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Multi-UUV Dynamic Cooperative Task Planning Method based on Multi-Objective Genetic Algorithm

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Abstract— **Aiming at the problems of scattered distribution, irregular shape, short underwater warning distance, limited carrying capacity of offshore islands and the inability for long term garrison, unmanned underwater vehicle (UUV) is used to search and explore the unknown underwater area near those islands. With the constraints on number of available UUVs, detection ability and energy consumption, a task planning framework of cooperative search and exploration mission of multi-UUV is urgently required. Meanwhile, in each round of task assignment, the most current algorithm could not dynamically assign the different task to corresponding UUV. For instance, the location and state of each UUV could be different during the searching and exploration process. In this paper, regarding the off-shore islands and reefs as the defense base, the models of UUV and its forward looking sonar are constructed, and a multi-UUV cooperative regional search and exploration algorithm is proposed based on multi-objective genetic algorithm (MGA). Aiming at the irregular distribution of targets in the search area and the different proportion of targets found by each UUV in their allocated search areas, we designed a multi-UUV dynamic cooperative (MDC) task planning method based on MGA to accomplish the multi-UUV dynamic scheduling. Finally, the underwater simulation environment is designed to simulate the distribution of offshore islands and reefs. The effectiveness of proposed MGA regional search and exploration algorithm and MDC-MGA task planning method is verified from the aspects of platform scale, time consumption and total distance of roadmap on regional search and exploration.**

Index Terms— **Multi-UUV; Evolutionary computing; Optimization algorithm; Task planning**

I. INTRODUCTION

The offshore islands and reefs are widely distributed and have the characteristics of scattered distribution, irregular shape, undeveloped infrastructure and inconvenient personnel garrison. Unmanned Underwater Vehicle (UUV) can navigate and perform tasks independently underwater. It has the characteristics of small size, strong autonomy and good concealment. Therefore, for the search and exploration tasks of remote island reef groups, UUV has broad development space in the implementation of tasks. Judging from the current technical level and development of UUV, individual UUV has made great progress and has been applied to many projects. However, in some distributed systems, due to the limited operation ability of individuals, individual UUV is difficult to meet the large-scale search and detection requirements [1, 2]. Therefore, the current research trend has developed to the technical field of multiple unmanned underwater vehicles (multi-UUV). The coordination of multiple UUVs is a key part of the research on underwater unmanned system. The cooperation of multiple agents can accomplish many complex tasks [3]. According to the characteristics of uneven distribution of underwater targets, the optimal dynamic task planning method of UUVs is designed and the cooperative operation mode is explored. In addition, the study of multi-UUV cooperative search and exploration strategy has important theoretical research significance for accelerating the practical process of UUV.

When solving the multi-UUV cooperative task planning method, excellent convergence performance and higher quality solution set are always the focus of attention. There are several bio-inspired algorithms applied to this field, such as ant colony optimization algorithm (ACO) [4-6], particle swarm optimization algorithm (PSO) [7] and genetic algorithm (GA) [8, 9] used the analytic hierarchy process (AHP) to layer the tasks of the UUV cluster. By processing the sub-tasks, the overall effectiveness is assured while the quality of result is ensured. [10] obtained Pareto solution set of multi-objective optimization problem through single objective optimization of single ant colony system and interaction between different ant systems, which provided a better solution for UUV cluster reconnaissance task planning. [11] presented a adaptive genetic algorithm method based on clustering, uniform cost search, greedy and bionic algorithm. Compared to single criterion objective function, the proposed adaptive GA method could find a path with consideration on travel time, road capacity and elevation, and number of traffic lights and turns. [12] proposed a dynamic extended consensus-based bundle algorithm (DECBBA) based on consistency algorithm. The problem of UUV swarms task planning under communication constraints is solved with high effectiveness and good performance. [13] addressed the dynamic task allocation problem with limited communication and velocity and proposed an improved evaluation index for each target to solve the futile selection problem during *k* fittest winner participant selection. [14] provided a distributed immune multi-agent algorithm (DIMAA) based on an immune multi-agent network framework to solve the distributed task allocation problems of search and rescue missions for multiple unmanned aerial vehicles (UAVs). The task allocation model established under three conditions: (1) new targets are detected; (2) UAVs break down; and (3) unexpected threat suddenly occurs.

To sum up, there are some problems in solving swarm task

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planning problems (see e.g. [15-17]), such as low solution quality, contradictory between randomness and convergence and weak ability of algorithms to jump out of local optimal, which greatly affect the global optimization ability and convergence performance of algorithms. In addition, most of the above studies focused on the static task planning and did not take the kinematic properties and sonar detection characteristics of UUV into account. Because the characteristics of UUV mentioned before, the individuals in UUV swarm may not start or end the searching process in the same positions which means most existed method cannot apply to the practical underwater searching and exploration missions.

