

A Self-Adaptive Heterogeneous Ant Colony Algorithm for Path Planning

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Abstract: To address the issues of traditional ant colony optimization (ACO) algorithms in path planning, including susceptibility to local optima, low convergence efficiency, and insufficient environmental adaptability, this paper proposes a Self-Adaptive Heterogeneous Ant Colony Optimization (SA-HACO). Firstly, a non-uniform pheromone initialization method is introduced to preset pheromone concentrations on feasible paths between start and end points, enhancing initial search efficiency. Secondly, a pheromone diffusion model is designed to enable pheromone spreading to adjacent grids, strengthening global exploration capability and preventing local optima. Meanwhile, a heterogeneous ant colony system is implemented, where Gaussian mutation functions assign differentiated parameters to individual ants, thereby improving population diversity. Combined with an information entropy-based adaptive mechanism that dynamically adjusts exploration-exploitation weight parameters, the algorithm achieves a balance between convergence speed and global optimization capability. Simulation experiments conducted on 30×30 and 50×50 grid maps demonstrate that SA-HACO significantly outperforms comparative algorithms (ACO, PS-ACO, and JOP-ACO) in path length, smoothness, and convergence speed. Particularly in complex environments, it consistently obtains optimal paths, verifying its robustness and adaptability. This research provides a novel methodology for path planning problems that effectively balances efficiency and global optimization capability.

Keywords: Path Planning; Heterogeneous Ant Colony System; Pheromone Diffusion Model; Information Entropy Adaptation.

1. Introduction

With the continuous advancement of automation technology, global path planning plays a vital role in fields such as autonomous vehicles, mobile robots, and industrial automation assembly lines. Its objective is to find an optimal path in a given environment that satisfies specific constraints, such as obstacle avoidance, minimizing path length, etc. [1]. Traditional path planning algorithms like the A* [2] and Genetic Algorithms [3] perform well in certain scenarios but often struggle to meet real-time and optimality requirements in complex environments, facing challenges such as high computational load, poor real-time performance, and susceptibility to local optima.

Dorigo [4] proposed the Ant Colony Optimization (ACO) algorithm in the 1990s, inspired by the foraging behavior of ants in nature. As a heuristic algorithm, ACO exhibits advantages like strong convergence and adaptability but also suffers from issues such as local optima entrapment and dependency on initial parameters. Many scholars have proposed improvements to address these limitations. For instance, Miao [5] proposed a hybrid algorithm integrating particle swarm optimization (PSO) and ant colony optimization (ACO), which significantly enhances path convergence speed through cooperative optimization of a dynamic pheromone update mechanism and particle swarm global search. To address the issues of rigid subgoal mapping and algorithm local convergence in robot path planning within static unknown environments, Xu [6] proposes a dynamic subgoal mapping strategy and an ACO-PSO hybrid optimization framework. By incorporating real-time path correction under a rolling window mechanism, the approach achieves collaborative optimization between global path length reduction and computational efficiency enhancement. Du Zhenxin [7] proposed a hybrid algorithm combining ACO with the Simulated Annealing

(SA) algorithm. After each iteration, paths are optimized using SA to ensure pheromone updates better reflect path quality, while also preventing premature convergence.

This paper proposes improvements based on the Ant Colony System (ACS) model. First, a non-uniform pheromone initialization method is adopted to preassign higher pheromone concentrations to feasible paths between the start and end points, enhancing early-stage optimization efficiency. Second, an adaptive mechanism based on information entropy is introduced to dynamically adjust the probabilities of exploration and exploitation by analyzing solutions generated during iterations, thereby accelerating convergence. Finally, a pheromone diffusion mechanism is incorporated to improve the algorithm's ability to escape local optima. These enhancements collectively balance convergence speed, global optimization capability, and robustness in complex environments.

