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Research on Real-time Communication Technologies for Cooperative Task Allocation and Path Planning in Multi-robot Systems

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ABSTRACT

The continuous advancement of intelligent levels in industry, agriculture, and services has led to an increasing demand for multi-robot systems to undertake tasks in complex environments. Task allocation and path planning are central to these systems, but traditional research often regards factors such as communication delay, bandwidth limitations, and dynamic environmental changes as secondary. As a result, cooperative efficiency is restricted. By integrating Particle Swarm Optimization (PSO) with the A* algorithm, and introducing improved Genetic Algorithm (GA) and Contract Net Protocol (CNP) mechanisms, this paper proposes a framework for cooperative task allocation and path planning considering real-time communication constraints. The framework couples task allocation, path planning, and communication delay modeling, significantly reducing communication load while maintaining task efficiency. Experimental results demonstrate that the proposed method outperforms traditional solutions in terms of task completion rate, path conflict rate, and delay control, showing promising prospects for practical engineering applications.

KEYWORDS

Multi-robot systems; Task Allocation; Path planning; Real-time communication; Genetic algorithm; Contract net protocol

1 Introduction

With the continuous advancement of industrial automation, intelligent manufacturing, and logistics systems, multi-robot systems (MRS) have been widely deployed in scenarios such as warehouse handling, flexible manufacturing, and emergency rescue. Group collaboration can enhance both efficiency and robustness. However, as the task scale increases and the environment becomes more complex, traditional algorithms often lead to high computational costs, frequent path conflicts, and significant communication delays. In particular, in real-world operations, the ability of robots to exchange information in real time directly influences the effectiveness of task allocation and path planning. Therefore, incorporating real-time communication modeling into path planning is of key importance for improving the overall performance of multi-robot systems.

Dynamic task allocation refers to the process in which, during the execution of tasks, a sudden disruption of certain tasks prompts the control system to immediately assess the status of robots and the operational environment, and subsequently reassign tasks. Compared to static allocation, this approach is more aligned with the real-world scenarios in agricultural production, though it introduces higher complexity. Currently, research on task reassignment for agricultural machinery collaboration primarily focuses on scheduling and optimization, with the Contract Net Protocol (CNP) being one of the most commonly referenced methods.

For example, Ding Cheng's team [1] proposed an improved Contract Net Protocol (CNP) with parallel multi-bidding, which enhances the real-time performance of multi-drone cooperation by setting evaluation time limits. Zeng Qingfei et al [2]. expanded the types of contracts by introducing exchange and clustering contracts, thereby constructing a multi-robot negotiation protocol to avoid local optima. Zhang Ning et al [3]. added a confirmation step during the contract authorization phase, designing an improved CNP with confirmation protocols, which effectively eliminates non-compliant bidders. Shi Haiyan et al [4]. introduced a process where the initial bidder filters subsequent bidders, and then tasks are allocated through parallel auctions, reducing communication volume while ensuring real-time performance. Wang Meng and others set bidding thresholds and introduced a priority mechanism to reduce the communication burden on the system.

In addition to the Contract Net Framework, researchers have also integrated various intelligent algorithms to complete dynamic task allocation for multi-robot systems. Niu Qichen et al [5]. continuously refresh the task set among distributed robots and reassign task sequences during the execution phase to reduce the overall task cost. Wang Huan et al. [6], inspired by the stimulus-response mechanism of dynamic ant colonies, mapped ant colony individuals to multi-AUV task allocation and resolved task conflicts through cyclic competitive strategies. Zhang Nana et al [7]. introduced multi-agent reinforcement learning into the scheduling of aerial emergency rescue operations, modeling the scenario as a stochastic game. The model is trained under the constraints of real-time performance and limited resources, thereby obtaining a high-return task allocation solution.

In recent years, mobile robots capable of autonomous navigation and flexible movements have shown increasingly

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prominent application prospects in smart agriculture, industrial manufacturing, and modern services. Path planning, as a core topic, aims to generate a continuous trajectory from the starting point to the destination that is collision-free and optimal in performance within complex environments. Based on the way the environment is perceived, this research can be divided into two main categories: global path planning and local path planning.