To solve the above problems, the main contributions are follows:

- According to the 3-DOF models of UUV and the forward looking sonar model, division of search and exploration area is designed.
- MGA and elite MGA are proposed to solve the multi-objective optimization in underwater environment.
- MDC-MGA is designed to solve the dynamic cooperation searching process which could adaptively reassign the task to individual UUV when the detected targets in one area is higher than average.

The organization of this paper is as follows: In the Section II, the models of UUV and its forward looking sonar are constructed. The area division method is proposed based on these models and environmental characteristics of the offshore islands and reefs. In the Section III, the multi-objective genetic algorithm (MGA) of UUV swarm searching method is designed to improve the solution quality and convergence performance through the process of selection, crossover and variation. Considering the irregular distribution of targets and the UUVs' dynamic cooperation searching process, a multi-UUV dynamic cooperative (MDC) task planning method based on multi-objective genetic algorithm (MGA) is designed. When the proportion of detected targets in one individual UUV allocated area is larger than the average, MGA module, which is in the framework of MDC-MGA, will be activated which means the UUV swarm will give priority to search this area and reduce the search path spacing, meanwhile the new task points assignments will be republished to each UUV. In the Section IV, the simulation results are presents to testify the effectiveness of the proposed methods. Finally, the conclusions are summarized in the Section V.

II. Problem Formulation and Modeling

According to the requirement of multi-UUV cooperative target search and exploration task in unknown environment, the application scenario of target search can be summarized as follows: in the task area, static targets with unknown positions and random number of obstacles are randomly distributed, and UUVs are required to perform target search tasks in this area, which requires collaborative control of multiple UUVs to search more unknown targets with less search cost in limited time.

A. 3-DOF Models for UUVs

The UUV model used in this paper is a mathematical UUV kinetic model with three degrees of freedom, also named the equation of UUV kinetic model in the horizontal plane. Given the following assumptions: Ignore the motion of roll, pitch and heave, and only consider the plane motion, i.e

1) Ignore the motion of roll, pitch and heave, and only consider the plane motion, i.e

$$z=0, w=0, \phi=0, p=0, \theta=0, q=0 \tag{1}$$

2) There is not interference from wind, wave and current during UUV movement process.

The mathematical model of UUV's three-degree-of-freedom motion can be obtained as follows:

$$\begin{cases} \dot{x}=u\cos\psi-v\sin\psi \\ \dot{y}=u\sin\psi+v\cos\psi \\ \dot{\psi}=r \end{cases} \tag{2}$$

where the components of velocity vector $\begin{bmatrix} u & v & r \end{bmatrix}$ are defined in the UUV frame, the components of velocity vector $\begin{bmatrix} \dot{x} & \dot{y} \end{bmatrix}$ are defined in the UUV NED coordinates and ψ represents the angle of yaw.

B. Forward Looking Sonar Model

In this paper, it is assumed that UUV carries Reson's SeaBat 8125-H forward looking sonar for target detection and obstacle identification. It detects a sector area with a horizontal level of 120° and a vertical opening angle of 17°. In ordinary mode, there are 240 beams, divided into three layers, each layer contains 80 beams, and the beam angle is 0.5°. The optional detection mode can contain 512 beams, with a maximum range of 120m and a maximum transmission rate of 40Hz. According to the [18], the function of Johnson's curve is defined as below:

$$\mathrm{f}(l)=\begin{cases} \frac{\lambda\alpha_2(l_2-l_1)}{(l-l_1)(l_2-l)\sqrt{2\pi}}e^{-\frac{1}{2}\left(\alpha_1+\alpha_2\ln\left(\frac{(l-l_1)}{(l_2-l)}\right)\right)^2} & l_1<l<l_2 \\ 0 & otherwise \end{cases} \tag{3}$$

where the Johnson parameters α_1, α_2, l_1, l_2 are selected as shown in Table I.

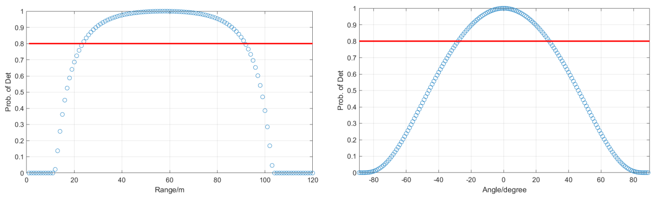
TABLE I: Definition of Johnson's parameters

	Johnson's parameters	
Range probability curve	$\alpha_1=0, \alpha_2=0.75$	$l_1=11.5m, l_2=103.75m$
Angular probability curve	$\alpha_1=0, \alpha_2=1.25$	$l_1=0, l_2=\pi$

As the Figure 1 shown, the probability of detection is quite high when the range of detection is between 20 to 100 meters and the angle of detection is between -60 to 60 degrees.

