Effect Analysis of Adaptive Ant Colony Algorithm with QoS Constraints Applied in Drone Disaster Area Search and Rescue System

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With the development of technology, drones have been widely used in disaster area search and rescue. This study proposes an adaptive ant colony algorithm based on service quality constraints for drone search and rescue models. The algorithm aims to address the low efficiency and long-time consumption in drone disaster area search and rescue. The model first constructs a disaster area drone search and rescue scenario, then introduces service quality constraints to optimize and improve the ant colony algorithm. Finally, Matlab R2017a is used for simulation experiments to test the algorithm's performance. The experiment conducted in a 32-scale area showed that the proposed algorithm achieved a minimum travel dealer length of 1.55km, which is 0.05km and 0.01km less than the traditional ant colony algorithm's 1.60km and particle swarm optimization algorithm's 1.56km, respectively. In the 128 scale and 512 scale regions, the proposed algorithm exhibited shorter average path lengths and higher stability. The data shows that research algorithms have better search and rescue efficiency and quality in dynamically changing disaster environments.

Povzetek: Prilagodljiv algoritem mravljiščne kolonije z omejitvami kakovosti storitve izboljšuje učinkovitost in stabilnost brezpilotnih letal pri iskanju in reševanju v območjih nesreč, kar zmanjša povprečno dolžino poti.

1 Introduction

With the increasing frequency of natural disasters, disaster response and disaster Search and Rescue (S/R) works have received great attention. Against the backdrop of difficult S/R efforts in disaster areas, drone technology has emerged in people's sight [1]. Drones have become an important tool in Disaster Area Search and Rescue (DAS/R) due to their high flexibility, convenience, and efficiency [2]. Through drone technology, disaster relief can conduct aerial surveys of the disaster area, locate trapped individuals, evaluate the level of disaster, and effectively improve the efficiency of disaster relief [3]. However, the sudden and strong disaster environment poses higher requirements for the path planning of unmanned aerial vehicles. At present, the number of drones in disaster relief is constantly increasing, but how to set the optimal S/R route for drones is still a problem that needs to be solved [4]. In Path Planning Algorithms (PPA), Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO) algorithms are common and have certain effectiveness in static scenes. However, in the face of dynamic and changing disaster environments, there are significant shortcomings in the stability and adaptability of ACO and PSO. Therefore, to optimize the S/R path of drones in disaster areas, improve the efficiency and quality of S/R tasks, this study proposes a Quality of Service Constrained Adaptive Ant Colony Optimization Algorithm (QSACO) based on service quality constraints. This study constructs a simulation environment for complex disaster areas, comprehensively considers the constraints of pheromone mechanism and Quality of Service (QoS), and improves its adaptability and efficiency in dynamic environments by optimizing algorithm parameters. The innovation of the research method is to constrain QoS to ACO and adaptively optimize the parameters in the ACO algorithm to improve the path planning efficiency of drones in DAS/R. The research content consists of four parts. Part 1 summarizes the research achievements of domestic and foreign scholars on drone S/R systems and PPA, analyzes the shortcomings of current research, and proposes the advantages of research methods. Part 2 is to build a disaster area environment, analyze the drone S/R process, and introduce QoS constraints into the ACO algorithm to build a model about the QSACO algorithm. Part 3 conducts performance analysis on the constructed QSACO algorithm, adjusts key parameters of the algorithm through simulation, and analyzes the impact of parameters on S/R results. Part 4 summarizes the experimental results and analyzes the shortcomings in the research, proposing future research directions.

2 Related works

When facing natural disasters, conducting S/R missions in disaster areas is urgent and important. Therefore, many scholars have conducted research on the DAS/R system of unmanned aerial vehicles. Albanese et al. proposed a S/R solution based on drones, which utilizes the high penetration rate of mobile phones in society to locate missing persons. Through on-site restoration experiments, it had been proven that this method could quickly locate missing victims through mobile phones, and had the characteristic of low battery consumption cost [5]. Dong et al. collected a dataset of thermal images captured by drones and conducted experimental analysis using different types of deep convolutional networks. The optimal point for pruning and fine-tuning the survivor detection network based on convolutional layer sensitivity was validated on NVIDIA's Jetson TX2 and achieved real-time performance of 26.60 frames per second [6]. Ribeiro et al. developed a mixed integer linear programming model for synchronous networks. This model considered the use of drones and mobile charging stations in a synchronous manner and was improved through genetic algorithms to adjust heuristic methods. This model had been applied in practical S/R missions, indicating that it provides efficient and fast response in S/R tasks [7]. Atif et al. proposed a customized online graph traversal method. This method minimized the search energy of drones and the number of unoccupied nodes, and further optimized the flight path and search energy of drones in the probability region through clustering. The proposed method could achieve linear scaling of the search area relative to the noise level. For a given noise level and an increasing number of nodes, this method had the drones search energy of the cluster, which can reduce the energy cost to 70% [8].

The core of drone’s DAS/R is PPA. In terms of PPA, there are already many and mature studies. Li et al. proposed a drone PPA based on an improved ACO approach. The algorithm utilized a grid method to create a 3D model of the target planning area for the drones. Secondly, the updating rules of pheromones were improved, and the weight factors of pheromones and heuristics were adjusted. The improved algorithm had better flight paths than traditional algorithms [9]. Mandloi et al. proposed a comparative analysis of path planning strategies for A-star, Theta-star, and Lazy Theta-star algorithms in a 3D environment. It verified the algorithm by calculating two performance indicators: time and path length. A-star guaranteed to find the shortest path on the graph, but could not guarantee to find it in a real continuous environment. The Lazy Theta-star algorithm could overcome the shortcomings of the A-star algorithm, but it would increase computational time [10]. Gul et al. proposed a multi-objective PPA, which first optimizes the path using the grey wolf optimizer PSO hybridization, and then combines all optimal and feasible points with local search techniques. Finally, relying on collision avoidance and detection algorithms, the mobile robot detected obstacles in its perception circle. This study conducted different simulations in various environments and found that the algorithm produces more feasible paths over shorter distances [11]. Chi et al. proposed a heuristic PPA based on a generalized Voronoi graph to generate heuristic paths, guide the sampling process of RRTs, and further improve the motion planning efficiency of RRTs. A series of simulations and practical verification have confirmed that the proposed algorithm has achieved better performance in heuristic path planning, free space feature extraction, and real-time motion planning [12].

In summary, the current PPA performs well in a preset environment. However, in a dynamically changing disaster area environment, the algorithm's performance may be challenged due to a lack of real-time response to changes and path optimization. The specific advantages and disadvantages of the above methods are shown in Table 1. Therefore, in view of the problems in Table 1, QSACO algorithm is proposed and QoS constraints are expected to be introduced to adapt to the changes in the disaster area environment.