2. Ant Colony System (ACS)

The ant colony algorithm is a heuristic path planning algorithm that simulates the foraging behavior of ants, belonging to the category of swarm intelligence optimization algorithms. It offers advantages such as positive feedback, parallel computation, and strong adaptability, and has been widely applied to path planning problems. The Ant Colony System (ACS), an enhanced version of the classic ant colony algorithm, improves convergence speed and optimization capability, making it one of the most classical ant colony algorithms. Key improvements in ACS include:

(1) Path selection rules for ants: Combines stochastic selection mode (for solution space exploration) with greedy selection mode (for exploiting optimal solutions), employing parameter q_0 to balance exploration and exploitation during solution construction.

(2) Global update rule: The global pheromone update after

each iteration is applied exclusively to the optimal ant rather than all ants.

(3)Local pheromone update: Introduces an additional local pheromone update rule during path construction.

3. Improvement of Adaptive Heterogeneous Ant Colony System

Compared with ACO, although the ACS algorithm enhances exploration efficiency and accelerates convergence speed, it still suffers from drawbacks such as susceptibility to local optima and low exploration efficiency in the early stages. This paper addresses these issues by employing an uneven pheromone initialization method, a heterogeneous ant colony system, adaptive strategy adjustments for algorithm parameters, and the introduction of a pheromone diffusion mechanism to improve the ACS algorithm.

3.1. Pheromone Diffusion Model

To prevent the ant colony algorithm from accumulating pheromones solely on a single path [9] and to enhance its exploration and local optima escape capabilities, this paper proposes a pheromone diffusion model.

When using a grid map for path planning, the pheromone is diffused to the eight surrounding grid cells for computational simplicity. Different diffusion coefficients are assigned based on distance. Assuming the central pheromone concentration is 5, the pheromone diffusion model is illustrated as Fig 1:

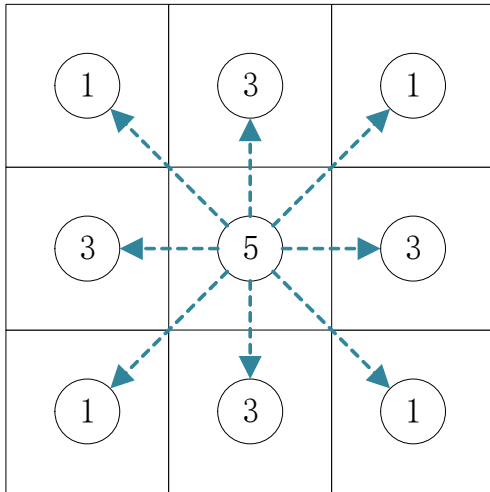


Figure 1. Pheromone Diffusion Model in Grid Map

3.2. Pheromone Initialization

To enhance the algorithm's search efficiency in the early stages, this paper employs a non-uniform pheromone initialization method[10]. Considering that the generated path must traverse each row between the start and end points, several random nodes are selected in each row of the map. The selection of these random nodes follows the formula below:

$$p_i = \begin{cases} \frac{d_{SG}}{d_{SJ} + d_{JG}} * a & i \in \text{feasible grid} \\ 0 & \text{others} \end{cases} \quad (1)$$

Here, p_i represents the probability of selecting a random node j , d_{SG} denotes the Euclidean distance between the start

point S and the goal G , while d_{SJ} and d_{JG} represent the Euclidean distances from the random node j to S and G , respectively. a is the probability coefficient, set to 0.7 here.

The aforementioned random nodes are connected to form a continuous path. If the path passes through obstacle grid cells during node connection, new nodes are inserted between the original nodes to ensure the newly generated path complies with navigational constraints.

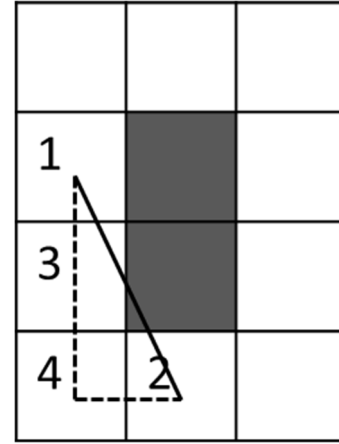


Figure 2. Schematic Diagram of Path Generation

As shown in Fig 2, if the path between Node 1 and Node 2 passes through an obstacle, Nodes 3 and 4 are inserted to form the dashed-line path illustrated in Fig 2. The initial pheromone concentration on these paths is calculated using the formula:

$$\tau_0 = \frac{c}{L_i} \quad (2)$$

Where τ_0 is the pheromone concentration, c denotes the initial pheromone value, and L_i represents the length of the i -th path.

