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Journal of Advanced Research Design

Journal homepage:
https://akademiabaru.com/submit/index.php/ard
ISSN: 2289-7984

An Enhanced Ants Colony Optimization Algorithm for Path Planning of Autonomous Robots in Continuous Environment

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ARTICLE INFO

Article history:
Received 3 January 2025
Received in revised form 14 February 2025
Accepted 23 May 2025
Available online 2 June 2025

Keywords:
Mobile robot; path planning; genetic algorithm; ant colony optimization algorithm

ABSTRACT

This paper presents a method for mobile robot path planning in complex environments. First, an advanced Ant Colony Optimization (ACO) algorithm is introduced to find viable paths in a discrete grid environment, connecting the starting point to the destination. The proposed ACO algorithm incorporates a probabilistic prediction mechanism to enhance the efficiency of node selection. By integrating ACO's inherent heuristic factors, this approach offers directional intelligence and significantly increases the likelihood of the ant colony finding feasible initial paths. In the improved ACO algorithm, both the pheromone and heuristic factors are integrated into the new probabilistic prediction mechanism, which further improves path planning efficiency. The effectiveness of the proposed algorithm was evaluated using three different planar environment models of varying sizes and complexities. The results show that the algorithm's performance is minimally influenced by its control parameters. Additionally, a comparative analysis was conducted to evaluate the proposed algorithm against A* and traditional ACO. The comparison results indicate that the proposed algorithm outperforms the others in terms of path length, runtime and success rate.

1. Introduction

With the rapid development of technology, unmanned driving has become a significant innovation in the automotive industry, attracting attention from the public [1]. The path planning algorithm pertains to the technology that analyses and perceives the surrounding environment of a vehicle to devise a secure and efficient driving path for unmanned vehicles [2]. Its goal is to ensure that unmanned vehicles can make intelligent decisions in complex urban traffic environments, adapt to different road conditions [3-5], and coordinate with other road users to achieve a safer and more comfortable driving experience [6].

Central to the development of self-driving vehicles is the ability to abstract complex traffic environments into data that can be understood and processed by computers [7]. Path planning is a crucial technology in unmanned driving. The main aim of path planners is to determine an optimal or

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https://doi.org/10.37934/ard.133.1.8091

near-optimal route free of collisions from the start point to the endpoint. The standards used to evaluate the best route differ according to the different robot adaptation scenarios [8]. Research on path planning can be divided into two main types: global path planning and local path planning. Initially, path planning methods were mainly focused on computer science and mathematics. Notably, Dijkstra's algorithm [9] and the A* algorithm [10] were among the initial significant algorithms used to determine the shortest path. However, as the environment scales up, these algorithms become increasingly complex, resulting in a decline in efficiency. Nevertheless, the real world is characterized by numerous unknown and intricate environments, necessitating the importance of random sampling path planning algorithms. The Random Rapidly-exploring Random Trees (RRT) algorithm accomplishes path planning through random sampling and the expansion of tree structures [11]. Unlike the A* algorithm, the RRT algorithm can operate without prior maps and relies solely on local perception. It proves to be a highly adaptive and scalable method, especially suitable for unknown environments, complex terrains, and high-dimensional state spaces [12]. However, due to the inherent nature of random sampling, it faces limitations in terms of time and computational efficiency. The field of path planning has introduced new methods, like intelligent bio-inspired algorithms, reinforcement learning, and neural networks, to enhance efficiency during path searches and reduce computational costs. This has been achieved with the development of artificial intelligence. However, in expansive and highly complex environments, despite the application of these efficient methods, path planning still faces challenges, especially in finding feasible paths after multiple iterations [13-15].

