Decentralized Task Assignment for Multiple UAVs using Genetic Algorithm with Negotiation scheme approach

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Abstract: This paper deals with a task assignment problem of cooperative multiple Unmanned Aerial Vehicles (UAVs). The problem about assigning the tasks to each UAV can be interpreted as a combinatorial optimization problem such as Travelling Salesman Problem (TSP), Vehicle Routing Problem (VRP), and Generalized Assignment Problem (GAP). These problems have NP-complete computational complexity which has features such that the computation time cannot be determined in polynomial scale and the problem cannot be solved correctly except for examining all possible solution cases. To solve this combinatorial optimization problem, Genetic Algorithm (GA) which is one of the meta-heuristic algorithms is adopted. By using GA, multiple UAVs-multiple targets-multiple tasks scenario example is simulated, and the results of GA are compared with those of Mixed Integer Linear Programming (MILP) method to verify the optimality. Then the decentralized task assignment method based on chromosomes negotiation scheme approach is employed, and the simulation for a decentralized task assignment scenario is performed to evaluate the validity of the proposed method.

Keywords: Decentralized Task Assignment, Multiple UAV, Genetic Algorithm, Combinatorial Optimization, Negotiation

1. INTRODUCTION

UAV (Unmanned Aerial Vehicle) has various applications in the area of military use such as reconnaissance, surveillance, attack, etc., and therefore the research on the UAV control has been actively performed. As the interests of the UAV control are increased, researches of Multiple UAVs' cooperative control are also increased. Many complicated missions related to the military purpose can be preformed efficiently through the multiple UAVs' cooperative control, and the insufficiency on the single UAV's operating condition can be compensated by using the cooperation of multiple UAVs. For those reasons, there are many research subjects about the cooperative control of multiple UAV systems [1]. In this study, a task assignment method is proposed in the process of the multiple UAVs' cooperative control.

To complete a given mission efficiently, resources of UAV should be distributed to each UAV properly. This is a kind of task assignment problem, and it can be interpreted as a combinatorial optimization problem that minimizes total cost of UAVs. In the aspect of the calculation complexity, the combinatorial optimization problem has Nondeterministic Polynomial (NP)-complete features such as Traveling Salesman Problem (TSP), Vehicle Routing Problem (VRP) and Generalized Assignment Problem (GAP) [2]. It is hard to solve the NP-complete problem within polynomial time scale, and therefore approximation methods and heuristic methods are generally used.

Recently, various methods are proposed to solve the task assignment problem [4, 7-18]. In [7], Mixed Integer Linear Programming (MILP) method is used to solve the problem. MILP is a representative linear approximation method. MILP can obtain a solution by composing constraints and environment variables through the linear approximation [5-7]. On the other hand, heuristic methods such as Particle Swarm Optimization Algorithm [8-9], Tree Search Algorithm [10], and Genetic Algorithm (GA) [11-14] are used to solve the problem. These methods find a solution gradually through the intensification and diversification process.

In this study, GA is adopted to solve the task assignment problem, and the results of GA are compared with those of MILP method to verify the optimality. GA emulates the law of heredity in nature to improve the probability of generating superior genes at next generation through the selection, crossover, mutation, and substation operators. By using GA, each UAV can generate a minimum cost path and perform the tasks successfully. Each UAV has the chromosomes related to the task assignment and forms a set of the chromosomes. UAV reorganizes the chromosome in the set on the given constraint conditions. In this way, GA solves the task assignment problem.

In case of a centralized task assignment problem, chromosomes of all UAV are integrated together, thus solution can approach nearly to the minimum cost solution. However, each UAV is generally controlled on decentralized, and therefore there are communication limits to each other. Also, the environments of task field may be changed abruptly. Therefore, the centralized task assignment cannot be applied to real time operation of multiple UAVs. To deal with this problem, we employ a decentralized task assignment problem using chromosomes negotiation scheme approach [18]. To evaluate the validity of this method, simulations with multiple UAVs-multiple targets-multiple tasks scenario are performed.

