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An Adaptive Improved Ant Colony System Based on Population Information Entropy for Path Planning of Mobile Robot

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ABSTRACT In this paper, an adaptive improved ant colony algorithm based on population information entropy(AIACSE) is proposed to improve the optimization ability of the algorithm. The diversity of the population in the iterative process is described by the information entropy. The non-uniform distribution initial pheromone is constructed to reduce the blindness of the search at the starting phase. The pheromone diffusion model is used to enhance the exploration and collaboration capacity between ants. The adaptive parameter adjusting strategy and the novel pheromone updating mechanism based on the evolutionary characteristics of the population are designed to achieve a better balance between exploration of the search space and exploitation of the knowledge during the optimization progress. The performance of AIACSE is evaluated on the path planning of mobile robots. Friedman's test is further conducted to check the significant difference in performance between AIACSE and the other selected algorithms. The experimental results and statistical tests demonstrate that the presented approach significantly improves the performance of the ant colony system (ACS) and outperforms the other algorithms used in the experiments.

INDEX TERMS Ant colony optimization, path planning, mobile robot, grid map, pheromone diffusion model, parameter adjusting strategy, pheromone updating strategy, population information entropy.

I. INTRODUCTION

Nowadays, the research of mobile robots has expanded widely, due to their effective use in repetitive and unattainable environments for humans [1]. There are many research topics on mobile robots, including simultaneous localization and mapping (SLAM), path planning, and trajectory tracking [2], in which path planning is one of the most essential and important research areas [3]. As a whole, path planning aims to provide a collision-free, optimal or approximate optimal path from the initial position to the destination position in an environment with obstacles and to optimize it in respect of some criteria [4], such as traveling distance (length of the path), traveling time, and/or efficiency, etc.

The study of path planning began in the 1960s [5], and various methodologies have been investigated to generate the optimal path involving cell decomposition [6], roadmap approaches [7], and potential field methods [8]. However, these methods suffer from a lack of robustness, adaptivity, and local minimum. So, many heuristic methods have been promoted to overcome the essential drawbacks of traditional methods. The representative methodologies include Artificial Neural Network (ANN) method [9], Genetic Algorithm (GA) [10], Biogeography-Based Optimization (BBO) [11], Particle Swarm Optimization (PSO) [12], Artificial Bee Colony (ABC) [13] and Cuckoo Search (CS) [14]. It is worth mentioning that some recently proposed meta-heuristics, such as Gradient-Based Optimizer (GBO) [15], Slime Mould Algorithm (SMA) [16] and Whale Optimization Algorithm (WOA) [17] have also contributed to the path planning problem. However, these intelligent optimization algorithms cannot be used directly for the path planning problem in grid environments. Besides, these methodologies were shown some drawbacks such as large search space, inefficient search, local minimum, etc. Therefore, the improvement of existing algorithms or the exploration of new path planning

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methods has become the current research hotspot [18]–[22]. The Ant colony optimization (ACO) algorithms are different from other swarm intelligence algorithms since a set of parallel artificial ants need to iteratively build the candidate solutions for a given optimization problem using a probabilistic transition rule which can make them more suitable for solving combinatorial optimization problems, such as the traveling salesman problem (TSP) and the path planning of mobile robots. Therefore, this study concentrates on an adaptive improved ant colony algorithm for robot path planning.

The first ant system (AS) algorithm was presented by Dorigo and Stutzle in the early 1990s. The basic idea of this algorithm has been inspired by the foraging activity that ants can determine the shortest path between their colony and a food source [23]. ACO algorithms have been successfully used in many various fields, including assignment problem [24], scheduling problem [25], image edge detection [26], constraint satisfaction problem [27], economic sciences [28] and robot path planning [29]–[31] because of the characteristics of distributed parallel computing, positive feedback, strong robustness and easily integrating with different algorithms. However, there are some deficiencies, such as stagnation and premature convergence, difficultly determining control parameters, slow convergence speed, and so on. Those drawbacks will be more obvious as the size of problem instances increases. In addition, it is difficult to keep a balance between efficiency and optimality. For example, some algorithms only focus on improving the efficiency of the algorithm but failed in guaranteeing the optimality of the algorithm, and vice versa. Some variants based on ant system have been proposed to overcome the disadvantages mentioned above.

The ant colony system (ACS) was proposed to improve the convergence rate by updating pheromones on the optimal path of each generation [32], however, these attempts reduce the overall exploration ability and easily falls into local optimum. Another improvement over AS is the Rank-based Ant System (RAS) where all ants should be sorted by the length, the top ranked ants release pheromones proportionally according to their ranks (i.e., better solutions contribute more pheromones) [33]. These classical improved algorithms bring some valuable experiences for future research.

Additionally, another research trend consists in the hybridization of ACO algorithms with other optimization algorithms to improve its global searching capability. A hybrid PS-ACO algorithm is developed by combining the mechanisms of PSO and ACO to expand the search space in the literature [38]. Dong et.al [39] presented a new hybrid approach that is designed to execute both AS and GA concurrently and cooperatively. The hybrid algorithms can obtain better optimization performance by making full use of the excellent advantages of the combined original algorithms, however, they still exist low search efficiency and slow convergence speed. Meanwhile, some attempts have been made to strengthen the performance of ACO algorithms by the collaborative work between multiple ant colonies. Sreeja and Sankar [40] proposed a hierarchical heterogeneous ant colony optimization with different ant agents and the minimal cost action rules to reduce time cost. Zhang *et al.* [41] proposed a dynamic multi-role adaptive collaborative ant colony optimization (MRCACO) based on heterogeneous multi-colony and multi-role adaptive cooperation mechanism. To determine a suitable path for application to mobile robots, a heterogeneous-ants-based path planner (HAB-PP) as a global path planner was proposed by Lee [2]. Even though multi colony ant algorithms is beneficial to balance the convergence and the diversity of the population, a suitable strategy for information exchange is difficult to design for improving the performance of the algorithm.

The above proposed works have been focused on some variants of basic ACO, the hybridization of ACO algorithms with other algorithms and multi ant colony optimization algorithms, at the same time, a variety of improved techniques, such as search strategy [35], pheromone initialization [30] and update strategy [4], state transition rules [36] and heuristic information [37], have been delivered by many scholars to effectively enhance the performance of the ant colony algorithm. Liu *et al.* [30] have combined the ant colony algorithm with the artificial potential field (APF) to accelerate the convergence speed of the path planning algorithm. To avoid blind search in the initial stage of the algorithm, the method of unequal allocation initial pheromone, which calculates the initial pheromone based on the relative distance between the current node, next node and the starting-ending point connection is proposed in the literature [4]. Uneven distribution of initial pheromone is introduced in [42] to improve the speed of convergence. However, these pheromone initialization methods exist some drawbacks that the scope of search space is small and the local optimal solution is easy to produce due to the loss of population diversity.