Table 1: Summary of related work

Method	Author	Property	
		Advantage	Shortcoming
Mobile phone-based drone search	Albanese et al. [5]	Use mobile phone location, fast response, suitable for densely populated areas; Low energy design, extended operating time.	Relying on mobile phone signal coverage, the effect is limited when the signal is poor in the disaster area; May be limited due to privacy concerns.
Thermal image and deep convolutional networks	Dong et al. [6]	High search accuracy; Strong real-time processing capability.	High requirements on computing resources require dedicated hardware support. The recognition rate may be reduced by environmental influences, such as smoke and dust.

Mixed integer linear programmin g model	Ribeiro et al. [7]	Combined with the use of drones and mobile charging stations, it increases the continuity and flexibility of operations. Provides a fast and efficient scheduling policy.	The solution of the model is complex and requires a long calculation time. In practical applications, frequent adjustments may be required due to large environmental changes.
Traversal method in line graph	Atif et al. [8]	Significantly reduce search energy consumption and improve S/R efficiency. The search path is optimized by clustering to reduce the invalid coverage area.	The initial knowledge and node distribution of the region are required. When environmental information is incomplete, the effect may decrease.

3 Drones DAS/R system with adaptive ACO based on QoS constraints

For the drone's DAS/R system, this study constructs a S/R scenario using drones in disaster areas, analyzes the S/R process, and optimizes drone's S/R using ACO. In the application process of ACO, QoS is introduced to improve and optimize the efficiency and quality of drones S/R.

3.1 Construction of Drones S/R scenes in disaster areas

The actual DAS/R involves a variety of scenario conditions, including Disaster Stricken Base Stations (DSBS), drones, and other devices. DSBS is used to build connections between users and Geographic Information System (GIS) databases, including Central Base Stations (CBS) and Temporary Base Stations (TBS) [13]. The setting of the CBS needs to cover all TBSs so that they can upload priority level information. Figure 1 shows the positional relationship between the two.

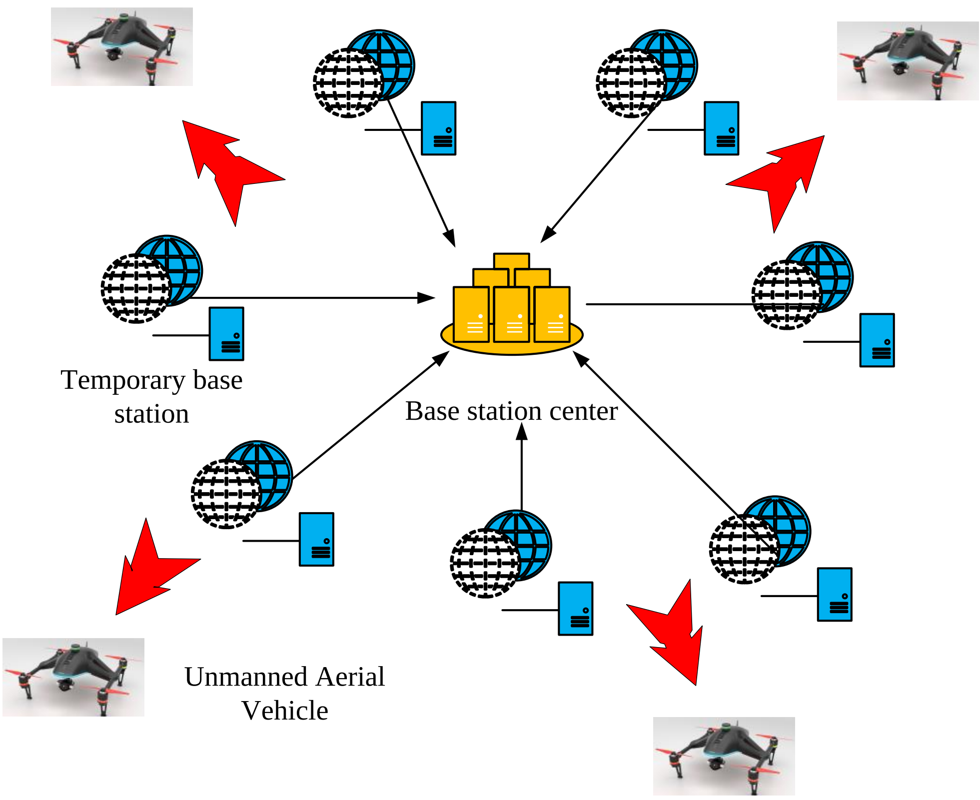


Figure 1: Position relationship between CBS and TBS

In Figure 1, CBS is located between each TBS. CBS obtains various geographic information indicators of disaster-stricken areas by applying for GIS access permissions. At the same time, it combines the severity of the disaster area transmitted by TBS to the main base station, as well as the level of demand for disaster relief materials, to obtain normalized processing of various data. Furthermore, the S/R priority in the disaster area is obtained, and the initialization parameters of the PPA are determined. Drones used for transporting disaster relief supplies and finding routes are dispatched from the base station to traverse all sub-disaster areas near the highest priority affected area. Until it is fully traversed, drones return to the base station and wait for the next round of S/R commands [14]. In the DAS/R scenario, Figure 2 shows the preliminary preparation work for drones.