Global path planning assumes that the environment information is completely known and can output a single efficient and collision-free route. Typical algorithms include A*, Ant Colony Optimization (ACO), and Rapidly-exploring Random Trees (RRT). On the other hand, local path planning focuses on dealing with unknown obstacles encountered by robots during their movement. It relies on onboard sensors to perceive and update the local map in real-time, dynamically adjusting the obstacle-avoidance trajectory. Common methods include the Dynamic Window Approach, Artificial Potential Field, and neural network-based learning strategies.

2 Relevant Theories

2.1 Improved Particle Swarm Optimization Algorithm

In traditional Particle Swarm Optimization (PSO) algorithms, the particle swarm is randomly initialized. If the initial search area is too narrow, the particle swarm tends to fall into local optima. To address the failure suppression demand for commutation, this paper adjusts both the generation method of the initial particle positions and the velocity update rules to enhance the global search capability [8].

2.1.1 Generation of Initial Particle Positions

If the particle coordinates are entirely based on random sampling, the samples often cluster in local regions, causing the particle swarm algorithm to prematurely converge to suboptimal solutions. Latin Hypercube Sampling (LHS) is a stratified sampling method that covers different levels of control variables and can maximize the solution space information when the sample size is limited. To enhance the dispersion of the initial particle swarm and strengthen global search, this paper adopts LHS for generating the initial population.

2.1.2 Improved Particle Swarm Algorithm with Parameter Updates

The inertia weight w and acceleration coefficients c_1 and c_2 in the particle swarm algorithm significantly affect search performance. A larger w enables particles to quickly converge towards the optimal region, accelerating convergence; a smaller w encourages the swarm to finely explore near the extremum, improving solution accuracy. Based on this, the paper decreases w with each iteration, and the update formula is as follows:

$$\omega(t)=\omega_{\max}-\frac{\omega_{\max}-\omega_{\min}}{N_{\max}}\times t \tag{1}$$

In the formula for w, w_{max} represents the upper limit of the inertia weight; w_{min} represents the lower limit of the inertia weight; t corresponds to the current iteration number of the particle swarm; and N_{max} refers to the maximum number of iterations.

The parameter c_1 represents the ability of the particle to draw on its own flying experience, while c_2 reflects the particle's ability to absorb information from the swarm's flight. In the early stages of the search, reliance on individual experience helps particles explore new solution spaces; as the algorithm progresses, the swarm gradually converges, and particles rely more on the swarm's experience to adjust their positions, moving toward the global optimum. Based on this, the update formula for the learning factors is improved as follows:

$$c_1=c_{1s}-\frac{t}{T}\times\left(c_{1s}-c_{1e}\right) \tag{2}$$

$$c_2=c_{2e}+\frac{t}{T}\times\left(c_{2s}-c_{2e}\right) \tag{3}$$

In this equation, c_{1s} and c_{1e} represent the upper and lower bounds of the individual learning factor, respectively, while c_{2s} and c_{1e} correspond to the maximum and minimum values of the social learning factor.

2.2 Genetic Algorithm

The Genetic Algorithm (GA) is a global search optimization technique derived from the computer simulation of biological systems. It draws inspiration from the processes of natural selection and genetic mechanisms, including replication, crossover, and mutation. Starting from an arbitrary initial population, the algorithm generates more environmentally adaptive individuals through random selection, crossover, and mutation operations, guiding the population towards better regions of the search space. Through generations of reproduction, the algorithm ultimately converges to a population of individuals that are most adapted to the environment, yielding a high-quality solution to the problem [9].