The parameters settings of ACO algorithms have a significant impact on the performance of the algorithm. Because of the disadvantage of static parameter values, various parameter-adaption methods have been designed to enable the most suitable parameter values to be identified in a more computationally efficient manner. An adaptive polymorphic ant colony algorithm based on the adaptive state transition strategy and the adaptive information update strategy was designed to ensure the relative importance of pheromone strength and desirability [36]. Akka and Khaber proposed an improved ACO algorithm in the paper [18] which adopts a new pheromone updating rule and dynamic adjustment of the evaporation rate to accelerate the convergence speed and to enlarge the search space. The main disadvantage of these methods is that the parameter value is related to the number of iterations carried out so far, resulting in insufficient adaptability. Mavrovouniotis and Yang *et al.* [44] used a self-adaptive evaporation mechanism to enhance the ability of global search for addressing dynamic optimization problems. Favuzza *et al.* [45] regulated control parameter q_0 to push exploration or exploitation as the search procedure stops in a local minimum. However, these adaption strategies are often challenged because these parameter values may have different performance for different problems, and these adaptive parameter adjustment strategies rarely consider the characteristics of the iteration progress. In fact, it has already been confirmed that different parameter settings are required not only for different problems but also for different stages of the optimization algorithm.

Although the studies mentioned above can achieve high algorithmic performances, there are still some inherent shortcomings that have not been effectively solved, such as low search efficiency, the problems of local optimum, and the contradiction between convergence speed and diversity loss. For this reason, the pheromone initialization strategy based on A* algorithm, pheromone diffusion mechanism, adaptive adjustment strategies of the parameter q_0, and dynamic pheromone updating mechanism, are introduced into the ACS to develop an adaptive improved ant colony system algorithm based on population information entropy(AIACSE). The path planning problem in mobile robotics is selected to verify the effectiveness of the proposed algorithm. The novelty in the presented approach is in the combination of the following strategies with the ACS:

1) We introduce a non-uniform distribution initialization strategy into ACS algorithm to avoid blindness in the starting of evolution phase and improve the convergence speed.
2) The pheromone diffusion model is embedded to promote the exploration and collaboration capabilities of the ant colony algorithm and reduce the probability of premature convergence.
3) The adaptive parameter adjusting strategy based on population entropy is developed to achieve a better balance between exploration of the search space and exploitation of the collected experiences during the steps of the process.
4) The adaptive global pheromone updating strategy based on the evolutionary characteristics of the population dynamically adjusts the pheromone increment caused by the iterative optimal ants to further increase the potential of the iterative optimal path.

Particularly, the adaptive parameter adjusting strategy and the adaptive global pheromone updating strategy are designed based on the evolutionary characteristics of the population measured by population entropy.

The remaining part of this paper is structured as follows: First, Section 2 briefly describes some preliminaries, such as ant colony systems, information entropy and pheromone diffusion model, and then Section 3 expatiates the design of our adaptive improved ant colony algorithm, including the initial pheromone settings based on A*, pheromone diffusion mechanism, adaptive adjustment strategies of the parameter q_0, dynamic pheromone updating strategy and the pseudo-code of the AIACSE algorithm. Section 4 reveals the experimental results, including experimental setup, the simulation test of the proposed algorithm for solving the path planning of mobile robots and the statistical tests of the obtained results. Finally, some conclusions and further works are discussed in Section 5.

II. PRELIMINARIES

A. ANT COLONY OPTIMIZATION ALGORITHM

ACO algorithm is a promising meta-heuristic algorithm for solving hard combinatorial optimization problems, inspired by the foraging behavior of ants in nature [32]. Generally, the classical ACS is described as the interplay of three phases: initialization, solution construction and pheromone update. ACO solves the problem by repeating the steps of solution construction and pheromone update until the termination conditions are satisfied.

The parameters of the ant colony algorithm need to be initialized during the initialization procedure, such as the initial value of the pheromone, the number of ants, the evaporation factor of pheromone, the parameters for controlling the comparative significance of pheromone and heuristic values in the state transition rule.

During the phase of constructing solutions in ACS, the pseudo-random proportional rule is used to choose the next node to be visited, which favors transitions toward nodes connected by short edges and with a large amount of pheromone. The decision rule of the ant to move from node i to node j is defined as the following equation [32]:

$$j = \begin{cases} \underset{j \in allowed_k}{\arg\max} \left[\tau_{ij}(t)\right]^{\alpha} \left[\eta_{ij}\right]^{\beta} & if\ q \leq q_0(\text{exploitation}) \\ J & otherwise(\text{exploration}) \end{cases} \tag{1}$$

$$p_{ij} = \begin{cases} \dfrac{\left[\tau_{ij}(t)\right]^{\alpha} \left[\eta_{ij}\right]^{\beta}}{\sum\limits_{s \in allowed_k} \left[\tau_{is}(t)\right]^{\alpha} \left[\eta_{is}\right]^{\beta}} & if\ s \in allowed_k \\ 0 & otherwise \end{cases} \tag{2}$$

where $q \in [0, 1]$ is a random variable parameter, $q_0 \in [0, 1]$ is a pre-defined parameter allowing to regulate the elitism of the algorithm, $\tau_{ij}(t)$ and $\eta_{ij} = 1/d_{ij}$ are, respectively, the amount of pheromone concentration and heuristic information on the edge between node i and node j, where d_{ij} is the distance between node i and node j, s in the Eq.(2) is a node that has not been visited by ants, $allowed_k$ is the set of unvisited nodes yet when ant k is located at node i, α and β are two constants that determine, respectively, the relative influence of the pheromone amount and the heuristic information on the decision of the ant, J is a random value selected using the probability distribution given by the Eq.(2).

The parameter q_0 determines the relative importance of exploitation versus exploration of the search space. With probability q_0, the ant moves to the node j for which the product between pheromone trail and heuristic information is maximum, while with probability $1 - q_0$, the ant operates a biased exploration in which the probability is the same as in AS. When q_0 is set to a value close to 1, exploitation is favored over exploration.

During the iteration process, the local and global pheromone update rules are used to update the pheromone values. The local pheromone update is performed by an ant after making a moving from node i to node j, while the global pheromone update is executed in the end of each construction process, these pheromone update rules are shown as follows:

1) Local update rule

$$\tau_{(i,j)}(t+1) = (1-\zeta)\cdot\tau_{(i,j)}(t) + \zeta\cdot\Delta\tau_0 \tag{3}$$

where ζ is a coefficient regulating evaporation of the pheromone over time, $\tau_0 = (n * L_{nn})^{-1}$ is the initial value of the pheromone trails, where n is the number of nodes in the TSP and L_{nn} is the cost produced by a greedy nearest-neighbor algorithm. The main object of the local update is to prevent premature convergence and to increase variety in the constructed solutions.

2) Global update rule

$$\tau_{(i,j)}(t+1) = (1-\rho)\cdot\tau_{(i,j)}(t) + \rho\cdot\Delta\tau_{ij}^{gb}(t) \tag{4}$$

$$\Delta\tau_{ij}^{gb}(t) = \begin{cases} \dfrac{Q}{L_{gb}} & \textit{if edge}(i,j) \in \textit{global best tour} \\ 0 & \textit{otherwise} \end{cases} \tag{5}$$

where $\rho(0 < \rho < 1)$ is the pheromone evaporation rate, Q is a non-zero positive constant, and L_{gb} is the total length of the globally best path from the beginning of the run. The global update rule gives the edges belonging to the best solution found so far higher probabilities of being selected in the subsequent iterations which is helpful to speed up convergence to the optimal solution.