The construction of this paper is as follows: Section 2 describes the task assignment scenario configuration, dynamic model for estimation, and combinatorial optimization problem. Section 3 deals with genetic algorithm for task assignment problem and section 4 introduces negotiation scheme for decentralization. Finally, section 5 shows the simulation results, and section 6 concludes the research.

2. PROBLEM DESCRIPTION

2.1 Task assignment scenario

When UAV is operated in a task field, some goals according to a given mission should be accomplished. Let us assume that a UAV flies in a battle field, it can perform various tasks. For example, UAV can search and observe targets for reconnaissance and patrol a specified area. Sometimes, UAV may have to attack dangerous facilities. Because UAV can take various tasks in this way, it is expected that many tasks can be distributed efficiently through multiple

UAVs. The total cost of the multiple UAVs can be reduced by the task assignment.

The task assignment problem varies according to the number of UAVs, targets, and tasks. The capabilities of the UAVs also affect the problem. Therefore, the configuration of the task assignment scenario is very important.

In this study, it is assumed that 3 homogeneous UAVs and 4 targets are located in a 2 dimensional task field, and UAVs are supposed to perform 2 tasks to each target. The tasks are divided into two stages {classification and attack, and target damage assessment (verification)} [7].

In addition, each UAV has its own source point and sink point as shown in Fig. 1. UAV starts from the source point, and it is terminated at the sink point. The capabilities of UAVs are assumed unrestricted in this scenario, because it is a relatively small scale example. For the simplicity of the problem, collisions each UAV and obstacles are not considered in the task field.

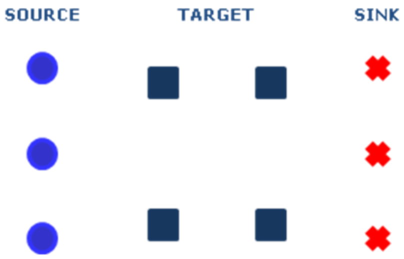

Fig.1 Task operation field

2.2 Dynamic model

To distribute the tasks, the information of each UAV's capabilities should be given to the decision maker. In this case, the dynamic model of UAV is directly related to the capabilities. Dynamic model may affect the complexity of the task assignment algorithm. In this study, the Dubin's model is considered for all 3 UAVs [12].

Eq. (1) shows the dynamic equations of the Dubin's model.

$$\begin{pmatrix} \dot{x} = v\cos\psi \\ \dot{y} = v\sin\psi \\ \dot{\psi} = \omega_{\max} u \end{pmatrix}, \tag{1}$$

where angular rate control input is bounded as $|u| \leq 1$ and v is constant.

The control of UAV is also related to the capability of each UAV. The trajectory of UAV is determined according to the control law. In this example, all UAVs are supposed to move as bang-off-bang control (minimum control input control), and therefore the travelling distance and time of each UAV can be estimated by the bang-off-bang control trajectory. Figure 2 shows Dubin's model and bang-off-bang control trajectory.

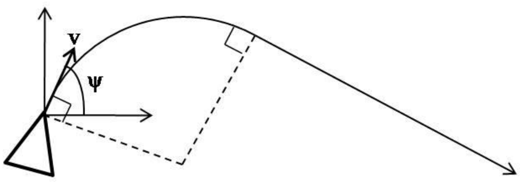

Fig.2 Dubin's model and its Trajectory

2.3 Combinatorial optimization problem

Task assignment problem about the scenario can be described in combinatorial optimization formulation. This problem has performance criterion which needs to be minimized or maximized subject to several constraints.

2.3.1 Performance criterion

In this study, the cumulative operation time of all UAVs is considered as a performance criterion.

$$J = \sum_{v=1}^{V} T_v , \tag{2}$$

It can be reduced the resources of the UAVs group such as fuel consumption or control input by minimizing the cumulative operation time.

2.3.2 Constraints

The constraints of the given task assignment scenario are described as follows.

