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Complete Coverage Autonomous Underwater Vehicles Path Planning Based on Glasius Bio-inspired Neural Network Algorithm for Discrete and Centralized Programming

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***Abstract*—For the complete coverage path planning of Autonomous Underwater Vehicles (AUVs), a new strategy with GBNN algorithm (Glasius Bio-inspired Neural Network) with discrete and centralized programming is proposed. The basic modelling for multi-AUVs complete coverage problem based on grid map and neural network is discussed first. Then, the design for single AUV complete coverage is introduced based on GBNN algorithm which is a new developed tool with small amount of calculation and high efficiency. In order to solve the difficulty of single AUV full coverage task of large water range, the multi-AUV full coverage discrete and centralized programming is proposed based on GBNN algorithm. The simulation experiment is conducted to confirm that through the proposed algorithm, multi-AUVs can plan reasonable and collision-free coverage path and reach full coverage on the same task area with division of labor and cooperation.**

***Index Terms*—Autonomous underwater vehicles, path planning, complete coverage, Glasius bio-inspired neural network.**

I. INTRODUCTION

AUV (Autonomous Underwater Vehicle) is an important tool for exploration, but one single AUV cannot complete complicated wide range coverage detection tasks due to its limited energy [1-3]. Therefore, cooperative multi-AUVs full coverage method comes into being which means that multiple robots form an integrated system to complete the entire coverage of designated areas efficiently through a certain collaborative strategy [4]. It needs the combination of path planning [5] and multi-vehicle cooperation [6-8]. So far, there have been some researches on the algorithm of multi-robot cooperative full coverage path planning [9].

There are some experts and scholars to improve or expand the whole coverage path planning algorithm of single robot to solve the problem of full coverage of multi-agent cooperation. For example, Janchiv [10] combines accurate unit decomposition method, template matching method, network graph method and heuristic algorithm, and applies it to multi-robot full coverage path planning. The algorithm can improve the efficiency of the whole coverage, but the algorithm does not take into account the multiple vehicle task assignment and robustness. Rekletis [11] introduced the Boustrophedon domain decomposition algorithm into the multi-robot cooperative complete coverage path planning. The algorithm can realize the complete coverage of the region, but usually the robot will return to the left subregion after covering the subregion of the far right, which may produce overlapping coverage problem. Hazon [12] proposed a multi-robot cooperation complete coverage path planning algorithm MSTC (Multi-robots Spanning-Tree Coverage). It can effectively enhance the robot traverse the robustness of whole area, but does not guarantee coverage time close to the optimal. In view of this, Zheng [13] improved the algorithm and proposed the MFC (Multi-robots Forest Coverage) algorithm, which can complete coverage in a number of times and achieve the approximately optimal coverage time. Kapanoglu et al. [14] put forward a kind of multi-robot cooperative coverage path planning methods based on genetic algorithm and template matching which is more suitable for static environment, and it is difficult to find suitable path template in dynamic environment. Recently, Luo [15] used biological inspired neural network algorithm to solve the cooperation of multiple ground robot to solve complete coverage path planning problem, in which each robot will treat other robots as obstacles, and can ensure the robot cooperation full coverage of the target area without collision, but it did not resolve problems such as large computation burden [16].

So far, there has quite a few research for complete coverage path planning technology of single robot and multi-robots, but many of them are the relevant study on mobile robot. And there is quite few reports related to autonomous underwater vehicles. It is necessary and important to study the full coverage path planning technique of multi-AUVs.

The innovation points of this paper mainly include the following two aspects:

(1) For the problem of large calculation burden and time cost, long time escaping from dead zone with biological inspired neural network algorithm in robot path planning, an improved algorithm called GBNN (Glasius Bio-inspired Neural Network) algorithm [16-18] is applied to complete coverage path planning of AUV for the first time. Compared with the differential equation of biological inspired

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neural network algorithm, the complexity is low with small amount of calculation, which can effectively reduce the AUV path planning time and improve the efficiency of AUV path planning, and also quickly escape from the dead zone without any stop and waiting.

(2) In order to solve the difficulty of single AUV full coverage task of large water range, the cooperative full coverage path planning algorithm for multi-AUVs based on GBNN discrete and centralized planning is proposed respectively. Both algorithms can guarantee accomplishing the complete coverage without collision between multi-AUVs and no repeat coverage, so as to effectively improve the task execution efficiency and reduce path planning time.

This paper is organized as follows: Second section describes the basic formulation of multi-AUVs cooperative full coverage path planning. Then, the design for single AUV complete coverage is introduced based on GBNN algorithm in section 3. In section 4, multi-AUVs full coverage path planning design with discrete programming and centralized planning are presented respectively. Simulation results are presented in fifth section for both multi-AUVs discrete programming and centralized planning in static and dynamic environment. Finally, conclusion remarks are given in section 6.

II. Modelling of Multi-AUVs Cooperative Coverage

A. Overview of Full Coverage Path Planning Problem

Multi-AUVs cooperative complete coverage mainly refers that multi-AUVs form a team through cooperation strategy, so that it can effectively improve the working efficiency of single AUV, and reduce the time needed for full coverage mission.

At present, there are three categories for multi-robot cooperative full coverage path planning [4]: non concentration, discrete planning and centralized planning. For the discrete planning, there is no centralized multi-robot task allocation mechanism, namely, there is no need to assign the task sub region for each robot. The robots share information with each other through the use of explicit or implicit communication, and achieve cooperative complete coverage with the same underwater working region. For centralized planning, it needs to obtain the global environment information in advance and divided into sub task regions for each robot. Each robot will only be responsible for planning their respective tasks of sub area, so as to realize multiple robots sub regional cooperation. In addition, in the unplanned algorithm, multiple robots are mainly planning paths through reactive motion, it is usually difficult to obtain the ideal regional coverage results, and this article will not make specific studies. In this paper, we will give a detailed multi-AUVs cooperative full coverage planning algorithm with discrete planning and centralized planning.

Complete coverage path planning needs to solve three problems: (1) AUV can traverse all the work area except obstacles, (2) AUV can avoid all obstacles effectively and safely during the traversal process, (3) In the traversal process, try to avoid path repetition to the greatest extent and achieve the shortest distance. In addition, for the multi-AUVs full coverage path planning problem, how to generate the planning path with cooperation is also a key problem. Fig. 1 shows the full coverage path planning for both single AUV and multi-AUVs condition in two-dimensional plane water space. In this paper, it is focused on multi-AUVs cooperative full coverage path planning. The detailed algorithm implementation process will be given in the following sections.

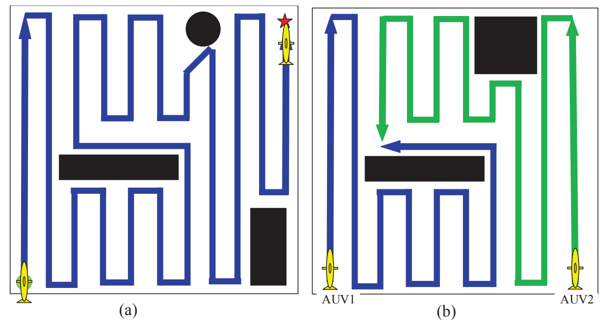

Fig. 1. Complete coverage path planning problem (a) Single AUV complete coverage path planning (b) Multi-AUVs complete coverage path planning

B. Modelling of Underwater Environment

When AUV is working in the underwater environment, it mainly collects the environment information based on sonar data. The sonar image will be transformed into binary image information, and the later full coverage path planning is actually conducted in the grid map.

In order to make it more clearly for readers, simple introduction about how to collect the environment information with sonar is introduced here. First, a sonar sensor model is established where the sensor provides relative distances and angles between them and surrounding obstacles located within the sensor beam [19-20], as shown in Fig. 2. Then, based on the sonar image shown in Fig. 3a, conduct image processing (segmentation, corrosion and expansion, map coordinates conversion) to obtain the final map, as shown in Fig. 3b. The AUV collects the local environment information when it moves and updates the global maps to conduct the later complete coverage.