This article introduces an innovative algorithm developed for planning robot paths within uninterrupted environments. The proposed upgrade to the ACO algorithm has the capability to identify the optimal or nearly optimal route in complex settings of diverse nature. The algorithm utilizes ACO to determine feasible paths in a discretized grid-based environment connecting the initial and final points [16]. To enhance the accuracy of ACO in determining viable primary routes, a probability prediction mechanism is implemented, enabling efficient selection of successive nodes and supplementing ACO's innate heuristic methodology for directional intelligence. This refinement appreciably amplifies ACO's effectiveness in planning feasible initial paths. In addition, the heuristic operation is enhanced by computing the aggregate angle information of path turns. Furthermore, this paper presents a new approach for path simplification which employs path reconnection techniques to create more efficient and seamless routes. The commonly accepted goals for path planning quandaries are generally threefold: (i) determining the shortest distance between the origin and destination points; (ii) minimizing directional variations in the path; and (iii) calculating the time necessary to navigate from the starting point to the end. The present study conducts a comparative analysis of three distinct path planning algorithms (the proposed algorithm, ACO and A*) in various simulated environments. The three main objectives of the proposed algorithm are evaluated against those of the other algorithms involved in this study. The subsequent sections of this paper are organized as follows: Section 2 offers a review of previous work, while Section 3 presents the proposed path planning method, including a detailed depiction of the algorithm, mathematical models, improved ACO path planner mechanisms. Section 4 presents and analyses the findings of the comparative experiments. Ultimately, Section 5 provides a conclusion to the study.

2. Related Works

Recently, the rapid development of autonomous robotics technology has sparked a great deal of research interest in autonomous robots, especially concerning automatic navigation algorithms. It focuses on three types of automatic navigation algorithms: deterministic algorithms, bio-inspired algorithms and hybrid algorithms.

2.1 Deterministic Algorithms

The deterministic path planning algorithm is employed to find a clear path between a starting point and a destination. Widely used deterministic algorithms comprise Dijkstra and A*. Wang *et al.,* [17] presents a study on a maze robot scenario and applies the Dijkstra algorithm for path planning. The model selects the shortest route while dealing with obstacles. The simulation outcomes affirm that the approach effectively tackles the path planning challenge posed by the maze robot. S. Julius Fusic *et al.,* [18] investigated robot path planning and trajectory planning. By modifying parameters in the Dijkstra algorithm and creating scenarios in different environments, the paper successfully identifies effective paths for the robot to reach its destination. The mobile robot model, developed using V-REP simulation software, demonstrates the effectiveness of the deceleration method in terms of both time and velocity in the created environments for robot path planning. Fu *et al.,* [19] introduced an improved A* algorithm optimized for industrial robot path planning. By planning local paths before neighborhood searches and optimizing paths in a post-processing stage, the algorithm enhances the search success rate and results in shorter and smoother robot paths. Due to the prolonged time taken by the A* algorithm in traversing the OPEN and CLOSED tables. To address this limitation, Peng *et al.,* [20] proposed an improvement by introducing a new array storage method, resulting in an efficiency improvement of over 40%. The enhanced A* algorithm retains the original advantages while effectively boosting the operational efficiency of A*. An optimization algorithm is introduced to enhance the A* algorithm's efficiency and path smoothness by incorporating Jump Point Search (JPS), pruning unnecessary nodes, and applying Bézier curves for smoothing. Simulations and real-world experiments confirm its effectiveness in achieving shorter and smoother paths [21].

2.2 Bio-Inspired Algorithms

The bio-inspired algorithm draws inspiration from biological principles and simulates the behavior of organisms in natural environments. These algorithms can search and optimize paths in complex environments, and are often used to solve real-world problems with uncertainty and dynamic variations. A self-adaptive Ant Colony Optimization (DEACO) is proposed, which improves the uncertain convergence time and random decisions through unique strategies. Experimental results demonstrate that DEACO outperforms traditional ACO in terms of convergence speed and search accuracy [22]. Li *et al.,* [23] introduced an effective method for planning trajectories of multiple UAVs in a static environment using the improved MACO algorithm, demonstrating success in optimal solutions, collision avoidance, and smooth trajectory planning. Yang *et al.,* [24] presents an effective Leader-Follower Ant Colony Optimization (LF-ACO) algorithm for collaborative multi-robot path planning. It introduces a new heuristic function, reconstructs the leader-follower structure and optimizes the path, successfully addressing path planning and formation problems in simulations and experiments conducted in MATLAB and ROS. Lin *et al.,* [25] proposed a two-layer path planning method that utilizes an optimized artificial potential field and an improved dynamic window approach at the global and local layers, enabling a robot to navigate in a multi-obstacle environment. Through particle swarm optimization and fuzzy control, this method obtains a better global path and quickly responds to moving obstacles at the local level, effectively planning paths in both static and dynamic scenarios.