1) Task 1 should occur earlier than Task 2 for each target. (Timing Constraint)
2) Each task is performed at once through all UAVs for each target.
3) If UAV performs all tasks or has no tasks, it should go to the sink point, and the mission is terminated.
4) Each path of UAV should be satisfied the continuity of its trajectory.
5) Because the task assignment scenario is relatively simple, the number of attacks to the target is regarded as enough to perform all tasks.
6) There are no collisions and obstacles.

3. GENETIC ALGORITHM

3.1 Chromosomes encoding

UAVs have their own gene, and each gene consists of a set of chromosomes which intend the task information of their own UAV. Therefore a proper chromosomes encoding should be chosen to match the problem. Various chromosome encoding can be considered; using bit array, gray coding, or real number. In this problem, we set the chromosomes encoding as a string of natural number to express the order of targets and tasks.

For centralized task assignment case, communication limits are not considered, And therefore each UAV's chromosomes can be integrated on one chromosome. That is, one chromosome includes all UAVs' task assignment information as summarized in Table 1.

Table 1 Centralized Chromosome Representation

UAV1 target	0	1	1	0	2	0	0	2
UAV1 task	0	1	2	0	1	0	0	2
UAV2 target	3	0	0	4	0	0	0	0
UAV2 task	1	0	0	1	0	0	0	0
UAV3 target	0	0	0	0	0	3	4	0
UAV3 task	0	0	0	0	0	2	2	0

On the other hand, if communication limits exist, each UAV's chromosome is disconnected each other, and only limited situation allows the chromosomes communication. In this case, UAVs' chromosomes cannot be integrated, and each UAV's chromosomes should be generated independently. Table 2 shows the decentralized chromosome representation.

Table 2 Decentralized Chromosome Representation

UAV1 target	0	1	1	0	2	0	0	2
UAV1 task	0	1	2	0	1	0	0	2

3.2 Genetic operators

Genetic Algorithm has four genetic operators which consist of selection, crossover, mutation, and substitution. For one generation from chromosomes of their parents, these four stages should be operated step by step.

3.2.1 Selection

The proportionate selection with roulette wheel method is employed for the selection operator in the task assignment problem. Each chromosome has its own fitness which is based on quality as a solution candidate. Therefore, it has the chance to be selected proportionally according to its own fitness.

The fitness of each chromosome is represented as follows.

$$f_i = \frac{(C_w - C_i) - (C_w - C_b)}{k - 1},\ k > 1\,, \tag{3}$$

where C_w is the worst chromosome, C_b is the best chromosome, and C_i is i-th chromosome in the chromosomes set.

Through the roulette wheel method, two chromosomes of the parents are selected.

3.2.2 Crossover

Crossover operator employs an order crossover method [11]. Order crossover rearranges the internal array of the chromosomes as shown in Fig. 3, and therefore it is suitable for structure such as figures arrangement. In this example, the order crossover method is adopted to solve the TSP in the task assignment problem.

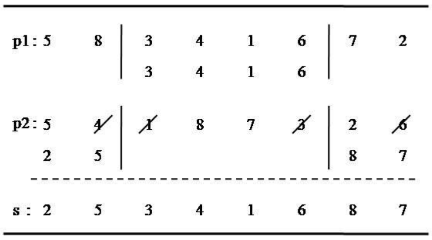

Fig. 3 Order Crossover

3.2.3 Mutation

Mutation occurs randomly to prevent the solution converging to the local minima. The mutation probability parameter is set to change the chromosome. In this problem, the mutation occurs as the way of reversed order chromosome form.

3.2.4 Substitution

When offspring chromosome is generated, it will be substituted with a chromosome in the set. In this step, the survival of the fittest concept is used. One chromosome is generated from the chromosomes set sequentially, the fitness of the generated chromosome is evaluated, and it is substituted with the worst chromosome in the set instead of setting elitism. Through this process, superior chromosome can survive naturally.

4. NEGOTITATION SCHEME FOR DECENTRALIZATION

4.1 Decentralization of the task assignment

When multiple UAVs group performs the assigned task, each UAV moves to the task field according to its own task plan. This plan is pre-allocated by solving the task assignment problem in the centralized method, and the optimal solution can be obtained on the fixed task environment. However, if the task environment changes, UAV cannot manage the changed circumstance actively by the centralized decision making structure. Moreover, when communication delays or limits exist among the UAVs group, each UAV cannot integrate the whole information of UAVs.

