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MULTI-AUV DISTRIBUTED TASK ALLOCATION BASED ON THE DIFFERENTIAL EVOLUTION QUANTUM BEE COLONY OPTIMIZATION ALGORITHM

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ABSTRACT

The multi-autonomous underwater vehicle (AUV) distributed task allocation model of a contract net, which introduces an equilibrium coefficient, has been established to solve the multi-AUV distributed task allocation problem. A differential evolution quantum artificial bee colony (DEQABC) optimization algorithm is proposed to solve the multi-AUV optimal task allocation scheme. The algorithm is based on the quantum artificial bee colony algorithm, and it takes advantage of the characteristics of the differential evolution algorithm. This algorithm can remember the individual optimal solution in the population evolution and internal information sharing in groups and obtain the optimal solution through competition and cooperation among individuals in a population. Finally, a simulation experiment was performed to evaluate the distributed task allocation performance of the differential evolution quantum bee colony optimization algorithm. The simulation results demonstrate that the DEQABC algorithm converges faster than the QABC and ABC algorithms in terms of both iterations and running time. The DEQABC algorithm can effectively improve AUV distributed multi-tasking performance.

Keywords: Differential evolution quantum artificial bee colony algorithm; Multi-AUV; Contract net; Task allocation

INTRODUCTION

Currently, research on underwater vehicle AUVs focuses on two dimensions: task allocation modeling and algorithm optimization. In recent years, to avoid the multi-robot centralized solution of the large calculation load of the central node, poor system robustness and other defects, scientific researchers worldwide have devised independent coordination and control technology for multi underwater vehicle AUVs according to the group behavior, which appears in biological group interaction mechanisms and reaction mechanisms. This effort provides a new method to solve the problem of distributed task allocation [1-3]. Distributed task allocation offers many advantages, such as strong autonomous system scalability, calculation simplicity, and the lack of a defined coordination control center. It has no prominent hierarchical system feature. This method uses the bottom-up data-driven form, which distinguishes it from the traditional up-down task-planning model. It represents a new direction in the research field of multi underwater robot AUV task allocation.

With the rapid development of swarm intelligence algorithms, many researchers have simulated insect foraging behavior and have introduced a response threshold model to assign tasks; other experts have introduced the ant colony algorithm to solve the large-scale task allocation problem based on the time series [4-6]. Some experts have also designed a task model and proposed an improved discrete particle swarm optimization algorithm to solve the problem [7,8]. These methods provide a new way to solve the problem of allocating tasks among multiple robots. The present paper explores AUV mission planning theory for multi-AUV task allocation, particularly to study distributed AUV dynamic task allocation, which uses the differential evolution quantum colony optimization algorithm in the bionic task allocation method.

MATERIAL AND METHODS

QUANTUM ARTIFICIAL BEE COLONY OPTIMIZATION ALGORITHM

The bee colony optimization algorithm is a type of meta-heuristic optimization method to imitate the behavior of natural bees. Ferrante et al. [9] proposed a self-organization model, which was applied to task partitioning. Grozinger [10] proposed a self-organizing model, which showed the communication in the bee colony through many methods, including "swing dance" and odor. This self-organization model can complete different tasks in different social classes. Karaboga and Bastruk. proposed a meta-heuristic bee colony algorithm to solve the maximum-weight problem [11, 12]. Tsai et al. [13] introduced an algorithm that imitated honeybees using the method of neighborhood search and random search for combinatorial optimization and function optimization. Karaboga et al. [14] successfully applied the colony algorithm to the problem of function extremum optimization and systematically introduced the artificial bee colony (ABC) model. Civicioglu and Besdok [15] analyzed a conceptual comparison of the Cuckoo search, particle swarm optimization, differential evolution and artificial bee colony algorithms. Loubière et al. [16] proposed a sensitivity analysis method for driving the artificial bee colony algorithm's search process, a new approach to random selection in neighborhood search. Karaboga and Akay [17] and Ozturk et al. [18] proposed an improved clustering criterion artificial bee colony algorithm.

In the quantum space, the particle state $ih\frac{\lambda}{\lambda t}\varphi(X,t) = \mathrm{H}\varphi(X,t)$ is represented by wave function $\varphi(X,t)$, where H is the Hamiltonian operator and h is Planck's constant. If the particle undergoes a one-dimensional potential well movement at the center point of Q, the position determined by the stochastic equation is $X = Q \pm \frac{h^2}{2m\gamma}\ln(1/u)$, which m is mass of the particle, u is the random number distributed on the interval (0, 1) uniformity [19].