C. Division of search and exploration area

Combined with sonar detection characteristics mentioned before, a grid network is established to ensure that the distance between task points in adjacent areas is equal, and any path can nearly cover the whole area where the adjacent task points are located.



(a) PDet-Range graph (b) PDet-Angle graph

Fig. 1: Probability of detection-range and angle graphs

As shown in Figure 2, using the UUV path $R = \{x_1, x_2, x_5, x_8, x_9\}$ which starts at $x_1 = (108.75, 108.75)$ and ends at $x_9 = (523.75, 523.75)$ as an example, the blue region of route R reflects the detection area during the search and exploration process. To achieve the highest coverage with shortest search time, for instance, when UUV arrivals at the center of one grid, its detected region should cover the current grid with the horizontal level under 120°. According to (3), the distance between two nearest task points is defined as

$$d_{\text{task\_point}} = \frac{2d_{\text{detect}}}{\sin(a_{\text{detect}}/2)} \tag{4}$$

where the range of sonar d_{detect} is set to 120m and the angle a_{detect} is set to 120°. For key areas, the density of task points is increased, so that the probability of target detection is greatly improved.

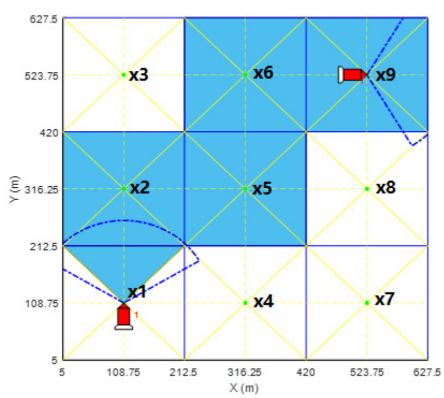


Fig. 2: Local map of region division

D. Fitness

During the multi-UUV search and exploration, the purpose of multi-UUV is to recognize and determine the target as far as possible in the task area. Thus, improving the certainty of target information in the environment is important from below aspects:

- Find and mark more targets within less time steps.
- Reduce the cost of multiple UUVs cooperating target search.
- Improve the certainty of targets' information in the task area.
- Allocate the search area of the individual UUV reasonably.

The distance of ith UUV's search route is defined as

$$W_1(i) = \sum_{j=1}^{n_i - 1} d_{j,j+1} \tag{5}$$

where n_i represents the last task point in route R_i and $d_{j,j+1}$ represents the distance between two adjacent task points.

At the view of base defense, each route begins as close to the base as possible and ends as far away from the base as possible. Thus, the weight function W_2 is defined as

$$W_2(i) = \sum_{j=1}^{n_i - 1} d_{j,base} \tag{6}$$

where $d_{j,base}$ represents the distance between each task point and base.

The ith UUV's search route accumulated turning angle is defined as

$$W_3(i) = \sum_{j=1}^{n_i - 1} a_{j,j+1} \tag{7}$$

where $a_{j,j+1}$ represents the turning angle between two adjacent task points.

To sum up, the following optimization equation is designed considering the base defense, search range and heading angle changes:

$$\min \sum_{i=1}^{m} f(i) = d_{start} + \alpha W_1(i) + \beta W_2(i) + \lambda W_3(i) \tag{8}$$

where d_{start} represents the distance between the ith UUV's current location and the first task point in route R_i and α, β and λ are the weight parameters.

E. Constraint

During the multi-UUV search and exploration process, the constraints are summarized as follows:

$$m \leq M \tag{9}$$

$$R_1 \cup R_2 \cup \cdots \cup R_m = X \tag{10}$$

$$R_i \cap R_j = \emptyset \quad i \neq j \quad 1 \leq i, j \leq m \tag{11}$$

$$W_1(i) + W_2(i) \leq D \tag{12}$$

where M is the total number of UUVs, R_i is the search route of the i-th UUV, X represents the collation of total task points and D is the maximum safe range of UUV. In addition, communication delay is not considered. The UUV could communicate with the base in the search area.