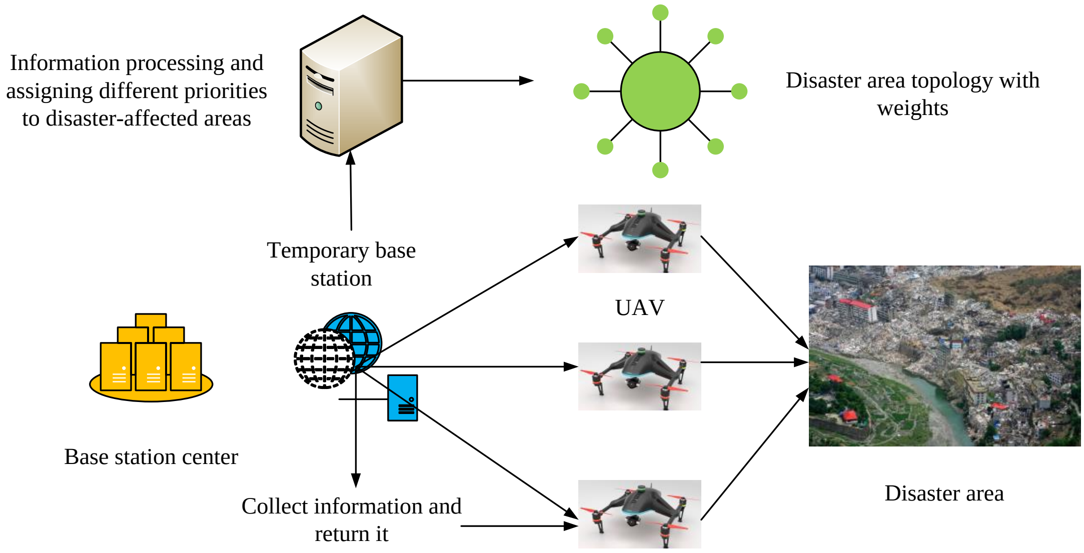


Figure 2: Scene construction of DAS/R

In Figure 2, the drones group is centrally managed by the base station. The main base station instructed a group of drones to perform a breadth-first search of the disaster area using geographic location information obtained from GIS. The drones group starts from the base station and prioritizes reaching the sub disaster areas adjacent to the base station until all sub disaster areas in the entire disaster area are traversed. Considering the dynamic characteristics of the disaster scene, new disaster areas may appear at any time. This study uses the new path exploration property of ACO to explore new disaster areas that GIS did not record in a timely manner, while prioritizing the breadth of drones search.

3.2 Analysis of ACO's solution to disaster relief issues

ACO is a path search algorithm based on ant foraging behavior. During the process of foraging, ants leave behind an information substance on their path, which is called a pheromone. Pheromones can guide later ants to choose paths with higher pheromone concentrations for foraging. Due to the large number of ants passing through a short path in a unit of time, the short path will leave behind a higher concentration of pheromones. Subsequent ants are likely to follow this path for foraging due to the stronger pheromones present. As the pheromone trail becomes stronger, more ants are expected to follow this path. This is the phenomenon of positive feedback of information [15].

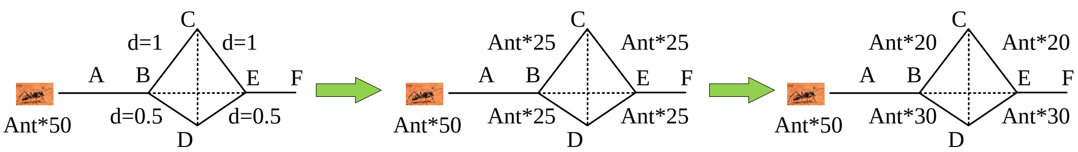


Figure 3: Schematic diagram of ACO path

In Figure 3, A represents the ant nest, and CD represents the obstacles encountered by ants during their foraging process. Obstacles divide the path into two parts, one is path BCE and the other is path BDF. F represents the target food, and d represents the path distance. This study assumes that 50 ants travel from point A to point F, and when faced with path selection, there are no pheromones present on the initial path. Therefore, ants will randomly choose a path with equal probability. Over time, 30 ants passed through BDE, while only 20 ants covered the path on BCE. This means that the concentration of pheromones left on the BDE pathway is 1.5 times higher than that on the BCE pathway. If 50 more ants depart from the ant nest or food source, these 30 ants will be influenced by the pheromones left by the previous ants when facing path selection, with 30 choosing BDE and only 20 choosing BCE [16]. In this research scenario, disaster relief is essentially a traveling salesman problem, so using ACO to solve disaster relief problems has significant advantages.

Ants select their next path during foraging based on the concentration of residual substances in the path. This study uses $tabu_k$ to represent the current disaster area that ants have passed through. Taboo table $tabu_k$ will be updated with the dynamic behavior of ants. During the journey, ants will calculate the corresponding Path Transition Probability (PTP) based on the content of pheromones and heuristic information on each path. The specific calculation is formula (1) [17].

$$p_{ij}^k = \begin{cases} \dfrac{[\tau_{ij}(t)]^\alpha \cdot [\eta_{ik}(t)]^\beta}{\sum_{s \subset allowed_k} [\tau_{ij}(t)]^\alpha [\eta_{ik}(t)]^\beta} \\ 0 \end{cases} \quad (1)$$

In formula (1), p represents the probability of path transition. $allowed_k$ represents the disaster area that has not yet been passed through. α represents the heuristic factor of information, mainly reflecting the impact of accumulated information on subsequent ants along the path. The magnitude of its value determines the strength of the collaborative ability within the ant colony. This parameter emphasizes the role of heuristic information in ants' decision-making process. A higher value of α makes ants more inclined to choose the path with higher heuristic value, which promotes the search of problem-specific heuristic information. β indicates the importance of heuristic information to the path selection process of ants, which directly affects the degree of dependence of ants on heuristic information in the path selection process. $\eta_{ij}(t)$ represents the heuristic function, and its expression is formula (2).

$$\eta_{ij}(t) = \frac{1}{d_{ij}} \quad (2)$$

In formula (2), d represents the distance between disaster areas. The smaller the value of d and the larger the value of $\eta_{ij}(t)$, the higher the probability of the path being selected. The update method of ant pheromones is formula (3).

$$\begin{cases} \tau_{ij}(t+n) = (1-\rho) \cdot \tau_{ij}(t) + \Delta\tau_{ij}(t) \\ \Delta\tau_{ij}(t) = \sum_{k=1}^{m} \Delta\tau_{ij}^k(t) \end{cases} \quad (3)$$

In formula (3), ρ represents the volatility coefficient of pheromones, with a range of values between [0,1) to avoid continuous accumulation of pheromones. $1-\rho$ represents the degree of residual pheromones. The evaporation coefficient of pheromone can be used to simulate the natural phenomenon of pheromone disappearing with time in real ant colonies. A higher volatilization coefficient indicates that pheromones dissipate more quickly. This helps the algorithm avoid premature convergence to local optimal solutions and improves its ability to explore new paths. $\Delta\tau_{ij}(t)$ represents the amount of pheromone increase on the path. This defines the concentration increase of pheromones on the path after the ant has walked it. This mimics ant leaving pheromones when they return to the nest after finding a food source. The pheromones guide later ants to the food source. $\Delta\tau_{ij}^k$ represents the residual content of pheromones along the path. According to the above steps, the ACO process is Figure 4.