B. INFORMATION ENTROPY

The concept of information entropy was introduced by Shannon [47]. It is a measure of the unpredictability associated with a random variable X with possible state $x_1, x_2, \ldots, x_n$, which occur with the probability $p(x_1), p(x_2), \ldots, p(x_n)$. In another word, it refers to the average of diversity or uncertainty in a system. The information entropy of X is defined as follows:

$$H(X) = -\sum_{i=1}^{n} p(x_i)\cdot\ln(p(x_i)) \tag{6}$$

If each state of the random variable X occurs with equal probability, the information entropy is rather high, otherwise, it is relatively low. In addition, an increase in entropy represents an increase in diversity. In this paper, we use the information entropy to measure the diversity and evolution of the ant colony during the run to improve the adaptability of the algorithm.

C. PHEROMONE DIFFUSION MODEL

The pheromone trails play an important role in the performance and collaborative capability of the ACO family of algorithms. In the classical ACO algorithms, the pheromone is only released on the edges of path or the nodes that ants passed through. This mode can only affect the following ants with the passed same point, and cannot guide the search of ants in a certain range of surrounding regions. This phenomenon leads to the problem of insufficient cooperation between ants and brings the risk of entrapment in the local optimum.

In fact, the pheromones are not only deposited on the path where ants passed through, but also spread to the neighboring regions of the path. It is usually more likely to get a better solution in the neighborhood of the optimal solution than in other regions. Therefore, the pheromone diffusion mechanism can make ants deposit pheromones at a certain point, and gradually affects the adjacent areas within a certain range [46]. The basic idea of the pheromone diffusion model is to take into account the pheromone influences among neighboring locations in the current grid while building solutions. Acknowledging these facts, the pheromone diffusion model which can enhance the exploration and collaboration capabilities of the ant colony algorithm is presented as follows. Fig. 1 illustrates the distribution model of unit pheromone diffusion. Assume that pheromone concentration is equal to one at the ant's current grid.

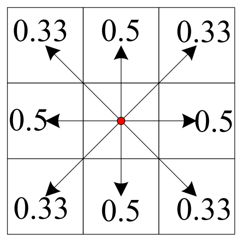


FIGURE 1. Distribution model of unit pheromone concentration.

There are eight neighboring grids around the current grid, then the amount of diffusion pheromone at a given grid is designed as follows:

$$f(g, g_0) = \begin{cases} 1 & d(g, g_0) = 0 \\ 0.5 & d(g, g_0) = 1 \\ 0.33 & d(g, g_0) = \sqrt{2} \end{cases} \tag{7}$$

where g_0 represents the grid where ant is located, g is a free given grid around the current grid, $d(g, g_0)$ is the distance between grid g_0 and g, the distance could be described as:

$$d(g, g_0) = \begin{cases} 1 & \text{if } g \text{ and } g_0 \text{ in vertical or horizontal} \\ \sqrt{2} & \textit{otherwise} \end{cases} \tag{8}$$

III. ADAPTIVE IMPROVED ANT COLONY SYSTEM BASED ON POPULATION INFORMATION ENTROPY

The proposed algorithm in this paper is based on ACS but presents some important differences in three aspects: pheromone initialization strategy, adaptive parameter adjusting strategy and pheromone updating strategy.

In the following sections, each modified strategies will be described, respectively.

A. PHEROMONE INITIALIZATION STRATEGY

The initial value of the pheromone should be initialized before running and is often important to the ACS's performance as it affects the relative importance of pheromone additions. This effect is especially exaggerated in the early stages of the optimization process when good solutions have not yet been established. However, the initial pheromone concentrations of all edges in the classical ant colony algorithm are equally initialized. As a consequence, it takes a long time to find a better solution from a great number of candidate solutions.

To avoid the blindness in the starting of evolution phase and accelerate the convergence speed of the algorithm, the non-uniform distribution initial pheromone based on A* algorithm is used to adjust the initial allocation of pheromone. First, an optimal path obtained by A* algorithm is used for pheromone initialization. The initial pheromone value can be defined as follows:

$$\tau_0(i,j) = \begin{cases} k * C & \textit{if } edge(i,j) \in T^* \\ C & \textit{otherwise} \end{cases} \tag{9}$$

where $\tau_0(i,j)$ represents the initial pheromone value between node i and node j, k (k>1) is a constant that express the difference of the pheromone between the optimal path and the other path, T^* is the optimal path found by A* algorithm, C is the initial pheromone value which is described as:

$$C = \frac{1}{L^*} \tag{10}$$

where L^* is the length of the path T^*.

In addition, the initial pheromones on the optimal path constructed by A* algorithm are diffused to the surrounding areas according to the pheromone diffusion model to enhance the cooperation among ants.

B. ADAPTIVE PARAMETER ADJUSTING STRATEGY BASED ON INFORMATION ENTROPY

The performance of ACO algorithms is strongly influenced by the settings of their parameters. The parameter value of q_0 in the basic ACO algorithms determines the ratio of the deterministic and probabilistic selection modes. Seeking an appropriate parameter value q_0 in different stages of the search process is useful to maintain a good balance between exploration and exploitation. If the value of q_0 is large, the transition rule is more likely to the deterministic mode, which improves exploitation of the best solution and increases the convergence speed, but reduces the global search ability. On the contrary, if the value of q_0 is small, the transition rule is apt to random mode, which increases the diversity of path construction to prevent premature convergence and further extends the exploration of unexplored search space regions to locate a better solution, but reduces the convergence speed. Therefore, the setting of q_0 value directly relates to the global search ability and convergence speed.

The randomness of path selection in the ACO algorithms results in the uncertainty of the fitness value of candidate solutions in each iteration. This uncertainty can reflect the diversity of the population to some extent. As mentioned earlier, the information entropy is a measure of the unpredictability of a random event, therefore, it can be used to describe the diversity and the evolutionary characteristics of the population. To make a search move efficiently and effectively, the parameter q_0 is adaptively controlled according to this entropy measure. The change of the population entropy is used as feedback to guide the parameter adjustment. More precisely, the parameter q_0 will be changed according to the following equation:

$$q_0 = q_{0min} + (q_{0max} - q_{0min}) \cdot (HR\_(pop(t))^{\frac{1}{2}}) \tag{11}$$

$$HR\_(pop(t)) = \frac{H\_(pop(t))}{\ln(n)} \tag{12}$$

$$H\_pop(t) = -\sum_{i=}^{N} p(x_i) \cdot \ln(p(x_i)) \tag{13}$$

where q_{0max} and q_{0min} indicate respectively the minimum and maximum values of the q_0, $HR\_(pop(t)) \in [0,1]$ is the relative value of the population entropy in the iteration t, $H\_pop(t)$ is the value of the population entropy, x_i represents the fitness value of candidate solution, $p(x_i) \geq 0$ is the probability of occurrence of the x_i in the current iteration, $\sum_{i=1}^{N} p(x_i) = 1$, N is the number of valid candidate solutions. The change curve of the parameter q_0 is shown in Fig. 2.

