], [19].

In nature, the erosion of the riverbed by the flow of water can form ravines on the surface of the riverbed. Water flow can be considered a group of unit droplets, and each drop has a velocity attribute and a sediment attribute. Under gravity, when the water droplet selects the path, it will choose the path with relatively little resistance, that is, the way with less sediment, so that the water droplet will obtain a more significant speed increment and take away more deposition. As shown in Figure 1, when two water droplets with the same properties pass through region (a) and region (b), respectively, the water droplets in Figure 1(b) will obtain a more significant velocity increment and carry more sediment.

In the abstract model, water droplets move according to discretization and carry two properties: the motion attribute *vel* (*IWD*) and the sediment carrying property *soil*(*IWD*).These two properties change with the movement of the water droplets. Suppose the current position of the water droplet is i; During the movement to the next position j, the water droplets will undergo the following changes.

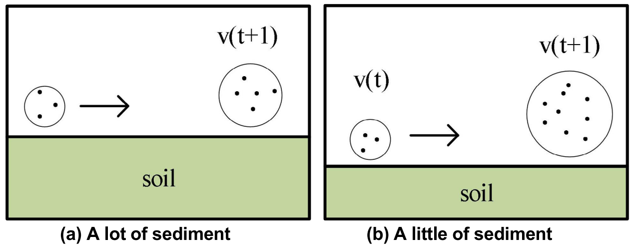

FIGURE 1. Effect of water droplet movement.

A. THE PROBABILITY OF SELECTION

First of all, water droplets tend to choose paths with less sediment when choosing a path, so $p\,(i,j)$ indicates the probability that the water droplets choose j at the i position as the next position, which is inversely proportional to the amount of sediment in the path (i,j) $soil\,(i,j)$, and the probability of selection is

$$p(i,j) = \frac{f(soil(i,j))}{\sum f(soil(i,k))} \tag{1}$$

$$f(soil(i,j)) = \frac{1}{\varepsilon + g(soil(i,j))} \tag{2}$$

where ε is the smallest positive actual number, and

$$g(soil(i,j)) = \begin{cases} soil(i,j), & \min(soil(i,k)) \geq 0 \\ soil(i,j) - \min(soil(i,k)), & else \end{cases} \tag{3}$$

B. THE INVERSELY INCREMENT

When a water droplet travels from position i to position j, its velocity properties change, and the velocity increment $\Delta vel\ (IWD)$ is inversely proportional to the sediment content $soil\ (i,j)$ on the running path,

$$\Delta vel(IWD) = \frac{a_v}{b_v + c_v(soil(i,j))^2} \tag{4}$$

where parameters a_v, b_v and c_v are the parameters preset by the algorithm.

C. EQUIVALENCE RELATIONSHIP

The amount of sediment carried away by the water droplet movement is equal to the amount of sediment reduction $\Delta soil(i,j)$ in the path (i,j), that is

$$\Delta soil(IWD) = \Delta soil(i,j) \tag{5}$$

The sediment reduction in the path after the operation of the water droplet is inversely proportional to the time required for the water droplet to pass through the path (i,j) variable. $time(i,j)$

$$\Delta soil(i,j) = \frac{a_s}{b_s + c_s(time(i,j))^2} \tag{6}$$

where parameters a_s, b_s and c_s are the parameters preset by the algorithm, and the time it takes for the water droplet to move from position i to position j

$$time(i,j) = \frac{HUD(i,j)}{vel(IWD)} \tag{7}$$

where $HUD\,(i,j)$ is the heuristic concerning the road segment (i,j).

D. FEEDBACK

when the water droplets arrive at the location j from the position i, the sediment in the section (i,j) will be updated to provide feedback on the path planning of other water droplets.

$$soil(i,j) = (1-\rho)\cdot soil(i,j) - \rho\cdot\Delta soil(i,j) \tag{8}$$

where ρ is the coefficient between 0∼1.

