Research on Dynamic Assignment of Distributed Tasks Based on Improved Contract Network Protocol

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Abstract. This paper introduces the basic idea and operation mechanism of contract network. In view of its shortcomings, it introduces an agent mental model and proposes a distributed task allocation algorithm based on improved contract network protocols. The algorithm improves the bidding process and the bidding process, reduces the system communication volume and fully considers the status information of the drone itself. Finally, a simulation experiment is designed to compare and analyze the advantages of the improved contract network over the traditional contract network.

Keywords: Contract Network Protocol (CNP) · Distributed task allocation · Combat mission modeling

1 Introduction

In the information battlefield, the various arms and operating entities distributed in different locations implement distributed interconnection and interoperability based on the operational network to realize dynamic allocation and coordination of distributed tasks. The battlefield situation is complex and changeable and the pre-war plan is very easy to be disrupted. Therefore, it is required that the accusation center be able to coordinate the battlefield resources and entities on the battlefield in real time. In a dynamic environment, reform the action plan for the new battlefield situation and select the appropriate battle The entity performs the corresponding combat mission. Before receiving an order from a superior, it is required that combat entities be able to autonomously implement combat task allocation and resource coordination in accordance with corresponding rules, so as to avoid jeopardizing fighters and causing mission failures. Therefore, it is of great significance to study the dynamic assignment of distributed tasks. This paper is based on the Contract Net Protocol (CNP) task allocation model. It analyzes the deficiencies and shortcomings in the traditional contract network,

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introduces the Agent mental model, improves the bidding and bidding stages, and performs simulation verification and analysis.

2 The Basic Theory

2.1 Basic Theory of Contract Network

The Contract Net Protocol (CNP) [1,2] is a method proposed by Smith and Davis in 1980 to solve distributed problems. In the contract network protocol model, it consists of multiple agents that can transmit messages to each other. According to the different responsibilities for each agent, the agents are divided into three types: bidding agent, bid agent, and winning agent.

As a blind bidding method, the contract net protocol can solve the single task assignment. However, the UCAV fleet needs to face multi-tasking concurrent situations. The negotiation process using the traditional contract net protocol has the following disadvantages [3,4]:

The bidding agent conducts bidding in the form of broadcast and all the agents that receive the message can participate in the bid, which will generate a large communication load, waste resources in the system and have low negotiation efficiency. The bid agent needs to communicate with the bidding agent multiple times during the evaluation stage, which leads to an increase in the communication volume of the system, and the negotiation process is long and cumbersome. The bid document evaluation mechanism is incomplete. In the contract net protocol, the bidding agent only judges the winning bidder by the value of the bid and does not evaluate the actual task amount of the bid winner.

The task assignment process of the entire contract net protocol is a distributed dynamic task assignment method [5,6], which depends on the independent decision-making ability and control strategy of each agent.

2.2 Agent Mental Model

The Agent mental model [7–9] records the capability information of the Agent, the relationship between the Agents, the mental state of the Agent and the changes in the system environment. The mental model consists of the following parameters: ability, trust, familiarity, positivity, risk, and busyness.

Agent mental model is defined as a two-group: $<Relation\_Agent, Parameter\_Metal>$. $Relation\_Agent = <Agent_i, Agent_j>$ represents the relationship between two agents and $Parameter\_Metal = <A, B, P, F, RT, Cl, BD>$ represents the mental parameters of the Agent mental model.

Ability A. In the contract net protocol, the bidding Agent tends to find Agent with stronger task execution capabilities to cooperate. The capability parameter update of the agent does not depend on the completion of the task, but depends on the capability of the agent. This paper considers the capability value of UCAV from the task load and weapon load. The parameter update function is:

$$A(Agent_i, T_k) = \frac{Load\_Task_i}{Load\_Task_{max}} + \frac{Load_i}{Load_{max}} \tag{1}$$

In the formula, $Load\_Task_i$ represents current mission load; $Load\_Task_{max}$ represents maximum mission load; $Load_i$ represents current weapon load; $Load_{max}$ represents maximum weapon load.