Generally, for autonomous UAV operation, UAV should have decentralized control/guidance law and its own decision making process. Therefore, decentralization of the task assignment is naturally required. To apply the decentralized task assignment algorithm, it is assumed that the tasks of UAV are determined by its own task assignment algorithm and there is no ground station which sends commands to the all UAVs. It is also regarded that UAV does not know about other UAV's plan unless it communicates with each other.

4.2 Negotiation scheme approach

In this study, a negotiation scheme approach is adopted to realize the decentralized task assignment [18]. It is assumed that UAV can communicate with only one UAV at the same time.

When communication is possible, UAV organizes a set of proposals and sends it to another UAV. Then, another UAV examines each proposal of the set and determines whether it will be accepted. If UAV accepts one proposal, it determines a task assignment policy as the proposed policy and notifies acceptance to another UAV. Otherwise, if UAV rejects all proposals, it should send a better proposal set to another UAV. The criterion of acceptance by the cumulative operation time of two communicating UAVs is set as follows.

$$\min J = \sum_{v=V1}^{V2} T_v\,, \tag{4}$$

After negotiation, GA of each UAV solves the task assignment problem within tasks in the policy until other communications occur. When other communications occur, the policy of the each UAV is updated by negotiation stage as shown in Fig. 4. In this way, decision making processes of UAVs can be decentralized for the communication limit existence cases.

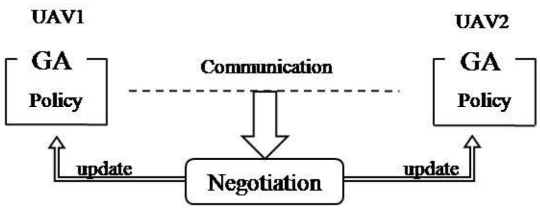

Fig.4 Negotiation Scheme approach

5. SIMULATION RESULTS

Simulations of the task assignment problem are performed using three methods - MILP, GA, and decentralized GA. MILP is an expanded linear programming method which can get the real number and integer solutions. For the simulations, each UAV has initial states such as (x, y) position and heading angle.

First of all, MILP and GA results are compared for none dynamic model, that is to say the turn radius of UAV is zero and the distance between each node is calculated in Euclidean distance. In this case, MILP and GA obtain the same allocation as shown in Fig. 5-6. The calculation time of MILP is shorter than that of GA as summarized in Table 3. Because GA may not converge to the optimal solution within given generations (1,000 times), MILP is better than GA in the sense of optimality and efficiency.