E. SELECTION OF THE OPTIMAL PATH

Selection of the optimal path. Through steps (1) to (4), each drop completes the course planning from the starting point to the target point; remember that the path of the kth droplet is T_k, and use the evaluation function $q\,(T)$ to select the optimal way in the droplet group T^{IB}, that is,

$$T^{IB} = \max_{all} q(T_k) \tag{9}$$

F. GLOBAL SEDIMENT VOLUME UPDATE

Global sediment volume update. To make the planned optimal path have a guiding effect on subsequent path planning and improve the ability of the next group of water droplets to search for the optimal way, it is necessary to form a feedback mechanism, as shown below, to update the global sediment amount on the optimal path, that is

$$soil(i,j) = (1-\rho)soil(i,j) + \rho\frac{2soil(IWD)}{N_{IB}(N_{IB}-1)} \tag{10}$$

where ρ is the update parameter between 0∼1, N_{IB} is the number of nodes for the path.

But the search process of the Intelligent Water Drops (IWD) algorithm relies on probability and heuristic information, making it susceptible to getting trapped in local optima, especially in complex, multi-modal problems.

III. PATROL ROBOT PATH PLANNING ISSUES

Raster maps have the advantages of accessible construction unique map locations, and are very helpful for route planning. The robot's operating area is built into a grid model, and the robot's working environment is established as a digital map mode. All environmental information in the model can be represented as an index of ordinal numbers. In a raster map model, the location coordinates (x_m, y_m) of the two-dimensional plane in which it is located can be used to represent the raster, which can be converted to and from the ordinal notation, and the conversion model is

$$\begin{cases} x_m = \mathrm{mod}(Num, N) \\ y_m = Num/N + 1 \end{cases} \tag{11}$$

the parameter Num is the ordinal number in the raster map model, the parameter N represents the value of the column parameter.

After constructing the above model, the data sensor can detect the operating environment information of the robot, mark the obstacles, set the location of the non-obstruction as a feasible area, process the challenges of the grid map by puffing method, and simplify the robot model to obtain the point model of its operation. Then, plan the robot's running path, and the way $path$ can be represented as

$$path_i = \{S, P_1, \cdots, P_n, \cdots, P_m, G\} \tag{12}$$

The parameter S is the starting point of the robot operation; the Parameter G is the end position of the robot operation, and the parameter is the intermediate point position passed by the robot operation, which can be expressed as $P_n = \left(x_{gn}, y_{gn}\right)$ or $P_n = Num_n$. The map coordinates can be obtained from Equation (10). The model form of the map coordinate transformation model is

$$\begin{cases} x_g = \mathrm{int}(x/w)\cdot w + \mathrm{int}(w/2) \\ y_g = \mathrm{int}(y/w)\cdot w + \mathrm{int}(w/2) \end{cases} \tag{13}$$

where parameters (x, y) are two-dimensional coordinate system parameters when the robot is running. The parameter w is the resolution of the structure of the built raster map model, from which the running length of the robot is:

$$PL = \|P_1 - S\| + \sum_{n=1}^{n=m-1}\|P_{n+1} - P_n\| + \|G - P_m\| \tag{14}$$

Based on the above model definition, the path planning of the inspection robot can be modeled as a constraint optimization problem. The optimization goal is to obtain the shortest line without obstacles, that is, select the path with the most petite running length PL to ensure that the inspection robot can reach the target node as quickly as possible.

IV. ALGORITHM IMPROVEMENTS

The path selection of the original algorithm is solely negatively correlated with the sediment content $soil\,(i,j)_1$ along the path, but in the process of path planning, the distance between the following location j and the target point is also a factor that must be considered, so this paper adds the distance between the following location j and the target point to the selection of the site,

$$f(soil(i,j)) = \frac{\eta(j,G)^Q}{\varepsilon + g(soil(i,j))} \tag{15}$$

$$p(i,j) = \frac{f(soil(i,j))}{\sum f(soil(i,k))} \tag{16}$$

where Q is the index of the new heuristic, $\eta(j,G)$ is the reciprocal of the distance from the position j to the target point, the larger the distance, the worse the location point; the smaller the distance, the better the location point, and the greater the probability of the alternative.