Believability B. Trust believability represents $Agent_i$'s evaluation of $Agent_j$'s completed tasks and the parameter update function is:

$$B(Agent_i, T_i) = \begin{cases} B_{init}, \\ i = 1, 0 <= B_{init} <= 1 \\ min(B(Agent_i, T_{i-1}) + G_s * \xi, 1), \\ i > 1, 0 < G_s <= 1, \xi > 0 \\ max(B(Agent_i, T_{i-1}) + G_f * \zeta, 1), \\ i > 1, 0 < G_f <= 1, \zeta > 0 \end{cases} \tag{2}$$

In the formula, G_s represents $Agent_j$ completes the completion degree of task T_{i-1} and the higher the degree of completion, G_s the closer to 1; G_f represents $Agent_j$ completes the failure degree of task T_{i-1}, the higher the failure degree, the closer to 1; ξ represents the reward coefficient for completing the task; ζ represents the penalty coefficient of the task failure.

Familiarity F. Familiarity represents that the number of bidding tasks for $Agent_j$ completion $Agent_i$ accounts for the proportion of each other's bidding tasks. The parameter update function is:

$$F(Agent_i, Agent_j, T_k) = \frac{N_{ij}}{N_{ij} + N_{ji}} \tag{3}$$

In the formula, N_{ij} represents the number of bidding tasks of $Agent_i$ completed by $Agent_j$; N_{ji} represents the number of bidding tasks of $Agent_j$ completed by $Agent_i$.

Positivity P. The positivity is the proportion of the number of bidding tasks $Agent_j$ participating in $Agent_i$ to the total bidding task of N_{lm}. The higher the proportion, the higher the enthusiasm of $Agent_i$ participating in the bidding. The parameter update function is:

$$P(Agent_j, T_k) = \frac{N_{lm}}{N_l} \tag{4}$$

Risk RT. The risk tolerance indicates the degree to which $Agent_i$ can bear the risk. The parameter update function is:

$$RT(Agent_i, T_k) = \begin{cases} RT_{init}, \\ i = 1, 0 <= RT_{init} <= 1 \\ min(RT(Agent_i, T_{k-1}) + G_s * \psi, 1), \\ i > 1, 0 < G_s <= 1, \psi > 0 \\ max(RT(Agent_i, T_{k-1}) + G_f * \phi, 0), \\ i > 1, 0 < G_f <= 1, \phi > 0 \end{cases} \tag{5}$$

Busyness BD. The busyness indicates the current busyness of the $Agent_i$. The parameter update function is:

$$BD(Agent_i, T_k) = \frac{N_b\_used}{N_b\_total} \tag{6}$$

3 Distributed Combat Mission Modeling

3.1 Task Performance Indicator Function

In distributed operations, each UCAV is regarded as an independent agent and the entire combat system forms a multi-agent system. Each agent has a high degree of autonomy, fully shares intelligence and performs task assignment and coordination through mutual negotiation. Given a UCAV set $V = \{V_1, V_2, ...V_{N1}\}$and a task set $T = \{T_1, T_2, ...T_{N2}\}$, each UCAV can complete one or more tasks T. Task performance is defined as the revenue of the task completion minus the corresponding cost. This paper mainly constructs the task performance index function from the perspective of benefit and cost and establishes the mathematical model of the index function. The task performance indicators are analyzed from the following aspects, including attack mission revenue, voyage cost, airtime cost, and fleet fitness.

