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Improved Swarm Optimization and Path Planning Intelligent Robot

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Abstract
This research provides an improved particle swarm optimization technique including features of differential evolution in response to the shortcomings of particle swarm optimization in mobile robot path planning, such as poor convergence accuracy and susceptibility to premature convergence. The method, which incorporates adaptive adjustment weights and acceleration coefficients to improve conventional particle swarm optimization, introduces the idea of corporate governance. This change speeds up algorithm convergence. Additionally, adaptive parameters are included to control the magnitude of the mutations in order to improve the performance of the differential evolution process. Additionally, a "high-intensity training" mode is created to precisely refine the search accuracy of the algorithm by intensely training the global ideal position of the particle swarm optimization using the improved differential evolution algorithm.A mathematical model for robot path planning is presented in the paper as a two-objective optimization problem that takes into account both the length of the path and the level of hazard. For path planning, the suggested method is put through a number of experiments and simulated tests. The outcomes demonstrate the algorithm's viability and efficiency in resolving path planning issues for mobile robots.
Key Words: Path planning, particle swarm optimization, differential evolution method, and self-adaptation are other related terms.

I. Introduction

Path planning, which entails the development of collision-free pathways that often aim for optimality in both static and dynamic surroundings to achieve a desired destination, is a crucial field of research in mobile robot technology [1,2]. Advanced path planning technology enables mobile robots to explore difficult and inaccessible places, undertake dangerous activities like fire rescue [4], aid in the navigation of people who are blind, and improve precision in delicate surgeries [5]. It is also useful for intelligent warehousing, enhancing the effectiveness of material transportation, and minimizing the demand for human labor and resources, making it a very pertinent research issue [6].

In order to get the global optimal value of an objective function, the conventional particle swarm optimization (PSO) technique, developed by Kennedy in 1995, simulates the foraging activity of birds. It is favored for its versatility, simplicity, and ease of implementation [7]. In path planning scenarios, a variety of augmented PSO algorithms have been used [8,9]. However, PSO algorithms have drawbacks such as delayed convergence and vulnerability to local optima.In order to plan the course of mobile robots, this work offers an improved particle swarm optimization method based on differential evolution (IPSO-IDE). To overcome the drawbacks of conventional PSO, IPSO-IDE expands on the optimized differential evolution (IDE) approach and joins it with enhanced particle swarm optimization (IPSO). These are the main contributions of this work:An optimized inertia weight, an adaptable parameter, and the idea of corporate governance are all combined in the modified IPSO technique to improve classical particle swarm optimization and speed up convergence.

The scaling factor F and cross-probability factor CR are adaptively improved in light of the drawbacks of the conventional DE technique. This modification improves the optimization accuracy of the algorithm by allowing fine control over the search accuracy and mutation degree.

The article presents a brand-new goal function for path planning that combines a penalty function with a path length function. With this formulation, the objective function optimization problem is reduced to a simpler version of the mobile robot path planning issue.

The sections that follow are organized as follows: A overview of relevant work, including the use of enhanced algorithms in path planning and traditional heuristic algorithms, is given in Section 2. The foundations of PSO and DE are discussed in Section 3. The IPSO-IDE algorithm is discussed in Section 4 in detail. Its application to path planning is covered in Section 5, together with experimental information and outcome analysis. The last paragraph includes conclusions and summary comments.

II. Related Work

Globally intensive research on path planning algorithms for mobile robots has produced outstanding outcomes. When dealing with complicated barriers, conventional path planning techniques as the artificial potential field approach [10], element decomposition method [11], and graph search algorithms [12] have drawbacks. The workload of mobile robots is increased by their frequent need for intensive computational resources, propensity for local optima, and production of non-smooth pathways with sharp points that do not match real-world circumstances [13,14]. Heuristic algorithms for path planning optimization have become popular among professionals as a solution to these problems [15]. them include differential evolution algorithm (DE) [21], artificial bee colony algorithm (ABC) [18], grey wolf algorithm (GWO) [19], ant colony algorithm (ACO) [20], genetic algorithms (GA) [16], particle swarm optimization (PSO) [17], artificial bee colony algorithm (ABC) [18], and PSO [17]. All of them have shown promise.