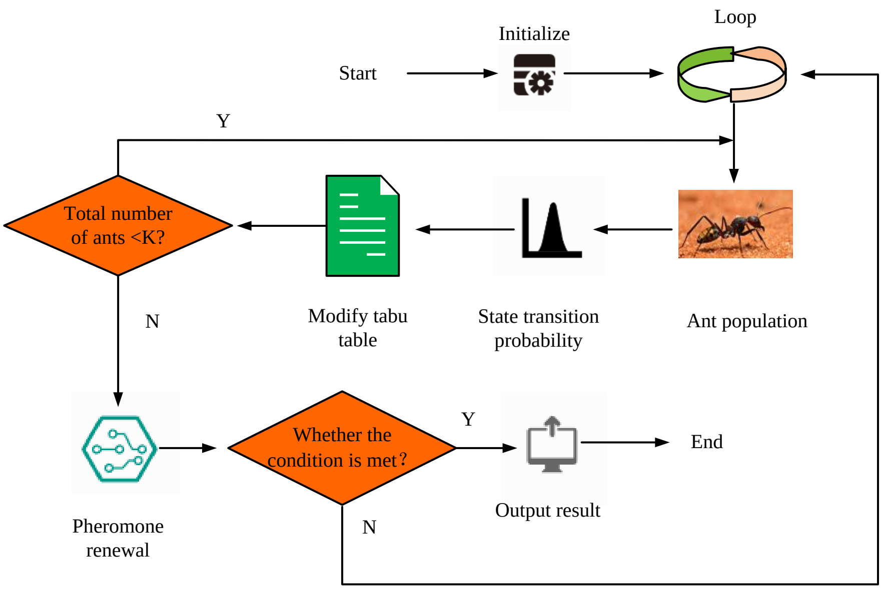


Figure 4: ACO structure

In Figure 4, ACO first initializes all parameters and sets the value of pheromones to a constant. Then the algorithm iterates, and all ants randomly select the next disaster area based on the state transition probability formula. Moreover, the disaster area that the ants have walked through is recorded in the taboo table. Next, it is determined whether the ants have traversed all the disaster areas. If they have not fully traversed, they will continue to iterate. If the ants fully traverse, the pheromones are updated globally. Finally, it is to determine whether the end condition of the outer iteration is met.

3.3 Adaptive ACO construction based on QoS constraints

Although ACO has significant advantages in DAS/R problems, it is inevitable that the algorithm will converge prematurely in the application process, resulting in the obtained results not being the global optimal solution. To address the issue of premature convergence, this study proposes introducing QoS constraints into the algorithm to obtain the QSACO algorithm. The QoS constraints introduced in the algorithm specifically include five aspects, namely time constraints, version constraints, security constraints, reliability constraints, and priority constraints. Meanwhile, this study uses utility functions to directly map QoS requirements to utility values. The utility function is expressed as formula (4) [18].

$$U_i(q_i) = \sum_{j=1}^{di} w_i^j U_i^j(q_i^j) \times p_i \tag{4}$$

In formula (4), $U_i^j(q_i^j)$ represents the utility value of task QoS. w represents the weight of QoS in different dimensions. The ultimate goal of task scheduling is to meet the maximum QoS requirements of users. However, as the computational scale gradually expands, the path finding time of the algorithm becomes too slow. This study further utilizes the Pseudo Random Proportional Rule (PRPR) and introduces a local search algorithm to optimize the efficiency of path finding. Firstly, the taboo table is initialized. Each ant starts crawling from its initial position until all tasks are added to the taboo list to form a closed loop. When ants choose the next task, they adopt PRPR, and the transition between tasks is represented by formula (5) [19].

$$t_j = \begin{cases} \arg_{l\in A}\max\left\{\tau_{il}[\eta_{il}]^{\beta}\right\} \\ p_{ij}^k(t) \end{cases} \tag{5}$$

In formula (5), q represents a random variable with a value range of (0,1), and t_j represents the task. The probability of path transition is directly related to the updating method of pheromones. The pheromone is updated using the total utility value, and the calculation of p is formula (6).

$$p_{ij}^k = \begin{cases} \dfrac{[\tau_{ij}(t)]^{\alpha}[\eta_{ik}(t)]^{\beta}}{\sum_{s\subset allowed_k}[\tau_{ij}(t)]^{\alpha}\cdot[\eta_{ik}(t)]^{\beta}} \\ 0 \end{cases} \tag{6}$$

In PRPR, the exploration of new pathways by ants can be altered by regulating q_0. In terms of updating pheromones, this study adopts a combination of global and local updates, and the pheromones of the update path are shown in formula (7).

$$\tau_{ij} = (1-\xi)\tau_{ij} + \xi\tau_0 \tag{7}$$

In formula (7), τ_0 represents the initial pheromone value. ξ represents the regulatory factor, with a value range of (0,1). The value of ξ can reduce the influence of pheromones to avoid affecting the path-finding of other ants, thus preventing premature convergence of the algorithm. The global update of pheromones is reflected in the pheromone update of the optimal path, and its expression is formula (8).

$$\begin{cases} \tau_{ij}(t+n) = (1-\rho)\tau_{ij}(t) + \rho\Delta\tau_{ij}(t) \\ \Delta\tau_{ij} = \sum_{k=1}^{m} \Delta\tau_{ij}(t), \Delta\tau_{ij}^{k} = QU_k \end{cases} \quad (8)$$

In formula (8), $\Delta\tau_{ij}(t)$ represents the change in total utility U_k. Q represents the regulatory factor, which takes a constant value. $\rho\Delta\tau_{ij}(t)$ represents the pheromone increment of the path. The above content is the completion of the QSACO algorithm construction, and the specific process is Figure 5.

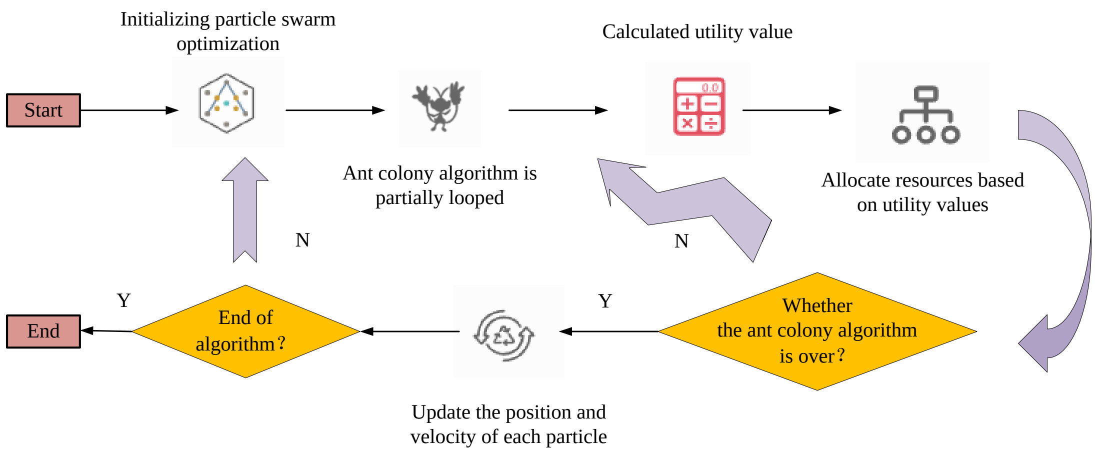


Figure 5: QSACO algorithm flowchart

In Figure 5, before the QSACO algorithm starts, it is necessary to determine the parameters α, β, and ρ of the algorithm. In this study, PSO is chosen to optimize ACO when determining parameters. α and β are the two dimensions of the PSO example location, and the result of ACO is used as the fitness value of PSO. Therefore, the values of α and β are obtained through the iteration of adaptive PSO. The value of ρ is not constant, and its adaptive update is formula (9).