Suppose the decision variable x_{ij} is:

$$x_{ij} = \begin{cases} 1, V_i performs T_j task \\ 0, V_i don't performs T_j task \end{cases} \tag{7}$$

Attack Mission Revenue. The benefits of an attack mission obtained by a drone depend on the capabilities of the drone performing the mission and the value of the mission. The capability of the drone is determined jointly by factors such as its comprehensive capabilities and the weapons it is mounted on. The value of the task is given by the accusation center according to certain rules before the task is performed. The expected reward function $Reward_{ij}$ of the attack task before executing the task. The expression is:

$$Reward_{ij} = \sum_{i=1}^{N_v} \sum_{j=1}^{N_t} \frac{x_{ij} * P_{Dij} * T\_Value(T_j)}{N_T * T\_Value_{max}} \tag{8}$$

In the formula, N_v represents total number of drones; N_t represents total number of task targets; P_{Dij}indicates the kill probability of the UAV V_i to mission target, calculated according to the weapon configuration on the aircraft and the enemy target information; $T\_Value(T_j)$ is the value of performing task objective T_j; $T\_Value(max)$ is the maximum value to perform the task.

Voyage Cost. Voyage costs consider UAV V_i fuel consumption from mission start to mission end. During the flight of the UCAV fleet, the pursuit of the least consumption and the shortest time to complete the flight process. Therefore, this paper simplifies the trajectory planning process and adopts a modified straight range method to perform fast calculations to adapt to the dynamic and complex flight environment.

$$PathCost_{ij} = \sum_{i=1}^{N_v} \sum_{j=1}^{N_t} \frac{x_{ij} * (D_{ij} + \overline{D_{ij}})}{N_T * D_{max}} \tag{9}$$

In the formula, D_{ij} indicates the straight flight of the drone to perform the mission; $\overline{D_{ij}}$ indicates the flight trajectory corrected after considering the threat source; D_{max} represents the maximum combat radius of UCAV.

Airtime Cost. While considering the UCAV flight range, we should also consider the flight time of the UCAV mission, balance the flight time of each UCAV in the formation, and avoid a dangerous event when an UCAV flight time is too long. Therefore, the airtime cost function is used to measure the flight time of the UCAV flight formation's execution mission.

$$\overline{T\_Cost_{ij}} = \frac{1}{N_V * max(T_i)} \sum_{i=1}^{N_v} T_i \tag{10}$$

Cluster Fitness. Cluster fitness refers to the ability of the UCAV to respond to uncertain risks and the ability to adapt to the environment in the face of complex and changing battlefield environments. The remaining combat power of the fleet is used to measure the fitness of the fleet. The stronger the remaining combat power is, the higher the fitness of the fleet is. The remaining ammunition and endurance flight capacity have greatly affected the remaining combat power of the fleet. The remaining amount of ammunition determines the attack capability of the UCAV fleet and the endurance determines the threat avoidance and continuous combat capability of the UCAV fleet.

Select the half-gradient distribution function as a single-item attribute function, expressed as:

$$\xi = \begin{cases} 0, f <= f_{min} \\ \frac{f - f_min}{f_{max} - fmin,} f_{min} <= f <= f_{max} \\ 1, f >= f_{max} \end{cases} \tag{11}$$

The remaining combat power of each UCAV is weighted according to the weight of the individual factors. The weighted value is set by the importance of the corresponding attribute, and the remaining combat power K is defined as:

$$K = a\xi_1 + b\xi_2 \quad (a + b = 1) \tag{12}$$

In the formula, ξ_1 represents the value of the single-item attribute function of the remaining ammunition; represents the single-item attribute function value of the endurance; a

b is the corresponding weighted value of the remaining ammunition and endurance, and $a + b = 1$.

The remaining combat power variance is:

$$Var = \frac{1}{N_v} \sum_{i=1}^{N_v} (K_i - \overline{K})^2 \tag{13}$$

The cluster fitness function is expressed as:

$$Margin = \frac{Var}{max(K_i - \overline{K})^2} \quad (i = 1, 2 \ldots N) \tag{14}$$

The above four index functions have been normalized, so that each index has a unified dimension, which is convenient for constructing task effectiveness functions.

3.2 Task Assignment Multi-constraint Optimization Model

Multi-UCAV task performance function is expressed as:

$$\begin{aligned} E_{ij} =& a * Reward(T_i) + b * (1 - PathCost(T_i)) \\ &+ c * (1 - \overline{T_Cost(T_i)}) + d * Margin \end{aligned} \tag{15}$$

In the formula, a, b, c, and d are weighted values of each index value and the weighted value is input according to a preset setting $(a + b + c + d = 1)$.