2.3 Hybrid Algorithms

Hybrid algorithm path planning refers to the integration of different path planning algorithms to fully leverage their respective strengths in addressing complex path planning problems. This approach typically enhances the performance and robustness of path planning, making it suitable for diverse environments and tasks. Chen *et al.,* [26] proposed an improved Unmanned Surface Vehicle (USV) path planning algorithm that integrates ant colony optimization and artificial potential field methods. Through simulations and field experiments, the effectiveness of this algorithm in complex environments has been validated. This algorithm enhances path planning efficiency and improves the navigation safety of USVs. He *et al.,* [27] presented a hybrid algorithm to tackle the problem of path planning for multiple UAVs in a three-dimensional environment, which integrates the timestamp segmentation model, enhanced particle swarm optimization, and modified symbiotic organism search methods. The experimental results exhibit remarkable advancements in accuracy, convergence speed, stability, and robustness compared to five other algorithms, thoroughly validating its efficacy. Previous studies focus on optimizing traditional path planning algorithms like Dijkstra, A*, bio-inspired and hybrid algorithms, improving efficiency and smoothness. In contrast, the proposed algorithm introduces a probabilistic prediction mechanism within the ACO framework. This mechanism enhances efficiency, prevents local optima and dead-ends, and increases the success rate of path planning. It also improves adaptability in complex environments, offering more reliable and feasible paths compared to traditional methods.

The main contributions of this paper can be summarized as follows:

i. Firstly, an advanced ACO algorithm is presented for discovering viable paths within a discrete grid environment, connecting the starting and destination locations. The proposed ACO integrates a probabilistic prediction mechanism for a more efficient node selection, merging ACO's inherent heuristic factors to offer directional intelligence and substantially enhance the probability of the ant colony planning feasible initial paths.
ii. Secondly, in the improved ACO algorithm, the pheromone and heuristic factors of this algorithm are integrated into the newly proposed probability prediction mechanism, allowing for more efficient path planning.
iii. Thirdly, a path reconnection procedure is utilized to acquire paths characterized by favorable length and smoothness.

3. Proposed Path Planning Method

In this section, we propose a heuristic algorithm to address the limitations of the traditional ACO algorithm, particularly its tendency to get trapped in local optima and its inability to avoid dead-ends, especially when encountering C-shaped obstacles. Our novel algorithm utilizes an enhanced ACO framework to determine the optimal path in a complex environment. We introduce three key mechanisms in our heuristic algorithm, starting with a mechanism to adjust the probability of selecting the next step. Additionally, we implement an improved heuristic function to enable forward planning and prevent the algorithm from getting stuck in deadlock situations. These improvements result in a new variant of the algorithm, called Enhanced Ant Colony Optimization (EACO), which incorporates the proposed mechanisms. Figure 1 illustrates the flowchart of the proposed EACO for finding optimal paths in a complex environment.