Many later algorithms are theoretically based on GA, an early intelligent bio-inspired algorithm. Initiating a population, determining individual fitness, and incrementally enhancing the population through crossover and mutation operations are all phases involved in simulating Darwinian biological evolution [22]. But GA's mutation operation lacks specificity, which restricts its capacity to produce elite progeny populations. As a result, to solve particular problems, GA is frequently supplemented with heuristic algorithms like ant colony optimization (ACO) or particle swarm optimization (PSO). For instance, Memon et al. suggested a hybrid optimization technique based on GA and APSO [24] while Kamel et al. integrated PSO and GA to improve the performance of predictive modeling. Improved GA is still ineffective for some problem areas despite these advancements [25].

PSO and DE are two popular heuristic algorithms that are preferred for their simplicity and ease of use [26]. PSO improvements frequently concentrate on modifying population structures and improving velocity and position updating algorithms [27]. To increase convergence speed, Burman R, for instance, added the idea of peer groups to the democracy-inspired particle swarm optimizer [28]. To eliminate local optima and boost particle variety, Zhao et al. devised a nonlinear recursive function to change the inertia weight [29]. Hybrid PSO algorithms have been proposed, including SDPSO [30], which integrates unique aspects to improve performance. In addition, hybrid algorithms that combine Particle Filter (PF) and PSO algorithms have been investigated [31], as well as PSO variants like MPSO [25].

These algorithms nevertheless have drawbacks, such as low convergence accuracy and susceptibility to premature convergence, in spite of these improvements. The differential evolution algorithm (DE), developed by R. Storn et al. in

1997, presents a technique that is more succinct and efficient by taking cues from genetic algorithms and evolutionary principles.

III. Improved Particle Swarm Optimization

The conventional particle swarm optimization (PSO) method [17] is based on the idea of single leadership, in which an ideal particle serves as the global optimum (G) and directs the entire swarm in the direction of the G. This single-leader strategy has drawbacks, though, and it can't always provide accurate guidance, which frequently leads to premature convergence and local optima entrapment. This study integrates the idea of corporate governance into PSO and optimizes its settings in order to meet this problem.Two key rights inside a firm are involved in corporate governance in economics: ownership and management rights. Effective administrators are strong owners and operators. The owner gives the operator management authority so they can guide the business and its staff to greater results. The owner may intervene, make decisions, and withdraw the operator's management privileges if the business performs poorly while the operator is in charge. To encourage the growth of businesses, these two rights serve as checks and balances.On the basis of these ideas, this work improves the algorithm by introducing the idea of administrator particles (Adm), which momentarily take on management roles. The Operator particle and the Owner particle are two prospective administrator particles that are chosen through a voting process. As a supervisor, the Owner particle makes sure that the Operator particle constantly directs the particle swarm to the ideal spot. The work also proposes the notion of peer groups, which is inspired by corporate culture. Neighboring particles are regarded as a peer group, and their optimal placements are interdependent. In the peer group, the local optimal value (Lbest) is chosen.Through the use of corporate governance, adaptive parameters, and acceleration coefficients, the conventional PSO is enhanced in this article. Figure 1 depicts the particle position updates for two repetitions in a row. The precise formulas for updating position and velocity are as follows:Equation (9)'s first component, which denotes the inertia factor, is created by multiplying the velocity from the previous iteration (t) by an adaptive inertia weight (*) that was suggested in the study. The original inertia weight () serves as the foundation for the adaptive inertia weight (*), which also includes a trigonometric function. In order to prevent premature convergence and to make it easier to enter the local ideal state, this change enables adjustments to the step size and acceleration of the speed, ultimately improving accuracy.