According to the expression of the mission performance function, it can be obtained that the multi-UCAV ground attack requirements are: Constraint 1: When task assignment, all task targets are assigned to UCAV, satisfying

$$\sum_{i=1}^{N_v} X_{ij} >= 1 \tag{16}$$

Constraint 2: The UCAV fleet has the best overall performance after completing combat missions.

$$max(\sum_{i=1}^{N_v} \sum_{j=1}^{N_T} X_{ij} * E) \tag{17}$$

Constraint 3: The task load of each UCAV cannot exceed the maximum capacity constraint, and is set to the maximum load of UCAV.

$$\sum_{i=1}^{N_v} X_{ij} \leq Load_{max} \tag{18}$$

4 Dynamic Allocation of Distributed Tasks Based on Improved CNP

4.1 Bidding Strategy

In order to reduce the communication volume occupied by the large-scale release of bidding tasks, this paper adopts an acquaintance bidding strategy, based on the Agent mental model, and designs a bidding decision function as a two-tuple:

$$Call\_for\_bidder =< Relation\_Agent, D\_Limit > \tag{19}$$

It consists of the bidding decision acquaintance relationship function *Relation_Agent* and decision threshold *D_Limit*, which indicates the number of bids issued. This function sets the decision threshold according to the network load and task level of the system at that time, and selects the bidding information sending object.

$$Relation\_Agent(agent_i, T_k) = \lambda_1 * A + \lambda_2 * B + \lambda_3 * F + \lambda_4 * P \tag{20}$$

Before issuing the task message, the bidding agent first calls the acquaintance relationship data from the knowledge base and substitutes it into the acquaintance relationship function *Relation_Agent* to obtain the acquaintance relationship sorting. Finally, the task publishing object is selected according to the decision threshold *D_Limit*.

4.2 Bidding Process

After receiving the bid invitation, the Agent needs to evaluate its own situation and give the bid value. The bid value of Agent is composed of two parts: the gain and the cost of completing the task. In addition to the consumption of the task itself, there are certain costs due to its state consumption and external environmental impact and task risk. The cost function given in this paper is:

$$Cost(Agent_i, T_k, C) = \sigma_1 * \frac{1}{RT} + \sigma_2 * CL + \sigma_3 * C_l \tag{21}$$

In the formula, σ_1, σ_2 and σ_3 are the weight coefficients of risk tolerance, busyness and fixed cost C_l.

The benefit of a task is measured by the amount of change in the task's performance value. First calculate the maximum overall performance value obtained by inserting a task into its own task sequence after assuming a buy task.

$$Efficacy(S\{T_j\} \bigcup T_K) = max(Efficacy(S\{T_i, T_k\})) \tag{22}$$

Then calculate the change in overall task performance after buying the task

$$\begin{aligned} Efficacy^+(T_k) = {} & Efficacy(S\{T_j\} \bigcup T) \\ & - Efficacy(S\{T_j\}) \end{aligned} \tag{23}$$

If the task performance change amount is < 0, indicating that the performance after the purchase task is lower than before, the "reject" message is sent directly to the bidding agent. Otherwise, continue to calculate the bid value and make a tender. The bid value of the tender is:

$$\begin{aligned} Price(Agent_i, T_k, C_l, E_i) = {} & \alpha * Cost(Agent_i, T_k, C) + \\ & \beta * Efficacy^+(T_k) \end{aligned} \tag{24}$$

In the formula,α and β are the weighting factors for the cost and the benefit

4.3 Bid Stage

After reaching the preset bid deadline, all the bids received by the bidding agent are selected, and the bidding agent with the highest bidding value is selected as the winning bidder. The highest bid value for all bids is:

$$Price_{Ui}(T_k) = max(Price(Agent_i, T_k, C_l, E_i)) \tag{25}$$

In the formula, $Price_{Ui}(T_k)$ represents the bidding value of the drone Ui participating in the bidding task T_k.