Thus, we can obtain a formula of the quantum artificial bee colony algorithm:

$$X_{i,j}(t+1) = Q_{i,j}(t) \pm \lambda \left| X_{i,j}(t) - X_{i\neq j,j}(t) \right| \ln(1/u_{i,j}(t)) \tag{1}$$

In the formula, i is the bee number, j is the dimension, $X_{i,j}$ is the bee optimization position, and λ is a constant. In addition,

$$Q_{i,j}(t) = \alpha_j(t) \times Q_{i,j}(t) + (1-\varphi_j) \times G_j(t) \tag{2}$$

In the formula, α_j is the random number distributed on the interval (0, 1) uniformity, $Q_{i,j}(t)$ is the best current position of an individual bee, and $G_j(t)$ is the best estimate of the current position of all bees.

The best estimate of the position of the i-th bee is

$$Q_i(t) = \begin{cases} X_i(t) & f\left[X_i(t)\right] < f\left[Q_i(t-1)\right] \\ Q_i(t-1) & f\left[X_i(t)\right] \geq f\left[Q_i(t-1)\right] \end{cases} \tag{3}$$

The best estimate of the global position is determined by $g = \arg\min_{1\leq i\leq m}\left\{ f\left[Q_i(t)\right]\right\}$ and $G(t) = Q_g(t)$.

OPTIMIZATION ALGORITHM OF DIFFERENTIAL EVOLUTION OF QUANTUM COLONY

The differential evolution algorithm incorporates the individual optimal solution in the group evolution and shares the internal information groups $X(0) = \left\{x_1^0, x_2^0, \cdots, x_{NP}^0\right\}$, through the cooperation and competition among individuals within the group to achieve the optimal solution. Assume that population size is NP, when the population evolves to the m generation, the population is $X(m)$, and the dimension of the solution space is K. In the initial population, the individual solution of I is $x_i^0 = \left[x_{i,1}^0, x_{i,2}^0, \cdots, x_{i,k}^0\right]$. The individual components are as follows:

$$x_{i,j}^0 = x_{j,\min} + rand(x_{j,\max} - x_{j,\min}) \tag{4}$$

where $x_{j,\max}$ is the upper bound of the solution space and $x_{j,\min}$ is the lower bound of the solution space. The differential evolution algorithm has three types of operation: mutation, crossover and selection [20-22].

The use of fewer colony algorithm parameter settings make the algorithm easier to obtain and allows effective solution of complex optimization problems but also risks falling into a local optimum. Differential evolution quantum approaches must incorporate many operations, such as variation, crossover and selection. The optimal solution is obtained by iterating. Many problems can arise during the optimization process, such as slower convergence speed and premature solution. Akay B et al. proposed a differential evolution algorithm with a search strategy for an artificial bee colony [23]. The differential evolution quantum artificial bee colony (DEQABC) algorithm incorporates the artificial bee colony search strategy into the iteration process, which can allow it to escape a local optimum and avoid the premature phenomenon [24,25].

$$v_{ij} = x_{ij} + \alpha(x_{ij} - x_{kj}), i \neq k \quad (5)$$

Because of the lack of development of the formula, Ozturk C et al. proposed a novel binary version of the artificial bee colony algorithm based on genetic operators (GB-ABC) such as crossover and swap to solve binary optimization problems [26].

$$v_{ij} = x_{ij} + \alpha(x_{ij} - x_{kj}) + \beta(x_j^{Global} - x_{ij}), i \neq k \quad (6)$$

Therefore, the differential evolution optimization algorithm improves the convergence speed and avoids the prematurity phenomenon. The specific steps are as follows:

(1) Initialize: F shrinkage factor, CR cross factor, maxCycle maximum iterations.

(2) Initial population: Randomly generate M solutions X_i, ($i = 1, 2, \cdots, M$).

(3) Execute the program:

```
While the stop conditions are not satisfied, do
  For i=1 to M, do
    Do mutation, crossover and selection for X_i .
      For k=1 to K, do
        Use formulas (1) and (2) to search the candidate solutions
        near Z_i .
          If f(Z_i) < f(X_i)
          X_i = Z_i
        End if
      End for
    End for
  End while
```

RESULTS

MULTI-AUV DISTRIBUTED TASK ALLOCATION OF THE CONTRACT NET WITH THE INTRODUCED BALANCE COEFFICIENT

To enable multiple AUVs to quickly complete the task and achieve global optimization, first, the task is distributed to the entire AUV team with the smallest cost using the contract net to ensure the global optimization of task implementation. Then, the balance coefficient is used to make the entire AUV team distribute and achieve the tasks in the shortest time.