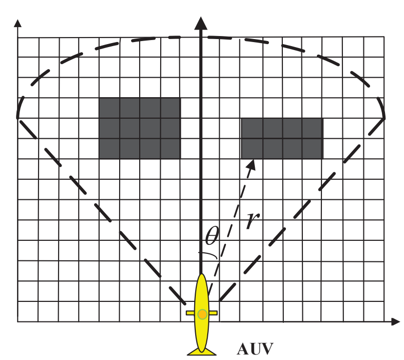

Fig. 2. The established sonar sensor model

GBNN algorithm will be introduced based on grid map. In addition, when the GBNN algorithm is applied to the AUV complete coverage path planning, the neural network

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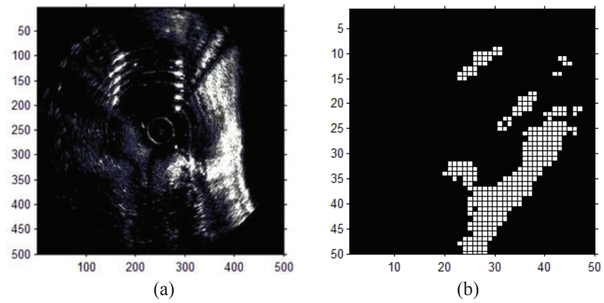

Fig. 3. Environment information collection with sonar image

must be closely combined with the underwater environment so that it can real-time reflect the environment changes to the neural network activity value. However, the environmental information is usually continuous, while the neural network is discretized. Therefore, it is necessary to discretize the underwater environment and establish a grid map, as shown in Fig. 4. Grid map is abstract representation of underwater environment [21-22], and the AUV working environment is decomposed into the same cell size called grid, where each grid is occupied by obstacle or free space [23], as shown in Fig. 4(a). Black grid represents an obstacle while white grid is free space. Thus the corresponding neural network of the grid map can be established, namely black neurons is obstacles in grid map and white neurons correspond to free space as shown in Fig. 4.

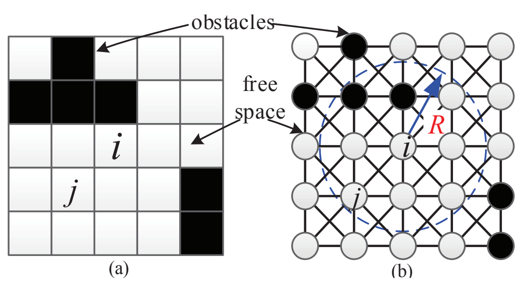

Fig. 4. The correspondence between 2-d underwater environment and the neural network (a) The grid map (b) The corresponding neural network

III. Single AUV Complete Coverage Path Planning Algorithm Based on GBNN Algorithm

In this section, a new method for single AUV full coverage path planning based on GBNN algorithm is proposed and will be extended to multi-AUV condition in the next section. GBNN algorithm is based on the work of biological inspired neural network algorithm [17] and improves the shortcomings like algorithm complexity and large amount of calculation etc. in order to make AUV path planning more efficiency.

A. Brief Introduction of Bioinspired Neural Network Algorithm

Yang proposed the bio-inspired neural network algorithm and applied it to the full coverage path planning of mobile robot. One thing that should be mentioned is that though the method is called neural network, but it is quite different compared with traditional neural networks. For the traditional neural network, it usually contains the input layer, output layer and hidden layer where it contains neuronal transfer functions. While for bio-inspired neural network, there is no such function. Indeed, it is sometimes called bio-inspired neurodynamic model. The state space of the topologically organized neural network is the 2-D Cartesian workspace of an AUV. The dynamics of each neuron is characterized by a shunting equation derived from Hodgkin and Huxley's membrane model for a biological neural system. There are only local lateral connections among neurons [17].

The dynamic characteristics of the neural network are described in the following formula:

$$\begin{aligned}\frac{du_k}{dt} &= -Au_k + (B - u_k)\left([I_k]^+ + \sum_{i=1}^{M} w_{kl}[u_l]^+\right) \\ &\quad - (D + u_k)\,[I_k]^- \end{aligned} \tag{1}$$

where u_k is the neural activity of k-th neuron, u_l is the active value of its adjacent neurons l; M is the neuron number adjacent to neuron k; I_k is the external input of neuron k where $I_k > 0$ represents external excitatory signals, $I_k < 0$ represents external inhibitory signal; w_{kl} is the connection weight between the ith neuron and jth neuron and is defined as:

$$w_{kl} = f\left(|q_k - q_l|\right) = \begin{cases} \mu/|q_k - q_l|, \ 0 < |q_k - q_l| < R_d \\ 0, \ |q_k - q_l| \geq R_d \end{cases} \tag{2}$$

For more details, the reader may be referred to [23]. But the problem is that though there is no learning process, due to the complex calculation, it has the problem of large amount calculation, long time and low efficiency path planning.

B. The Basic Principle of GBNN Algorithm

To solve the disadvantages of biological inspired neural network algorithm, inspired by two-layer feedforward neural networks algorithm proposed by Glasius [16-17], Luo et al. proposed an improved method called GBNN algorithm and apply it to the path planning of mobile robot [18]. Compared with differential equation of biological inspired algorithm, the GBNN method with difference equation can not only get the benefit numerous learning and adaptive, but also effectively reduce the amount of calculation and improve the operation speed of the algorithm, which can improve the efficiency of AUV path planning. Next, the GBNN algorithm model will be introduced first.

GBNN algorithm is a discrete-time Hopfield-type neural network, and the corresponding neural network model has been given in Fig. 4(b) where the idea is basically the same as bio-inspired neural network algorithm, and the difference mainly lies in the neural activity value calculation. Among them, each circle indicates one neuron, and there is a straight line/diagonal connection relationship between each neuron and its neighboring neurons around. The neuron activity values can be passed to each other through these connections, and

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the dynamic characteristics of individual neuron activity are described by the following law.

$$x_i\left(t+1\right)=g\left(\sum_{j=1}^{M}W_{ij}[x_j\left(t\right)]^{+}+I_i\right) \tag{3}$$

where the transfer function is chosen as

$$g\left(x\right)=\begin{cases}-1,\ x<0\\ \beta x,\ 0\leq x<1,\ \beta>0\\ 1,\ x\geq 1\end{cases} \tag{4}$$

In Eq. (3), $x_i(t+1)$ represents the neural activity of the ith neuron at $t+1$; $x_j(t)$ is the neural activity of the jth neuron at t, and the jth neuron is laterally connected with ith neuron. $[x_j(t)]^{+} = max[x_j(t), 0]$ represents that only the positive neural activities can influence other neurons and propagate globally, but the negative neural activities cannot propagate outward and only have local effect; M is the number of neural connections of the ith neuron to its neighboring neurons within receptive filed R; W_{ij} is the connection weight between the ith neuron and jth neuron and is defined as

$$W_{ij}=\begin{cases}e^{-\alpha|i-j|^2},\ 0<|i-j|\leq R\\ 0,\ |i-j|>R\end{cases} \tag{5}$$

where $|i-j|$ is the Euclidean distance between ith neuron and jth neuron, α and R are all positive constants. I_i is the external input of the ith neuron. In the complete coverage path planning, the state of each grid can be classified into three types: uncovered area, obstacle, or covered area. Therefore, the external input I_i can be defined as:

$$I_i=\begin{cases}+E, & \text{if it is an uncovered area}\\ -E, & \text{if it is an obstacle area}\\ 0, & \text{if it is an covered area}\end{cases} \tag{6}$$

In the grid map, the corresponding neuron external inputs for the uncovered area include the external excitatory input $I_i = +E$ and sum of excitatory inputs from the lateral neural connections $\sum_{j=1}^{M} W_{ij}[x_j\left(t\right)]^{+}$, where $\sum_{j=1}^{M} W_{ij}[x_j\left(t\right)]^{+} + E \gg 1$. Therefore, the neural activity of the uncovered neuron is 1. If the ith neuron is obstacle, its external input includes the external inhibitory input $I_i = -E$ and the sum of excitatory inputs from the lateral neural connections: $\sum_{j=1}^{M} W_{ij}[x_j(t)]^{+}$, and $\sum_{j=1}^{M} W_{ij}[x_j(t)]^{+} - E < 0$, which guarantees that the neural activity of the obstacle area is -1. If the ith neuron is covered, its external input $I_i = 0$ and the excitatory inputs are only from the sum of excitatory inputs from the lateral neural connections.