3.3. Heterogeneous Ant Colony System

In the classical ant colony optimization (ACO) algorithm, the state transition rule for ants is defined by the formula as follows:

$$p_{ij}^k(t) = \begin{cases} \frac{[\tau_{ij}(t)]^\alpha [\eta_{ij}(t)]^\beta}{\sum_{s \in allowed_k} [\tau_{is}(t)]^\alpha [\eta_{is}(t)]^\beta}, & j \in allowed_k \\ 0 & \text{otherwise} \end{cases} \quad (3)$$

All ants utilize identical parameter values α and β , resulting in homogeneous characteristics within the entire ant colony. When the algorithm becomes trapped in local optima, this homogeneity causes the algorithm to fail in exploring broader problem spaces. To address this issue, this paper proposes a heterogeneous ant colony algorithm[11]. The modified calculation method for the state transition rule is defined as shown in the following equation:

$$p_{ij}^k(t) = \begin{cases} \frac{[\tau_{ij}(t)]^{\alpha(k)} [\eta_{ij}(t)]^{\beta(k)}}{\sum_{s \in allowed_k} [\tau_{is}(t)]^{\alpha(k)} [\eta_{is}(t)]^{\beta(k)}}, & j \in allowed_k \\ 0 & \text{otherwise} \end{cases} \quad (4)$$

As evident from the equation above, each ant possesses its

own independent control parameters $\alpha(k)$ and $\beta(k)$, thereby enabling distinct behavioral characteristics across the ant population. The parameter construction formula for the heterogeneous population is defined as follows:

$$\alpha(k) = \alpha_0 + M(0, \sigma) \quad (5)$$

$$\beta(k) = \beta_0 + M(0, \sigma) \quad (6)$$

where $\alpha(k)$ and $\beta(k)$ are the parameters of the k -th ant, α_0 and β_0 are predefined initial values, and $M(0, \sigma)$ denotes a Gaussian mutation function with a mean of 0 and standard deviation σ . To prevent excessive mutations that could degrade the overall quality of the ant colony, σ is set to 0.05, allowing only small-scale mutations.

3.4. Self-Adaptive Ant Colony System

In the ant colony system, the selection mechanism for ants relies on the parameter q_0 to balance probabilistic exploration versus deterministic exploitation, as mathematically formulated in the following equation:

$$\mathbf{s} = \begin{cases} \arg \max_{j \in allowed_k} [\tau_{ij}(t)]^\alpha [\eta_{ij}(t)]^\beta, & \text{if } q \leq q_0 \\ S & \text{otherwise} \end{cases} \quad (7)$$

Where s denotes the next selected node, S represents the solution constructed according to Equation (4), and q is a random number within the interval $[0,1]$. The parameter q_0 determines the algorithm's exploration capability. A smaller q_0 value causes the algorithm to favor constructing candidate solutions based on Equation (4), resulting in better population diversity in the ant colony system. This increases the probability of finding the global optimal solution, but it expands the search space and requires longer optimization time. Conversely, a larger q_0 drives the algorithm to prioritize selecting the current best solution, which accelerates convergence speed but reduces population diversity. This trade-off may lead to premature concentration on local optima, highlighting the critical role of q_0 in balancing exploration-exploitation dynamics during optimization.

3.4.1. Population Information Entropy

Shannon introduced the concept of information entropy, which quantifies the information content of a system or describes its degree of disorder. In information theory, entropy is commonly used to represent the uncertainty associated with each possible state of a random variable. A higher entropy value indicates that each state has an equal probability of occurrence, suggesting greater system randomness. Conversely, a lower entropy value implies that only a few states are likely to occur, reflecting higher system stability.