III. MDC-MGA TASK PLANNING METHOD

A. Chromosome Representation

For path planning of regional task points, this paper adopts sequential coding, also known as natural number coding. According to the number of task points in this paper, K represents the number of chromosomes, and the length of each chromosome is set to n which depends on the number of total task points,

$$X_k = (x_1, x_2 \cdots, x_n) \quad 1 \leq k \leq K \tag{13}$$

B. Selection

For individuals in the population of each generation, each chromosome is randomly sorted and evenly divided into l groups according to K individuals. According to the (9), the number of breakpoints is defined as $n_{breakpoint} = l - 1$, where $n_{breakpoint} \leq (M-1)$. Without considering the arrangement of groups, the size of its solution space is $K!C_{K-1}^{n_{breakpoint}}$. To simplify the illustration of proposed MGA, the length of each chromosome is set to $n = 8$, the number of chromosomes is set to $K = 9$ and the individuals are divided into $l = 3$ groups in this section. As shown in the Figure 3 below, the core idea is to select the chromosome with the highest fitness value from each group. But different from directly screening out the optimal l individuals with the highest fitness value from the contemporary population, this random grouping method ensures the diversity of the population.

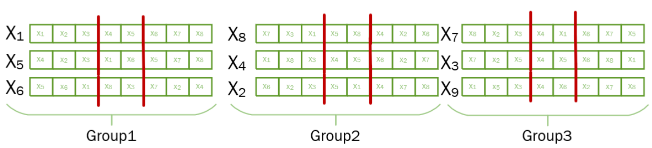


Fig. 3: Schematic diagram of chromosome selection and grouping

C. Crossover

The direct application of the single-objective crossover algorithm to multi-objective problems will produce many infeasible solutions. To solve this problem, the following methods are generally adopted to deal with it.

- Discard infeasible solutions.
- Use a penalty function to reduce the fitness of infeasible solutions.
- Construct operators so that only viable solutions are generated.
- Turn an infeasible solution into a viable one.

However, those solutions could cause the losing of several populations in current generation or continuity information between task points. As shown in Figure 4, this paper proposes the method of changing the position of the breakpoint to carry out crossover operation. In Table II, the changing of route R_2 and route R_3 reflects the population evolution after changing the position of $Break\_Point_2$.

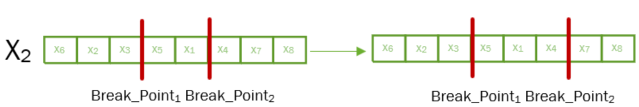


Fig. 4: Schematic diagram of chromosome crossover

TABLE II: UUV path updated after crossover operation

UUV path	task points sequence before crossover	task points sequence after crossover
R_1	$\{x_6\} \to \{x_2\} \to \{x_3\}$	$\{x_6\} \to \{x_2\} \to \{x_3\}$
R_2	$\{x_5\} \to \{x_1\}$	$\{x_5\} \to \{x_1\} \to \{x_4\}$
R_3	$\{x_4\} \to \{x_7\} \to \{x_8\}$	$\{x_7\} \to \{x_8\}$

In traditional methods, more time may be consumed in the searching process of the solution space where the non-global optimal solution is located. This algorithm will obtain a larger solution space, while retaining the connectivity information between task points. Meanwhile, through changing the breakpoint, all the individuals of offspring generations are viable, so as to find the global optimal solution with higher probability and efficiency.

D. Mutation

Due to the sequential coding adopted in this paper, it ensures the legitimacy of the mutated chromosomes. As shown in Figure 5, switching, sliding and flipping are all adopted. In Table III, the changing of route $R_1 - R_3$ reflects the population evolution after mutation operation.

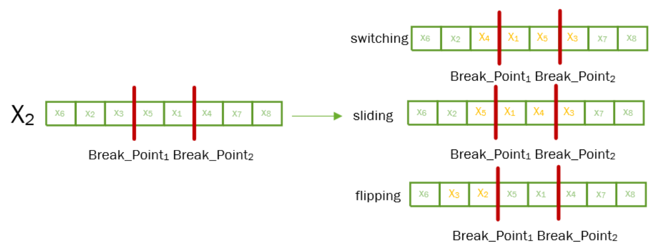


Fig. 5: Schematic diagram of chromosome mutation

TABLE III: UUV path updated after mutation operation

UUV path	Task points sequence before mutation	Task points sequence after mutation		
		switching	sliding	flipping
R_1	$\{x_6\} \to \{x_2\} \to \{x_3\}$	$\{x_6\} \to \{x_2\} \to \{x_4\}$	$\{x_6\} \to \{x_2\} \to \{x_5\}$	$\{x_6\} \to \{x_3\} \to \{x_2\}$
R_2	$\{x_5\} \to \{x_1\}$	$\{x_1\} \to \{x_5\}$	$\{x_1\} \to \{x_4\}$	$\{x_5\} \to \{x_1\}$
R_3	$\{x_4\} \to \{x_7\} \to \{x_8\}$	$\{x_3\} \to \{x_7\} \to \{x_8\}$	$\{x_3\} \to \{x_7\} \to \{x_8\}$	$\{x_4\} \to \{x_7\} \to \{x_8\}$

In addition, three crossover-mutation evolution mechanisms, including switching, sliding, flipping and breakpoint selection, are applied as shown in Figure 6. In Table III, the changing of route $R_1 - R_3$ reflects the population evolution after crossover and mutation operation.