When the bidding agent issues a task invitation to the winning agent, it also publishes its status information and waiting time together with the task information. After receiving the invitation, the winning bid agent needs to give feedback to the bidding agent. If it refuses, it will directly reply to the "reject task" message. If the bidding agent receives the "accept" message within the time limit, it will sign a contract with it and announce the signing success message to other agents. If the waiting time is exceeded, the bidder will re-select the winning Agent to sign the contract according to the rules.

4.4 Task Execution Phase

Until the bidding task is completed, the entire task allocation process based on the improved contract net protocol does not end. After signing the contract, both parties still need to be responsible for the completion of the task. The winning agent needs to feedback the completion of the task at a certain time. If the bidding agent has not received the feedback message of the winning agent within the time limit, it will be considered that the winning agent has failed to complete the task successfully and the task will be put into the auction sequence and auctioned again. This paper makes strict time series requirements for the task auction process, so that all task coordination processes can be coordinated and operated, which improves the stability of the system and ensures the smooth execution of the task auction process.

The state transition timing of the Agent in the task allocation process based on the improved contract network protocol is shown in Fig. 1:

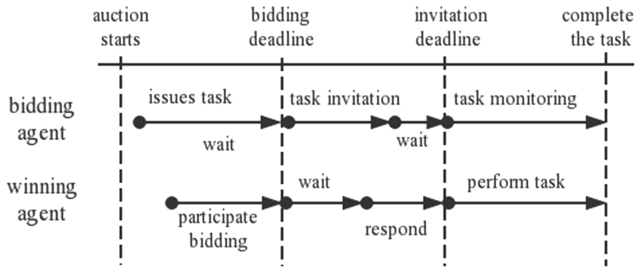

Fig. 1. State transition timing.

The task assignment and coordination mechanism designed in this paper has the following advantages:

Reducing the Waste of Time or Traffic. This paper determine the order of change of auction rights by using the principle of task priority, change the auction order according to the urgency and importance of the task, optimize the bidding process and reduce the waste of time or traffic;

Reducing Communication and Computing Load. In the bidding stage, the acquaintance bidding strategy is established by the capability, trust, enthusiasm and familiarity in the agent mental model, avoiding the blind broadcast method to waste system traffic, fully considering the subjective will of the candidate agent, and reducing the communication and computing load.

Combining Agent State and Task Efficiency Changes. In the bidding stage, the busyness and risk tolerance of the Agent mental model and the change of mission performance are combined to obtain the final bidding value, which fully considers the Agent's own state and the overall mission performance change of the mission.

Meet Real-Time Requirements. The entire task auction process has strict timing constraints to ensure the real-time requirements of the system. The process of distributed dynamic task allocation and coordination based on improved CNP [10] is shown in Fig. 2.

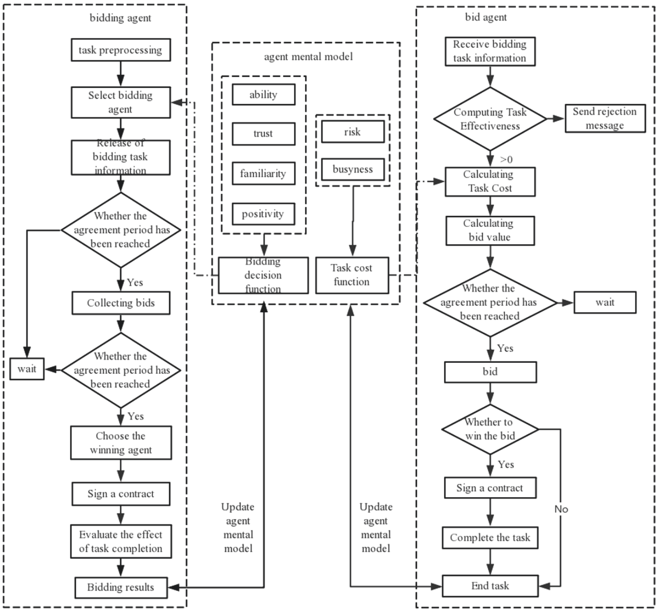

Fig. 2. Dynamic task allocation and coordination mechanism based on improved contract network protocol.