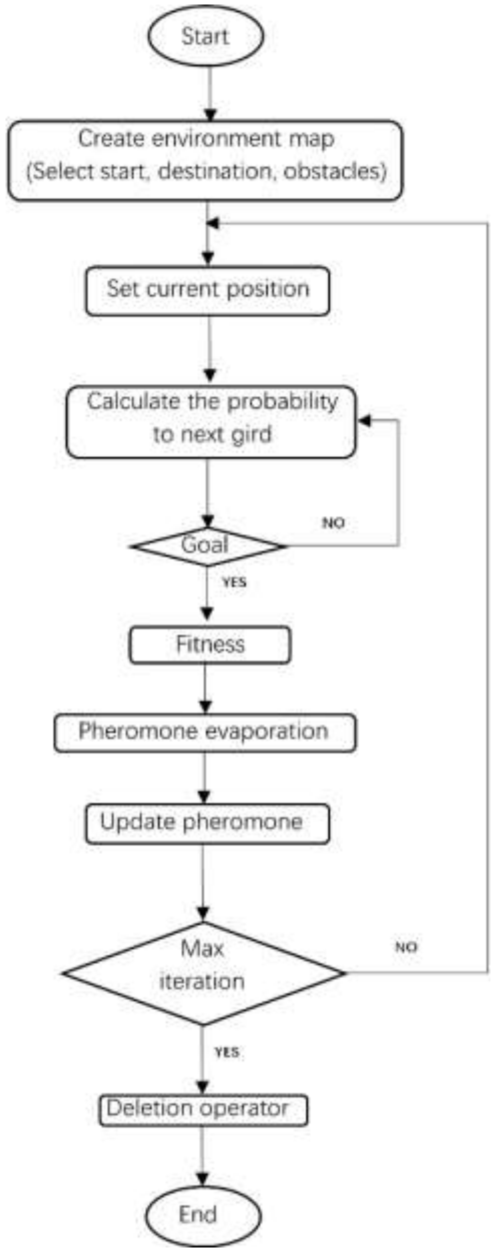

Fig. 1. The proposed EACO flowchart for path planning in a complex environment

3.1 Model and Mathematical

The proposed algorithm gains from the environmental modelling approach. Therefore, all simulation and comparison work of this paper's proposed algorithm was carried out on a grid-based map. Initially, the ACO algorithm allocated a relevant heuristic value to all environment nodes. In classical ACO, each ant may select one of eight potential nodes as its next node, provided there are no obstacles nearby, when examining the current node. Figure 2 depicts this scenario, with N representing the current node and N1, N2, N3, N4, N5, N6, N7 and N8 representing the eight possible next nodes. The probability of each node being selected is determined by a combination of pheromone and heuristic values. The enhanced ACO algorithm generates feasible paths between the starting point and destination. The improved ACO creates this path. Then, each path's coordinates transform into a solution. Figure 3 displays the initial feasible path in green. To calculate the distance between two cells, it is crucial to acquire the x-y coordinates of the center point of a cell. This can be achieved by using Eq. (1) based on the cell number.

$$\begin{cases} x = ceil\left(\frac{N}{Size_{row}}\right) \\ y = mod(N, Size_{col}) \end{cases} \tag{1}$$

Where, N is the number of cells, $ceil$ and mod are the functions to calculate the row and col. $Size_{row}$ and $Size_{col}$ are the row and col of model. In the improved ACO algorithm, $fitness$ value is defined through Eq. (2).

$$fitness = \frac{1}{\sum_{i=1}^{N-1} \sqrt{(x_{i+1}-x_i)^2+(y_{i+1}-y_i)^2}} + \frac{1}{\sum_{i=1}^{N-2} \arccos\frac{c_i+b_i-a_i}{2\sqrt{b_i c_i}}} \tag{2}$$

Where, x_i and y_i are node i coordinate, a_i , b_i , c_i are the sides of three nodes. a_i , b_i , c_i can be defined by Euclidean distance function:

$$dis\tan ce = \sqrt{(x_{i+1} - x_i)^2 + (y_{i+1} - y_i)^2} \tag{3}$$

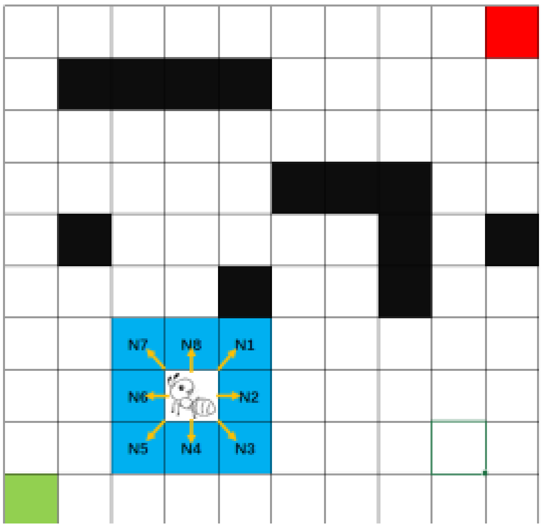

Fig. 2. Eight potential nodes in ACO algorithm

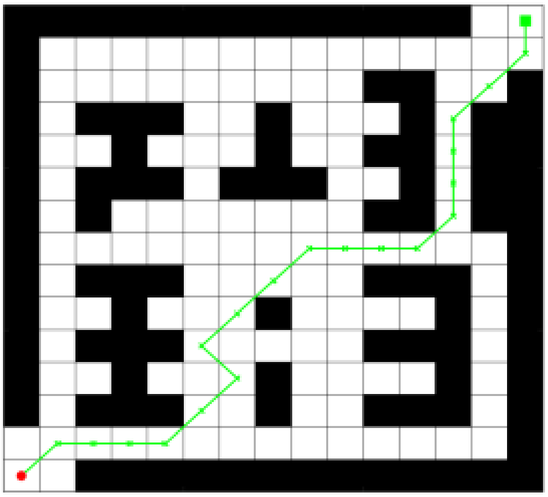

Fig. 3. 15*15 grid environment and initial path

3.2 Original ACO Model

In traditional ACO, ants release pheromones as they forage for food, and other ants are able to detect these pheromones. Over time, these pheromones gradually evaporate, leaving a higher concentration of pheromones on shorter paths. As a result, effective selection of the optimal path is achieved. To implement this algorithm: (a) First, the parameters for the ACO must be initialised, including the maximum number of iterations ($Iter_{max}$), the population size (pop), the heuristic factor (β), the pheromone factor (a) and the pheromone evaporation rate (ρ), among others. (b) Next, the roulette wheel method is used to determine the next node in the environmental model. (c) Finally, once each ant has established a path from the starting point to the destination, the pheromone levels at each node are adjusted according to the fitness of the path.

3.3 Improved ACO Mechanisms

In the enhanced ACO, one mechanism is proposed to improve ACO. Firstly, a novel heuristic mechanism is proposed to increase the probability of finding a path in complex environment. ACO algorithm builds on the basis of the original ACO and focuses on the accuracy of finding viable paths. In addition to levels and fitness value, the enhanced ACO algorithm introduces a dynamic selection mechanism, which takes into effect the number of choices available at each individual decision point. Dynamic selection probabilities can be defined by Eq. (4).

$$p_{ij} = \frac{[\tau(i,j)]^{\alpha} * [\eta(i,j)]^{\beta}}{\sum_{r,c\in s}[\tau(r,c)]^{\alpha} * [\eta(r,c)]^{\beta}} * \frac{N_{ij,pre}}{\sum_{r,c\in s} N_{rc,pre}} \tag{4}$$

Where, $N_{ij,pre}$ represents the number of nodes, $\tau(i,j)$ represents the pheromone value, $\eta(i,j)$ is the heuristic information. Secondly, the path planning approach has been improved through the incorporation of advanced prediction techniques inspired by Model Predictive Control. This involves using predictive calculations to determine the probability of mobility for the next node, and improved heuristic factors for selecting nodes. We use normalization principles to distribute the likelihood of selecting each node, as demonstrated in Eq. (5) and (6).

$$\begin{cases} p_{ij} * \frac{N_{ij,pre}}{\sum_{r,c\in s} N_{rc,pre}} & N > 2 \\ 0 \quad N \leq 2 \end{cases} \tag{5}$$

$$p_{normalization} = \frac{p_{update}}{\Sigma p_{update}} \tag{6}$$

The improved ACO algorithm pseudo-code is presented in Algorithm 1. By using this method, the optimised algorithm significantly increases the proportion of successful path generation.