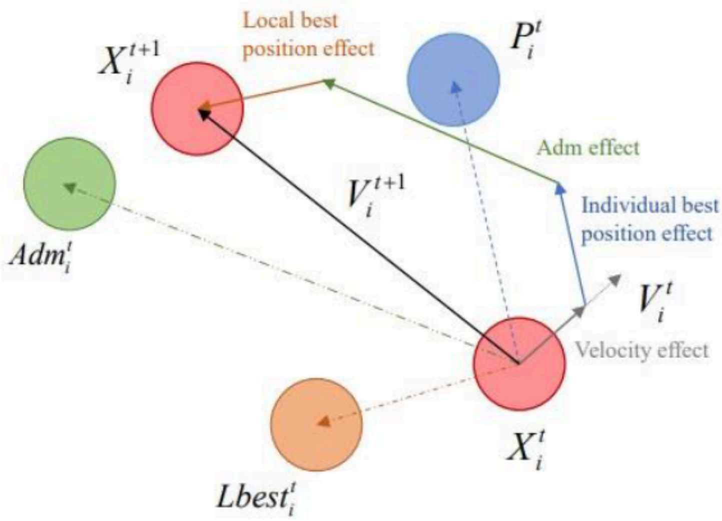

Fig.1:Particle Positions

Opvote increases and Owvote decreases as the iteration goes on, indicating that the Operator particle's impact is gradually growing. Convergence is accelerated while the Owner particle's effect is diminished. The Owner must take charge, though, if the Operator is unable to guide the particles to their best position. In certain situations, the Owner's influence must be increased even if Owvote is minimal. The paper introduces the Administrator regulatory factor = e(1voteAdm) in order to do this.The work adds asymmetric processing to the initial voting range of the two administrator particle candidates in order to impose a preference on the initially randomly produced population. It is standardized for the asymmetric range to lie between [0, 1]. As a result, in the earliest versions, particles are more inclined to select the Operator as Adm, with the Owner acting as a backup option to manage. Vote bias is produced when Opvote's starting value is set to and Owvote's initial value is set to 1-.A roulette algorithm is used to implement the voting process [16]. Each particle votes for a leader voteid, a random number between [0, 1], by casting a single vote. The decision to choose Adm can be stated as follows:

IV. Mathematical Formula for updating the positions

The algorithm's updated mathematical formula for updating the position is as follows:

By multiplying the particle's historical position Xi at iteration t and velocity Vi at iteration t+1 by the acceleration factor c4 and a random number r4 [0, 1], equation (10) calculates the particle's position Xi at iteration t + 1.

Additionally, because particles move through the solution space with a specific velocity v, it might have a detrimental effect on the algorithm's outcome if a particle's velocity is too high and causes it to leave the solution area. In order to solve this problem, the study adds boundary handling to the particle's velocity vd and promptly modifies it if it exceeds the velocity

Vd is set to vmax if it exceeds the maximum permitted velocity (vmax).

It is set to vmin if vd is less than the minimum allowable velocity (vmin).

Here, vd stands for the velocity vi component at generation t in dimension d, while vmin and vmax are the minimum and maximum permitted values for velocity, respectively.

A better differential evolution algorithm with adaptive parameters is shown in section 4.2.

The Differential Evolution (DE) algorithm is renowned for being straightforward and achieving quick convergence. The scaling factor F and the crossover probability factor CR are its two main inputs. These parameters are fixed throughout the optimization process in the conventional DE. The paper proposes adaptable parameters for F and CR in order to improve convergence performance and iterative accuracy.

Optimizing the Scaling Factor F Adaptively

The algorithmic variation is managed by the scaling factor F. The search space of the algorithm is expanded by a higher F, which might be favorable for overall progress but may cause premature convergence in subsequent iterations. A lower F, on the other hand, denotes a reduced degree of variation, favoring local search to increase search accuracy but perhaps leading to the algorithm becoming stuck in local optima.

The paper uses the following expression to adaptively alter F in order to address this:

Fi is equal to Fmax minus Fmin. (Fit (xp2(t)) Fit (xp1(t)) / Fit (xp3(t) Fit (xp1(t)))

Where:

Fi stands for the population's ith vector's scaling factor.

The fitness values of the vectors xp1, xp2, and xp3 are denoted by the formulas fit(xp1(t)), fit(xp2(t), and fit(xp3(t)).

The scaling factors' minimum and maximum values are denoted by Fmin and Fmax, respectively.The difference between the fitness values for xp2 and xp3 is taken into account by the adaptive adjustment of F. If this difference is substantial, it broadens the search window to avoid a too-small F, which might reduce search precision. In contrast, if xp2 and xp3's fitness scores are similar, Fi is increased to enhance the degree of variance.

Adaptive Crossover Probability Factor CR Optimization

The crossover probability factor CR is improved to hasten the convergence of the algorithm. The amount of crossover between the parent vector and the mutant vector is influenced by CR. A high crossover degree can potentially harm individuals who are more fit due to excessive mutation if the CR is too high. Conversely, if CR is too low, there may not be enough crossover, which could result in local convergence and less effective search.