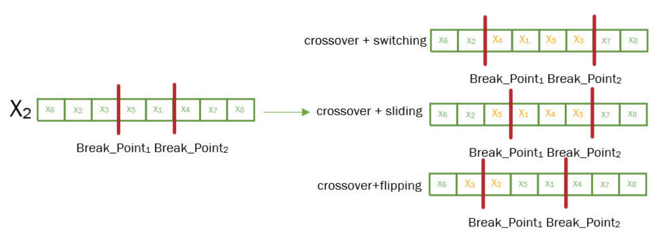


Fig. 6: Schematic diagram of chromosome crossover-mutation

TABLE IV: UUV path updated after crossover and mutation operation

UUV path	Original task points sequence	Task points sequence after crossover and mutation		
		crossover + switching	crossover + sliding	crossover + flipping
R_1	$\{x_6\} \to \{x_2\} \to \{x_3\}$	$\{x_6\} \to \{x_2\}$	$\{x_6\} \to \{x_2\} \to \{x_5\}$	$\{x_6\} \to \{x_3\}$
R_2	$\{x_5\} \to \{x_1\}$	$\{x_4\} \to \{x_1\} \to \{x_5\} \to \{x_3\}$	$\{x_1\} \to \{x_4\} \to \{x_3\}$	$\{x_2\} \to \{x_5\} \to \{x_1\}$
R_3	$\{x_4\} \to \{x_7\} \to \{x_8\}$	$\{x_7\} \to \{x_8\}$	$\{x_7\} \to \{x_8\}$	$\{x_4\} \to \{x_7\} \to \{x_8\}$

In each group of the current population, a selection mechanism is introduced to select the optimal parent individual, and operations of crossover and mutation are carried out to improve the quality of the offspring individuals.

E. Elitism

The idea of elitism is that the best individuals should be preserved for the next generation. There are two steps to ensure elitism in MGA.

- Preserve elite individuals within the group.
- Store historical elite individuals and reintroduce them into the group in later generations.

The elite MGA adopts elitism to perform full-space parallel search and focuses on the part with high performance, which can improve efficiency and avoid trapping local minima.

F. Steps of applying the MGA cooperative regional searching method

To sum up, the proposed MGA cooperative regional searching method is integrated in the MGA module. The pseudo-code of the MGA module described above is shown in Algorithm 1.

Algorithm 1: MGA cooperative regional searching method

Input: the current position and course of each inidividual UUV
Output: the pathpoint of each individual UUV

Initialize the parameters and generate the initial population X_k;
while *not meet the stopping criterion* **do**
    for *s=1:K //K represents the number of population.* **do**
        calculate the optimization equation $\min \sum_{i=1}^{m} f(i)$ of each population using (8);
    end
    update the global best route of each UUV $gBestRoute_m$;
    divide the population into l groups randomly;
    for *i=1:l* **do**
        generate the breakpoints $n_{breakpoint} = l - 1$ randomly; generate the randon number $P_1 = rand(0,1)$ and $P_2 = rand(0,1)$;
        if $P_1 < P_c$ **then**
            if $P_2 < P_m$ **then**
                do the crossover and mutation operations mentioned in Section III-C and Section III-D;
            else
                do the crossover operation mentioned in Section III-C;
            end
        else
            reserve the orginal chromosome in the current group;
        end
    end
end

The steps of applying the MGA method are as follows:

Step 1: Set encoding and decoding schemes. This paper adopted iteration counter and sequential encoding scheme to encode unlocked areas in the island surveillance area. Random generation of primary population containing K chromosomes.

Step 2: Calculate the fitness of each individual in the population and record the optimal individual in the current population. Fitness function is the only index to measure whether an individual can survive, which provides screening basis for the subsequent individual selection algorithm. The setting of fitness function is determined referring to (8), that is, in the MGA, the size of fitness value determines the quality of an individual.

Step 3: Randomly group the population generated in the previous step into l groups, and select the optimal individuals in each group, that is, the individuals with the greatest fitness in each group. Individuals with greater fitness have a greater probability of inheriting their genes to the next generation, so as to continuously eliminate individuals with lower fitness. At the same time, the selection of the best individuals in each group also ensures genetic diversity.