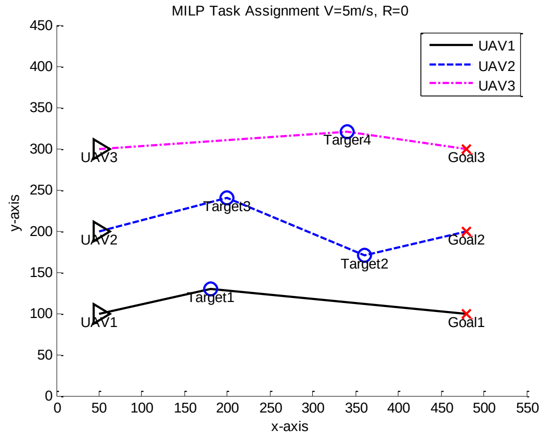

Fig. 5 MILP Task Assignment for R=0m

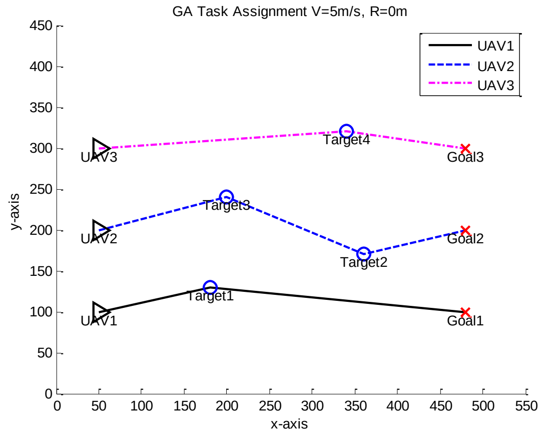

Fig. 6 GA Task Assignment for R=0m

However, if a dynamic model is considered, these two methods show different features. In this case, MILP does not know the travelling distance with dynamic model; it should be estimated as a constant variable by using approximation. However, GA can calculate the distance accurately by examining the chromosomes set, and therefore GA can provide a better solution. This feature is showed in Fig. 7-8. As summarized in Table 3, the computation time of GA is also favorable.

Table 3 Minimum Cost and Calculation Time for The Methods

	Min. Cost (sec)	Cal. Time (sec)
MILP (R=0m)	264.1	0.7617
GA (R=0m)	264.1	1.3600
MILP (R=40m)	369.4	1.7100
GA (R=40m)	347.3	1.5831
Decentralized GA (R=40m)	347.3	1.1421

Figure 9 and 10 show Monte Carlo simulation result of GA for 1,000 generations and 2,000 generations. More generations will improve the probability of convergence to the optimal solution. However, it cannot guarantee the optimal solution. This is a weak point of GA. However, although it is not optimal solution, it can be used as a reasonable solution for task assignment.

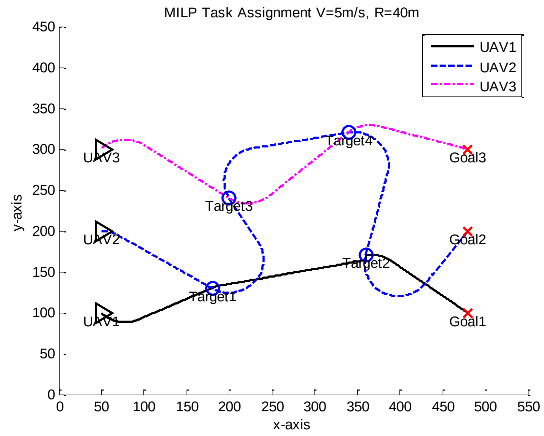

Fig. 7 MILP Task Assignment for R=40m

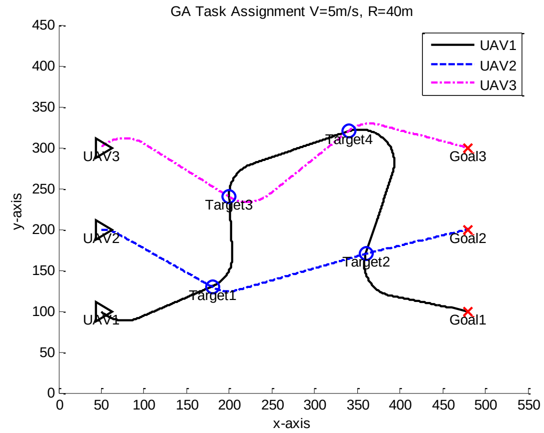

Fig. 8 GA Task Assignment for R=40m

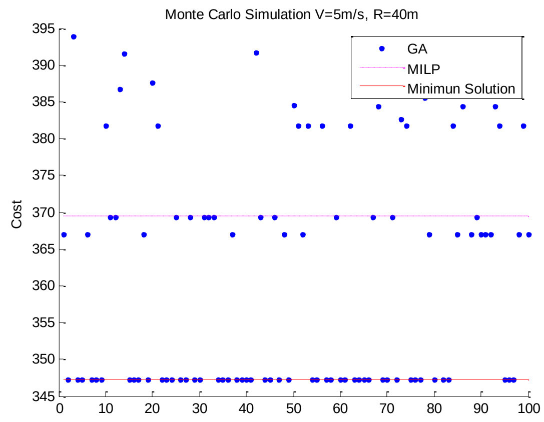

Fig. 9 Monte Carlo Simulation of GA (1,000 Generations)