The approach for contrasting a given person's fitness level with the mean fitness of the population is suggested in this study. When an individual's fitness is better than the average, the cross-variation is smaller, indicating that the individual is better. The individual may need more investigation if their level of fitness is higher than the average.The convergence and search effectiveness of the algorithm are enhanced by these adaptive modifications to F and CR.

V. Hybrid IPSO

The principles of corporate governance and voting are integrated into the Particle Swarm Optimization (PSO) in this work to increase its optimization capabilities. Adaptive elements are also introduced to speed up convergence. To get closer to the ideal position, PSO's concept calls for updating particle velocity and position through repetitive procedures. When tackling optimization issues, PSO can occasionally converge to non-optimal positions due to the simplicity of particle movement and susceptibility to the impact of other particles. Differential Evolution (DE), on the other hand, can support PSO and converges quickly in the early stages.

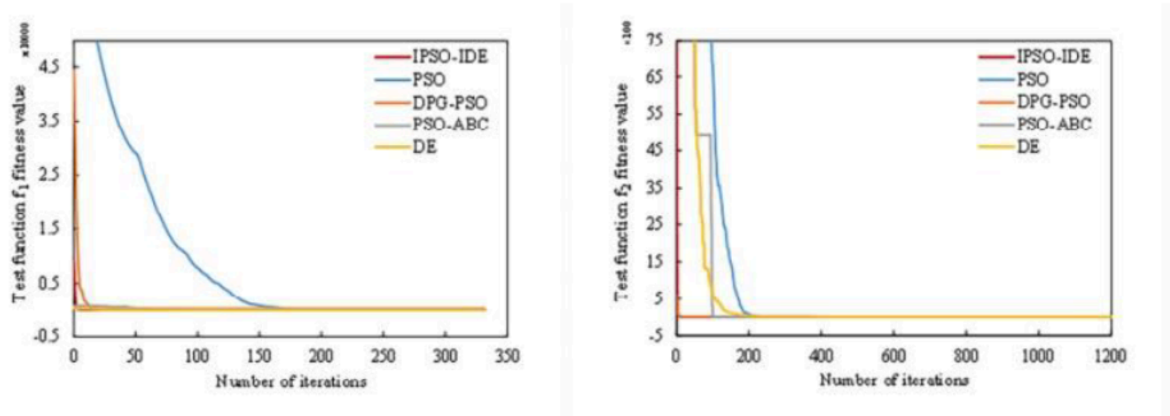

Fig.2 : Test Function Result

In conclusion, the study integrates and enhances conventional PSO and DE to produce a novel hybrid PSO-DE optimization mechanism. Through this method, the two algorithms are encouraged to work together to improve their skills in a way that is beneficial to both parties. The enhanced Particle Swarm Optimization based on Differential Evolution (IPSO-IDE) is the name of the enhanced algorithm. Both IDE and IPSO function in collaborative modes. The Administrator (Adm) of IPSO is improved by IDE, bringing it closer to the ideal position and boosting its capacity to direct particles there. After each cycle, this causes the population to perform better, known as the "elite population." The IDE algorithm can be trained using the elite population to produce better results.

The following are the steps for implementing the suggested IPSO-IDE:

Initialization of parameters, including, among others, the acceleration factor, the quantity of affirmative votes (Opvote), and the quantity of unfavorable votes (Owvote).

Initialization of the particle swarm at random, comprising dimension (D), population particle count (N), position (X), velocity (V), and other parameters.

Particle fitness values (Fit) are computed using the chosen objective function.

To determine the overall best position, one must calculate the individual best positions (Pit), the local best positions (Lbestit), and choose the administrator based on equation (12).

The updated Equations (9) and (10) are used to update positions (X) and speeds (V) in order to produce a high-quality elite population.

Boundary processing using Equation (13).

IDE algorithm with Equations (14) and (15) for adaptive parameters, Equations (6), (7), and (8) for "high-intensity" iterative optimization, and the elite population as the initial population.

application of the IDE algorithm's optimized output to the updated particle swarm's leader.

Stop the algorithm if the termination condition is satisfied and output the best outcomes. If not, go back to Step 2.

technique 2 towards the end of the article has a full description of the technique.

The IPSO and IDE working together to drive the proposed algorithm's two sections. The advantage of DE is its early rapid convergence, which makes it especially useful for optimizing the initial population of IPSO. The goal of this collaboration between the two methods is to boost optimization performance overall.