Algorithm 1: Enhanced ACO For Feasible Initial Path

```
Input:  M, X_init, X_goal
Output: A initial path Γ from X_init to X_goal
Parameter initialization;
Calculate the heuristic factor;
while Iter <= Iter_max
    for ant = 1:m
        delete the nodes which have been visted;
        determine if next node is the goal;
        calculate the number of available grid;
        update probability of moving from the current;
        combine the probability with heuristic factor;
        record the route;
    end for
    update the pheromone;
end while
```

4. Result

In this section, we evaluated the effectiveness of the suggested EACO across three distinct environmental models, as illustrated in Figure 4. The three environmental models vary in terms of dimensions, contour, and blockage density. This assortment of environmental models affords an opportunity to investigate the proposed algorithm's success rate, path duration, and run-time. Figure 5 presents the dimensionless path lengths and runtimes. As anticipated, Figure 5 indicates that the parameter set (pop=50, Iter=50) yields the shortest paths, whereas the parameter set (pop=5, Iter=5) results in the longest paths. Concurrently, the parameter set (pop=5, Iter=5) consistently manifests the fastest runtimes. In addition to the parameters pop and Iter, we also conducted a thorough parameter tuning process using the single-variable method to adjust each parameter for optimal performance. This included fine-tuning the key ACO parameters, such as α (the importance of pheromone), β (the importance of the heuristic factor), and ρ (pheromone evaporation coefficient). The final optimal parameter settings for these parameters were found to be α = 6, β = 2, and ρ = 0.1. These values were consistently used throughout the experiments and contributed to the robustness and efficiency of the EACO algorithm.

Fig. 4. Three different environment models

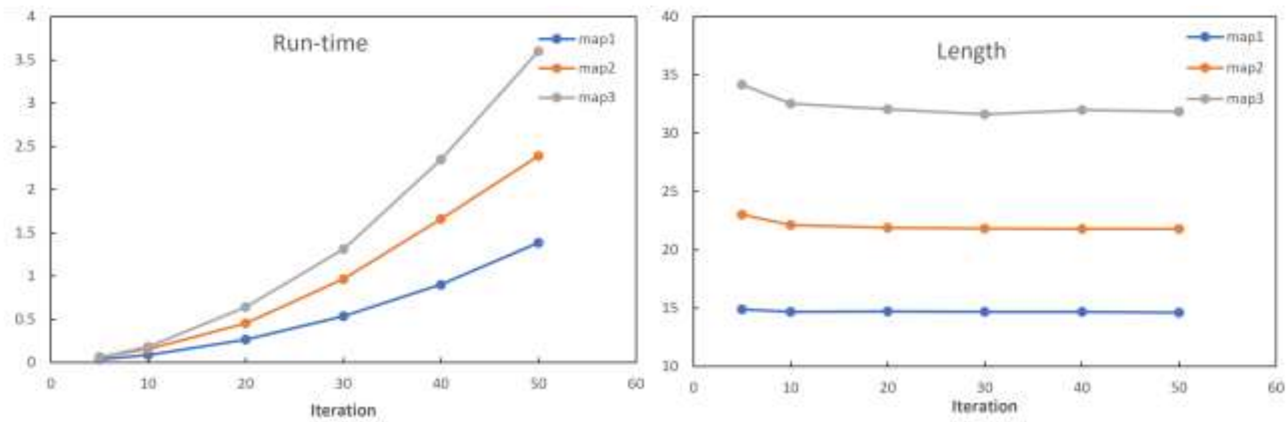

Fig. 5. Path length and run-time for 20 executions

In order to compare the superiority of the proposed EACO algorithm, the path planning lengths, runtime, and success rates of A*, ACO, and EACO algorithms were compared in three different environments. The comparison results are shown in Table 1. The data in Table 1 are the average values obtained by running each algorithm with different parameters 20 times in each environment. From the table, it can be observed that EACO is able to plan the shortest path in all three different environments, and it also has the fastest runtime.