It is easy to fall into local optimum so that a reasonable path cannot be planned, or even the target point cannot be reached, which is a defect of the group intelligence algorithm. This article introduces the roulette method in path selection to optimize this defect. The algorithm creates a random number *rand* located at $0 \sim 1$, and when the formula (17) is satisfied, the node j is selected as the following position node. This prevents the algorithm from falling into a local optimal and cannot plan the complete path.

$$P_j = p_1 + p_2 + \cdots + p_{j-1} + p_j \tag{17}$$

$$rand \notin \left[0, P_{j-1}\right] \& \, rand \in \left[0, P_j\right] \tag{18}$$

For the heuristic function $HUD\,(i, j)$ in formula (7) concerning path (i, j), replace it with $\eta\,(i, j)$, which allows an efficient update of the amount of sediment in the better way,

$$time(i, j) = \frac{1}{\eta(i, j) \cdot vel(IWD)} \tag{19}$$

For the update of sediment, the use of coefficient $(1 - \rho)$ does not correspond to the actual situation; in the real case, the update of the amount of deposit only needs to subtract the amount washed away from the original amount, so in the improved algorithm, the sediment update of the local path planning is changed to

$$soil(i, j) = soil(i, j) - \rho \cdot \Delta soil(i, j) \tag{20}$$

The global sediment volume update should be changed to

$$soil(i, j) = soil(i, j) - \rho \cdot \frac{soil(IWD)}{(N_{IB} - 1)} \tag{21}$$

While the planned path may offer the advantage of being the shortest in terms of length, it may not be directly applicable to the inspection robot. In the case of wheeled inspection robots, the path's level of smoothness directly impacts the robot's traversal speed. In practical applications, these factors constitute critical criteria for evaluating the algorithm-generated route's merits and drawbacks.

The Floyd algorithm is a classic algorithm used to find the shortest paths between all pairs of vertices in a weighted graph. It refines the paths through a process of iteratively updating the shortest paths between pairs of vertices. First, initialize a two-dimensional array known as the path matrix, which is used to record the shortest paths between nodes. Initially, the values in the path matrix are determined by the graph's adjacency matrix. For each pair of nodes, denoted as i and j, examine whether there exists an intermediate node k such that the path from i to j through k is shorter. If such an intermediate node k exists, update the shortest path from i to j in the path matrix. This update involves combining the shortest path from i to k with the shortest path from k to j. Continue iterating through this process in Step 2 until all the shortest paths within the path matrix have been determined. But, Floyd algorithm time complexity makes it less suitable for very large graphs.

Consequently, following the path planning by the enhanced IWD algorithm, this paper integrates the Floyd algorithm to optimize the route and ensure path smoothness. This optimization aims to minimize or eliminate the need for the robot to decelerate during turning maneuvers, thereby enhancing the operational efficiency of the inspection robot.

A. PREPROCESS THE PATH

For the path planned by the improved IWD algorithm, find the vector of each adjacent node. From the starting point, compare the initial vector α with the following vector β. If the vector angle is 0, the vector is combined, and the next vector is named β repeatedly. If the tip is not 0, proceed to the next step.

B. ADD VECTOR α INITIAL TO THE FOLLOWING VECTOR β

If the new vector does not intersect with the obstacle interval, proceed to step (1). When the new vector intersects with the obstacle interval, the original vector becomes the optimized path segment, and the process repeats with the vector serving as the initial vector. This cycle continues until the final vector reaches the target point.