VI. Signal suppression's impact

The fitness function plays a crucial role in evolutionary algorithms, significantly impacting their performance. To address the specific requirements of the path-planning problem, the evaluation criteria in this paper encompass two main factors: path length and risk degree. The construction of the fitness function is based on these evaluation criteria, resulting in an objective function composed of a path length function and a penalty function.

1. Path Length Function: The path length function, denoted as fL, is used to calculate the length of the path taken by the mobile robot from the starting point (Start) to the target point (Goal). It is expressed by the following formula:

$FL=(xG-xS)2+(yG-yS)2$

$fL=(xG-xS)2+(yG-yS)2$

by the following formula:

- xG and yG are the coordinates of the goal point (Goal).
- xS and yS are the coordinates of the starting point (Start).

2. Penalty Function: Ensuring the safety of the generated path is crucial in mobile robot path planning. Paths that intersect with obstacles are considered riskier, and a penalty function is used to penalize path nodes that intersect with obstacles. To simplify the calculation, the obstacles in the environment are modeled as circles (Ck) with centers (Ok) and radii (R). Even for irregular obstacles, circular approximation is employed. The obstacle radius (R) is treated as the safety threshold, and the distance between path nodes and obstacles must be greater than this threshold. Additionally, lines connecting adjacent path nodes should not intersect with obstacles. To assess path intersections with obstacles, mid-nodes are introduced. Mid-nodes are points on the line segments connecting two adjacent path nodes.

3. The penalty degree between node i and node i-1 is determined based on their proximity to obstacles. The calculation method for the penalty degree is as follows:

$Disk=(xi-Oxk)2+(yi-Oyk)2$

0 & Disk \leq r_k \\

1 & Disk > r_k

\end{cases}

- penalty degree is as follows: Disk represents the Euclidean distance between a node (mid-node or path node) and the center of obstacle Ck.
- riskk is the penalty factor for obstacle Ck. It takes the value 1 if Disk > rk (distance exceeds the safety threshold rk) and 0 if Disk ≤ rk (within the safety threshold).

$fP=\eta\sum j=1m+2\sum i=1n+1Risk(xi,yi)$

penalty degree function Where:

- n is the number of path nodes.
- m is the number of mid-nodes.
- η is a weight coefficient that determines the influence of the penalty degree (Risk(xi, yi)) on the fitness function.

The penalty function considers the accumulated penalty across all path nodes and mid-nodes, weighted by η. It effectively captures the degree of risk associated with the path in terms of obstacle intersections.