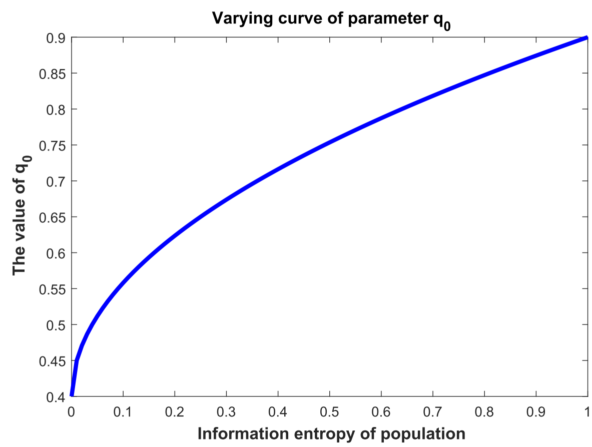


FIGURE 2. The varying curve of parameter q_0.

Observing Fig. 2, we can conclude that the value of the parameter q_0 is automatically tuned according to the change of the population entropy in the evolutionary process. When the information entropy of the population is small, it means that the candidate solutions are relatively concentrated, so a smaller q_0 value is adopted to allow the generation of a broad distribution of solutions. When the information entropy value is large, it means that the distribution of the candidate solutions is relatively scattered, and a larger q_0 value should be adopted to accelerate the convergence speed of the algorithm. To balance the trade-off between search diversification and intensification, q_0 has a range of values between 0.4 and 0.9 [43]. In summary, this adaptive parameter control strategy based on the characteristics of the optimization progress can automatically adjust the value of the parameter q_0 to keep a better balance between exploration and exploitation.

C. ADAPTIVE PHEROMONE UPDATING STRATEGY

The ACS is one of the popular ACO variants over AS. There are two types of pheromone update rules in the ACS algorithm: the local pheromone updating and the global pheromone updating. Global pheromone updating only allows the ants on the best solution found so far to update pheromone, which accelerates the convergence speed of the algorithm. In the existing literature, the ACO algorithms only evaporate and enhance pheromone when applying the pheromone updating rules and do not consider the dynamic information of the evolutionary process. So, we designed a dynamically weighted global pheromone updating strategy to improve the optimization performance of the ACS algorithm, which updates the pheromone adaptively based on the information entropy of the population and the iterative optimal solution. The formula of pheromone updating is defined as follows:

$$\begin{aligned}\tau_{(i,j)}(t+1) = (1-\rho)\cdot\tau_{(i,j)}(t) + \rho\cdot\Delta\tau_{ij}^{gb}(t)\\ +(1-HR\_(pop(t)))\cdot\Delta\tau_{ij}^{ib}(t)\end{aligned} \tag{14}$$

$$\Delta\tau_{ij}^{ib}(t) = \begin{cases}\dfrac{1}{L_{ib}} & if\ edge(i,j)\in T^{ib}\\ 0 & otherwise\end{cases} \tag{15}$$

where $\rho(0<\rho<1)$ is the pheromone evaporation rate, the calculation method of $HR\_(pop(t))$ has been detailed in Section 3.2, $\Delta\tau_{ij}^{gb}(t)$ denotes the increase of trail level on the global-best solution and is defined as the Eq.(5), $\Delta\tau_{ij}^{ib}(t)$ represents the total amount of pheromone released by the ant on the iteration-best solution, L_{ib} is the cost of the iteration-best solution, T^{ib} is the current optimal solution.

The proposed pheromone updating mechanism looks similar to that in MMAS [34], however, MMAS only allows the best ant to update the pheromone trails after each iteration, the proposed pheromone updating strategy not only considers the iterative optimal and the global optimal path concurrently but also dynamically adjusts the pheromone increment caused by the iterative optimal ants according to the evolutionary characteristics of the population.

Besides, to enhance the cooperation among ants and improve the global optimization ability, the pheromone diffusion model presented in section 2 is also applied to the pheromone updating strategy designed above. This modification provides the ability to achieve a better balance between exploring new paths and reinforcing popular paths. Moreover, it also improves the solution quality of the algorithm to some extent.

D. THE PSEUDO-CODE OF THE AIACSE ALGORITHM

The detailed steps of the proposed AIACSE algorithm for path planning of mobile robot are shown as follows:

Step1 The environment model is loaded and the initialization process takes place during which the initial pheromone value and many other parameters are set.

Step2 Ants are placed at the start point and construct the paths according to Eq.(1) and Eq.(2). This cycle is repeated until the ant reaches the goal point or occurs deadlock state. Then the local pheromone update is executed in terms of Eq.(3) for the feasible paths.

Step3 When all ants have completed a search, we evaluate all feasible paths generated by the ants, and find the best one.

Step4 The global pheromone update is performed for the best path found so far by Eq.(14), and the pheromones on the optimal path are spread according to Eq.(7).

Step5 Calculate information entropy by Eq.(12).

Step6 Adaptively adjust the value of q_0 based on Eq.(11).

Step7 The algorithm repeats the above step2 to step6 continuously until the maximum number of iterations is reached.

Step8 Output Optimal path.

The pseudo-code of the proposed AIACSE algorithm is illustrated in Algorithm 1.

Algorithm 1 Pseudo-Code of the AIACSE Algorithm

```
Input: start, goal, k, NC_max, m, α, β, ρ, ζ, q0, Q
Output: Optimal path
Load environment model
Calculate the initial pheromone according to Eq.(9)
for i = 1 to NC_max do
    for ant = 1 to m do
        while node ≠ goal and allowed_k ∉ Ø do
            Construct path according to Eq.(1) and
            Eq.(2)
        end
        Local pheromone update of feasible paths by
        Eq.(3)
    end
    Evaluate all the feasible paths obtained by the ants
    Global pheromone update of the best path by Eq.(14)
    Pheromone diffusion of the best path by Eq.(7)
    Calculate information entropy by Eq.(12)
    Adjust the value of q0 based on Eq.(11)
end
return Optimal path
```

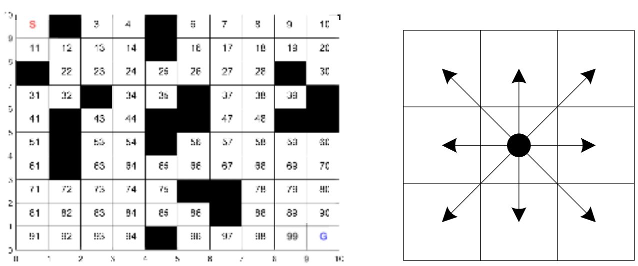
IV. EXPERIMENTAL RESULTS AND DISCUSSION

The different experimental scenarios, as well as the experimental results and discussions, are presented in this section. Three experiments were carried out to demonstrate the validity and the performance of the proposed AIACSE in solving path planning of mobile robots. All the experiments and analysis were performed using the same PC(with a 3.40 GHz Core i5 CPU and 8 GB RAM) with Windows 7 64-bit professional for a fair comparison. The MATLAB(R2016b) programming language was used to implement the proposed algorithm and other comparing algorithms. To avoid occasional cases and have a more accurate deduction, all experiments were executed independently 30 times with the same parameters. All results are reported and compared based on the average performance of the algorithm over 30 independent runs. The maximum number of iterations is used as the stopping condition for all algorithms.