For a random variable X with n possible states X_1, X_2, \dots, X_n . its information entropy can be calculated using the formula shown in Equation (8):

$$H(t) = -\sum_{i=1}^N p(x_i) \ln p(x_i) \quad (8)$$

Where x_i represents the i -th state of a random system, and $p(x_i)$ denotes the probability of state x_i occurring. The information entropy increases when the probabilities of all states are more uniformly distributed, and decreases when the probabilities become more concentrated. Information entropy quantifies the proportional distribution of various states within a system. As a probabilistic optimization algorithm, the ant colony algorithm generates candidate solutions through stochastic events, making it inherently suitable for characterizing the diversity features of its evolutionary process using information entropy.

3.4.2. Population Information Entropy-Based Adaptive Parameter Tuning Strategy

The parameter q_0 in the Ant Colony System (ACS) directly influences the candidate solution construction process and is closely related to the algorithm's convergence speed and search capability. Therefore, during the optimization process, we propose automatically adjusting the value of parameter q_0 based on changes in information entropy. This adaptive adjustment mechanism regulates the proportion of random candidate solution construction in subsequent iterations, enabling dynamic modification of solution-building rules according to population diversity variations during optimization. This approach effectively mitigates the local optima problem caused by rapid decline in algorithm diversity while accelerating convergence and maintaining exploration capability. The adaptive adjustment rule for parameter q_0 is formulated as shown in Equation (9):

$$q_0 = q_{0min} + (q_{0max} - q_{0min}) * \sqrt{\sin\left(\frac{\pi}{2} * \frac{H(t)}{\ln N}\right)} \quad (9)$$

Where q_{0min} and q_{0max} are the lower and upper bounds of the parameter q_0 , respectively, N is the number of candidate solutions. The value of $H(t)$ is calculated according to Equation (8).

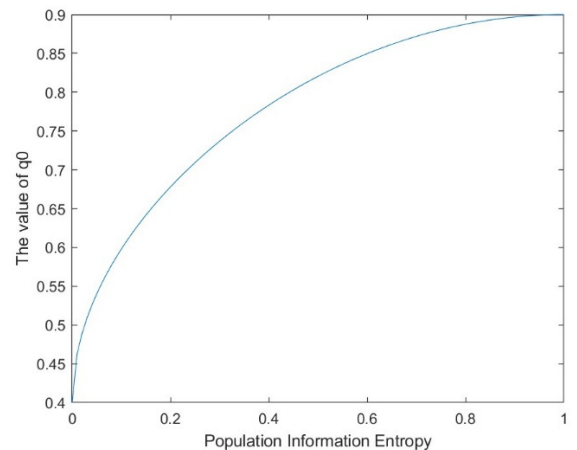


Figure 3. The varying curve of parameter q_0

As shown in Fig 3, a smaller population information entropy indicates reduced diversity within the population, where individuals cluster densely in the problem space. To maintain optimization quality, a smaller q_0 should be employed to increase the proportion of stochastic candidate solution construction, thereby enhancing the algorithm's

exploration capability. Conversely, a larger population entropy reflects higher diversity, with individuals distributed broadly across the solution domain. In this scenario, a larger q_0 is adopted to prioritize the exploitation of optimal solutions, accelerating convergence speed. To balance exploration and exploitation, the q_0 is constrained within bounds: the lower bound is set to 0.4 to prevent excessive exploitation, while the upper bound is fixed at 0.9 to avoid unguided exploration, as implemented in this study.

4. Simulation Experiments

To validate the feasibility of the proposed algorithm, simulations were conducted on the Matlab R2023B platform in a 2D grid environment. To verify the effectiveness and adaptability of the proposed adaptive heterogeneous ant colony algorithm (SA-HACO) in path planning, comparative experiments were performed against baseline algorithms, including ACO, JOP-ACO[13], and PS-ACO[14], in two grid environments with varying sizes and obstacle configurations (map dimensions: 30×30 and 50×50). The start point was set at the top-left corner, and the goal at the bottom-right corner. To mitigate randomness effects, all experimental results were averaged over 20 independent trials.