Table 1
Comparison of path length, run-time and success rate

Model	Algorithm	Path Length	Run-time	Success Rate
Map1	A*	15.0710678	1.373417	100%
	ACO	15.3781747	0.045339	100%
	EACO	14.9040531	0.035628	100%
Map2	A*	22.1421356	3.329968	100%
	ACO	24.5906637	0.24391	100%
	EACO	22.1448604	0.156305	100%
Map3	A*	34.4852814	24.39297	100%
	ACO	36.847518	0.29791	92%
	EACO	32.5417043	0.183545	100%

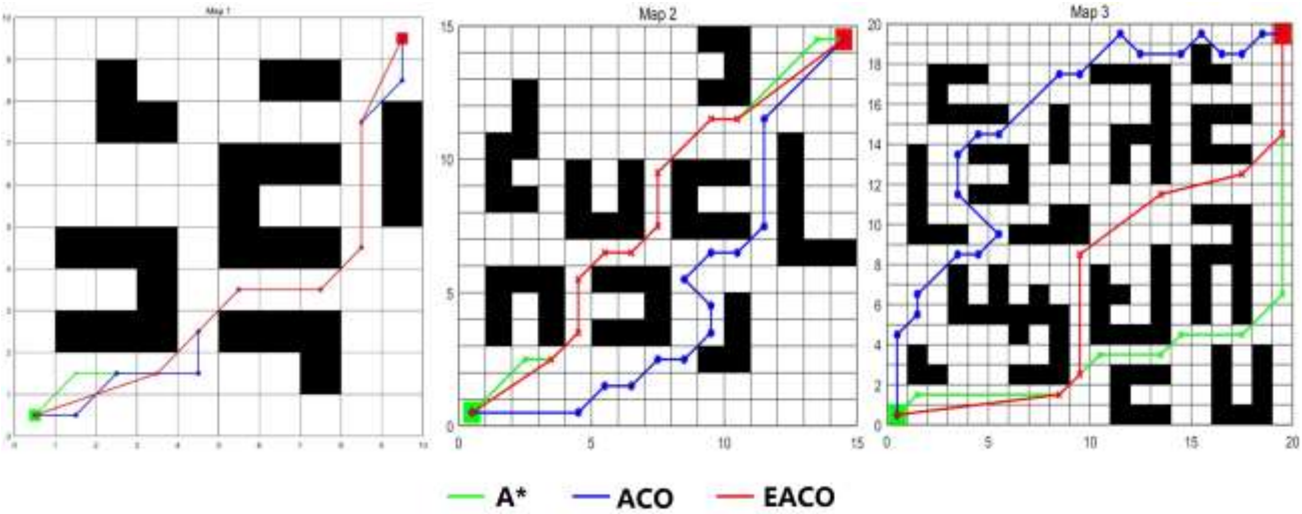

Fig. 6. Comparison of different algorithm optimal paths

This indicates that the EACO algorithm is more stable and computationally efficient compared to the original ACO algorithm. Figure 6 displays the optimal paths of different algorithms in three different environments.

5. Conclusions

This paper presents the EACO algorithm, a new approach for robot path planning in complex environments. The algorithm can find optimal or near-optimal paths in any complex environment. To start with, we introduce an advanced ACO algorithm to explore feasible paths in a grid-based environment that connects the start and end points. To increase the effectiveness of node selection in the ACO algorithm, we integrate a probabilistic prediction mechanism that combines ACO's heuristic factors. This improves the likelihood of planning feasible initial paths for the ant colony. The improved ACO algorithm also incorporates pheromone and heuristic factors into the newly proposed probability prediction mechanism, thus enhancing path planning efficiency. Additionally, a method of path reconnection is utilised to obtain paths characterised by advantageous length and smoothness.

Path length and planning time are the chosen objectives to assess the quality of the obtained paths. A composite objective function enables adjustments of the fitness function to achieve paths that meet the desired criteria for path length and smoothness. Comparative research using A* and ACO demonstrates that the EACO algorithm exhibits superior performance concerning path length, runtime, and success rate. Notably, it achieves shorter computation times while maintaining similar path lengths. The findings indicate that the EACO algorithm can rapidly plan optimal paths and ensure optimal or almost-optimal smoothness. It is recommended that future work involves extending the EACO algorithm to scenarios with moving obstacles and incorporating multi-robot path planning.

Acknowledgement
This research was funded by Collaborative Research in Engineering, Science and Technology (CREST) under Grant 304/PELECT/6050444/C121.

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