Step 4: Genetic operation is carried out on each group of selected individuals, as mentioned in Section III-C and Section III-D, new chromosomes are produced by all sort of crossover, mutation and crossover-mutation operations on the genes of selected chromosomes with probability of crossover and mutation. On the basis of preserving excellent genes to a large extent, genetic manipulation increases gene diversity through variation, so as to improve the probability of finding the optimal solution.

Step 5: Judging whether the algorithm terminates according to the convergence condition, this paper chooses the maximum number of iterations as the stopping criterion. If the termination condition is not reached, the iteration counter is updated and the Step 2 is returned to continue the iterative evolution. Otherwise, find individual with the highest fitness among all the recorded optimal individuals and return as the global optimal solution and end the program.

G. Steps of applying the MDC-MGA task planning method

The framework of applying the MDC-MGA task planning method to multi-UUV cooperative regional search and exploration is shown in Figure 7.

Step 1: According to the actual underwater environment, divide the searching region into K areas. Meanwhile, set key search areas based on previous experience which means the distance between the adjacent task points in key areas is smaller than others.

Step 2: Initialize the MGA Module as mentioned in Section III-F and publish the task route to each UUV.

Step 3: Obstacle avoidance and cooperative target searching. During this process, the priority of obstacle avoidance

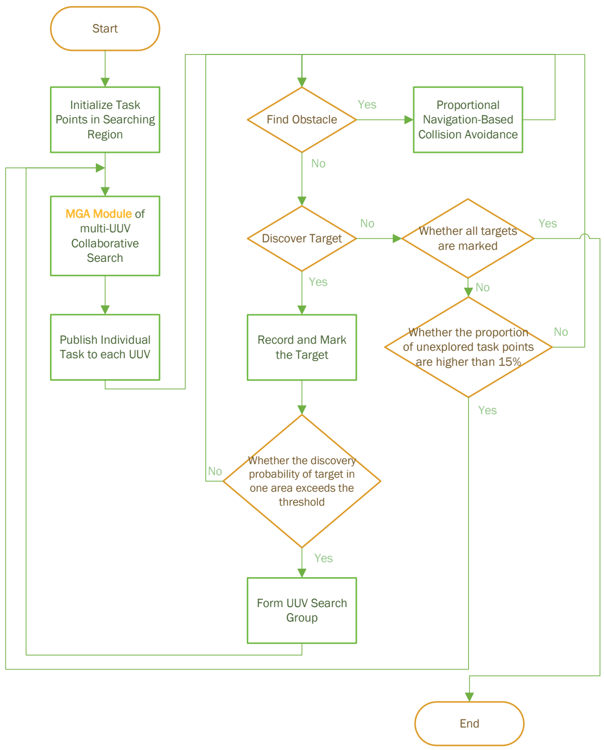


Fig. 7: MDC-MGA task planning framework

is higher than the target searching. When the avoidance process is active, the searching progress will pause until the avoidance process finished.

Step 4: All UUVs will follow the given route through the various mission points for task search. However, there are two cases that go back to Step 2 and MGA Module will activated to republish the task route to each UUV respectively.

- Case 1: If the targets found in one area is much higher than the others, the MGA Module will republic the task route to each UUV and form a group of UUVs. Aiming at discovering the targets of that area in shortest time, the routes of UUVs in that group start near that area.
- Case 2: If one of the UUVs finished all the task points in it's route and the proportion of left task points are higher than 15%.

Step 5: Judging whether the task points have been searched or all of the targets have been detected. If one of the conditions satisfied, the program will end. Otherwise, the Step 2 is returned to continue the searching and exploration process.

IV. Simulation Results

The simulation environment of this paper is a horizontal plane of a certain depth with an area of $2500m \times 2500m$ (see Figure 8). Firstly, according to the Section II-C, the entire search and exploration environment is decomposed into 36 first-level task regions, and each first-level region is decomposed into 4 second-level sub-regions with a side length of $d_{\text{task\_point}} = 207.5m$. Secondly, under the global communication condition, static targets (the number of static targets is set to 40 in advance) are set with random positions and distribution. The black rectangles represent the obstacles. The blue circle in the middle represents the base of offshore island. One key region is set with blue dotted rectangle. At last, refer to Table V, UUVs are sent from initial positions to carry out the target search and exploration task, with the specified running time $T = 2500(step)$.