Commencing from the initial node along the optimized path, intervals are established for placing guide nodes, and inflection points along the path are designated as guide nodes as well. As the inspection robot approaches a guide node, the subsequent guide node assumes an active role, directing the robot's trajectory until the guidance node ultimately aligns with the target node. This guides the robot to the endpoint of the path, completing the guidance process. Under the influence of the guidance node, the inspection robot refrains from prematurely decelerating when making turns, instead maintaining a consistent speed toward the next guide node. This approach not only reduces the time the robot spends navigating corners but also minimizes acceleration and deceleration, enabling the robot to sustain its speed and execute turns smoothly.

The flow of the path planning algorithm is depicted in Figure 2. The enhanced IWD algorithm initially undertakes preliminary path planning, charts the path for processing, optimizes the route using the Floyd algorithm, and ultimately generates the definitive track.

V. SIMULATION AND RESULTS ANALYSIS

This paper establishes various simulation environments to validate the practical efficacy of the enhanced IWD algorithm in the context of path planning. A comparative analysis is conducted between the algorithm under consideration and the original IWD algorithm, thereby confirming the viability of path planning when coupled with the Floyd algorithm.

Table 1 presents the initial parameters for both the original IWD algorithm and the improved Intelligent Water Drop algorithm.

A. SIMULATION OF LOCAL OPTIMAL PROBLEMS

For the problem that the IWD algorithm quickly falls into local optimization and cannot plan a reasonable path, this paper simulates a unique environment to verify the ability of

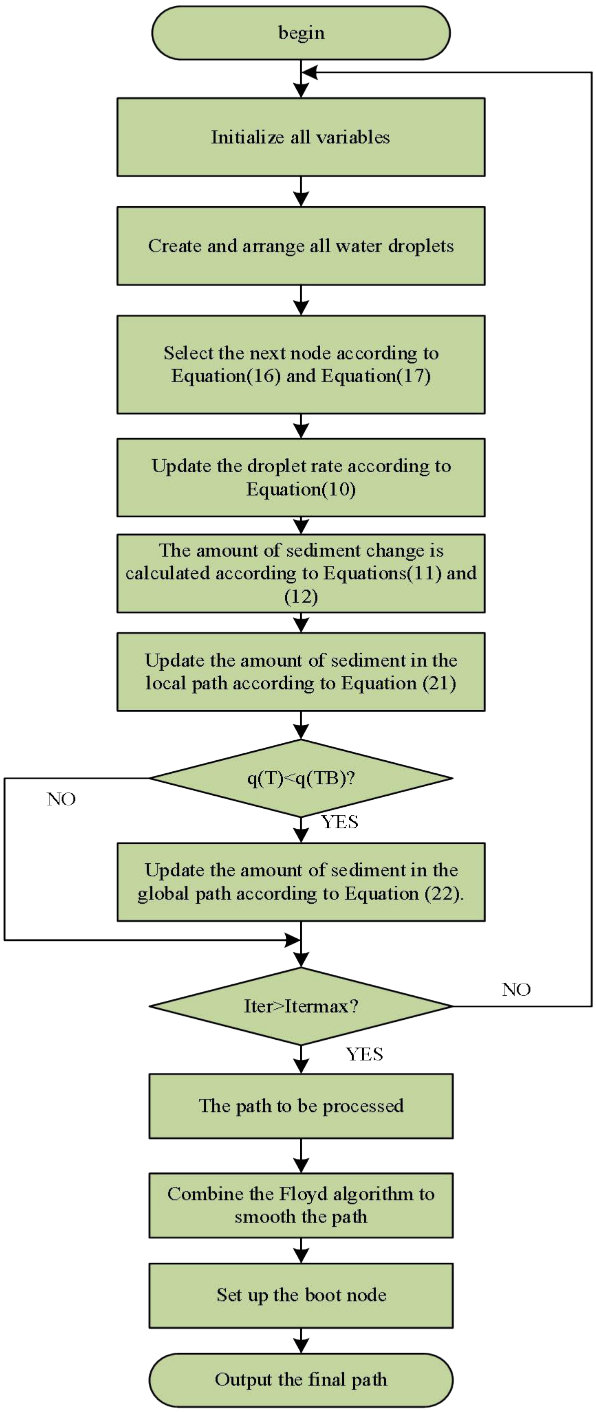

FIGURE 2. Flow chart of the path planning algorithm.

the improved algorithm to get rid of the local optimum, and the experimental results are shown in Figure 3.