4.1. Parameter Settings

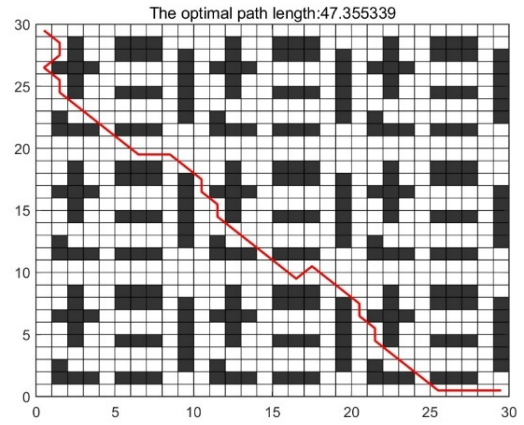
The ant colony algorithm involves multiple parameters that require predefined configurations, such as the number of ants m , global pheromone evaporation rate ρ , pheromone quantity Q , pheromone heuristic control parameter α , heuristic information parameter β , and maximum iteration count I_{max} . In the PS-ACO algorithm, parameters $c1$ and $c2$ are both set to 2, while the JOP-ACO algorithm adopts parameters provided in reference[13]. The parameter settings for other algorithms are listed in Table 1:

Table 1. The parameter settings of algorithms

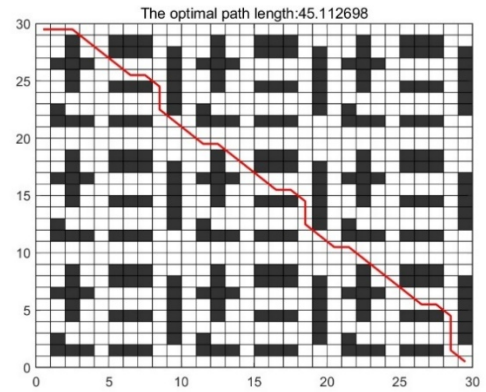
algorithms	m	ρ	Q	α	β	I_{max}
ACO	50	0.2	1	1	7	100
PS-ACO	50	0.15	10	1	7	100
JOPACO	50	0.3	1	1	7	100
SAHACO	50	0.3	1	5	7	100

4.2. Experimental Results and Analysis

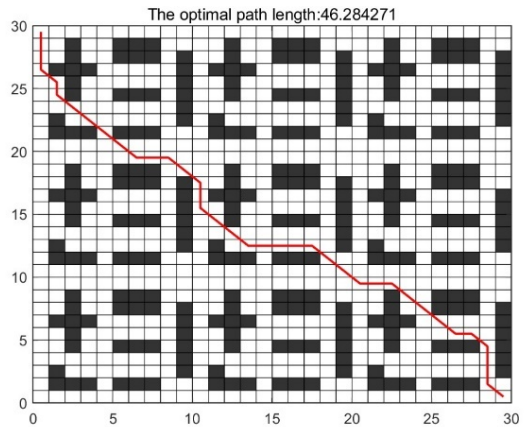
Fig 4 illustrates the path simulation results in a 30×30 grid map (Map1). The conventional ACO algorithm (a) generates a longer path with excessive turns and multiple instances of local optima entrapment, demonstrating poor overall quality. In comparison, the PS-ACO algorithm (c) and JOP-ACO algorithms(d) produce shorter paths with fewer turns, showing reduced average turning curvature and curvature variation, thus achieving moderate quality improvement. Notably, the SA-HACO algorithm(b) significantly enhances path quality through pheromone diffusion and adaptive strategies, generating a shorter path with minimal turns. Although its total path length approximates that of JOP-ACO, SA-HACO achieves smoother trajectories with smaller average variation in turning angles. These results demonstrate that the SA-HACO algorithm achieves the highest-quality path planning.