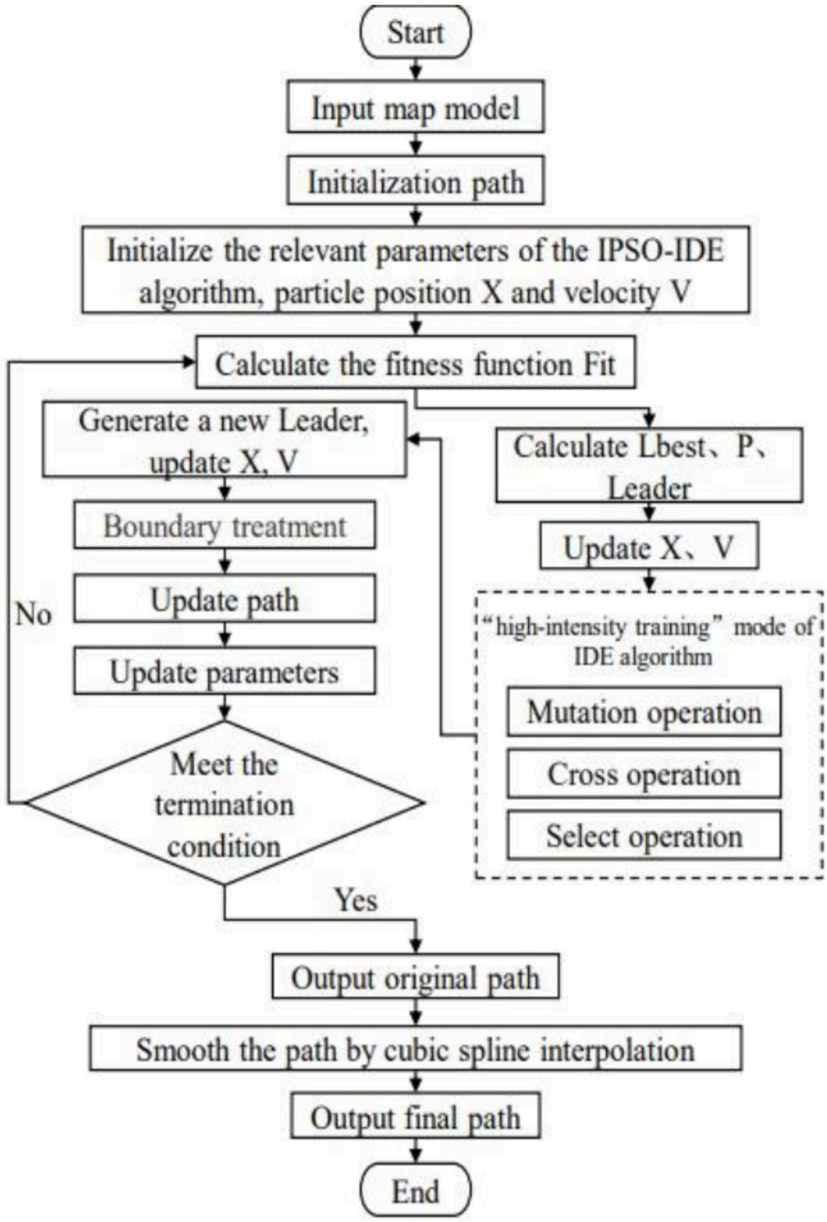

Fig.3: Proposed Algorithm

A number of path-planning simulation experiments are run under various conditions to confirm the algorithm's viability. These tests are designed to show how the path-planning algorithm can be used in mobile robots in the future. The Move_base path-planning algorithm package included with the ROS (Robot Operating System) is used by the mobile robot to carry out path-planning activities based on its dynamic model. Planning both a global and local path is included in this.

Using data from global maps, global path planning entails creating the shortest route between the starting point and the destination.

Analyses, experiments, and simulations

Simulated experiments are carried out using Python 3.7.5 software to validate the algorithm suggested in this research for addressing path planning problems and to examine the effect of the number of path nodes on algorithm performance. The performance of the suggested algorithm is compared to those of PSO, DE, ABC, PSO-ABC, DPG-PSO, PSO-DE, and IDE, as well as a number of additional algorithms.

6. Test different numbers of path nodes

This experiment aims to investigate the impact of path node density on path planning efficiency. The experiment will take place in Environment 1, with x and y coordinates spanning from 0 to 10. The beginning point is shown as (0, 0), which is represented by a red square, and the ending point is shown as (10, 10), which is symbolized by a red "X." The red line shows the final path, and the blue circles show the path nodes.

During this test:

There are 15 people in the population.

There are anywhere from 1 to 10 route nodes.

There can be a maximum of 100 iterations.

Figure 7 shows the experimental findings. When there are between 1 and 10 path nodes, Figure 8 shows the convergence curve of path length based on the IPSO-IDE algorithm.

VII. Conclusion

Nine traditional test functions were used to thoroughly test the proposed technique, and the results are quite encouraging. Without requiring a lot of sample data, it displays significant optimization abilities and effective search. The algorithm frequently arrived at the best solution. The worst-case accuracy nonetheless managed to reach an astounding level of 10-6 even for the most difficult test function (f9), where the ideal solution wasn't found. When compared to benchmark algorithms like PSO, DPG-PSO, PSO-ABC, and IDE, this performance superiority is clear.

Additionally, the algorithm was tested for path-planning studies in a variety of experimental settings. The experimental results showed that the suggested IPSO-IDE algorithm, in contrast to conventional path-planning algorithms, not only boasts improved convergence accuracy but also avoids premature convergence difficulties. The IPSO-IDE algorithm beats previous algorithms by finding better pathways and obtaining higher ultimate convergence accuracy, even if it may still show evidence of premature convergence.

These findings confirm the algorithm's ability to improve global search capabilities and demonstrate its usefulness. It's important to remember that the method is intended to resolve path planning issues involving mobile robots and intricate static maps. The work aims to expand the applicability of the technique to path planning in dynamic situations. To further increase the efficacy of path planning, this entails improving real-time scene gathering and processing capabilities.

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