Based on the simulation outcomes depicted in Figure 3, it is evident that the original IWDalgorithm produces an ineffective path as a consequence of being influenced by local optimal solutions. In practice, this susceptibility to local optima can lead to an inability to generate a viable route. Conversely, the enhanced IWD algorithm introduces a "roulette" element in the probability selection process, thereby enhancing the randomness inherent in path planning. This strategic addition mitigates the impact of locally optimal solutions and results in the creation of a comprehensive and uninterrupted path.

TABLE 1. Initial parameters of the original, intelligent water drop algorithm and the improved algorithm.

name	symbol	IWD	Improved_IWD
Number of water droplets	N	50	50
Number of iterations	$iter\max$	200	200
Sediment update parameters	ρ	0.5	0.8
The initial value of the amount of sediment	$InitSoil$	1000	1000
Heuristic strength index	Q	-	5
Speed change parameters	a_v	1000	100
	b_v	0.1	0.01
	c_v	1	10
Sediment volume change parameters	a_s	1000	100
	b_s	0.1	0.01
	c_s	1	10
Water droplet initial velocity	$InitVel$	100	100
The initial sand content of the water droplet	$Soil(IWD)$	0	0

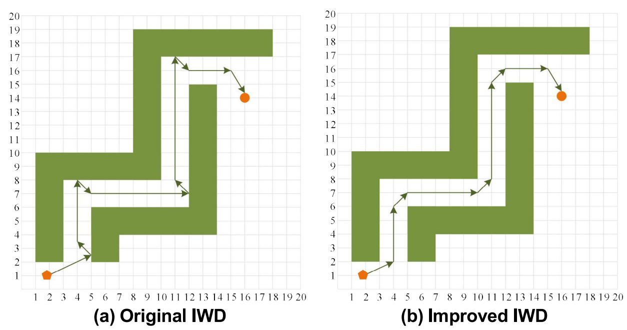

FIGURE 3. Simulation results of two intelligent water drop algorithms.

B. SIMULATION OF THE ACTUAL ENVIRONMENT OF THE ALGORITHM

For the problem that the IWD algorithm quickly falls into local optimization and cannot plan a reasonable path, this paper simulates a unique environment to verify the ability of the improved algorithm to get rid of the local optimum, and the experimental results are shown in Figure 4.

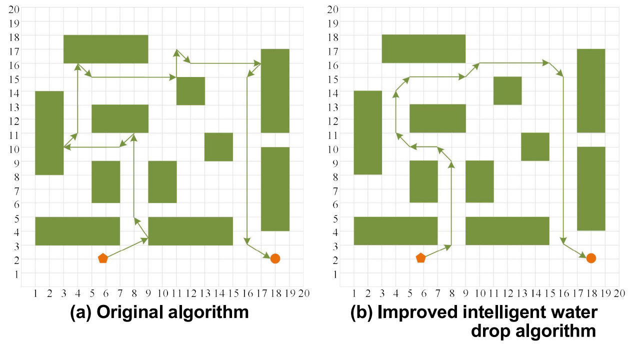

FIGURE 4. Path planning of two algorithms in a conventional environment.