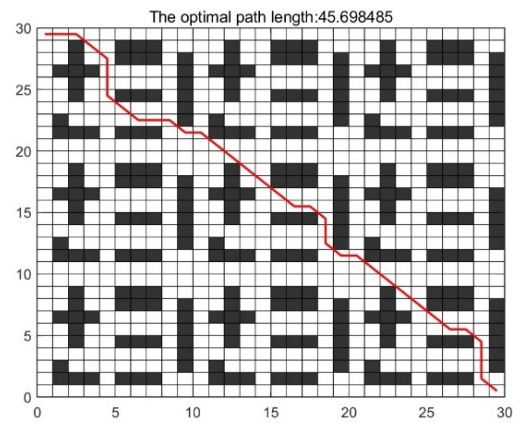
(a)ACO



(b)SA-HACO

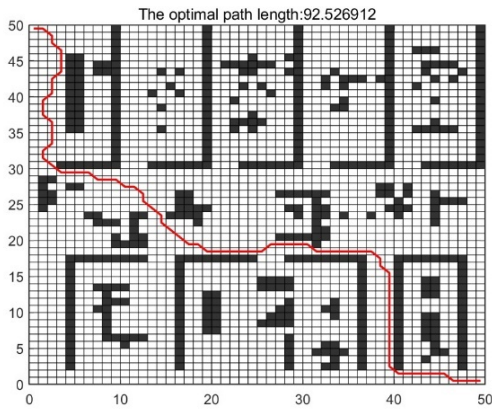


(c)PS-ACO

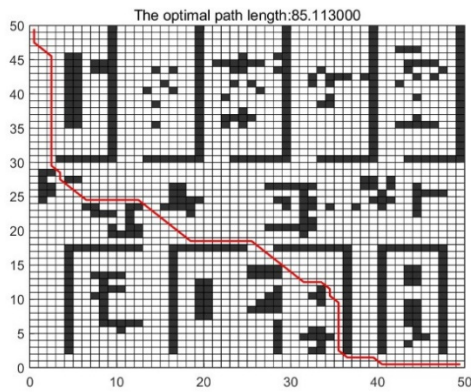


(d)JOP-ACO

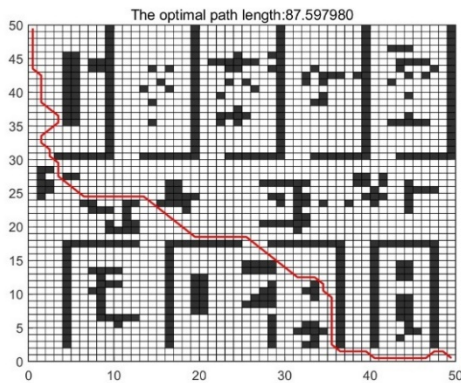
Figure 4. Schematic Diagram of the Path in a 30×30 Grid Map