$$\rho(t+1) = \begin{cases} 0.1 & \rho_0 \\ 1-0.95(1-\rho(t)) & \rho_{\max} > \rho(t) > \rho_0 \\ 1 & \rho_{\max} \end{cases} \quad (9)$$

In formula (9), the maximum value of ρ is set to 1 to avoid the situation where ρ is infinitely large. After determining the QSACO parameters, the algorithm begins inner iteration and calculates the utility value of the task. Then, based on the maximum utility value of the task, corresponding computing resources are allocated and the taboo table is updated. By locally updating pheromones, the optimal utility value of the iteration is set as the start of the next iteration. If the iteration ends, the pheromones are globally updated. The output result of ACO serves as the fitness value for each particle, and updates the optimal individual value and optimal population value of the particles. Finally, the position and velocity of each particle are updated. If the iteration end condition is met, the algorithm ends and outputs the result.

4 Drones DAS/R System based on QSACO

This study conducted simulation experiments on the performance of the proposed QSACO model. The experiment analyzed the key parameters of the algorithm and explored the S/R effects of the model under different disaster area scales. In the experiment, this study used traditional ACO and PSO algorithms for comparative experiments.

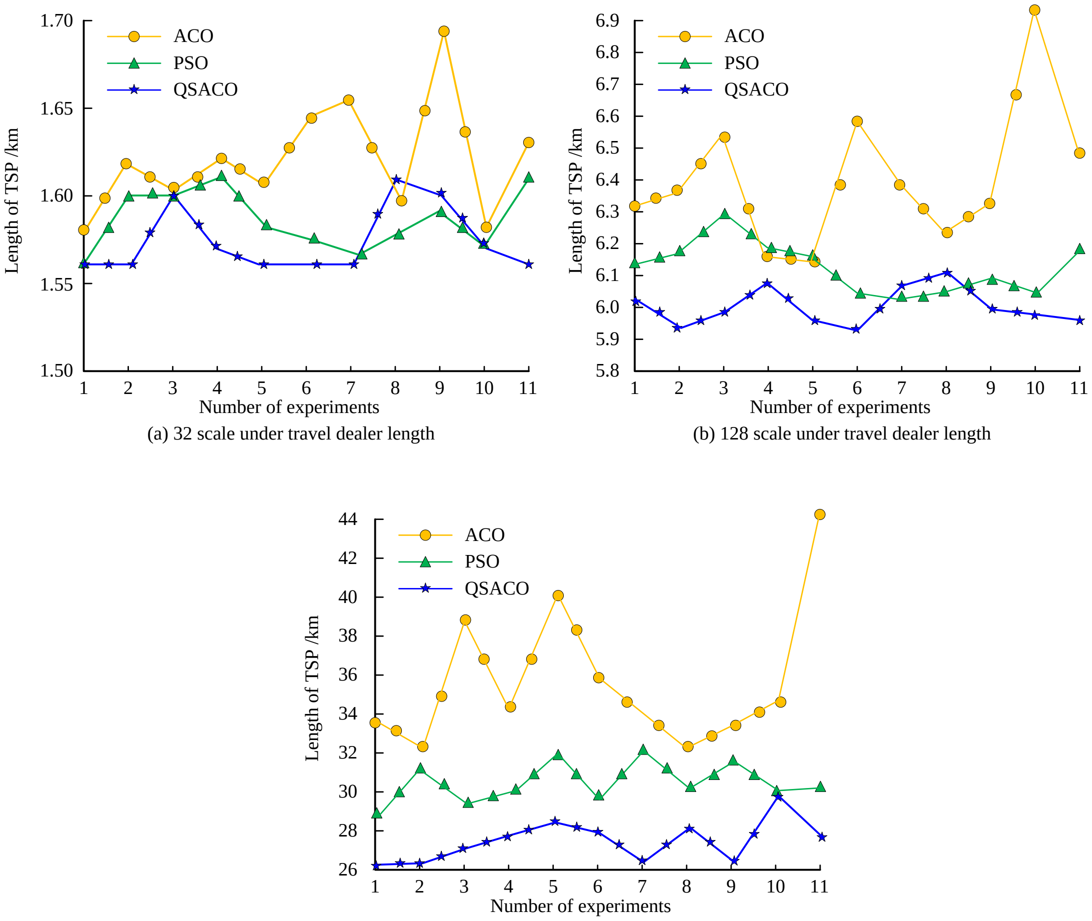
4.1 Simulation results of parameter optimization

This study used Matlab R2017a as an experimental tool to simulate the QSACO algorithm for disaster relief and path-finding in disaster areas. The relevant parameters of the algorithm are set as follows: The initial number of ants was 20, and the appropriate population number could effectively adjust the search strategy of the ant colony algorithm, balance its exploration and utilization capabilities, and obtain better performance on specific problems. The value of pheromone volatilization coefficient was 0.5, and the value of pheromone increase intensity coefficient was 0.8. The above parameters all had a certain influence on QoS constraints. Volatilization coefficient affected how QoS constraints decay with time. The increase in pheromone concentration could lead ants to preferentially choose paths that conform to QoS standards. The higher information heuristic factor highlights the importance of heuristic information in path selection. β determines whether ants will prefer those with better QoS performance when considering paths. Firstly, this study discussed the improvement methods of ACO parameters α and β for several sets of topologies with different input scales. The selected input scales were divided into topologies of 32, 128, and 512. Table 2 shows the horizontal and vertical coordinate information of area 32.