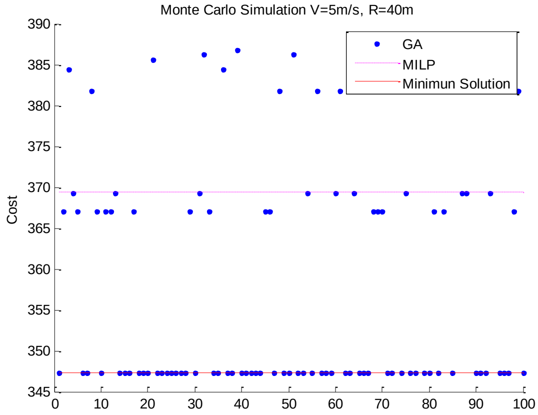

Fig. 10 Monte Carlo Simulation of GA (2,000 Generations)

In the decentralized GA case, it is assumed that the communications between two UAVs occur one after another in the middle of GA process. Then, GA only solves the TSP problem with its own tasks which is given by the negotiation. In this scenario, the communications of UAVs are separated, but limits of communications do not exist. As shown in Fig. 11-12 and Table 3, the solution of decentralized GA is valid, and it is also efficient in the sense of computation.

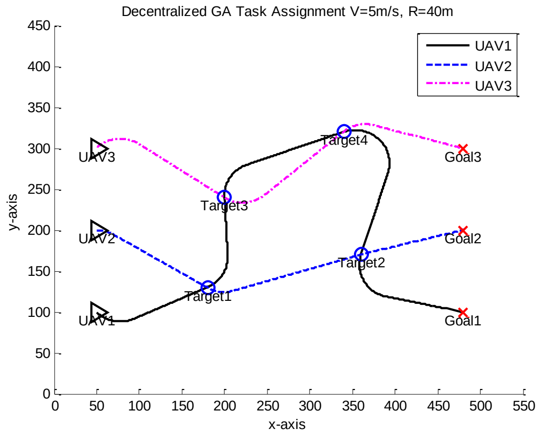

Fig. 11 Decentralized GA Task Assignment for R=40m

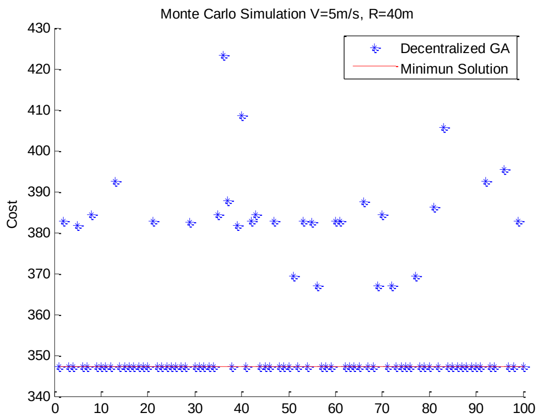

Fig. 12 Monte Carlo Simulation for Decentralized GA (1,000 Generations)

6. CONCLUSIONS

Task assignment problem for multiple UAVs is interpreted as a combinatorial optimization problem according to the number of tasks, UAVs, and targets, etc. In this study, GA which is a kind of meta-heuristic algorithms is adopted to solve the problem, and the results are compared with MILP method. In simple linear cases, MILP can solve the problem accurately and efficiently. However, if the problem is more complex such as nonlinear dynamic models or difficult constraints cases, it cannot guarantee the accuracy and efficiency of the solution. Moreover, if constraints are clashed to each other, it cannot solve the problem. On the other hand, GA can solve the problem at all times and adapt to the complex assignment cases by organizing feasible chromosomes. The calculation time is controlled by adjusting generation times. However, there is a conflict between the calculation time and solution convergences. In order to use GA method, it always keeps in mind the insufficient convergence.

In addition, a negotiation scheme is adopted to deal with the decentralized task assignment problem. It is assumed that the communications of UAVs are divided into UAV to UAV, and a specific scenario example is considered. The simulation result shows the validity of this approach. Although this method cannot apply to real time simulation yet, it could be used for real time multiple UAVs task assignment with low computational efforts and low risk of the solution.

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