5 Algorithm Simulation and Results Analysis

In order to verify the distributed dynamic task assignment problem based on improved contract network protocol, a simulation experiment was designed to verify. The simulated battlefield environment is a space area of 100*100*20. There are 5 threat sources and 10 enemy targets in the battlefield. After the reconnaissance and detection of the battlefield, the combat command center dispatched 4 drones to attack the enemy targets.

5.1 Initial Data

Due to the limitations of the simulation environment, it is necessary to preset the battlefield environment, including the initial data such as the UCAV mental state, the target value and the damage probability of the UCAV to the target. The specific data is shown in Table 1, 2, 3, 4, 5.

Table 1. Threat source information table

Threat SourceID	X Axis	Y Axis	Threat radius
1	20	25	7
2	12	60	5
3	42	48	13
4	73	36	8
5	68	69	10

Table 2. Target attribute table

Target taskID	Coordinate	Target value
T1	(71,51)	4
T2	(80,61)	8
T3	(53,69)	10
T4	(7,33)	7
T5	(33,22)	5
T6	(12,82)	9
T7	(29,30)	6
T8	(86,42)	8
T9	(45,76)	7
T10	(33,91)	5

5.2 Simulation

In the following, two experimental scenario hypotheses will be carried out, including initial task assignment, emergence of new threat sources, and comparison with traditional contract networks to verify the effect of task allocation based on improved contract network protocol on battlefield emergencies.

Experiment 1: Firstly, the task is randomly assigned to the drone, and the task assignment is based on the improved contract network protocol. The distribution result is shown in Fig. 3 and the task performance change curve is shown in Fig. 4.

The task allocation process based on the improved contract network tends to be stable in the auction 21 rounds, while the traditional contract net tends to be stable in the auction 26 rounds. The results show that the distributed task assignment based on the improved contract network protocol is efficient and stable.

Experiment 2: A new threat source is suddenly detected on the UCAV4 mission execution route. If the original task sequence {T3,T6} is continued, it will be greatly threatened by security. Therefore, UCAV4 auctions the task

Table 3. UCAV attribute table

UCAV ID	Coordinate
U1	(0,70)
U2	(0,20)
U3	(10,0)
U4	(50,0)
U5	(80,0)

Table 4. Candidate UCAV mental status table when task T1 is executed

Agent parameter	U1	U2	U3	U4	U5
Ability A	0.1	0.3	0.7	0.4	0.5
Believe ability B	0.3	0.1	0.5	0.4	0.2
Familiarity F	0.6	0.3	0.4	0.5	0.2
Positivity P	0.7	0.6	0.4	0.2	0.6
Risk tolerance RT Ability A	3.0	1.5	5.0	4.5	10
Busyness BD	0.1	0.5	0.2	0.1	0.4

Table 5. Weight setting table

Weight name	Value
Tender decision	$\lambda_1 = 0.4, \lambda_2 = 0.2, \lambda_3 = 0.3, \lambda_4 = 0.1$
Decision function D_limit	4,3,2,2,3
Cost function weight	$\sigma_1 = 0.4, \sigma_2 = 0.4, \sigma_3 = 0.2$
Bidding value weight coefficient	$\alpha = 0.4, \beta = 0.6$