The balanced coefficient B_{eq}^R is introduced in the contract net distributed robot task allocation. Each robot uses its cost function to count the workload: the workload is the cost of robot R in the entire process of the work. Each robot broadcasts its workload to the entire team and calculate its B_{eq}. The formula of the balance coefficient for robot R is as follows:

$$B_{eq}^R = \frac{wa(R) - \overline{wa}}{\overline{wa}} \quad (7)$$

where $\overline{wa}$ is the average workload of all robots in the team. B_{eq}^R <0: robot R has a lighter workload than the other robots; B_{eq}^R >0: robot R has a heavier workload than the other robots; $B_{eq}^R > B_{eq}^{R1}$ 0: robot R has a heavier workload than robot R1.

In the contract net, the robot can take the task at the minimum cost, and the workload to be obtained should not be excessive. Thus, the task can be estimated from the balance coefficient B_{eq} . The formula of the task is estimated by robot R as follows:

$$rt'^R(T_1) = rt^R(T_1) - B_{eq}^R \times \left| rt^R(T_1) \right| \quad (8)$$

The task can be estimated using the balance coefficient B_{eq} of robot R. The following effects can be obtained:

(1) A robot with a larger workload cannot easily obtain new tasks, and its tasks are more likely to be reassigned because its task utility is low.

(2) A robot with a smaller workload easily obtains new tasks and does not easily give up its task because its task utility is high.

CONTRACT NET TASK ALLOCATION MODEL BASED ON DIFFERENTIAL EVOLUTION QUANTUM BEE COLONY ALGORITHM

The managers are denoted by AUV_α in the distributed contract net. They are responsible for managing the task, and the other AUV_i are responsible for bidding the task. The task allocation process includes four steps: task bidding, bid, bid winning and task execution based on the contract net. The contract net task allocation model based on the differential evolution quantum bee colony algorithm is as follows:

Assume that there are N_V AUVs, $Task = \{Task_1, Task_2, \cdots, Task_{N_M}\}$, the number of task targets is N_M , $V = \{V_1, V_2, \cdots, V_{N_V}\}$, the number of AUVs is N_V , $Menace = \{Menace_1, Menace_2, \cdots, Menace_{N_Q}\}$, and the number of threat sources is N_Q . The AUVs, task targets, and threat sources can include many types. If the same type of task is performed by different AUVs, the implementation effect is different. Assuming that the task set assigned to AUV_i is $T_i = \{Task_i^1, Task_i^2, \cdots, Task_i^{n_i}\}$, the multi-AUV distributed task allocation problem can be translated as follows: Assign the existing tasks to multiple AUVs in the shortest possible time, i.e., $\bigcup_{i=1}^{N_V} T_i = Task$; each AUV has only one task, i.e., $\forall i, j \in \{1, \cdots, N_V\}$, $i \neq j$ and $T_i \bigcap T_j = \varnothing$ .If the maximum number of tasks executed by the multi-AUV system is less than the number of tasks that should be allocated, the assignment can be optimized to improve the overall efficiency of the multi-AUV task allocation system according to the following objectives.

Objective one: To maximize the overall effectiveness $\sum_{i=1}^{N_V} \theta_i(T_i)$ of the AUV after finishing the task, $\theta_i(T_i)$ is the performance after the task set T_i is completed by V_i .

Objective two: To minimize the required time $\max_{i \in V} Time_i(T_i)$ of the task to be completed by the AUV, $Time_i(T_i)$ is the time at which the task set T_i is finished by V_i .

Objective three: To balance the task load of each AUV, $\sum_{i=1}^{N_V}\left|Tload_i(T_i)-\overline{Tload}\right|$ is minimized, where $Tload_i(T_i)$ is the task load of V_i, $\overline{Tload}$ is the average task load for each AUV.

DISCUSSION

EXPERIMENTAL PARAMETER ASSIGNMENT

To evaluate the performance of the distributed task allocation model based on the differential evolution quantum bee colony algorithm, the study included the corresponding simulation experiment. The conditions of the simulation experiment are as follows:

A set of thirty task items to be assigned is selected. The thirty tasks can be divided into three categories: T_1, T_2, and T_3. AUV_1, AUV_2, and AUV_3 are involved in the bidding of the AUVs and all tasks of the bid. The bid value of the completed task, trust and initial ability are shown in Table 1. The influence factors of the AUV load, ability and trust degree are 0.3, 0.4 and 0.2, respectively, in the bidding strategies of the contract net task allocation based on the differential evolution quantum bee colony algorithm.