Table 2: Area 32 coordinates

32 area coordinates			
(X, Y)	(X, Y)	(X, Y)	(X, Y)
(1426,2434)	(3761,1437)	(4299,2366)	(3834,1521)
(3610,1657)	(3448,1678)	(3360,1351)	(4318,1126)
(4434,912)	(4508,692)	(3129,2092)	(2684,1878)
(2910,1613)	(2503,1798)	(1454,817)	(3837,1800)
(4040,2301)	(4183,2492)	(3902,2334)	(3798,2700)
(4151,2960)	(4385,3053)	(3551,2030)	(3629,2489)
(3516,2765)	(3561,3323)	(3057,3362)	(3262,3672)
(2667,2479)	(2900,2948)	(2492,3097)	/

This study conducted experiments on different algorithms using the above three input scales, and Figure 6 shows the obtained Travel Dealer Length (TDL). Figures 6 (a), (b), and (c) represent the TDL with sizes of 32, 128, and 512. In Figure 6 (a), the traditional ACO obtained the shortest TDL of 1.60km during the 10th experiment. PSO was more stable in 10 experiments, with the shortest TDL being 1.56km. The QSACO algorithm had a shorter average length for travelers, with a minimum length of 1.55km. In Figure 6 (b), the average length of QSACO was 5.98km, which is shorter, while PSO was 6.16km. The shortest length of ACO was 6.08km, and the longest length was 6.89km. In Figure 6 (c), the shortest and longest lengths of ACO were 32.18km and 44.03km, respectively. The shortest PSO was 28.55km and the longest was 31.98km. The shortest and longest lengths of QSACO were 26.03km and 29.10km. This indicates that QSACO has greatly improved stability compared to ACO, and although it is poorer than PSO, its path optimization efficiency is higher.



(a) 32 scale under travel dealer length

(b) 128 scale under travel dealer length

(c) 512 scale under travel dealer length

Figure 6: Results of TDLs of different sizes

This study analyzed QSACO with introduced weights, and the mutual constraint results of parameters α and β are shown in Figure 7. The horizontal axis in Figure 7 represents the experimental period, and the vertical axis represents the trend of parameter changes. The experimental period was in the range of 0 to 10, and the trend of α value change first increased from 3 to 20, and then decreased from 20 to 12. The value of β's change increased from 5 to 32, and then decreased from 32 to 18. The experimental period was between 10 and 40, and the values of α and β remained stable. This indicates that the two parameters have the same trend of change, and only by maintaining consistency between the two can the balance of the algorithm be ensured.

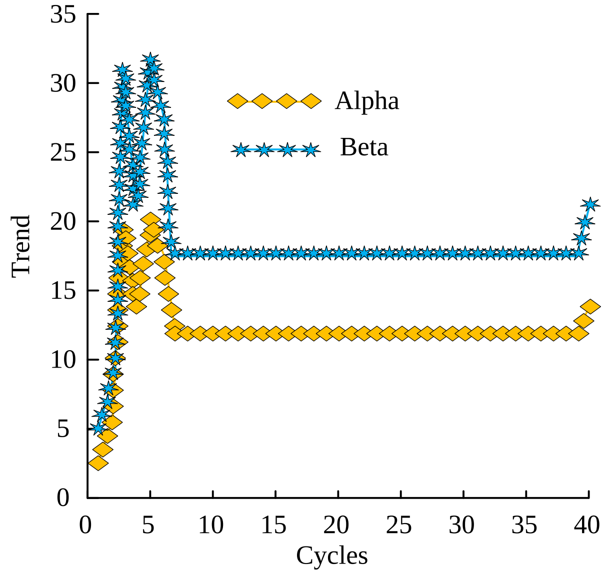


Figure 7: Result of parameter change trend

4.2 Simulation analysis of drones disaster area search

In the drones disaster relief DAS/R scenario, this study further analyzed the impact of PTP on S/R efficiency. The initial value of PTP was set to 0.1 in the experiment, and PTP was adjusted each time. 50 experiments were conducted on the same value, and the results are shown in Figure 8.

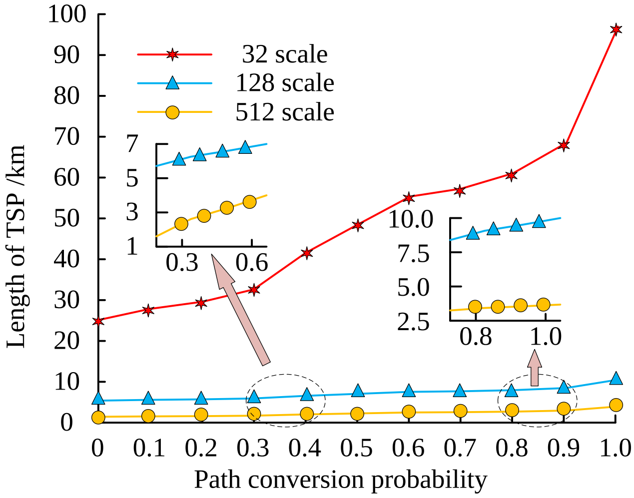


Figure 8: Results of the impact of PTP on S/R efficiency

Figure 8 shows the impact of PTP on different S/R scales. In small-scale areas, when PTP>0.3, the path length increased rapidly. Therefore, in small-scale environments, with a PTP of around 0.3, the model could balance the needs of priority and path length. In medium scale regions, when PTP=0.5, the path growth of the model was relatively slow. In large-scale regions, the difference in path growth between any two points was relatively small. At this time, priority conditions should be considered first, and the optimal PTP value was 0.8. This study analyzed the rescue effect with and without TBS, as shown in Figure 9.

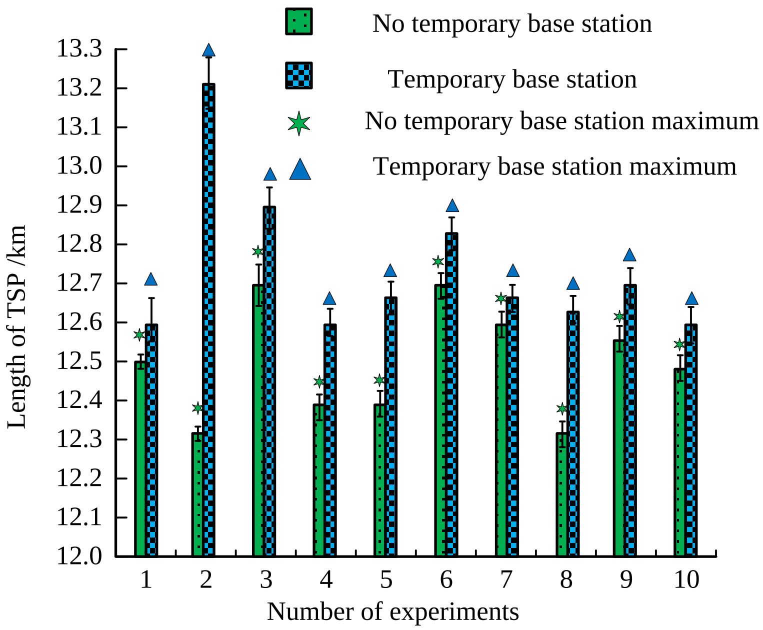


Figure 9: The impact of TBS on S/R efficiency

Figure 9 shows that for drones S/R without TBS. The average path length reached 12.8km. The drones with TBS S/R had an average path of 11.4km. This indicates that the size of PTP is related to the scope of the collection area. The setting of TBS can effectively reduce the length of S/R paths and improve S/R efficiency. This study constructed a S/R map based on the data in Table 1, and the path simulation results at PTP=0.3 are displayed in Figure 10.