In a word, the core idea of complete coverage is driven by the propagation of neural activity values. The excitatory input results from uncovered area and lateral neural connections, while the inhibitory input results from obstacles. The dynamics of the kth neuron in the neural network is characterized by formula (3). The AUV moves with the path selection of maximum neural activity value.

Fig. 5 is the activity value distribution of the neural network. Under the action of external excitation signal with uncovered areas, the active value maintains in peak state. For the obstacles, under the action of external inhibit signal, the active value keep the valley. In addition, the external input of the neuron of covered area is zero and the active value will decay from 1 and 0 continually. To sum up, in GBNN algorithm, the active output value of the corresponding neurons in the uncovered area has a maximum value 1, and can be transmitted through the neuron connections to ”attract” AUV. The neuron activity value in the obstacle area will remain the minimum and only have local effects, and it will not be transmitted outward to avoid the collision of AUV. For covered area, all the external excitation input corresponding to neurons return 0, and will no longer be able to ”attract” AUV heading to.

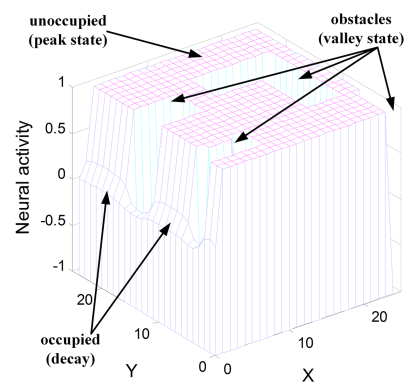

Fig. 5. Distribution of neural network activity values

C. Full coverage path planning algorithm based on GBNN for single AUV

In this section, single AUV complete coverage path planning algorithm is introduced. First of all, according to the given two-dimensional grid map, a counterpart neural network can be established according to the state of grid map (uncovered, covered, obstacles). Initialize the neural network and update the neural network activity value dynamically using GBNN algorithm, and AUV choose the next position according to the path selection strategy. Repeat the process until the whole water space is covered. In addition, when AUV is on the edge of certain obstacles, the obstacle avoidance path of AUV can be optimized by optimization template given below. Fig. 6 shows the flowchart of single AUV full coverage path planning algorithm based on GBNN algorithm.

1) AUV Path Selection Strategy: Due to the power limit, when AUV performs coverage tasks, it should sail the shortest path and make turns as fewer as possible to avoid consuming excessive energy. Thus, the previous AUV sailing direction must be taken into account in the complete coverage path planning. For a given current AUV location P_c, the next AUV location P_n is defined as [24]:

$$P_n \Leftarrow x_{P_n} = max\left\{x_k + cy_k,\ k=1,2,\ \dots,m\right\} \tag{7}$$

where c is a positive constant; x_k is neural activity of the kth neuron; m is the number of neighboring neurons of the P_cth neuron; y_k is a monotonically increasing function which is

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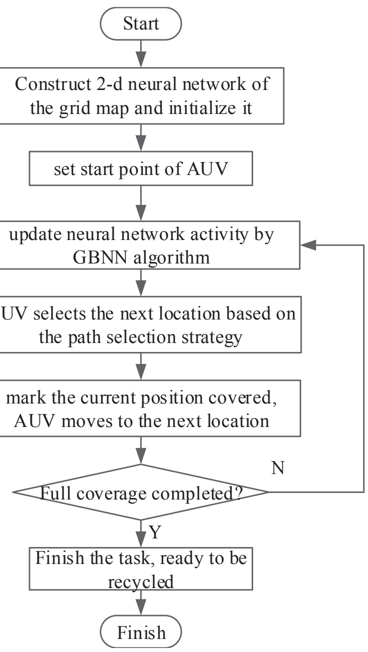

Fig. 6. The flowchart of single AUV full coverage path planning based on GBNN algorithm

related with the included angle $\Delta\varphi_k$ between the current and next AUV sailing directions and given as

$$y_k = 1 - \frac{\Delta\varphi_k}{\pi} \tag{8}$$

$$\begin{aligned} \Delta\varphi_k = |\varphi_k - \varphi_c| = |a\tan 2(y_{P_k} - y_{P_c},\ x_{P_k} - x_{P_c}) \\ -a\tan 2(y_{P_c} - y_{P_p}, x_{P_c} - x_{P_p})| \end{aligned} \tag{9}$$

where (x_{P_p}, y_{P_p}), (x_{P_c}, y_{P_c}) and (x_{P_k}, y_{P_k}) represents the coordinates of last step position P_p, current position P_c, and next possible position P_k in the grid map, as shown in Fig. 7.

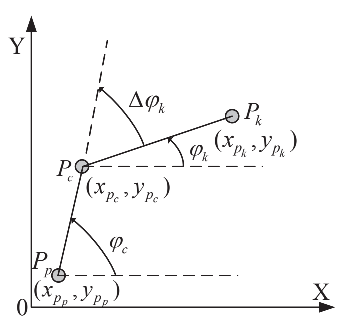

Fig. 7. The sailing direction of AUV

In addition, in the process of AUV navigation, sometimes it may trap into a deadlock area, where the area around is borders, or covered area, or obstacles. It needs to reset the parameter c, namely, without consideration of AUV heading problem at this moment, and choose paths only according to the size of the peripheral neuron activity values, so that the AUV can escape the dead zone along the shorter path as early as possible to the recently uncovered area.

2) Template Optimization of the Obstacle Edge Path: If AUV is simply relying on GBNN algorithm to plan full coverage path, then it may have a chaotic and repetitive situation when avoiding some obstacles. For this problem, some optimization template is designed for AUV complete coverage path planning, and the overall trend of complete coverage of AUV detection is from top to bottom, from left to right. The final five path optimization templates to optimize the AUV in some obstacles on the edge of the path are shown in Fig. 8. Therefore, if there are obstacles found around, check if the current position matches some kind of path optimization template. If matched, depending on the corresponding template rule in Fig. 8, try to optimize the AUV path with obstacle avoidance in order to reduce repetition and disorder.

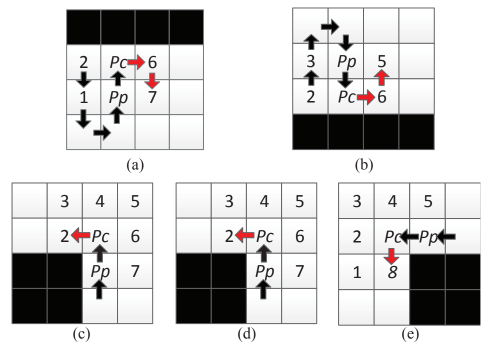

Fig. 8. Optimized template of AUV obstacle avoidance (a) obstacle above (b) obstacle below (c) obstacle at bottom left (4) obstacle at upper left (e) obstacle at the bottom right

IV. Multi-AUVs Complete Coverage Path Planning for Discrete and Centralized Programming Based on GBNN Algorithm

Since AUV can only carry limited energy, one single AUV is usually only able to perform small scope coverage of limited water task. For a wide range complete coverage operation like underwater environment detection, exploration, it has been beyond one single AUVs working ability. Therefore, GBNN algorithm is mainly applied to deal with multi-AUV cooperative complete coverage problem, and discrete planning and centralized programming is put forward respectively.