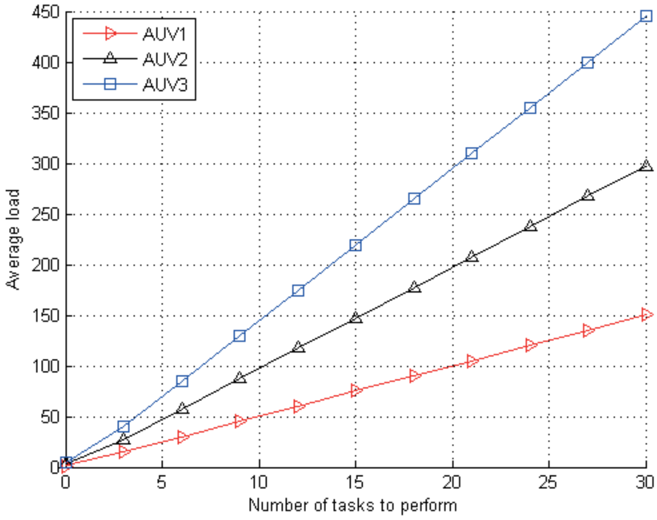

Fig. 1. Average Load of AUV1, AUV2 and AUV3 in the Contract Net Traditional Model AUV.

Tab. 1. Initial value of the completed task, trust and ability.

T1			T2			T3		
Bidding value	Trust degree	Ability	Bidding value	Trust degree	Ability	Bidding value	Trust degree	Ability
3	0.6	0.8	2	0.5	0.6	2	0.8	0.7
4	0.8	0.6	2	0.9	0.8	3	0.9	0.6
5	0.9	0.7	3	0.7	0.7	4	0.6	0.8

The simulation experiment has 2 objectives. When the bidding and tendering stage are identical, the first objective is to test and compare the contract net model based on the differential evolution quantum bee colony algorithm and the contract net traditional model. The second objective is to compare the performance in four aspects: efficiency of task allocation, average AUV load, number of bid AUV allocated tasks, and proportion relation of the corresponding type of task ability.

EXPERIMENTAL VERIFICATION

After the experiment, the simulation results are as follows. Figure 1 shows the average load of AUV_1, AUV_2 and AUV_3 in the contract net traditional model AUV. Figure 2 shows the reduced proportion (%) when AUV_1, AUV_2 and AUV_3 execute tasks in the contract net traditional model.

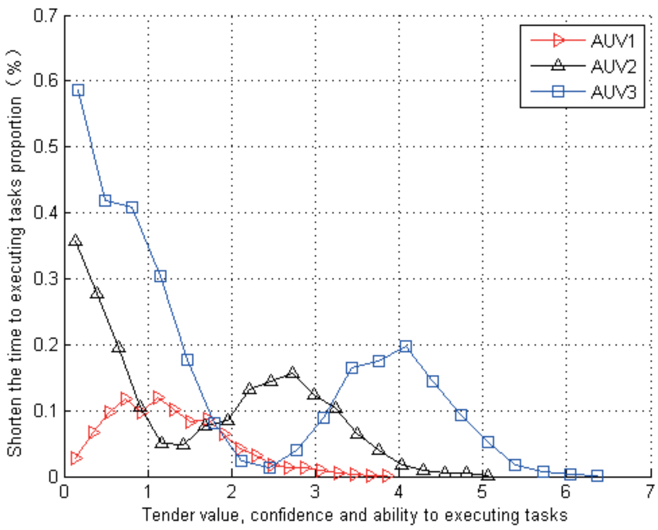

Fig. 2. Reduced Proportion (%) of AUV1, AUV2 and AUV3 when they Executed Tasks in the Traditional Contract Net Model.

Figure 3 shows the average load of the AUVs in the contract net model based on the differential evolution quantum bee colony algorithm. Figure 4 shows the reduced proportion (%) of execution time in the contract net model with the introduced balance coefficient based on the differential evolution quantum bee colony algorithm.