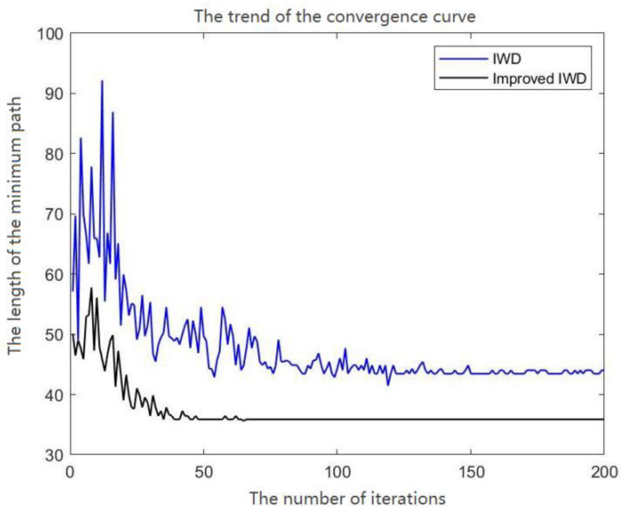

FIGURE 5. From the Comparison of iterative convergence curves of the two algorithms.

The comparison in Figure 4 shows that in the same environment, the path planned by the improved IWD algorithm is shorter than the original IWD algorithm. The path length designed by the improved IWD algorithm is 35.89m, while the original IWD algorithm has a planned path length of 43.46m due to the interference of the local optimal solution.

The iterative convergence diagram of the two algorithms is shown in Figure 5. The original IWD algorithm began to oscillate and converge after 100 iterations. Finally, it joined at 43.46, the improved IWD algorithm began to converge after 50 iterations, and the final path length assembled at 35.89. From Figure 5, it can be seen that the enhanced IWD algorithm has faster path planning speed and more robust stability.

Considering the complexity of the actual working environment, to thoroughly compare the path planning capabilities of the two algorithms, this paper conducts simulation experiments on the two algorithms in three different simulation environments, and the results are shown in Table 2:

The comparison between Figure 4 and Table 2 shows that the improved IWD algorithm is improved compared with the

TABLE 2. Statistics of simulation results of the two algorithms under different environments.

Raster map size	algorithm	Average length/m	Min-length/m	Average elapsed time/s
20×20	IWD	44.59	42.38	6.93
	Improved_IWD	37.62	35.89	4.54
30×30	IWD	64.87	61.91	10.58
	Improved_IWD	54.71	52.52	8.36
40×40	IWD	107.01	93.42	19.56
	Improved_IWD	87.25	85.69	15.78

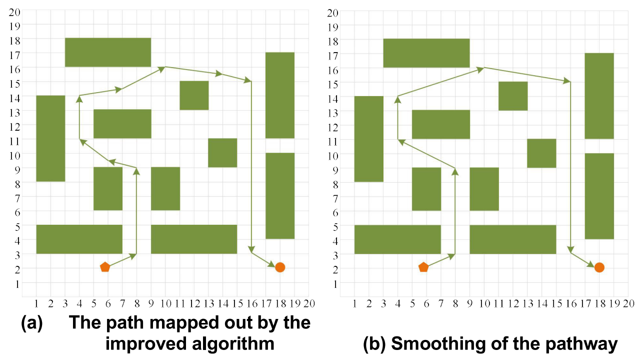

FIGURE 6. Combines the path planned by floyd's algorithm.

original algorithm in terms of path length and average time of path planning in different environments. Compared with the path planning results of the two algorithms in different environments, the improved algorithm improves the way length by 17.42% compared with the original algorithm, and the algorithm planning time is reduced by about 19.7%.

Figure 4(b) presents the initial path configuration prior to optimization. Within this path, certain inflection points fail to adhere to the kinematic principles governing wheeled robots. By applying the Floyd algorithm to this pattern, the trajectory is smoothed, as depicted in Figure 6. In comparison to the pre-optimization path, the optimized route exhibits a 7.7% reduction in length and a 36.3% decrease in the number of inflection points. This reduction in inflection points translates to fewer abrupt turns for the inspection robot, streamlining its path traversal and enhancing operational convenience.