Genetic algorithms first map real-world problems into evolvable mathematical models. Subsequently, the process involves encoding, initial population generation, fitness function design, followed by genetic operations including crossover, mutation, and selection, until the termination criteria are satisfied. The iterative optimization procedure is illustrated in the figure. During the iteration process, the algorithm only needs to compute the fitness score for each individual, without requiring the objective function to be differentiable or even to have an explicit derivative form. This enables the handling of optimization problems with complex mathematical expressions that are difficult or even impossible to differentiate. Since fitness evaluations are mutually independent, the fitness of all individuals in the population can be calculated simultaneously, inherently supporting parallel and distributed implementations. However, prior to initiating the iterations, the fitness function, chromosome encoding scheme, and genetic operators such as crossover and mutation must be customized for the specific problem. Furthermore, the interpretability of the iterative process is relatively weak. If an individual in the early stage exhibits significantly higher fitness than others, its genes may rapidly dominate the entire population, causing the algorithm to prematurely converge to a local optimum rather than the global optimum.

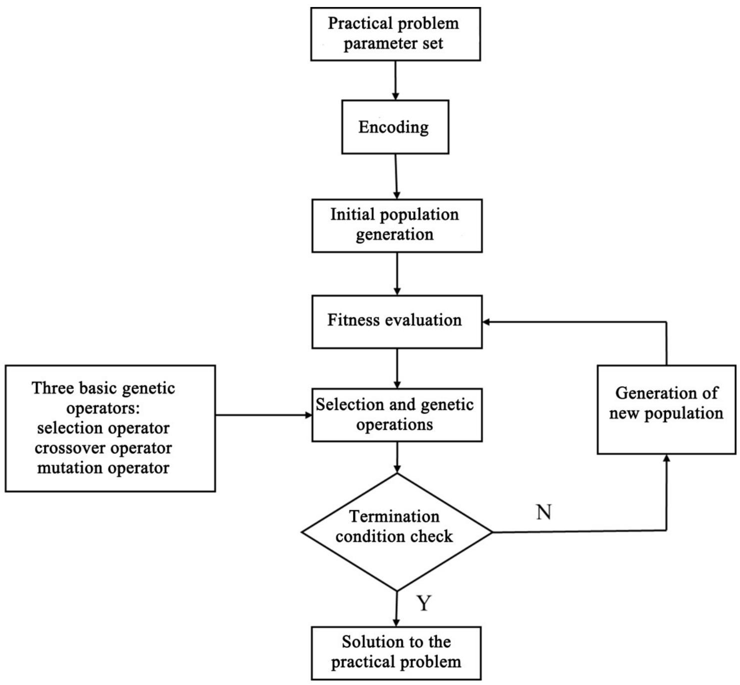

Figure 1 Genetic Algorithm Iterative Process

2.3 Problem Modeling

Consider a group consisting of N robots that need to perform tasks at M task points. The objectives are:

(1) To reasonably allocate tasks such that the total cost is minimized;

(2) To plan feasible paths for each robot to avoid conflicts and collisions;

(3) To control communication overhead and delay to improve real-time performance.

Define $x_{ij} \in \{0,1\}$, where 1 indicates robot i is assigned task j and 0 otherwise. The task allocation objective function is:

$$\min F = \sum_{i=1}^{N} \sum_{j=1}^{M} c_{ij} x_{ij} \tag{4}$$

where, c_{ij} represents the cost for robot i to perform task j, including time, energy consumption, and path length.

Constraints:

$$\begin{aligned} \sum_{i=1}^{N} x_{ij} &= 1, \forall j \in \{1,2,\cdots,M\} \\ \sum_{j=1}^{M} w_j x_{ij} &\le C_i, \forall i \end{aligned} \tag{5}$$

where, w_j is the task load and C_i is the maximum capacity of robot i.

2.4 Real-Time Communication Technology and Cooperative Control

In the communication process between robots and the control center, the delay consists of three components: transmission delay, propagation delay, and processing delay:

$$T_{\text{comm}} = \frac{L}{B} + \tau_{\text{prop}} + \tau_{\text{proc}} \tag{6}$$

where L is the packet size, B is the bandwidth, τ_{prop} is the propagation delay, and τ_{proc} is the processing delay.