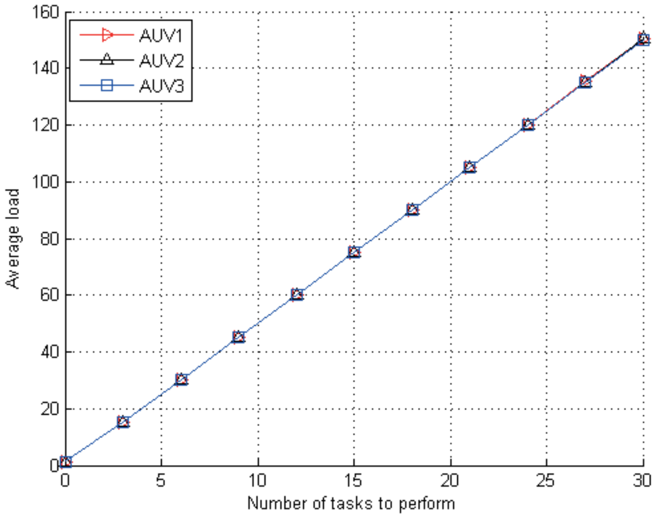

Fig. 3. Average Load of AUV1, AUV2 and AUV3 in the Contract Net Improved Model AUV.

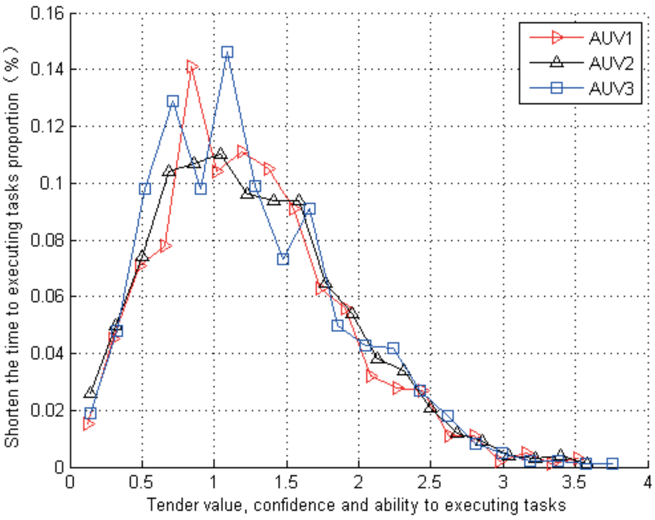

Fig. 4. Reduced Proportion (%) of AUV1, AUV2 and AUV3 Tasks in the Contract Net Improved Model.

Comparing the front and back images, we observe that the traditional contract net does not consider the load balance of the bidding AUV, which causes a large load difference for the bidding AUV. The improved contract net model satisfies the requirement of load balance because the proportions of load and task execution time of three bidding AUVs are basically equivalent.

Figure 5 shows that the comparison of the executive entirety effectiveness of multiple AUVs in the distributed task allocation experiment in the traditional contract net model and the contract net model with the introduced balance coefficient based on the differential evolution quantum bee colony algorithm.

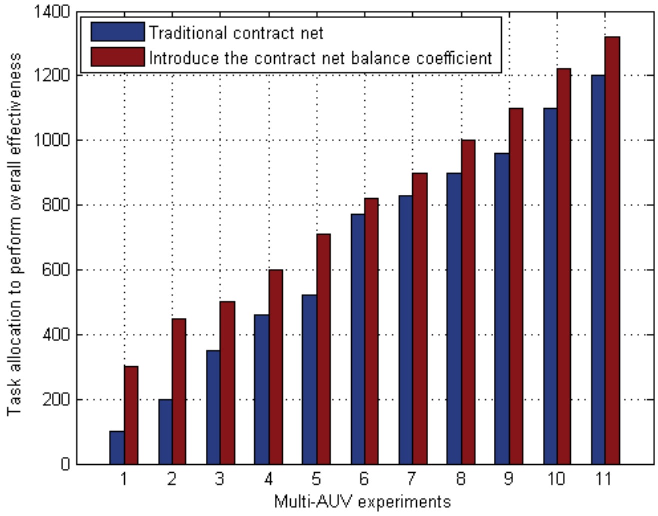

Fig. 5. Comparison of the Executive Entirety Effectiveness of the Multi-AUV Distributed Task Allocation.

Figure 6 shows the comparison of the convergence performance of the ABC, QABC, and DEQABC algorithms in the process of multi-AUV distributed task allocation.