A. Multi-AUVs Complete Coverage Path Planning Based on GBNN and Discrete Programming

In this section, a multi-AUV co-coverage path planning algorithm based on GBNN and discrete programming is proposed for multi-AUV cooperative full coverage. In the proposed algorithm, the cooperation strategy between all the AUVs are designed as: all the AUVs share environment information, and each AUV considers the other robots as moving obstacles within the work area, so as to make the multi-AUVs be implemented with cooperation without collision for the whole specified underwater space. Among them, all AUVs share environmental information which can ensure that each AUV does not repeatedly cover areas that have been covered by other AUV. In addition, each AUV regards as other AUVs

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in the region as moving obstacles, ensuring that no collisions occur between multiple AUVs.

The following will give a specific algorithm flow. First of all, set up the grid map to represent the working environment. Secondly, construct the neural networks of the grid map, where each AUV corresponds to a neural network. And if there is multiple N AUVs, N neural network should be established. Then, the various neural networks are initialized. Since in multi-AUV system, each AUV will treat other AUVs in the region as moving obstacles, so the external input signal of neurons in the neural network should be redefined: The external input of the corresponding neurons in the obstacle area and other AUV is the inhibitory signal to avoid the collision between AUV and the obstacle, AUV and AUV while other definition is the same. Finally, update the activity value of neural network by GBNN algorithm.

B. Multi-AUVs Complete Coverage Path Planning Based on GBNN and Centralized Programming

In some cases, each AUV is only responsible for its own assigned area like the guardians in the museum. Therefore, it will focus on solving the problem of multi-AUV cooperative full coverage planning with the combination of centralized planning and GBNN algorithm. The specific ideas are as follows. First of all, divide the water space region into several non-overlapping sub regions and each AUV occupies for one area. Then, each AUV plans their respective subdomain full coverage path tasks by GBNN algorithm. In the end, when all the AUVs are completely traverse their respective area, they complete the entire coverage task with the division of labor cooperation. Therefore, the division of mission area for each AUV is the first problem that needs to be solved. At present, Voronoi tessellation is one of the most commonly used domain decomposition method [25-26]. For Voronoi tessellation $V(P) = \{V_1, \ldots, V_n\}$, any of the sub area can be represented as:

$$V_i = \{q \in Q \mid \| q - p_i \| \leq \| q - p_j \|, \forall i \neq j\} \quad (10)$$

where Q is a collection of polygons. Fig. 9 is a Voronoi diagram generated by five random points which leads to the unequal distribution of resources. If each point is assumed to be an AUV, then each task region is assigned to an AUV, and will be responsible for the completion of its own area coverage. It will cause severe unbalance of the work load for each AUV.

In view of this, a CVT (Centroidal Voronoi Tessellation) distribution method proposed by Cortes [27] is introduced to divide the area. It is a special kind of Voronoi Tessellation, where the points that constitute the CVT distribution are not only the initial point to generate Voronoi diagram, but also the center of mass for each Voronoi regions V_i. The distribution of the CVT transmission can be controlled by movement from the initial points to the center of mass of the respective sub area V_i gradually. The definition of center of mass is [28]:

$$C_{V_i} = \frac{\int_{V_i} q\phi(q)\, dq}{\int_{V_i} \phi(q)\, dq} \quad (11)$$

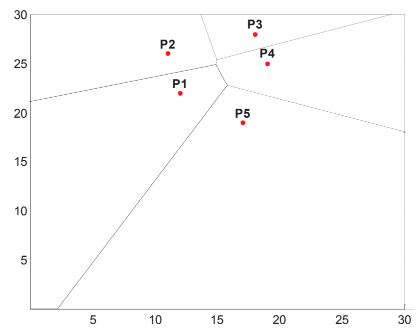

Fig. 9. Voronoi tessellation

where q is the random point of the sub region, $\phi(q)$ is the regional density function which is mainly used to describe the importance of the area. When the regional density is uniform, the initial points can be distributed evenly in the plane, and the Voronoi diagram with evenly division can be obtained, namely the CVT distribution [29].

Fig. 10 is the CVT partition generated by 5 points. It is clear to see that the CVT division has a more balanced area distribution than Voronoi division with of each region size approximate, and that makes it more suitable for cooperative coverage with a number of AUV of same performance in division of labor.

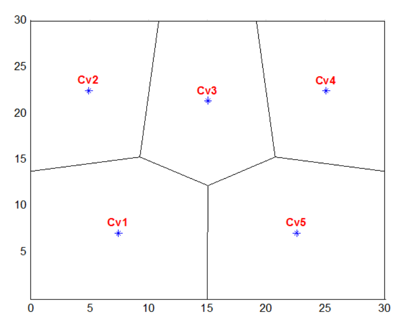

Fig. 10. CVT division

In order to obtain uniform CVT distribution, the key is to calculate the centroid of each area. The given equation (11) is relatively complicated with the slow calculation speed. The method of solving convex polygon centroid point value with the uniform density is applied to solve the problem. Set V_i a convex polygon with N_i vertices, where each vertex can be represented as $\{(x_0, y_0), \ldots, (x_{N_i-1}, y_{N_i-1})\}$, so the center of mass can be expressed as:

$$\begin{aligned} C_{V_{i,x}} &= \frac{1}{6M_{V_i}} \sum_{k=0}^{N_i-1} (x_k + x_{k+1})(x_k y_{k+1} - x_{k+1} y_k) \\ C_{V_{i,y}} &= \frac{1}{6M_{V_i}} \sum_{k=0}^{N_i-1} (y_k + y_{k+1})(x_k y_{k+1} - x_{k+1} y_k) \end{aligned} \quad (12)$$

where $V_N = V_0$, M_{V_i} is the mass of the polygon. The specific form is defined as follows:

$$M_{V_i} = \frac{1}{2} \sum_{k=0}^{N_i-1} (x_k y_{k+1} - x_{k+1} y_k) \quad (13)$$

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When a stable CVT is obtained, the entire working space needs to be discretized, and the grid map and corresponding neural network are constructed and initialized. The AUVs will start from the centroid point of their own region, and plan their respective full coverage path to reach collaborative full coverage of the entire region. A detailed process flow for multi-AUV co-coverage algorithm based on GBNN and centralized planning is given as follows:

Step 1: Put N AUVs randomly in a uniform density task area, and generate the initial Voronoi diagram $\{V_i\}_{i=1}^{N}$ according to the AUV positions.

Step 2: Calculate the center of mass $\{C_{V_i}\}_{i=1}^{N}$ of each sub region using equation (13).

Step 3: AUVs move to centroid area position. If the difference between the new centroid point and the centroid point calculated in the last iteration is less than a small integer σ, namely, $|C_{V_{i,x}^j} - C_{V_{i,x}^{j-1}}| \leq \sigma$ and $|C_{V_{i,y}^j} - C_{V_{i,y}^{j-1}}| \leq \sigma$. Then, the iteration ends and an evenly distributed CVT division is obtained. If not satisfied, go back to step 2.

Step 4: Discrete the entire mission area, and construct the overall grid map.

Step 5: Construct neural networks corresponding to the grid map where each AUV corresponds to a neural network.

Step 6: Initialize the N neural network. The process is basically the same as single AUV coverage. For each of the AUV, other AUV mission areas are all treated as obstacles, to ensure that each AUV are only covering their respective area task, and will not cover other AUVs mission area.

Step 7: Update neural network activity values. Each AUV plans the corresponding area coverage path according to their corresponding dynamic characteristics of the neural network with path selection strategy, until completely cover their respective task areas.

Step 8: All AUVs complete coverage of the sub region, which means the complete coverage of the entire mission area.