Figure 7 showcases a simulation depicting the inspection robot's movement along the optimized path. In this visualization, the dashed line represents the optimized path, while the solid line traces the inspection robot's trajectory. As evident from the illustration, the inspection robot's travel path is remarkably smooth, ensuring a seamless travel experience. When the inspection robot approaches a guidance node,

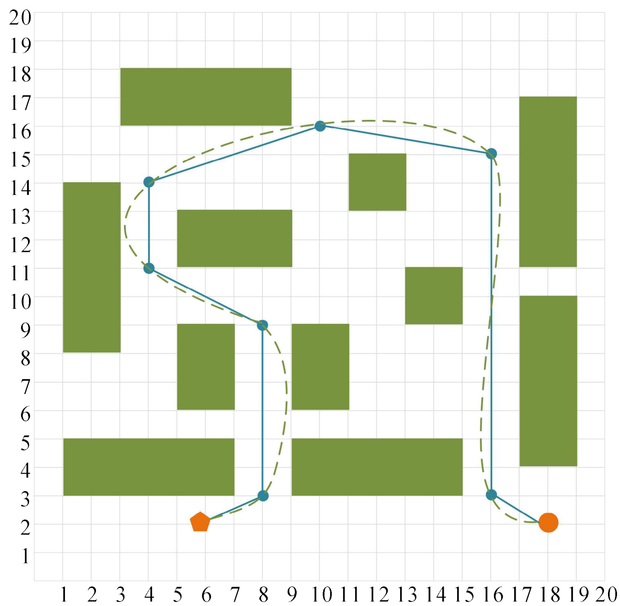

FIGURE 7. **The running trajectory of the optimized inspection robot.**

it proceeds directly towards the subsequent guidance node, facilitating stable-speed steering. This approach minimizes the need for acceleration and deceleration during turns, resulting in time savings and a substantial enhancement in the inspection robot's operational efficiency.

VI. CONCLUSION

One of the most crucial domains within robotics research revolves around the intricate challenge of robot path planning. This research paper introduces a path-planning algorithm tailored for inspection robots, leveraging an enhanced IWD algorithm. Addressing the inherent deficiency in heuristics when originally devising the path through the IWD algorithm, the enhanced IWD algorithm is amalgamated with the Floyd algorithm to optimize the route. This optimization entails a reduction in the path's inflection points, the establishment of guide nodes, and a simulated assessment of the path. The empirical findings demonstrate that the optimized path is notably shorter and adheres more closely to the kinematic principles governing wheeled robots, thereby significantly enhancing the operational efficiency of inspection robots. In the future, further investigation will compare and scrutinize the algorithm's path-planning efficacy under diverse environmental models. Additionally, the algorithm will be deployed to address more intricate path-planning scenarios, with the expectation of achieving superior outcomes.

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(Xuhui Zhang and Chunyang Wang contributed equally to this work.)

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XUHUI ZHANG received the master's and Ph.D. degrees in test and measurement technology and instrumentation from the Harbin University of Science and Technology, in 2003 and 2009, respectively. She is currently a Professor with the School of Measurement and Control Technology and Communication Engineering, Harbin University of Science and Technology. Her main research interests include automatic tests, machine vision, and image processing.

YING JI is currently pursuing the master's degree with the Harbin University of Science and Technology. Her main research interests include path planning and visual navigation.

HAIJUN LIN is currently a Professor with the School of Measurement and Control Technology and Communication Engineering, Harbin University of Science and Technology. He is also the Director of the Electromagnetic Measurement and Information Processing Branch of the China Instrumentation Society. He is an Advanced Individual of the Ninth Five-Year Plan National Key Science and Technology Research and an Advanced Individual of the China Machinery Industry Federation.

CHUNYANG WANG (Member, IEEE) is currently pursuing the master's degree with the Harbin University of Science and Technology. His main research interests include machine vision and image processing.

YUEQIANG WANG is currently pursuing the master's degree with the Harbin University of Science and Technology. His current research interest includes obstacle avoidance.