The communication cost function is:

$$C_{\text{comm}} = \alpha T_{\text{comm}} + \beta N_{\text{msg}} \tag{7}$$

In multi-robot systems, communication always plays a critical role. Traditional methods such as Wi-Fi and Bluetooth are limited by bandwidth and latency, making it difficult to support real-time interactions. With the maturation of 5G and Time-Sensitive Networks (TSN), communication delays in multi-robot groups can be reduced to the millisecond level, opening the door for real-time collaboration. However, most studies have paid insufficient attention to communication latency and packet loss, and the conclusions drawn from simulations often differ significantly from those observed in real-world scenarios. Therefore, deeply integrating communication models with task allocation and path planning is a key breakthrough for enhancing the robustness of multi-robot systems [10].

2.5 Algorithm Framework

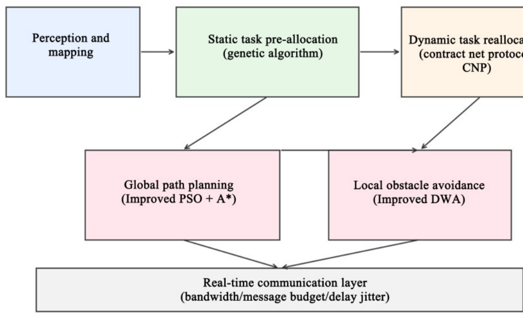

Figure 2 Path Planning Architecture Diagram

(1) Static Task Pre-allocation Phase: The improved genetic algorithm is introduced, employing dynamic crossover and mutation operators in combination with the simulated annealing acceptance criterion. This approach not only expands the global search range but also suppresses premature convergence.

(2) Dynamic Task Reallocation: Utilizing the parallel contract net protocol, the robot swarm can complete distributed bidding and award assignment locally. When environmental changes occur, the system quickly reassigns tasks, reduces redundant communication, and enhances robustness.

(3) Path Planning and Real-Time Obstacle Avoidance: The global path planning integrates the improved PSO algorithm with A*, leveraging the global search capability of PSO and the heuristic information of A* to generate more optimal global paths. For local obstacle avoidance, the improved dynamic window approach (DWA) is adopted, where the path is adjusted in real-time to avoid collisions when they occur.

3 Experimental Design and Result Analysis

3.1 Experimental Environment

The experiment was conducted on the ROS+Gazebo platform, replicating a multi-robot cooperative task scenario with a fixed number of 6 robots. A total of 10 task points were set, and the environment was simultaneously configured with both static and dynamic obstacles. The communication module operated under different bandwidth and latency parameters.

3.2 Experimental Results and Analysis

In a typical multi-robot cooperative task scenario, the proposed method was compared with the baseline method (GA + A*, without considering communication constraints). The experimental results were analyzed across several dimensions, including task completion time, communication delay, path conflict rate, energy consumption, bandwidth-delay relationship, task scalability, and communication overhead [11].

The experimental results showed that the proposed method reduced the average time to 105.6 seconds, compared to

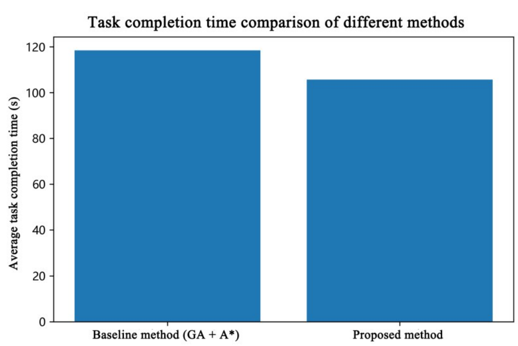

Figure 3 Time Comparison Results

the baseline method's 118.4 seconds, representing a reduction of approximately 10.8%. The improved genetic algorithm provided a better initial task allocation, followed by dynamic task reallocation through the contract net protocol. When new tasks or failures occurred, robots did not need to wait for long periods, leading to an overall improvement in execution efficiency.