V. Simulation and Discussion

In this section, the MATLAB platform is used to conduct the simulation experiment where the underwater working environment is represented by grid maps. Among them, all AUVs are treated as particle, and the parameters in GBNN algorithm are set as: $\beta = 0.6$, $\alpha = 2$, the external excitation input $E = 100$, the radius of side connection area $R = \sqrt{2}$, the parameters for path selection strategy $c = 0.5$.

A. Multi-AUVs Complete Coverage Path Planning Based on GBNN and Centralized Planning

1) Multi-AUV cooperative full coverage path planning in 2d static environment: In this section, the experimental results of multi-AUVs in the static underwater environment are presented. As shown in Fig. 11, there exist various static obstacles with different shapes and sizes in the underwater space. AUV1 starts from the top left corner grid S1 (1, 30), and AUV2 starts from the lower left corner grid S2 (1, 1) at the same time to begin the detecting coverage work on the same water space.

Fig. 10 shows the active values distribution of two AUVs' corresponding neural networks. As can be seen from the figure, both AUV will treat each other as moving obstacles and share environmental information. For example, Figure 12(a) gives the neuron network activity value distribution of AUV1, while the neuron activity value in the location of AUV2 is -1. Namely for AUV1, AUV2 is a regarded as moving obstacle. In Figure 12(b), the activity value of the neurons in AUV1 is also -1, which means that AUV2 also regards as AUV1 as an obstacle. In addition, all the neuron activity values corresponding to the uncovered areas are 1 and all neuron activity values of obstacles are -1. Meanwhile, all the neuron activity values of covered areas by two AUVs begin to decay from 1 which illustrate that both AUVs share environment information.

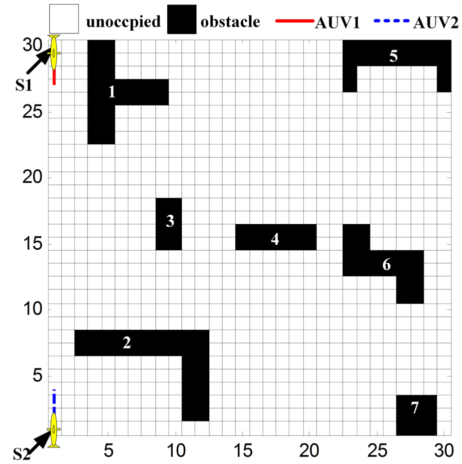

Fig. 11. The initial grid map of a two-dimensional static environment

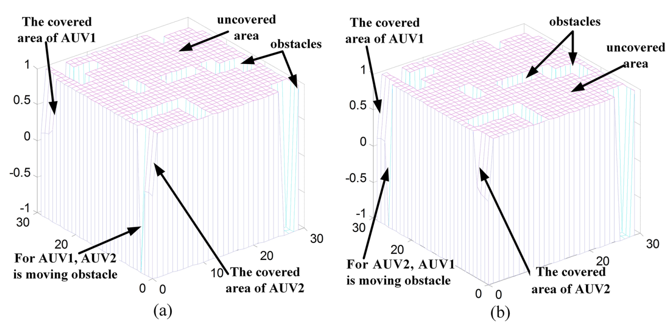

Fig. 12. The corresponding neural network activity value distribution diagram of two AUVs (a) The corresponding neural network activity value of AUV1 (b) The corresponding neural network active value of AUV2

In the process of sailing, AUV1 and AUV2 plan their full coverage path based on the dynamic activity value with path choice strategy and path optimization template. Among them, each AUV shares environmental information and sees each other as a moving obstacle, which can effectively avoid collision between AUV and overlapping coverage.

For example, in Fig. 13(a), when AUV1 sails to the grid (11, 30) and AUV2 sails to (11, 29), the two AUVs encounter each other. At this time, both AUVs find the environment changes in front of them, and then plan their path to avoid each other according to their respective dynamic characteristics of

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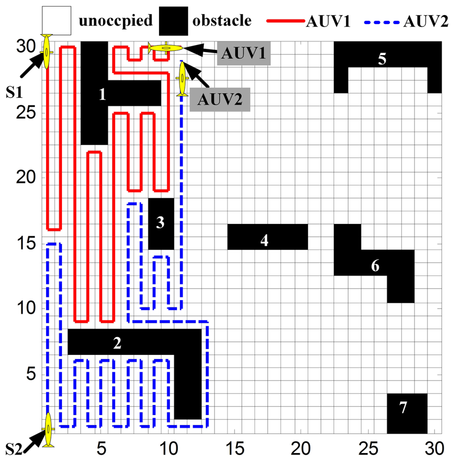
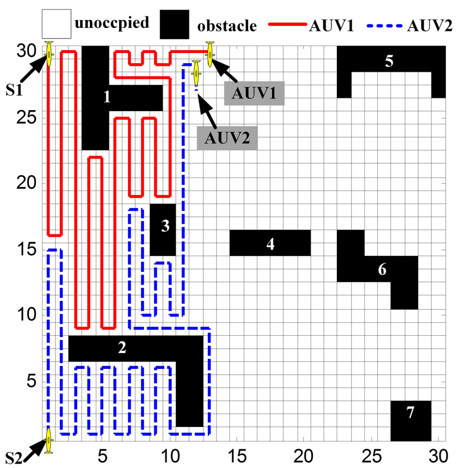


(a)



(b)

Fig. 13. The condition when two AUV encounters (a) AUV1 and AUV2 encounters (b) AUV1 and AUV2 avoid each other's paths

the neural network with the combination of path optimization templates. As shown in Fig. 13(b), AUV1 sails two grids to the right and begins to sail down. At the same time, AUV2 navigates to one grid right, and begins to sail down. That is to say, no collision happens between two AUVs, and avoids each other successfully.

In Fig. 12, when AUV1 arrives in F1 (30, 26) and AUV2 arrives at F2 (30, 1), the whole water space has been covered without any omissions, namely two AUVs complete the full coverage cooperation task, and each AUV does not visit the area that has been traversed by other AUVs.

As stated in the former section, for the bio-inspired neural network method, when AUV traps into the dead lock, it needs some step time to escape. While for GBNN method, it can solve this problem very well. When AUV1 sails to the grid D1 (22,30), it falls into the dead zone. And at this point, the neuron value from uncovered areas have spread through the lateral connection relationship between neurons to dead zones around the grid D1, enabling the surrounding neuron activity values greater than the activity value of dead zone D1. Therefore, AUV1 can rapidly plan a point-to-point path and do not make any stops to escape from the dead zone. Similarly, when AUV2 falls into the dead zone D2 (26, 1), it can also quickly escape from the dead zone to the most recent uncovered grid.

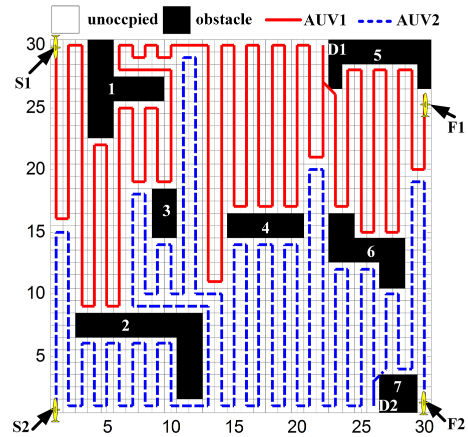


Fig. 14. Two AUV complete coverage the same water space with cooperation in a static environment

In addition, Figure 15 shows complete coverage path planning result with cooperation of three AUVs. As can be seen, three AUVs perform their duties and plan the coverage path orderly. The coverage area can be separated with nature, and complete the whole coverage task with cooperation without any collision, omission and repeat coverage. Figure 16 shows the complete coverage path planning result under a new environment with small scale to show the robustness of the proposed method. Two AUVs and three AUVs cooperative coverage are both conducted with a satisfied performance.