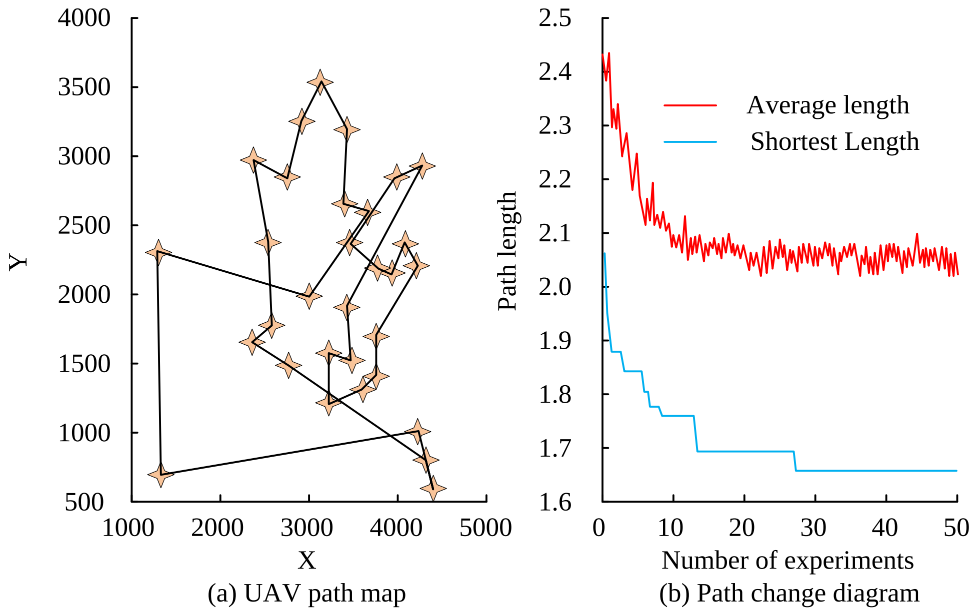


Figure 10: Trend of path changes in small-scale S/R areas

Figure 10 (a) shows the motion trajectory of drones in a S/R environment. Due to the small scale of the S/R environment, sparse topology, and large distance in the Xiangling area, drones ensured priority access to areas with higher priority while also prioritizing the shortest distance factor to a greater extent. Figure 10 (b) shows the adjustment of path length during the operation of the QSACO algorithm. The average S/R length of the algorithm was 2.06km, and the shortest path length was 1.65km. The results indicate that in small-scale S/R scenarios, the QSACO algorithm has a shorter S/R path, reduces the S/R distance of drones, and improves the S/R efficiency of drones. To further verify the progressiveness of QSACO algorithm, this study used Cuckoo Search Algorithm (CSA) for comparative analysis, as shown in Figure 11 [20].

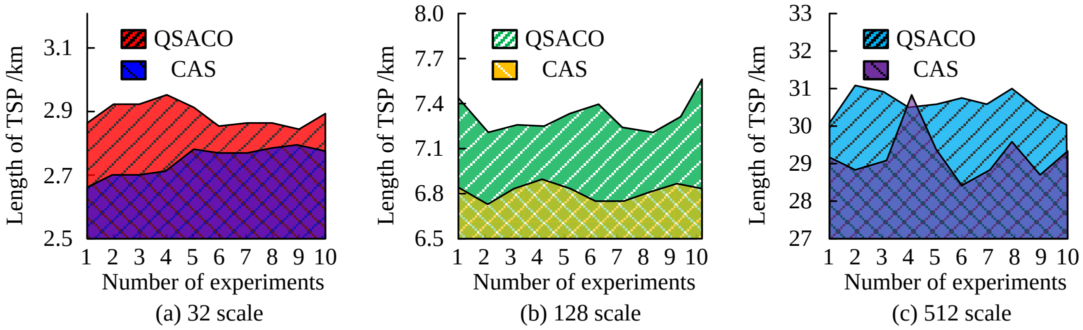


Figure 11: TDL under different scale scenarios

Figures 11 (a), (b), and (c) show the TDL results in small, medium, and large-scale S/R scenarios. In Figure 11 (a), CAS and QSACO had similar performance effects, with a minimum TDL of 2.72km for both algorithms. In Figure 11 (b), the minimum TDL of QSACO was 6.83km, and the minimum TDL of CAS was 7.25km. In Figure 11 (c), the minimum TDL of QSACO was 28.5km, and the minimum TDL of CAS was 29.6km. The data shows that research methods can effectively find the shortest path and avoid duplicate paths. In small-scale S/R environments, research methods and advanced methods have similar performance. With the expansion of S/R scale, research methods also have certain advantages, so the proposed QSACO method has certain feasibility and reliability.