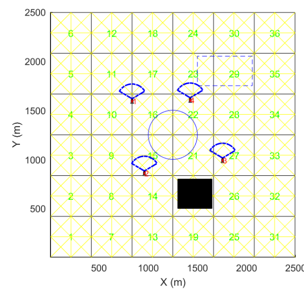


Fig. 8: Global map of region division

TABLE V: UUV initial positions

Num. of UUV	Position Parameter X(m)	Position Parameter Y(m)
1	835	1617
2	960	882
3	1757	1014
4	1427	1627
5	479	535
6	2100	2050
7	510	2400
8	2111	487

As the obstacle avoidance problem is not the main focus of this paper, it is only used to verify the rationality of the task planning module, and to avoid collision in the process of multi-UUV search and exploration, as well as to avoid the location of the base, so only one obstacle is set up in the simulation environment. In addition, the parameters of MGA are set as follows, the population size K is set to 240, the number of maximum iterations $Iter$ is set to 10000. According to experts' experience [20], the total parameters used in MGA, elite MGA and elite MDC-MGA are summarized in Table VI.

TABLE VI: Parameters of MGA, elite MGA and elite MDC-MGA

Name	Symbol	Parameter	Name	Symbol	Parameter
The number of chromosomes	K	240	The length of chromosome	n	144
The probability of crossover	P_c	0.5	The probability of mutation	P_m	0.1
The maximum iteration	$Iter$	10000	Dist. between task points(m)	$d_{\text{task\_point}}$	207.5
The number of chromosome group	l	30	Weight parameter of fitness	α	0.1
Weight parameter of fitness	β	1	Weight parameter of fitness	λ	0.8

According to the [19], the adapted genetic algorithm with three modified crossover operators were applied to multiple traveling salesmen problem (MTSP). As [19] mentioned in the experiment, the partially mapped crossover (PMX) operator had the best performance. The core of PMX is to swap the segment of two parent chromosomes. Unlike the methods mentioned in the Section I, the PMX can handle the TSP with different start points. Using the mappings in the original parent chromosome corrects the rest part of the child chromosome which makes the generated offspring are feasible. However, PMX is unsuitable for the multi-UUV searching mission. Because the start and end points of each individual in PMX are same. PMX-GA is inspired by the

PMX operator which adds the mutation operator mentioned in Section III-C with the crossover probability P_c is set to 0.5, the mutation probability P_m is set to 0.1. Thus the PMX-GA could solve the cooperative searching problem with different start and end points.

In the task planning experiments, five algorithms are introduced to testify the performance as the Table VII shown. The GA with cluster algorithm (GACA) [21], PMX-GA and modified two-part wolf pack search algorithm 2 (MTWPS2) [22] are used to testify the performance of proposed MGA and elite MGA.

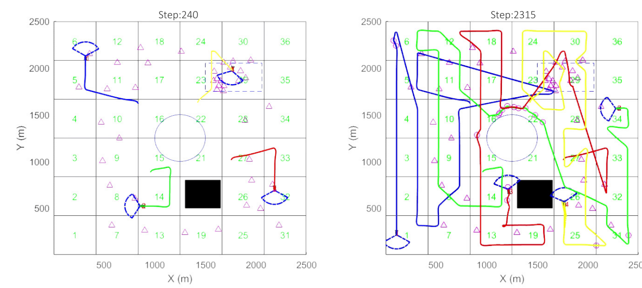
TABLE VII: Comparison results among these algorithms

Num of UUV	Algorithm	Mean (m)	Best (m)	Worst (m)	Mean of Iterations	Regional coverage over 90% (s)
4	GACA	30849	30302	31820	5611	1951
	PMX-GA	30756	**29631**	**32647**	4713	1802
	MTWPS2	30415	29714	31043	4563	1790
	MGA	30409	29652	30958	6650	1776
	elite MGA	**30218**	29945	30571	**2851**	**1756**
6	GACA	31266	30028	31961	**7957**	1204
	PMX-GA	30659	29885	31736	8037	1182
	MTWPS2	30927	29582	**32501**	8126	1175
	MGA	31182	30837	31522	8054	1151
	elite MGA	**30578**	**29423**	31150	9492	**1140**
8	GACA	34241	33053	**35462**	8326	913
	PMX-GA	33437	32923	34068	**4972**	876
	MTWPS2	32625	31408	33562	8276	870
	MGA	**32230**	31584	33074	8170	868
	elite MGA	32585	**30145**	33206	9688	**785**

Table VII shows the results of the comparison among GACA, PMX-GA, MTWPS2, MGA and elite MGA in 30 rounds of simulation. "Mean", "Best" and "Worst" in this table respectively represent the average, minimum and maximum value of total search and exploration trajectory of all UUVs' individuals obtained by relevant algorithms. The bold text shows the best results in that column of indicator.