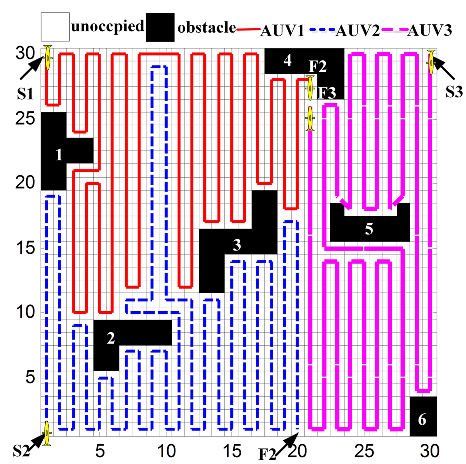


Fig. 15. Three AUVs complete coverage detection tasks in static environment

B. Multi-AUVs Complete coverage path planning in dynamic environment

In the underwater environment, AUV should not only be able to avoid all static obstacles, but also be able to avoid the dynamic obstacles autonomously until completes the full

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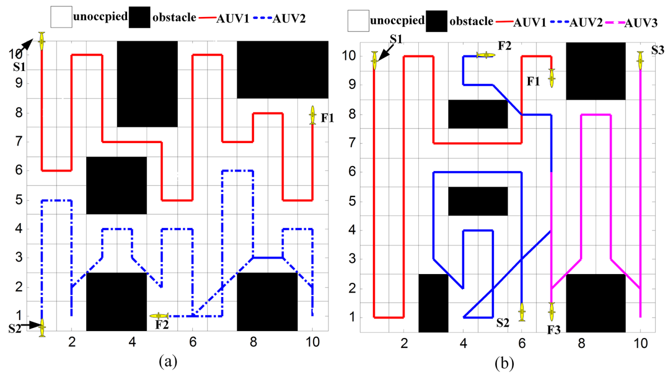

Fig. 16. Multi-AUVs complete coverage detection tasks in small scale environment

coverage task. As shown in Fig. 17, multiple irregular obstacles are distributed, and the task area is dynamically variable, i.e. the distribution of obstacles can be changed indefinitely. AUV1 and AUV2 start to cover the task waters. During the voyage, both AUVs reach fully coverage together by the dynamic characteristics of the corresponding neural networks.

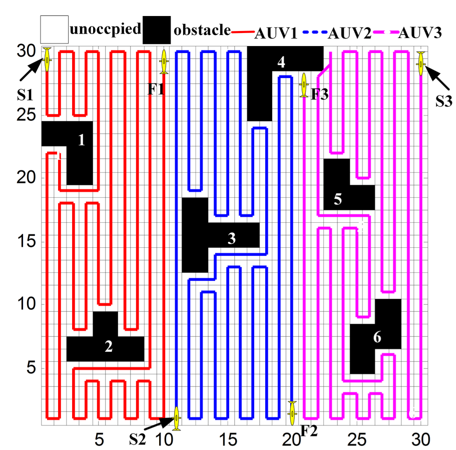

Fig. 17. The initial grid map of the dynamic environment

As shown in Figure 18(a), when a rectangular shape obstacle 8 suddenly appears between two AUVs, the active values change from 1 to -1 at the same time. At this point, both AUV can plan reasonable path according to the neural network activity changes and path optimization templates, and then continue to implement the whole task, as shown in Fig. 18(b).

In Figure 18(c), when AUV1 reaches F1(30, 30), it completes the full coverage of the upper area. At this moment, AUV2 has sailed to the grid (30, 19), and is also about to complete the coverage task of the lower area. However, at this time, the dynamic obstacle 8 is detected to be moving out of the working area, and the previously occupied area becomes a new uncovered area. Since the current AUV2 is still in the line of duty while AUV1 has complete the task and closer to the new uncovered areas. Hence, AUV1 will start again from F1, and plan the point-to-point routes to the area only according to the neuron activity value. As shown in Fig. 18(d), when AUV1 reaches the grid (18, 18), the additional coverage of the new uncovered area is completed, and the two AUVs complete the full coverage task of the mission area through cooperation.

From the above simulation experiments, it shows that multi-AUVs can finish designated water space coverage in a dynamic environment. And the AUVs are able to plan reasonable obstacle avoidance path for the sudden obstacles. In addition, when there is an uncovered new area, multi-AUVs system can also realize reasonable coverage tasks for the new area according to the real-time path planning situation.

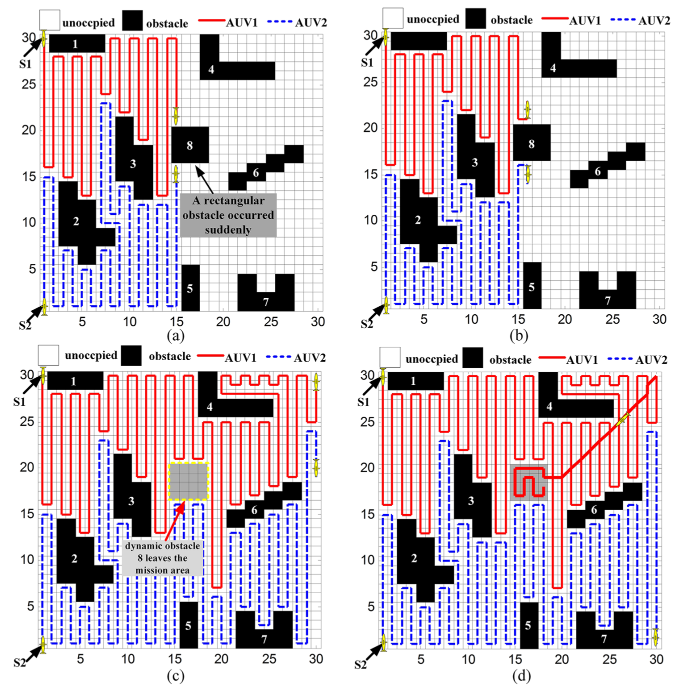

Fig. 18. The results of the complete coverage path of the two AUVs in dynamic water space (a) A rectangular obstacle suddenly appears between AUV1 and AUV2 (b) AUV1 and AUV2 avoid dynamic obstacle 8 (c) Dynamic obstacle 8 removes the working area (d) Two AUVs complete full coverage of the working water space with cooperation

Some readers may raise the question that for the underwater environment, it is three-dimensional space, but the former section is mainly focused on the horizontal plane. In 3D underwater environment, the AUV coverage work mainly refers to the following case. It is infeasible to visit each grid in the whole 3D map. The solution is task decomposition to different depth of underwater plane. The AUV will traverse each task plane with different depths to realize a complete coverage of the whole water space. In each depth plane, the full coverage solution is just the same as in former section. A simulation experiment is conducted to confirm the idea in Fig. 18 where the underwater space is $25 \times 25 \times 25$. The AUV starts from the initial position S(20,20,25) and complete the full coverage detection task at three depth levels $z = 20$, $z = 12$, $z = 4$ in turn.