The performance metrics used to compare the relative performance of our proposed algorithm with the comparing algorithms include the best path length (denoted as best), the worst path length (denoted as worst), the mean path length (denoted as mean) and the standard deviation of path length (denoted as std) over 30 independent runs. Also, the two novel performance metrics, denoted as fbest and rate, are introduced to describe the number of iterations when the optimal solution is obtained for the first time, and to some extent also reveals the convergence speed of the algorithm and the success rate of finding the optimal path in all runs. Besides that, it is worth pointing out that the length of each grid is 1 unit (1m) and the length of the path is measured in terms of the number of grid units in all experiments hereafter unless stated otherwise.

A. EXPERIMENTAL SETUP

In all experiments, the working environment is divided into grid cells of binary information in which the grids are numbered from left to right and from top to bottom. Fig. 3(a) gives an example of a grid map with a dimension of 10 × 10 nodes representing an environment. The black grids represent obstacles and the white ones represent the free spaces to move, *S* represents the start grid, *G* remarks the goal grid. From Fig. 3(b), the robot can move in eight directions which are forward, backward, right, left, right-up, right-down, left-up and left-down.



(a) A grid map example (b) Possible directions of motion

FIGURE 3. **Environment model:(a)A grid map example (b)Possible directions of motion.**

B. PARAMETERS SETTINGS

In the ant colony algorithm, there are several parameters, such as the number of ants (m), the global pheromone evaporation rate (ρ), the local pheromone evaporation rate (ζ), the pheromone total amount (Q), information heuristic factor (α), expected heuristic factor (β), the maximum iteration times (NC_{max}), the minimum and maximum values of the parameters (q_{0min} and q_{0max}). The parameter values of the PS-ACO are identical to those in [38]. The parameter values for the MRCACO are the same as the recommended settings in the literature [41]. In all experiments of the following sections, the common parameters for the other algorithms are shown in Table 1 [4].

C. VERIFICATION FOR THE EFFECTIVENESS OF THE PROPOSED STRATEGIES

In the first experiment, we independently study the effects of adaptive adjusting strategy and pheromone diffusion model on the performance of the algorithm.

1) THE EFFECT OF ADAPTIVE ADJUSTING STRATEGY

The adaptive strategy is used to adjust the degree of exploration and intensification of the search space and the global pheromone updating mechanism according to the evolutionary characteristics of the population. The grid map1 is selected for this experiment, the ACS algorithm combined with the proposed adaptive parameter q_0 and adaptive pheromone updating mechanism are introduced to demonstrate the effect of the adaptive adjusting strategy. Fig. 4 shows the optimal path generated by the ACS with the adaptive adjusting strategy. The statistical results of different values of q_0 and adaptive adjusting strategy are listed in Table 2, and the best ones are in bold.

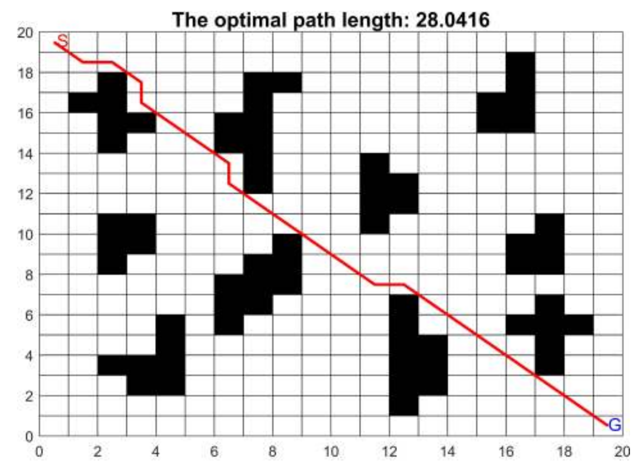


FIGURE 4. **The optimal path generated by the ACS with adaptive adjusting strategy($q_0 = 0.8$) under the grid map1.**

As it is seen from Table 2, the performance of the ACS algorithm in the grid map1 can be improved with the increase of the parameter q_0 in terms of the best distance, the worst distance, mean distance, standard deviation, convergence rate, and success rate towards optimal paths. This shows that the parameter q_0 can effectively improve the optimization ability of the ACS algorithm. Furthermore, the ACS algorithm with

TABLE 1. The parameter settings of different algorithms.

Parameter	Number of ants	α	β	ρ	ζ	Q	q_0	NC_{max}
AS	2*width	1.1	7	0.2	-	100	-	200
RAS	2*width	1.1	7	0.2	-	100	-	200
ACS	2*width	1.1	7	0.2	0.2	100	0.8	200
AIACSE	2*width	1.1	7	0.2	0.2	100	$q_{0min} = 0.4, q_{0max} = 0.9$	200

TABLE 2. Obtained results of the grid map1. The best result for each section is highlighted in bold.

q_0	best	worst	mean	std	fbest	rate
0.4	**28.0416**	29.2132	28.3150	0.3683	53.97	60
0.5	**28.0416**	28.6274	28.0612	0.1069	46.10	96.67
0.6	**28.0416**	**28.0416**	**28.0416**	**0**	25.13	**100**
0.7	**28.0416**	**28.0416**	**28.0416**	**0**	4.87	**100**
0.8	**28.0416**	**28.0416**	**28.0416**	**0**	1.23	**100**
0.9	**28.0416**	**28.0416**	**28.0416**	**0**	**1**	**100**
adaptive	**28.0416**	**28.0416**	**28.0416**	**0**	**1**	**100**

adaptive adjusting strategy can obtain better performance than the classical ACS algorithm with the different parameter q_0. Particularly, the proposed method does not set the initial value of q_0. In this case, we can deduce from Table 2 that the proposed strategy not only increases the optimization ability of the ACS algorithm but also improves the adaptability and robustness of the algorithm.

2) THE EFFECT OF PHEROMONE DIFFUSION STRATEGY

In this section, we designed a comparative experiment to validate the effectiveness of the pheromone diffusion strategy in the grid map2. In case I, the ACS algorithm without the pheromone diffusion strategy is performed. In case II, the ACS algorithm without the pheromone diffusion strategy is executed. The parameter q_0 is set to 0.8, and other parameters of the ACS algorithm are shown in Table 1. The pheromone distribution of the ACS algorithm at different iterations are shown in Fig. 5 and Fig. 6. The statistical results of the experiment are listed in Table 3, and the best ones are in bold. The optimal path generated by the ant colony system with and without the pheromone diffusion strategy is shown in Fig. 7.