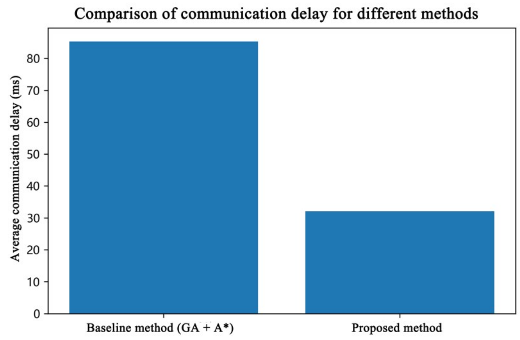

Figure 4 Comparison of Communication Delay

Under bandwidth constraints, the average communication delay for the baseline method reached 85.3 ms. The proposed method, using message budgeting and delay constraint control, reduced the delay to 32.1 ms, a decrease of over 60%. This demonstrates that the proposed method can significantly enhance the stability and real-time performance of communication in cooperative scenarios.

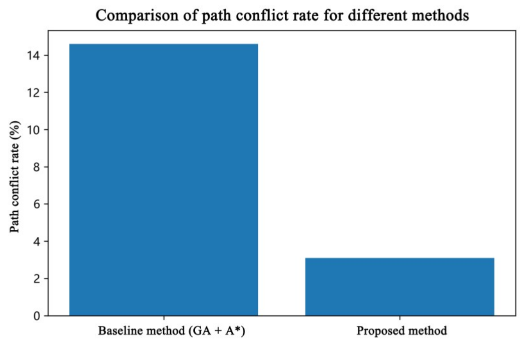

Figure 5 Comparison of Path Conflict Rate

The path conflict rate for the baseline method was 14.6%, while the proposed method achieved only 3.1%, representing a reduction of approximately 80%. The improvement is due to the enhanced PSO+A* algorithm, which avoids potential congestion areas at the global level, while the modified DWA incorporates delay compensation for local obstacle avoidance. This allows for real-time obstacle avoidance and dynamic trajectory adjustments, significantly reducing the conflict probability.

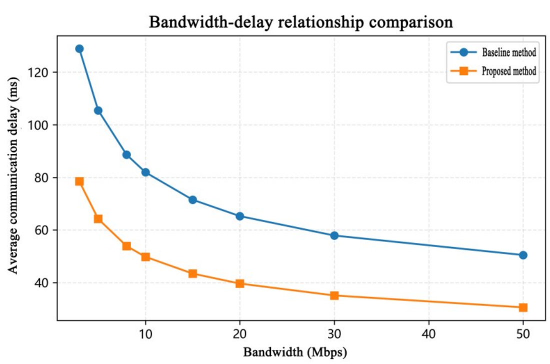

Figure 6 Bandwidth-Delay Relationship

As the bandwidth increases from 3 Mbps to 50 Mbps, the communication delays of both methods decrease progressively. However, the proposed method consistently maintains a lower delay with a steeper decline. This clearly demonstrates that under bandwidth-constrained conditions, the proposed framework is more capable of sustaining timely communication and exhibits superior robustness.

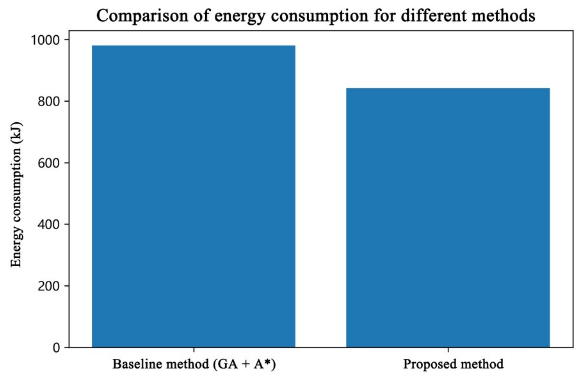

Figure 7 Energy Consumption Comparison

The energy consumption results show that the proposed method has an average energy consumption of 842 kJ, which is a 14.1% reduction compared to the Baseline Method's 980 kJ. This optimization is primarily attributed to the shortened path length, reduced redundant obstacle avoidance actions, and decreased communication overhead, which together significantly save energy while ensuring task efficiency.