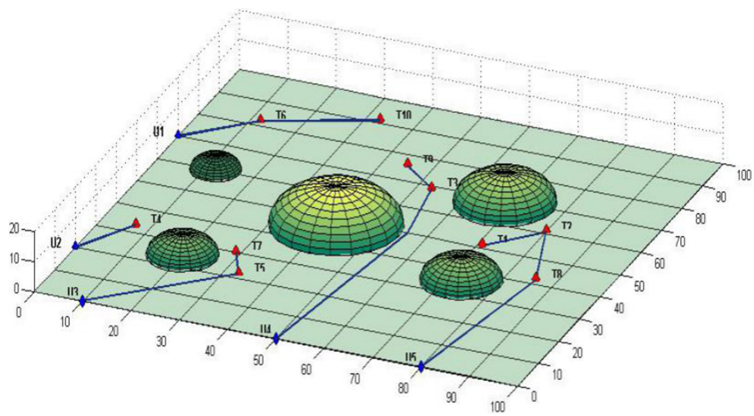

Fig. 3. Experiment 1 assignment results.

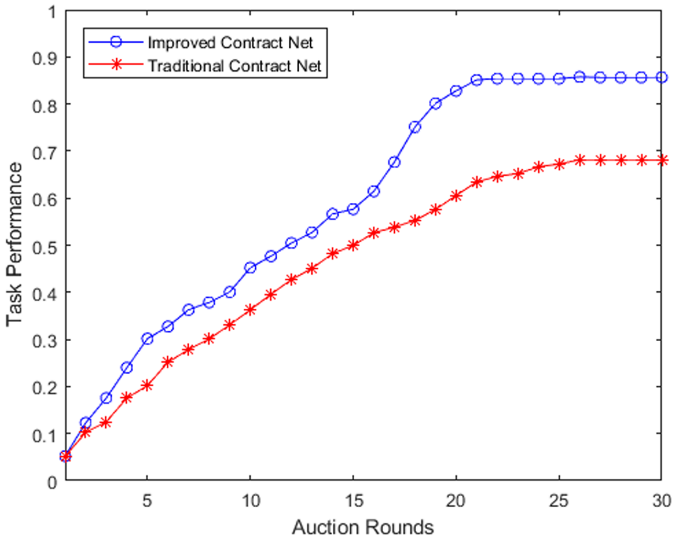

Fig. 4. Experiment 1 performance curve.

sequence, re-allocates and coordinates the task, and gets the assignment. The result is shown in Fig. 5 and the task performance curve is shown in Fig. 6.

UCAV4 hands over the task sequence to UCAV2 through auction, and through task negotiation, UCAV5 hands task T1 to UCAV4. The UCAV4 avoids the threat and obtains new task execution, and also avoids the waste of combat resources. After five auction rounds, the mission performance reaches a steady state.

Experiment 3: Multiple UCAV formations received new combat mission instructions {T11,T12} during the execution of the mission. The new missions were randomly handed over to existing combat units for auction. The distribution results were shown in Fig. 7 and the curve of mission effectiveness was shown in Fig. 8.

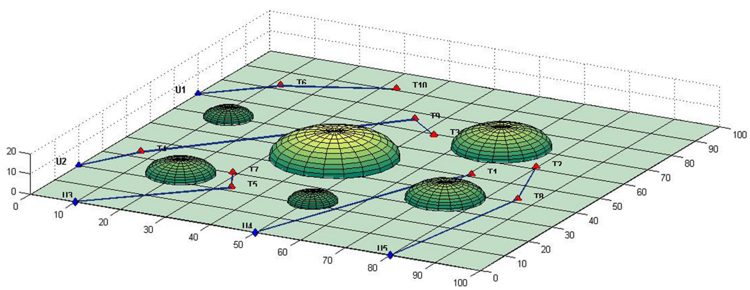

Fig. 5. Experiment 2 assignment results.