TABLE 3. Obtained results of the grid map2. The best result for each section is highlighted in bold.

strategy	best	worst	mean	std	fbest	rate
No diffusion	**30.9706**	**32.6274**	31.9323	**0.5453**	40.07	13.33
Diffusion	**30.9706**	**32.6274**	**31.8923**	0.5712	**37.83**	**16.67**

By comparing Fig. 5 and Fig. 6, it could be obviously noticed that the pheromone diffusion strategy increases the pheromone concentration of the adjacent areas of the optimal solution, enlarges the searching range, and reduces the probability of premature convergence. From Table 3, we can see that the two cases have almost similar experimental results in terms of best, worst, and mean. Besides, the ACS without pheromone diffusion mechanism has a smaller standard deviation. This could be because the pheromone diffusion strategy leads to a more dispersed distribution of feasible solutions. Even so, the ACS with pheromone diffusion mechanism slightly outperforms the original ACS according to convergence speed and success rate.

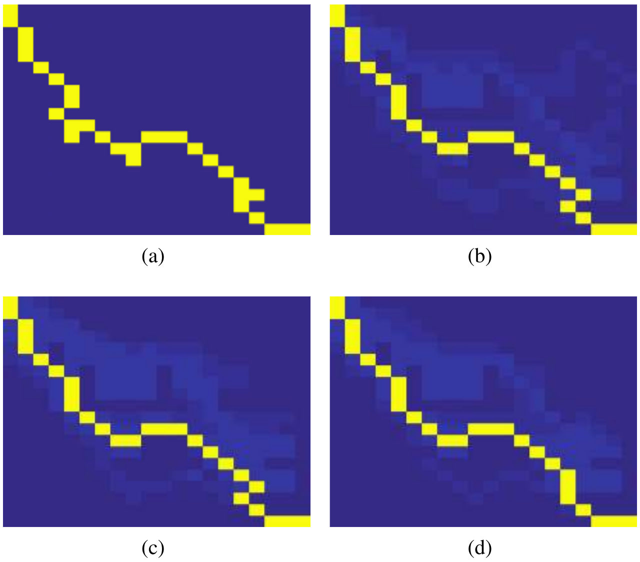


FIGURE 5. Pheromone distribution of the ACS without pheromone diffusion at 1, 10, 50 and 200 iterations(q_0 = 0.8).

D. PERFORMANCE COMPARISON BETWEEN AIACSE AND OTHER ALGORITHMS

To investigate the efficiency of the proposed AIACSE in the path planning of mobile robots, the second experiment is conducted to compare the AIACSE approach with other algorithms such as the classical Ant System [23], two variants of Ant System (RAS [33] and ACS [32]), and two state-of-the-art optimization algorithms based on ant system (PS-ACO [38] and MRCACO [41]) based on the best, worst, average of the results, standard deviation, convergence rate and success rate towards optimal solutions. Here, brief reviews of the comparison methods are discussed to understand the difference between them.

1) AS. Ant System is the first and basic ACO algorithm. This algorithm proved that the methodology was promising and provided the valuable experiences to further research, but it also showed some drawbacks, such as premature convergence, long search time, low convergence rate.

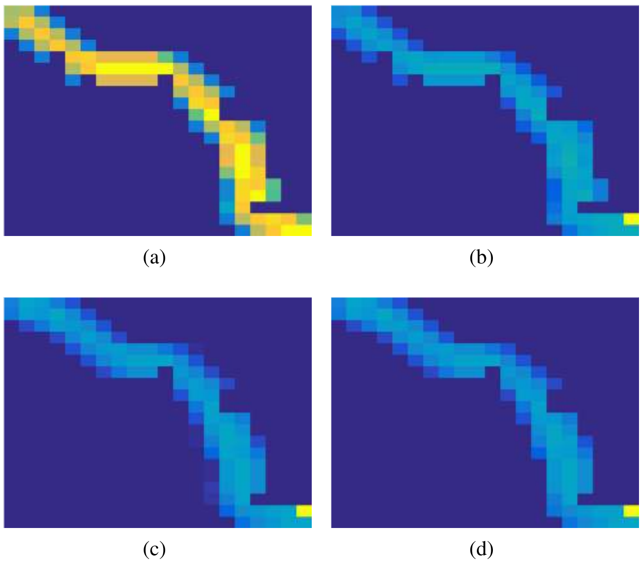


FIGURE 6. **Pheromone distribution of the ACS based on pheromone diffusion at 1, 10, 50 and 200 iterations($q_0 = 0.8$).**

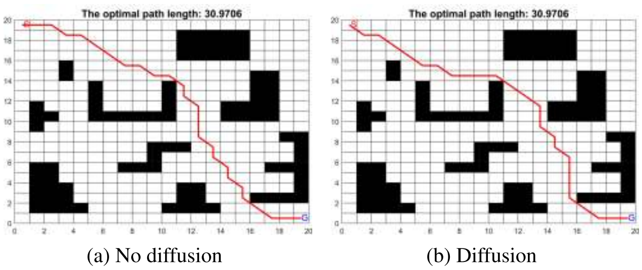


FIGURE 7. **The optimal path generated by the ACS with and without pheromone diffusion strategy($q_0 = 0.8$).**

2) RAS. Rank-based Ant System is a well-known improvement of AS where all ants should be sorted by the length, the top ranked ants release pheromones proportionally according to their ranks (i.e., better solutions contribute more pheromones).
3) ACS. Ant Colony system is another improvement of AS and is the most widely used ACO algorithm. It differs mainly in three aspects: (a) ACS introduces a local pheromone update into AS to diversify the solutions; (b) ACS applies the global pheromone updating rule only to the global best tour found by the ant; and (c) ACS adopts a modified state transition rule called the pseudo-random proportional rule to determine the ratio of the deterministic and probabilistic decision modes.
4) PS-ACO. It is a hybrid optimization method based on the ACO with the difference that it uses PSO's particle velocity vector for doing the pheromone updates to expand the search space. Readers are encouraged to refer to [38] for further detail of PS-ACO.
5) MRCACO. It is a dynamic multi-role adaptive collaborative ant colony optimization. The main features of the algorithm are summarized that an adaptive dynamic complementary algorithm (ADCA) is proposed to form a heterogeneous multi-colony together with ACS and MMAS. Besides, a multi-role adaptive cooperation mechanism is proposed to realize the exchange and sharing of information. Readers are suggested to refer to [41] for a detailed process of MRCACO.
6) AIACSE. Our approach is an improved version of the classical ACS by combining the improvement strategies proposed in our paper with the classical ACS.

As this study uses ACS as the base algorithm, AS and RAS will not be discussed here and readers can refer to the related literature for further detail.

The test is performed in the grid map3 and map4 of the same size with a different distribution of obstacles. The simulation results of the optimal paths in both grid map are shown in Fig. 8 and Fig. 9 respectively. Table 4 and Table 5 show the statistical results of the performance metrics obtained by the AIACSE and other algorithms for the grid map3 and map4 respectively.