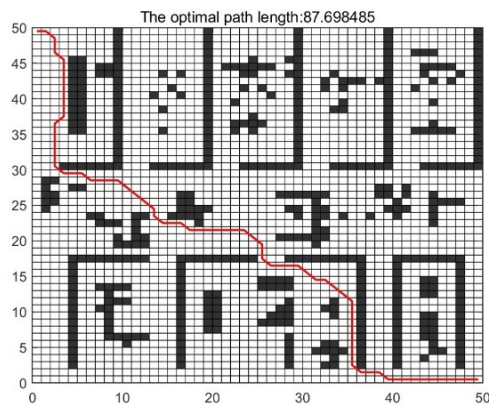
(a)ACO



(b)SA-HACO



(c)PS-ACO



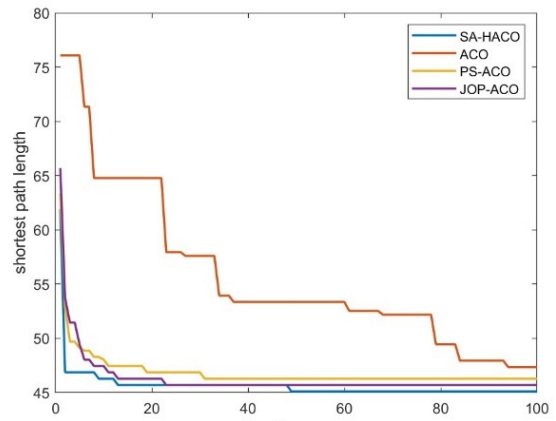
(d)JOP-ACO

Figure 5. Schematic Diagram of the Path in a 50×50 Grid Map

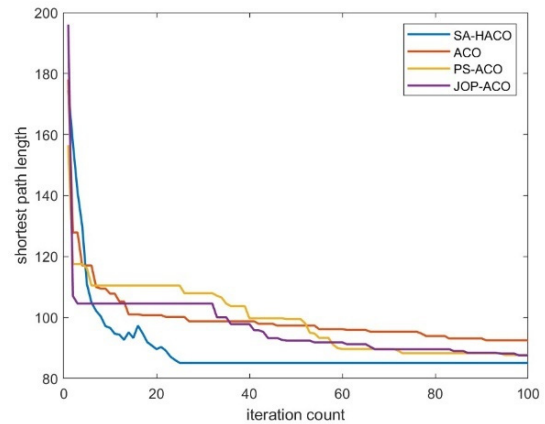
Fig 5 illustrates the simulated path results in a 50×50 grid map (Map2). The SA-HACO algorithm achieves the shortest path length in all tested environments, demonstrating

remarkable optimization superiority. Experimental findings reveal that while all algorithms perform well in smaller maps, traditional algorithms exhibit significant performance degradation as map complexity increases. SA-HACO outperforms others across all metrics except convergence speed. Notably, when confronted with complex environments characterized by irregular obstacles and overlapping local optima, SA-HACO stands out as the sole algorithm capable of consistently obtaining the shortest path. Its average path length also maintains a clear advantage, further validating the algorithm’s stability and adaptability to complex environments. These results underscore SA-HACO’s robustness in balancing optimization quality and environmental challenges.

Overall, compared to other algorithms, the SA-HACO method consistently identifies optimal paths in all tested environments and demonstrates significant advantages in other performance metrics. To further analyze the superior optimization performance of the SA-HACO algorithm, Fig 6 presents the convergence curves of various algorithms under different maps.



(a)map1



(b)map2

Figure 6. Algorithm convergence curves in different environments

Experimental results demonstrate that the SA-HACO algorithm consistently converges to optimal solutions across all tested scenarios. In Map1, although PS-ACO and JOP-ACO also exhibit the ability to find relatively good paths, their convergence efficiency differs. Specifically, PS-ACO and JOP-ACO converge to suboptimal solutions by the 30th and 22nd iterations, respectively, while SA-HACO discovers a superior path at the 48th iteration. When the test environment complexity increases in Map2, SA-HACO demonstrates even more pronounced advantages. It

achieves faster convergence speed and identifies paths with shorter lengths compared to other algorithms. This indicates that, even when other algorithms stagnate at local optimal paths in complex obstacle-rich environments, SA-HACO retains strong optimization capabilities. These findings validate the feasibility and effectiveness of the proposed improvements, which not only enhance the algorithm's optimization performance but also improve its convergence speed.

5. Conclusion

To address the challenges of low convergence efficiency, poor environmental adaptability, and the inherent trade-off between population diversity and convergence efficiency in traditional ant colony optimization (ACO) for static environment path planning, this study implements optimizations from two dimensions: algorithm framework and parameter system. By developing novel algorithmic mechanisms and parameter regulation strategies, the performance of the algorithm is significantly enhanced, achieving accelerated convergence while improving environmental adaptability.

First, an adaptive optimization model based on population information entropy theory is established. By introducing a population information entropy metric to monitor diversity dynamics during optimization, a parameter self-adaptation mechanism is constructed, overcoming the limitations of traditional empirical parameter settings. This ensures global exploration capability while maintaining search efficiency. Additionally, a dynamic pheromone adjustment system is designed: a non-uniform initialization scheme effectively reduces early-stage random search probability, while a diffusion-based pheromone update model strengthens synergistic effects among individuals, mitigating the inherent conflict between convergence speed and diversity preservation. To resolve the local optima issue, a single-population heterogeneous adaptive algorithm is proposed. This approach achieves behavioral diversity through differentiated parameter configurations, expanding the exploration scope of the solution space.

Multiple comparative experiments conducted in 2D grid simulation environments demonstrate significant improvements in convergence speed and stability. Experimental data confirm that the optimized strategy effectively balances global exploration and local exploitation, with statistical significance tests validating the efficacy of the algorithmic enhancements. Path planning case studies further illustrate the robust adaptability of the improved algorithm across diverse scenarios, offering a novel technical pathway to overcome the inherent limitations of traditional ACO.

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