VI. Multi-AUVs Complete Coverage Path Planning Based on GBNN and Centralized Planning

The simulation environment is basically the same as section A. As shown in Fig. 20, three AUVs are randomly distributed

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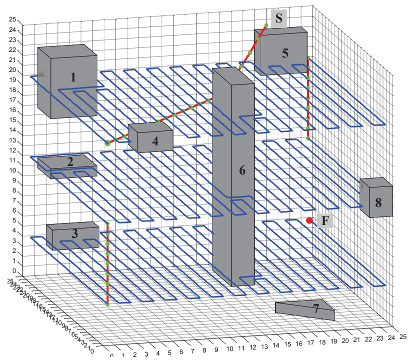

Fig. 19. Three dimensional complete coverage

in the unobstructed task water, and the initial Voronoi diagram is obtained according to the initial position of each AUV. Each AUV occupies one area, but due to the large difference of each sub-region, CVT division is required. Then, the center of mass $\{C_{V_i^1}\}_{i=1}^3$ for each sub region is calculated and Voronoi diagram is divided again according to the centroid set, and CVT distribution is obtained for the first iteration. Next, the centroid for the new obtained Voronoi region $\{C_{V_i^2}\}_{i=1}^3$ is calculated, and Voronoi diagram is divided again according to the mass center point. And that cycle repeats until the difference of the absolute value for each Voronoi region V_i mass center in the two successive is less than or equal to 0.1. In Fig. 21, the 1st, 2th and 5th iteration result and final

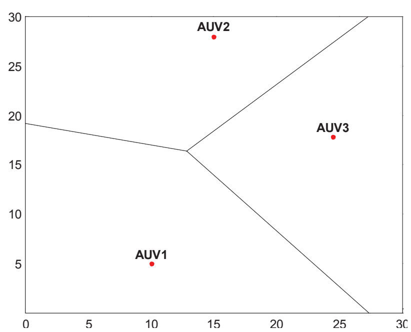

Fig. 20. The initial Voronoi diagram

CVT results are given respectively. It can be seen from the diagram, in the process of iteration, the distribution of three AUVs becomes uniform, and eventually form a stable CVT distribution where each AUV is in the mass center of the region. Compared with the Voronoi diagram in Fig. 20, the regional division is significantly more uniform, thus makes each AUV workload close to realize reasonable resources allocation.

Then, the entire task area is discretized, and the grid map is constructed as shown in Fig. 22 where each grid size is 11. In addition, for the grid that is at the boundary of the region, determine its assigned area according to the size of the area it occupies in each sub region. For example, the grid (15,15) in Fig. 22 occupies a large space in the area of AUV1, so it belongs to the AUV1s task sub region.

Next, build the neural networks and initialize. Take AUV1 for example. Figure 23 gives the active value distribution of

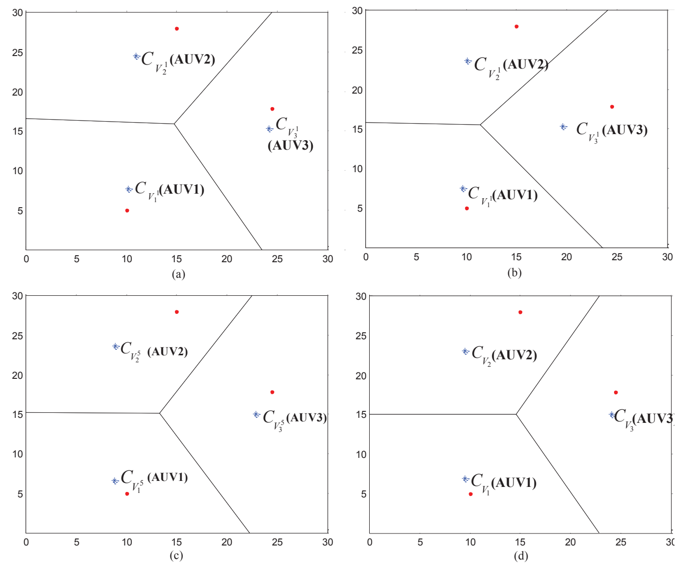

Fig. 21. The iterative process of CVT division (a) CVT division in the 1st iteration (b) CVT division in the 2th iteration (c) CVT division in the 5th iteration (d) Stable and uniform CVT division

AUV1. The neuron activity values are 1 for the sub region not covered by AUV1, and can spread globally. And the rest of task area is under the effect of external inhibitory signal where the neuron active values are -1. AUV1 will take the region as obstacles and avoid automatically in the process of path planning, thus guaranteeing AUV1 won't cover the non-mission area. Similarly, AUV2, AUV3 would also not cover the non-task area.

Finally, each AUV will plan their sub area tasks until the sub region is completely covered according to their corresponding active output values respectively with path choice strategy and obstacle avoidance path optimization template for the principle. As shown in Figure 24, when AUV1, AUV2, AUV3 sails to the grid (1, 1), (23, 30), (16, 17), the entire respective sub region coverage task has been completed, namely three AUVs reach the full coverage of the whole work space with cooperation.

To sum up, in this section, the specific task area can be divided into several non-overlapping, uniform areas according to the number of AUVs with the proposed algorithm. And each AUV occupies one region and reach full coverage planning according to their corresponding sub neural network dynamic characteristics. The cooperative full coverage of the whole work space can be achieved eventually. In addition, each AUV performs its own duty, thus there will be no collision between AUVs or repeated coverage of other AUV task area.

At the end of the simulation experiment, a simple comparison study with the proposed GBNN method and bio-inspired neural network method (hereinafter referred to as BINN method) is conducted to show the efficient performance. Fig. 25 is the simulation result with the above two methods. AUV starts at grid S(1,30) to cover the whole area. In the process of AUV navigation, there exists five dead zone grid D1(11,21), D2(16,30), D3(26,23), D4(30,30) and D5(28,14). By contrast of the two figures, the complete coverage before dead zone

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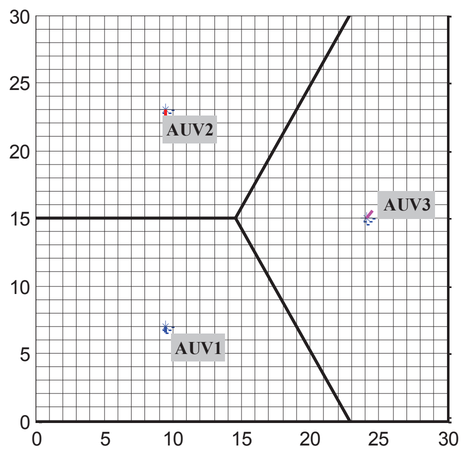

Fig. 22. The initial grid map

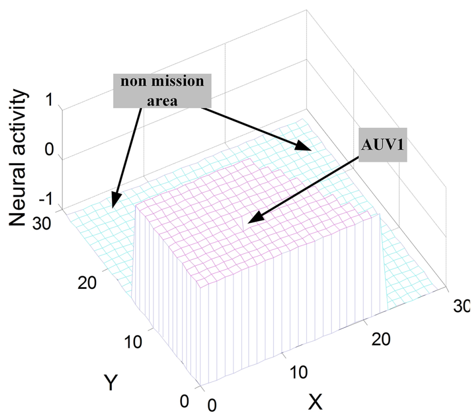

Fig. 23. The distribution neural network active value of AUV1

TABLE I
COMPLETE COVERAGE COMPARISON WITH GBNN AND BINN METHOD

algorithm	BINN method	GBNN method
coverage of the region	100%	100%
time complexity /s	2894	136
total voyage steps of AUV	665	565
repeated coverage steps	164	64
repeated coverage in the region	24.7%	11.3%
number of AUV course changes	35	26

is no difference, but escape path is different where the AUV escape path in dead area of Fig. 25(b) is significantly longer and more clutter. In addition, in order to further prove the superiority of GBNN algorithm, Table I is listed in comparison under the following aspects: (1) coverage of the region; (2) time complexity; (3) repeated coverage in the region; (4) total voyage steps of AUV; (5) the number of AUV course changes to check whether it is suitable for AUV complete coverage. From the quantitative result, it can be easy to conclude that though both methods can reach 100% coverage of the whole working space, but the performance with GBNN method is better in any respect than BINN method.