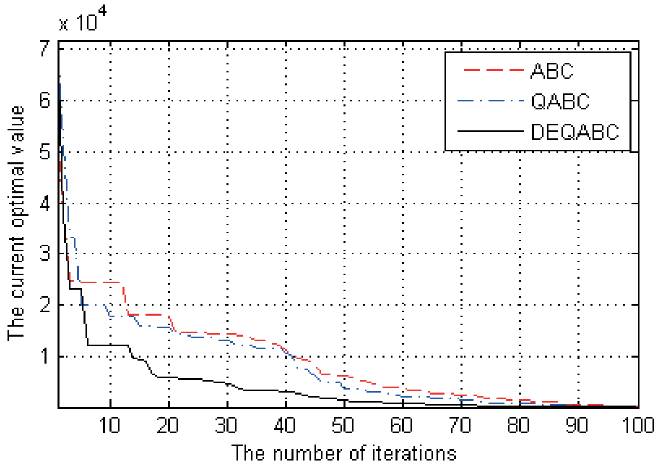

Fig. 6. Comparison of the Convergence Performance of the ABC, QABC, and DEQABC Algorithms.

Figure 7 and Figure 8 show the comparison of the number of iterations and running time when the ABC, QABC, and DEQABC algorithms are used to solve 10 task allocation cases to obtain the optimal solution.

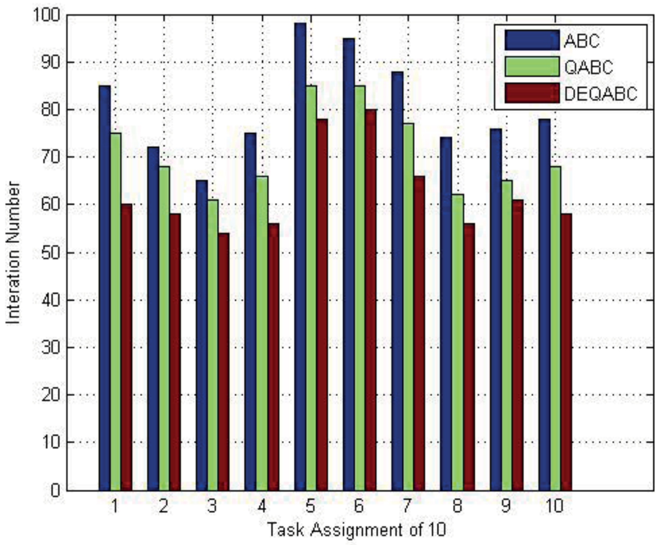

Fig. 7. Comparison of the Number of Iterations for the ABC, QABC, and DEQABC Algorithms.

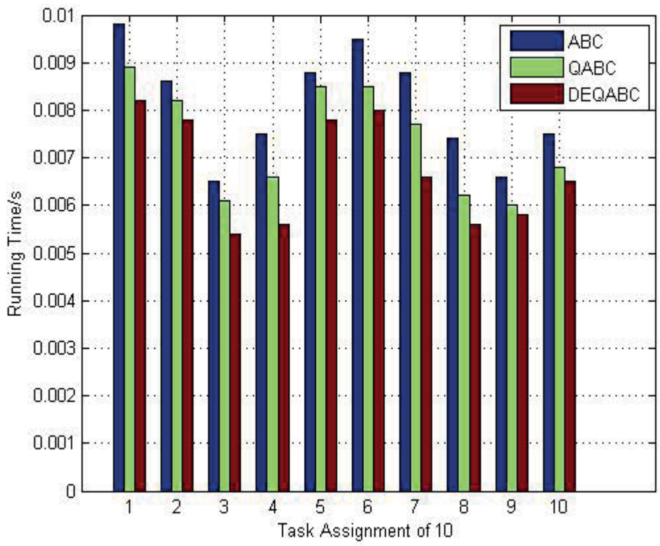

Fig. 8. Comparison of the Running Time for the ABC, QABC, and DEQABC Algorithms.

CONCLUSIONS

In this paper, we propose a distributed task allocation model based on the differential evolution quantum bee colony algorithm to allow more rapid task allocation for a greater number of AUVs and achieve global optimization in the multi-AUV distributed task allocation. The balance coefficient is introduced to distribute the robot task allocation of the traditional contract net. The unbalanced load and other defects are improved in the multi-AUV distributed task allocation of the traditional contract net. The differential evolution quantum bee colony algorithm is applied to the process of multi-AUV dynamic distributed task allocation. The simulation experiment verifies that the quantum bee colony based on differential evolution can avoid falling into local optima; shorten the convergence time; reduce the number of iterations; enhance the global, dynamic and adaptive capability of the bee colony algorithm; and effectively improve the overall performance of distributed task allocation for multiple AUVs.

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