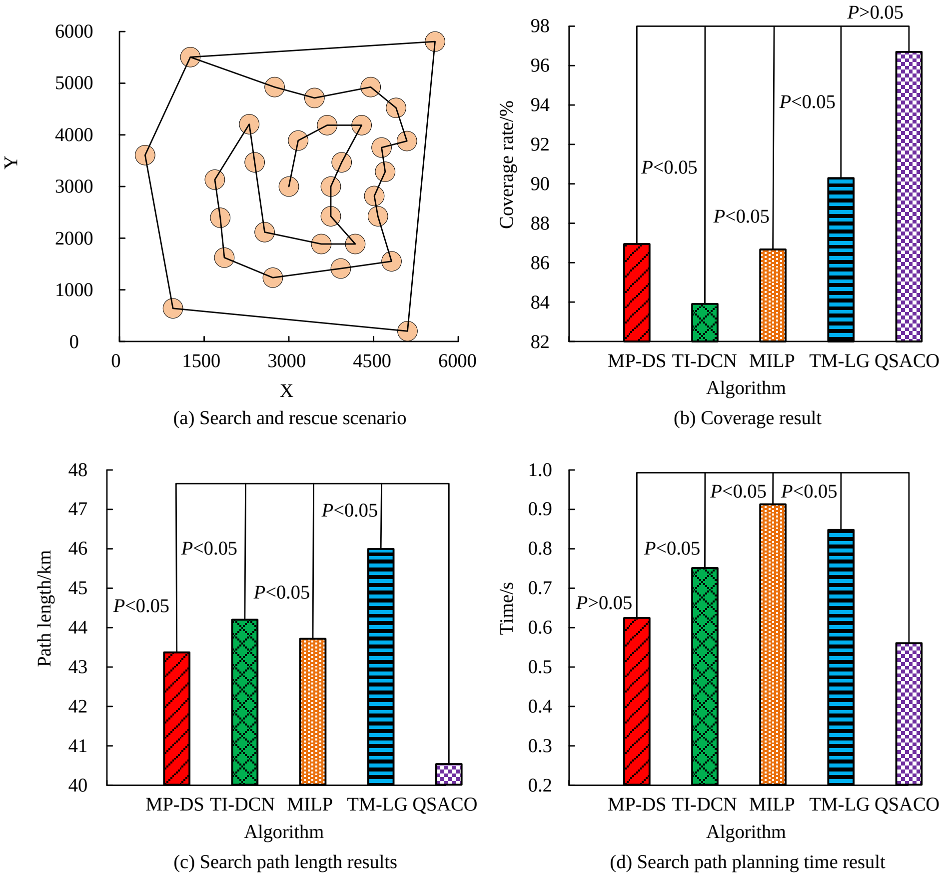


Figure 12: Search and rescue results of different algorithms

To evaluate the research method more comprehensively, the study used a more diverse set of disaster scenarios for S/R validation. The simulated disaster scenario was shown in Figure 12(a). In Figure 12(a), there were a total of 32 scenic spots with S/R sites. S/R evaluation index adopted coverage rate, S/R path length and S/R path planning completion time. The obtained index data were analyzed using SPSS22.0 statistical software and the comparison algorithms were MP-DS, TI-DCN, MILP and TM-LG. The results were shown in Figure 12(b) to Figure 12(d). Figure 12(b) showed that the coverage rates of MP-DS, TI-DCN, MILP and TM-LG algorithms were 87.50%, 84.38%, 87.50% and 90.63%, respectively, and the coverage rate of QSACO was 96.88%. Among them, MP-DS, TI-DCN and MILP had statistically significant differences compared to QSACO algorithm ($P<0.05$). In Figure 12(c), from the analysis of S/R path length, the search path length of MP-DS, TI-DCN, MILP and TM-LG algorithms was 43.27km, 44.17km, 43.87km and 46.01km, respectively, and the search path length of QSACO was 40.56km. The search path length between the above four methods and QSACO algorithm had statistical significance ($P<0.05$). In Figure 12(d), from the analysis of the completion time of S/R path planning, the time of MP-DS, TI-DCN, MILP and TM-LG was 0.62s, 0.74s, 0.91s and 0.84s, respectively, and the time of QSACO was 0.54s. The difference of search path planning time between TI-DCN, MILP and TM-LG algorithm and QSACO algorithm was statistically significant ($P<0.05$).

From the above simulation results, the search path planning time of QSACO algorithm was the shortest. Therefore, this paper analyzed the complexity of QSACO algorithm. In the matrix that stores the pheromone concentration on each path, its magnitude was proportional to the square of the number of nodes, denoated as (O(m2)). The path of each ant needed to be recorded, and in the worst case, the length of this record was equal to the number of nodes, i.e. (O(m)). Thus, all ant path records required (O(n\times m)) space. The amount of space required to store the QoS parameters associated with each node or path depends on the number and complexity of QoS constraints. In summary, the QSACO algorithm's spatial complexity can be expressed as approximately (O(m2 + n \times m)), and its algorithmic complexity is dependent on the rescue point and number of iterations, resulting in low complexity.

5 Discussion

According to the above experimental results, the high coverage of QSACO algorithm can be attributed to its optimized search strategy and efficient path planning. By introducing QoS constraints, QSACO algorithm can not only ensure S/R quality, but also optimize S/R paths to ensure that more areas are covered. In addition, the adaptive properties of the ACO algorithm enable it to adjust search strategies based on real-time feedback, further improving the coverage of S/R missions. QSACO algorithm performs better than other algorithms in S/R path length, mainly due to its improvement of pheromone update mechanism and effective use of QoS constraints. The optimal configuration of pheromone volatility coefficient and pheromone increase intensity coefficient enables the algorithm to effectively explore and strengthen those short paths and high QoS performance paths. This not only improves the optimization speed of the path, but also avoids premature convergence to the local optimal solution, thus reducing the length of the S/R path as a whole. The superiority of QSACO algorithm in the completion time of path planning indicates its efficient computing power and fast decision-making mechanism. The algorithm achieves fast path search and decision making by precisely adjusting ant population and information heuristic factors. This increase in efficiency, especially in the face of complex S/R scenarios, significantly reduces S/R preparation time and enables UAVs to be deployed to S/R sites more quickly. In short, through the improvement of ACO algorithm and the effective integration of QoS constraints, QSACO algorithm can flexibly respond to changes in various S/R scenarios, and the introduction of QoS constraints ensures the dual guarantee of efficiency and quality of S/R tasks. Additionally, the algorithm's improvement considers the drone's ability to dynamically adjust in real-time. This allows the S/R system to promptly respond to changes in the disaster area environment, optimize S/R path planning, and ultimately accomplish efficient and precise S/R tasks.

6 Conclusion

Traditional drones S/R systems have certain limitations in terms of efficiency and quality in response to complex and ever-changing disaster environments. Therefore, this study proposed a drones S/R model based on QSACO by constructing a disaster area drones S/R scenario and simulating the ACO process while introducing QoS constraints. This study validated the performance of the proposed algorithm through simulation using S/R areas of different scales. The simulation results showed that in scales of 32, 128, and 512, the QSACO achieved the shortest TDL of 1.55km, 5.98km, and 26.03km, respectively, with significant improvement compared to the ACO and PSO. In the comparative experiment with the CAS algorithm, the minimum TDL of QSACO algorithm was similar to or even better than the CAS. In summary, the proposed QSACO effectively met the path planning requirements in drones S/R scenarios in disaster areas, avoided duplicate path planning, and could solve local optimal solutions. Although the simulation results are good, there are still some limitations. Simulation experiments were based on hypothetical disaster environments, which might not fully capture the complexity and unpredictability of real disaster scenarios. For example, there may be dynamically changing obstacles, unstable weather conditions, complex terrain and other factors in the real disaster environment, which may affect the efficiency of UAV S/R and the accuracy of path planning. When conducting S/R in disaster areas, it is important to plan a path that covers the affected area as quickly as possible. In addition to this, the drones may also need to perform various tasks such as locating and rescuing injured individuals and delivering emergency supplies. These tasks may require further adjustment and optimization of the ACO algorithm. To improve the accuracy of simulation experiments, future research should build simulation models by collecting more realistic environmental data, so as to better simulate the challenges that may be encountered in real disaster environments. Due to the diversity of S/R tasks, the algorithm design should also consider how to combine path planning with task scheduling strategies such as casualty rescue and material delivery, so as to achieve a more comprehensive S/R task planning.

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