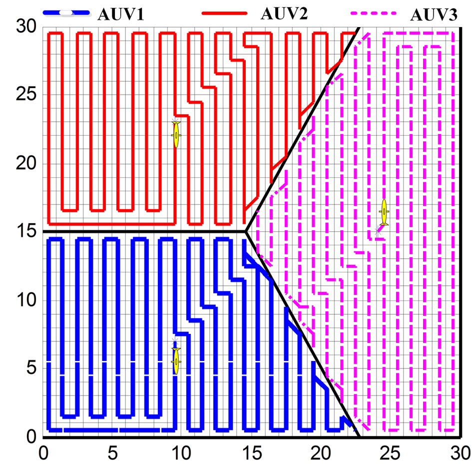

Fig. 24. Three AUVs complete coverage of the whole space with specialization and cooperation

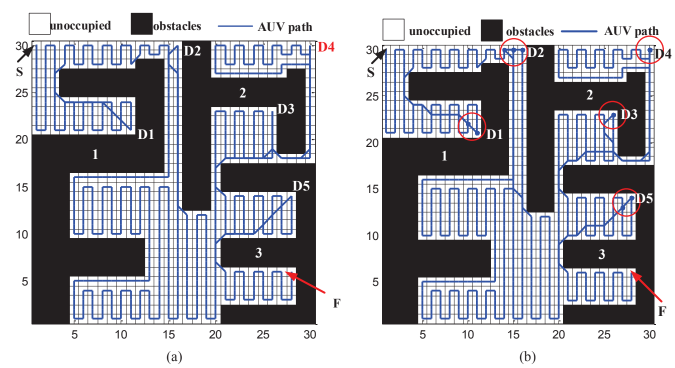

Fig. 25. Simulation result with different complete coverage method (a) GBNN method (b) BINN method

VII. CONCLUSION

In this paper, a new strategy for multi-AUVs cooperative full coverage path planning methods based on GBNN algorithm is proposed. In the GBNN and discrete programming AUV cooperative full coverage algorithm, all the AUVs share environment information, and each AUV will consider other AUVs in the area as moving obstacles, which can guarantee AUV covering the detection task in the designated water space without collision. In full coverage cooperative algorithm with GBNN and centralized programming, the CVT distribution is given for multi-AUVs to divide non-overlapping region, uniform size task sequence. Each AUV is only responsible for the planning of its sub area. When the AUV completely traverse each task sequence region, namely complete coverage of the entire work area detection task is realized with the division of labor cooperation. Finally, simulation experiment results show that, through the proposed two kinds of algorithm, multi-AUV can plan reasonable and collision-free coverage path and reach full coverage on the same task area with division of labor and cooperation.

REFERENCES

[1] Xiang X, Yu C, Zhang Q. Robust fuzzy 3D path following for autonomous underwater vehicle subject to uncertainties, Computers & Operations

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Research, 2016, 84: 165-177.
[2] Xiang X, Lapierre L, Jouvencel B. Smooth transition of AUV motion control: From fully-actuated to under-actuated configuration, Robotics & Autonomous Systems, 2015, 67: 14-22.
[3] Xiang X, Yu C, Zhang Q. On intelligent risk analysis and critical decision of underwater robotic vehicle, Ocean Engineering, 2017, 140:453-465.
[4] Portugal D, Rui P R. Cooperative multi-robot patrol with Bayesian learning. Autonomous Robots, 2016, 40(5):929-953.
[5] Sun B, Zhu D, Yang S X, An optimized fuzzy control algorithm for three-dimensional AUV path planning, International Journal of Fuzzy Systems, 2017, DOI: 10.1007/s40815-017-0403-1.
[6] Xiang X, Yu C, Lapierre L, et al. Survey on Fuzzy-Logic-Based Guidance and Control of Marine Surface Vehicles and Underwater Vehicles, International Journal of Fuzzy Systems, 2017, DOI: 10.1007/s40815-017-0401-3.
[7] Zhu D, Cao X, Sun B, Luo C, Biologically Inspired Self-Organizing Map Applied to Task Assignment and Path planning of an AUV System, IEEE Transactions on Cognitive and Developmental Systems, 2017, DOI: 10.1109/TCDS.2017.2727678.
[8] Xiang X, Liu C, Su H, Zhang Q. On decentralized adaptive full-order sliding mode control of multiple UAVs. ISA Transactions, 2017, 71: 196-205.
[9] Sipahioglu A, Kirlik G, Parlaktuna O. Energy constrained multi-robot sensor-based coverage path planning using capacitated arc routing approach. Robotics and Autonomous Systems, 2014, 74(3): 945-963.
[10] Janchiv A, Batsaikhan D, Kim G H. Complete coverage path planning for multi-robots based on. Proceedings of the 2011 11th International Conference on Control, Automation and Systems, 2011: 824-827.
[11] Rekleitis I, New A P, Rankin E S, Choset H. Efficient Boustrophedon multi-robot coverage: an algorithmic approach. Annals of Mathematics and Artificial Intelligence, 2008, 52(2): 109-142.
[12] Hazon N, Kaminka G A. On redundancy, efficiency, and robustness in coverage for multiple robots. Robotics and Autonomous Systems, 2008, 56(12): 1102-1114.
[13] Zheng X M, Koenig S. Robot coverage of terrain with non-uniform traversability. 2007 IEEE/RSJ International Conference on Intelligent Robots and Systems, 2007: 3757-3764.
[14] Kapanoglu M, Alikalfa M, Ozkan M. A pattern-based genetic algorithm for multi-robot coverage path planning minimizing completion time. Journal of Intelligent Manufacturing, 2012, 23(4): 1035-1045.
[15] Luo C M, Yang S M. A real-time cooperative sweeping strategy for multiple cleaning robots. Proceedings of the 2002 IEEE International Symposium on Intelligent Control, 2002: 660-665.
[16] Glasius R, Komoda A, Gielen S. A biologically inspired neural net for trajectory formation and obstacle avoidance. Biological Cybernetics, 1996, 74(6): 511-520.
[17] Glasius R, Komoda A, Gielen S. Neural network dynamics for path planning and obstacle avoidance. Neural Networks, 1995, 8(1), 125-133.
[18] Luo C, Gao J, Yi L M. A computationally efficient neural dynamics approach to trajectory planning of an intelligent vehicle. IEEE International Joint Conference on Neural Networks, 2014: 934-939.
[19] Yan M, Zhu D, Yang S X. Complete Coverage Path Planning in an Unknown Underwater Environment Based on D-S Data Fusion Real-Time Map Building. International Journal of Distributed Sensor Networks, 2012, 2012(9): 69-72.
[20] Yan M , Gao F, Qin X , Zhu D, Sonar-based local path planning for an AUV in large-scale underwater environments, Indian Journal of Geo Marine Sciences, 2017, 46(12), 2527-2535.
[21] Lingelbach F. Path planning using probabilistic cell decomposition. Stockholm, 2005.
[22] Jaillet L, Simeon T. Path deformation roadmaps: Compact graphs with useful cycles for motion planning. International Journal of Robotics Research, 2008, 27(11): 1175-1188.
[23] Yang S, Luo C. A neural network approach to complete coverage path planning. IEEE Transactions on Systems, Man, Cybernetics, Part B: Cybernetics, 2004, 34(1): 718-724.
[24] Luo C M, Yang S X, Mo H W, et al. Safety aware robot coverage motion planning with virtual-obstacle-based navigation. IEEE International Conference on Information & Automation, 2015: 2110-2115.
[25] Aurenhammer F. Voronoi diagrams-a survey of a fundamental geometric data structure. ACM Computing Surveys, 1991, 23(3): 345-405.
[26] Korman M, Mulzer W, Renssen A V, et al. TimeCspace trade-offs for triangulations and Voronoi diagrams. Computational Geometry, 2017, 9214:482-494.
[27] Cortes J, Martinez S, Karatas T, et al. Coverage control for mobile sensing networks. IEEE Transactions on Robotics and Automation, 2004, 20(2): 243-255.
[28] Gross D, Ehlers W, Wriggers P, et al. Center of Gravity, Center of Mass,Centroids. StaticsCFormulas and Problems. Springer Berlin Heidelberg, 2017.
[29] Zhao Q, Wang Y, Li Y. Voronoi tessellation-based regionalised segmentation for colour texture image. Iet Computer Vision, 2017, 10(7): 613-622.

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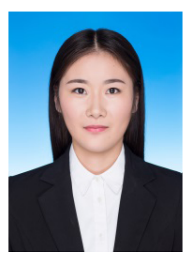

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