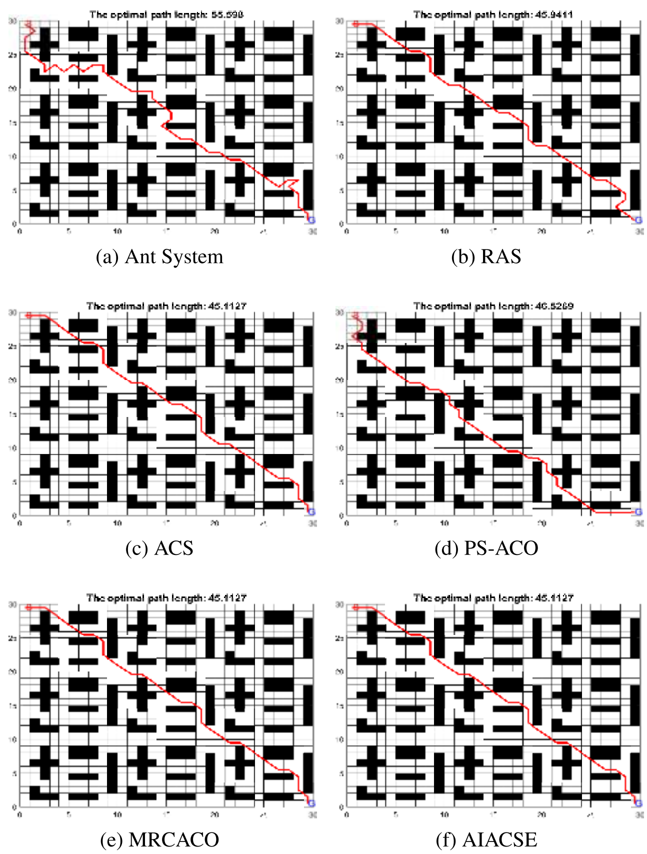
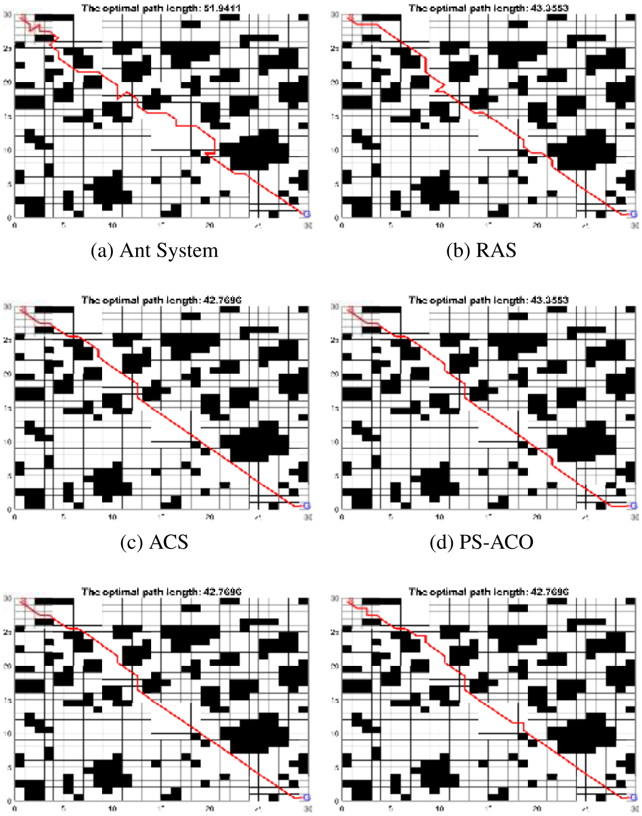


FIGURE 8. **The optimal path generated by the different algorithms in the grid map3.**

As it can be deduced from Table 4 and Table 5, AIACSE, MRCACO and ACS found shorter paths than the other algorithms, however, AIACSE can obtain the best results among presented methods in terms of performance metrics used in this paper. Besides, the proposed algorithm demonstrates its superiority and efficiency in cases of convergence speed and



(a) Ant System (b) RAS (c) ACS (d) PS-ACO (e) MRCACO (f) AIACSE

FIGURE 9. The optimal path generated by the different algorithms in the grid map4.

TABLE 4. Statistical results of the different algorithms in the grid map3. The best result for each section is highlighted in bold.

Algorithm	best	worst	mean	std	fbest	rate
AS	55.5980	62.7696	58.6024	1.7638	76	3.33
RAS	45.9411	51.6985	47.6095	1.4034	72.63	6.67
ACS	**45.1127**	46.5269	45.2070	0.3588	84.4	93.33
PS-ACO	46.5269	55.3553	50.1364	2.1066	6.6333	6.67
MRCACO	**45.1127**	46.5269	45.4803	0.4215	77.8333	50
AIACSE	**45.1127**	**45.1127**	**45.1127**	**0**	**2.3**	**100**

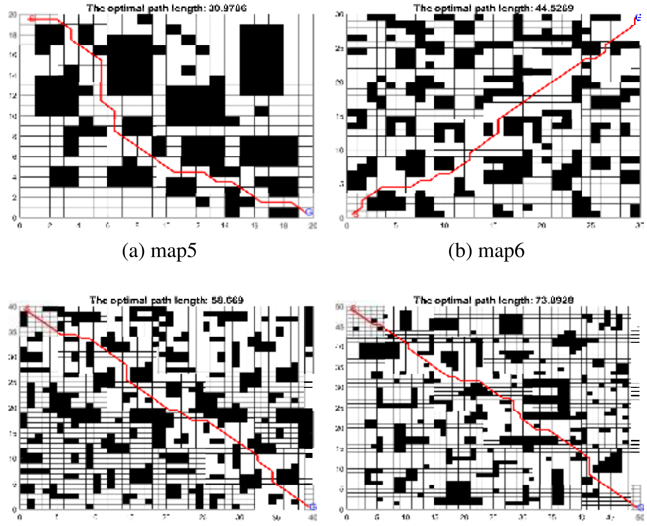
TABLE 5. Statistical results of the different algorithms in the grid map4. The best result for each section is highlighted in bold.

Algorithm	best	worst	mean	std	fbest	rate
AS	51.9411	58.2843	55.2173	1.8318	108.07	3.33
RAS	43.3553	47.6985	45.2117	1.2182	72.87	6.67
ACS	**42.7696**	**42.7696**	**42.7696**	**0**	11.37	**100**
PS-ACO	43.3553	50.7696	45.4234	1.7904	4.3	13.3333
MRCACO	**42.7696**	**42.7696**	**42.7696**	**0**	1.9333	**100**
AIACSE	**42.7696**	**42.7696**	**42.7696**	**0**	**1**	**100**

success rate. Therefore, it can be concluded that the proposed AIACSE can improve the quality of the solution and perform better overall.

E. SIMULATIONS IN VARIOUS ENVIRONMENTS

To evaluate the performance and adaptability of the AIACSE algorithm in the path planning of the robot, the third experiment is conducted under four different size environments, as shown in Fig. 10. The optimal path of each grid map generated by AIACSE is also depicted in Fig. 10. Table 6 provides the statistical results of the performance metrics obtained by AIACSE and other algorithms under different grid maps in terms of performance metrics mentioned above.



(a) map5 (b) map6 (c) map7 (d) map8

FIGURE 10. The optimal path generated by the AIACSE in the gird maps with different scales.

TABLE 6. Statistical results obtained by the different algorithms under the grid maps of different scales. The best result for each section is highlighted in bold.