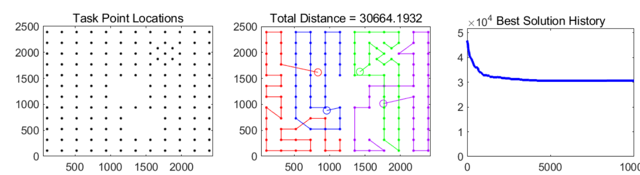
As can be seen, in case of four UUVs cooperative search task, elite MGA had almost the same performance as MGA. But elite MGA took only a third of the number of iterations of the MGA. For the six and eight UUVs cooperative search task, it seems that GACA and PMX-GA had the smallest number of iterations respectively. But combined with the mean distance, it is not difficult to find that they fell into local optimality. For first and second trials, compared to MGA, elite MGA had the larger search space and achieved better performance. Although in the third trial, MGA got better result on mean distance. The reason is that elite MGA introduced the historical elite chromosome. Meanwhile, because of the number of UUV also increased, larger search space brought negative effect on convergence of elite MGA and the average number of iterations increased. In addition, from the aspect of time consuming on regional coverage over 90%, proposed MGA and elite MGA also have a certain advantage.

The whole simulation results of MDC-MGA task planning method are shown in Figure 9. The purple Δ represents the static target. The results show that two task planning phases are included in the regional search and exploration. In Figure 10-(a) and Figure 11-(a), the task points are generated referring to the model of forward looking sonar. In Figure 10-(b) and Figure 11-(b), the lines represent the paths of each UUV. The small circle of each line is the current position of each UUV and is also the start point in the searching process. Figure 10-(c) and Figure 11-(c) verify the effectiveness of proposed algorithm. Due to UUV4 marked with yellow path, it found the probability of targets in the key area was above the average level of others. The two nearest UUVs, which were marked with blue and red paths, mustered and formed a search group. The UUV marked with green path kept on the current task. It could not only shorten the total search time but also save the energy consumption. When the search group arrived the key area as shown in top right of the Figure 9-(a), the task planning of phase 2 started. The elite MGA module mentioned in Figure 7 would publish the new individual task. The UUVs in search group started from the key area. As shown in the top right of Figure 11-(a), the density of task points in the key area is higher than average.



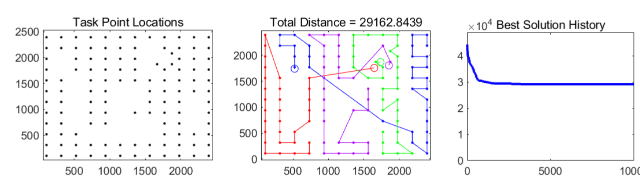
(a) Task planning phase 1 (b) Task planning phase 2

Fig. 9: Trajectory of multi-UUV task planning



(a) Task Points (b) multi-UUV Paths (c) Convergence

Fig. 10: Task planning phase 1



(a) Task Points (b) multi-UUV Paths (c) Convergence

Fig. 11: Task planning phase 2

Compared to the task planning in phase 1 which is the process before dotted line marked point of purple curve in

Figure 12, the benefit of MDC is the targets in key area would be found at once. In phase 1, MTWPS2 has almost the same performance as elite MGA and elite MDC-MGA, especially before the 180th second. The slope of purple curve after marked point increased proves the benefit of task planning module. The potential danger near the base would be relieved in time. Because all the cooperative searching algorithms are worked on the path planning based on the 3-DOF UUV model and forward looking sonar model. The positions of static targets were not known before the missions. The total searching time may not reflect the performance of the algorithm completely. From the view of time axis, elite MGA and elite MDC-MGA have better performance at most second which can prove the effectiveness of proposed algorithms to a certain extent.

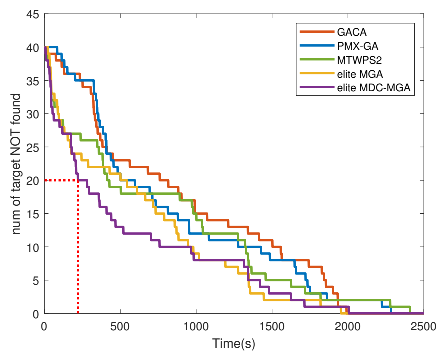


Fig. 12: Static targets searching process

V. Conclusions

In this paper, a multi-UUV task planning module is designed to coordinate UUVs collaborative search and obstacle avoidance. Proposed MGA and elite MGA have global data digging ability and are good at searching complex and nonlinear problems. Because of uneven distribution of targets and the randomness of UUVs' positions and states, a multi-UUV dynamic cooperative (MDC) task planning method based on multi-objective genetic algorithm (MGA) is established. The simulation results illustrate the effectiveness of proposed MDC-MGA task planning method.

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