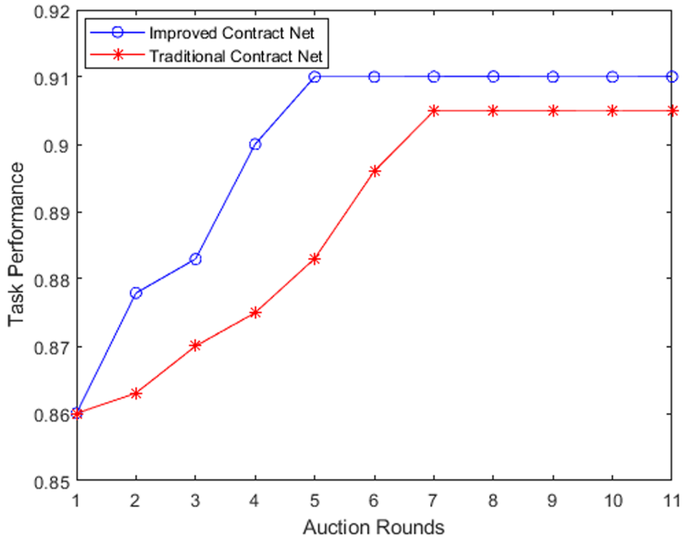

Fig. 6. Experiment 2 performance curve.

After the auction, the new task T11 was assigned to UCAV5, and the new task T12 was assigned to UCAV1, which affected the result of the original task assignment. Through resource coordination, task T2 was assigned to UCAV4 for execution. After 9 rounds, the task performance reached stable state.

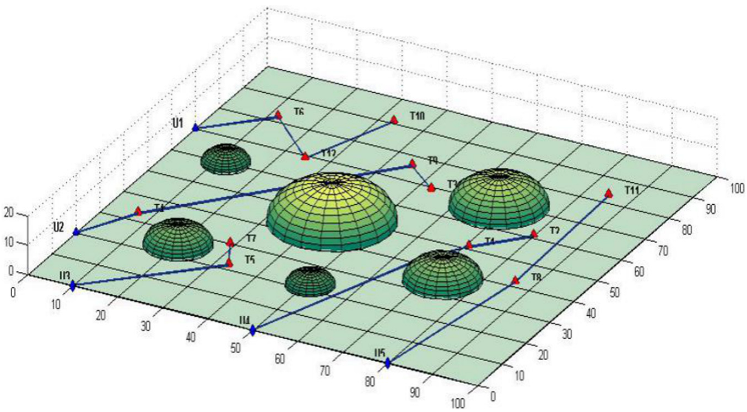

Fig. 7. Experiment 3 assignment results.

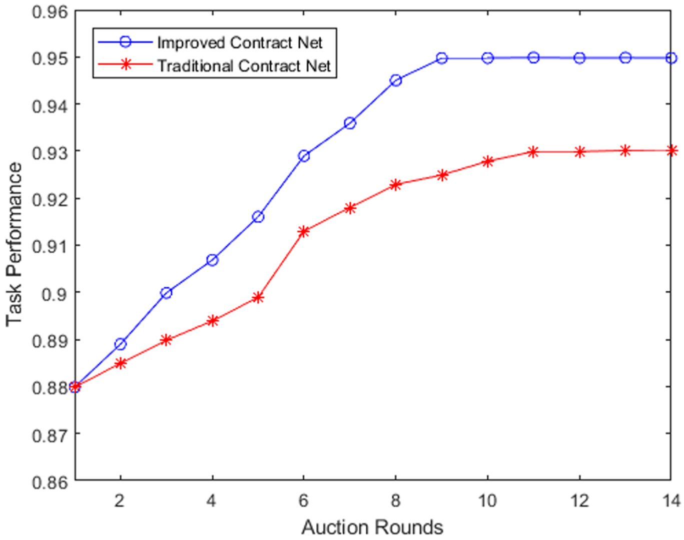

Fig. 8. Experiment 3 performance curve.

6 Conclusion

Facing the unexpected situation in the execution task, compared with the traditional contract network, the distributed task assignment based on the improved CNP can achieve a reasonable distribution result through a relatively small number of task auction rounds. Task assignment based on improved CNP is based on local shared information, and iteratively and quickly achieves reasonable task assignment results. Applied in a complex and dynamic battlefield environment, multiple UCAVs can respond quickly to dynamic tasks and distribute assignments to distributed concurrent tasks with a coordinated negotiation mechanism.

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