Env	Algorithm	best	worst	mean	std	fbest	rate
map5	AS	31.5563	33.5563	32.6763	0.4941	104.17	3.33
	RAS	**30.9706**	32.1421	31.1658	0.4441	18.17	83.33
	ACS	**30.9706**	**30.9706**	**30.9706**	**0**	3.3	**100**
	PS-ACO	31.5563	37.4558	33.3362	1.5102	4.3	3.33
	MRCACO	**30.9706**	**30.9706**	**30.9706**	**0**	2.43	**100**
	AIACSE	**30.9706**	**30.9706**	**30.9706**	**0**	**1.4**	**100**
map6	AS	50.8701	59.1127	55.9646	1.9142	85.97	3.33
	RAS	**44.5269**	49.6985	46.1766	1.1414	67.9	3.33
	ACS	**44.5269**	45.3553	44.574	0.1282	38.27	93.33
	PS-ACO	45.3553	52.4264	47.5877	1.7943	**1.2**	3.33
	MRCACO	**44.5269**	**44.5269**	**44.5269**	**0**	29.77	**100**
	AIACSE	**44.5269**	**44.5269**	**44.5269**	**0**	3.87	**100**
map7	AS	76.0833	88.3259	83.1784	3.2615	115.1	3.33
	RAS	**58.669**	66.4264	62.7631	2.4816	103.6	3.33
	ACS	**58.669**	60.6690	59.0886	0.5731	90.27	56.67
	PS-ACO	59.8406	69.8406	65.1329	2.3965	1.37	3.33
	MRCACO	**58.669**	60.0833	58.7909	0.3824	34.57	90
	AIACSE	**58.669**	**59.4975**	**58.7243**	**0.2102**	**24.3**	**93.33**
map8	AS	110.3675	128.9533	121.5344	5.0381	89.33	3.33
	RAS	75.9828	88.8112	81.2514	3.4095	169.47	6.67
	ACS	**73.9828**	77.6396	76.0240	0.927	89.37	3.33
	PS-ACO	76.4680	91.2965	82.0114	3.2223	6.3	3.33
	MRCACO	**73.9828**	76.2254	75.0212	0.6295	84.6	16.67
	AIACSE	**73.9828**	**74.8112**	**74.3956**	**0.3784**	**54**	**43.33**

It can be seen from Table 6 that RAS, ACS, MRCACO and AIACSE can find the optimal path for all runs in case of small-scale environments, such as map5 and map6. With the scale of the environment expansion, such as map7 and map8, ACS, MRCACO and AIACSE can still obtain the optimal path, but there is a decreasing trend in the performance index of fbest and rate. This means that more time or more iterations are needed to get the optimal path when facing large-scale environments. Generally speaking, the proposed AIACSE algorithm performs well overall in all of the environments, and we can conclude that AIACSE has better algorithmic performance when compared against the other algorithms in terms of the given metrics.

F. STATISTICAL ANALYSIS OF THE EXPERIMENTAL RESULTS

Although the experimental results shown above show that the AIACSE algorithm outperforms the comparative algorithms, we cannot judge whether there are significant differences among all the methods due to the probabilistic characteristics of ACO algorithms. According to the guidelines given by Derrac *et al.* in [48], a statistical test should be conducted to improve the evaluation of the different algorithms' performance. Therefore, to obtain rigorous and fair conclusions, we have performed two statistical tests with the results obtained in previous subsections. The statistical software package SPSS is used for this test based on the results in the Table 4,Table 5 and Table 6.

First, Friedman's non-parametric test is used to check whether there are any significant differences in performance among all the algorithms. The mean ranking achieved by this statistical test for each of the compared algorithms is given in can be seen in Table 7 (the lower the rank, the better the performance). The obtained Friedman statistic is equal to 28.33. Considering that the confidence interval has been stated at the 95%, the critical point in a χ^2 distribution with 5 of freedom is 11.07. Since 28.33 > 11.07, we can say that there are statistically significant differences among the algorithms based on the mean ranking returned by Friedman's test, thus AIACSE can be regarded as the method having the lowest rank.

The above results achieved by the Friedman test only show whether there are overall differences, but do not pinpoint which groups in particular differ from each other. Therefore, to adequately evaluate the statistical significance of the better performance of AIACSE, we present a test in which the AIACSE algorithm will be compared with the rest algorithms using multiple comparison procedures. Table 9 summarizes the results of multiple comparisons, where the column 'Adj. Sig.' shows the p-values adjusted by the Bonferroni correction for multiple tests. From the results reported in Table 9, we can see that the adjusted p-values between AIACSE and PS-ACO and AS are 0.008 and 0.001, respectively, which are lower than 0.05, so AIACSE is significantly better than PS-ACO and AS at the 95% confidence level. Although AIACSE is not significantly better than MRCACO, RAS, and ACS, AIACSE performs better than them according to the average rankings shown in Table 7.

TABLE 7. Mean rankings achieved by Friedman's non parametric test.

Algorithm	Average Ranking
AS	5.83
RAS	4.00
ACS	2.50
PS-ACO	5.17
MRCACO	2.08
AIACSE	**1.42**

TABLE 8. Test summary between AIACSE and the other compared algorithms.

AIACSE vs.	Test Statistic	Std. Error	Std. Test Statistic	Sig.	Adj. Sig.
AMRC	0.667	1.08	0.617	0.537	1.000
ACS	1.083	1.08	1.003	0.316	1.000
RAS	2.583	1.08	2.392	0.017	0.252
PS-ACO	3.750	1.08	3.472	0.001	**0.008**
AS	4.417	1.08	4.089	0.000	**0.001**

V. CONCLUSION AND FUTURE WORK

In the present paper, an adaptive improved ant colony algorithm based on the non-uniform distribution initial pheromone, the pheromone diffusion model, the adaptive parameter adjusting strategy, and the novel pheromone updating mechanism are proposed to enhance the optimization ability and efficiency of the ACS algorithm. The non-uniform distribution initial pheromone can avoid the blindness in the starting of the evolution phase and improve the convergence speed. The pheromone diffusion model is utilized to enhance the exploration and collaboration capabilities of the ant colony algorithm and reduce the probability of premature convergence. The adaptive parameter adjusting strategy based on population entropy is proposed to achieve a better balance between exploration of the search space and exploitation of the knowledge during the steps of the process. The adaptive global pheromone updating strategy dynamically adjusts the pheromone increment caused by the iterative optimal ants and further utilizes the potential of the iterative optimal path. The proposed AIACSE algorithm is applied to mobile robot path planning. Several comparative experiments were carried out to evaluate the validity and performance of the proposed methodology. Additionally, Friedman's non-parametric test was further applied to demonstrate the efficacy of the algorithm more scientifically. The results of the simulation experiment and statistical test show that the AIACSE algorithm outperforms all the other algorithms in terms of performance metrics used in this paper, as well as adapting to different scale maps.

For further studies, it would be interesting to modify the algorithm to perform path planning in dynamic environments. In addition, it is recommended to apply AIACSE to other practical applications, such as the routing problem, feature subset selection, vehicle scheduling problem, disassembly sequence planning, and so on. Another interesting direction is to further study the performance improvement and parameters analysis of the ACO algorithms.

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