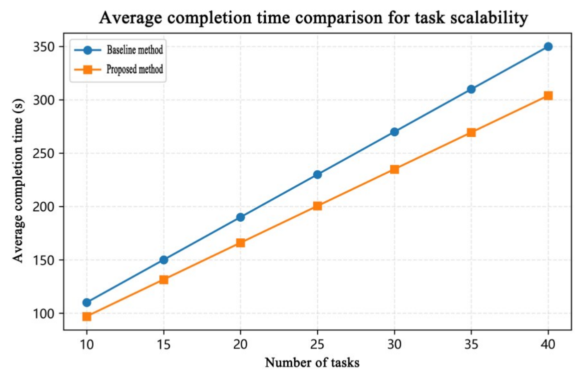

Figure 8 Task Scalability

When the number of tasks increased from 10 to 40, the Baseline Method showed a completion time slope of 8.0 s/task, while the proposed method had a slope of 6.9 s/task. The results indicate that the proposed method demonstrates better scalability in large-scale task scenarios and can handle the computational and communication pressure caused by task growth more smoothly.

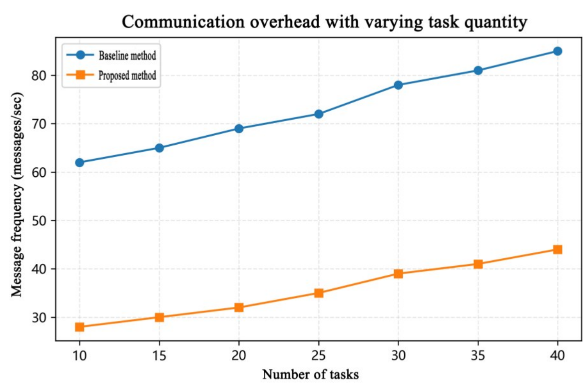

Figure 9 Communication Overhead Comparison

As the number of tasks increases, the communication overhead of the Baseline Method rises sharply, while the proposed method consistently maintains a lower level. When the number of tasks reaches 40, the message frequency of the proposed method is approximately 54% of that of the Baseline Method, significantly reducing the risk of link congestion and ensuring real-time performance and reliability.

4 Conclusion

This paper proposes a multi-robot task allocation and path planning method for scenarios with limited real-time communication. Experimental results demonstrate that the task allocation mechanism, which integrates an improved genetic algorithm and the CNP, significantly suppresses the communication overhead caused by dynamic task changes while maintaining global optimality. This enhances the task response and allocation efficiency in complex environments. For path planning, the paper combines an improved ant colony algorithm with the heuristic search of the A* algorithm. This approach leverages the global optimization advantage of the ant colony algorithm while retaining the fast guiding characteristics of A*, and introduces a dynamic window method for real-time obstacle avoidance and conflict resolution. As a result, the multi-robot cooperative task execution exhibits higher robustness and safety [12].

Experimental results further indicate that the proposed method is indeed feasible: compared to the Baseline Method, four key metrics—task completion time, communication latency, path conflict rate, and energy consumption—are all significantly reduced. The bandwidth-latency curve and task scalability tests simultaneously show that the proposed method maintains low latency even under bandwidth constraints and preserves scalability and stability as the task scale increases. These advantages make it highly suitable for engineering applications in scenarios such as smart manufacturing, warehouse logistics, and multi-robot collaborative operations in unmanned systems.

Future work aims to further explore the potential of deep reinforcement learning (DRL) in task allocation and path planning. By leveraging its adaptive and policy optimization features, DRL will be used to address increasingly complex and dynamic operational environments. Additionally, the plan is to incorporate emerging communication technologies such as Vehicle-to-Everything (V2X), edge computing, and 5G/TSN, to enhance the system's real-time responsiveness and reliability. Furthermore, this framework could be integrated with multimodal perception, environmental uncertainty modeling, and energy optimization strategies, to create a more intelligent, efficient, and low-carbon multi-robot collaborative control system, providing theoretical and technical support for the deployment of large-scale robots in complex environments.

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