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A Novel Cooperative Hunting Algorithm for Inhomogeneous Multiple Autonomous Underwater Vehicles

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ABSTRACT Cooperative hunting of multi-autonomous underwater vehicle (AUV) is an important research topic. Current studies concentrate on AUVs with the same speed abilities and mostly do not consider their speed differences. In fact, AUVs in a hunting group are often of different types and possess different maximum sailing speeds. For inhomogeneous multi-AUV, a novel time competition mechanism is proposed to construct an efficient dynamic hunting alliance. Hunting team with AUVs possessing higher speed abilities is more suitable for the vast underwater environment. In the pursuing stage, AUV needs to act fast enough to avoid the escape of evader. To achieve a quick and accurate pursuit, a combined path planning approach is presented, which combines a Glasius bio-inspired neural network model and a belief function. Simulation experiments demonstrate the feasibility and efficiency of the proposed algorithm in the cooperative hunting of inhomogeneous multi-AUV under dynamic underwater environment with intelligent evaders and multi-obstacle.

INDEX TERMS Cooperative hunting, multi-AUV, GBNN, belief function, time competition mechanism.

I. INTRODUCTION

An autonomous underwater vehicle (AUV) is a robot that has intelligence and can complete tasks in the ocean by itself without the guidance of operator [1]. It has been widely used in both civilian areas (deep ocean investigation, maintenance of underwater devices and so on) and military field [2]–[5]. Since one single AUV has limited capacity, multi-AUV system has become a more and more hot topic. With the cooperation and coordination, the multi-AUV system can improve the capacity of a single AUV [6]–[8]. Researchers has finished many studies on multi-AUV system, including underwater cooperative search [9], [10], mine sweeping [11], [12], formation control [13], dynamic task assignment [14], [15], cooperative hunting [16]–[18] and so on. These studies on multi-AUV system are all interesting and worthy of studying, but cooperative hunting is more comprehensive. The comprehensive hunting problem includes three sub tasks: search of evaders, formation of a dynamic hunting alliance, and path planning until successful capture [19], [20].

There has been many researchers completing some remarkable studies on the overall hunting problem. Korf's approach [19] is a manually derived greedy strategy as well as a non-learning algorithm. The method uses a fitness function that makes each predator attracted by the prey and repelled from the closest predators. Denzinger *et al.* [21] proposed an approach combining near neighbor rule and genetic algorithm. They classify current status with the near neighbor rule, and then decide the optimal action with the genetic algorithm. The efficiency of the approach is demonstrated in the experiment of hunting game since it can guide the hunters with an optimal path. Nevertheless, it may fail in complex situations sometimes. Vidal *et al.* [22] presented two greedy hunting policies. Both simulation and experimental results of real pursuit-evasion games are achieved in the study. In paper [23], contract net protocol was presented to fulfill the hunting game. It is a distributive algorithm, but communication among pursuers in the hunting process may be too heavy.

Most of the researches mentioned above need much negotiation and calculation, which causes delays before the robot takes its first step to pursue the evader. When the environment changes it costs much time to reorganize the path too, so they are unsuitable for hunting in the dynamic varying environment. Yamaguchi [24], [25] studied the problem of capturing a target with Hilare-type mobile robots in time-varying environment, and presented a smooth time-varying feedback control law to solve the problem. The control law is efficient, but it may fall in deadlock in some arrangement of obstacles. Wu *et al.* [18] and Cao *et al.* [26] applied artificial potential field and limit-cycle based method for hunting formation control to accomplish the cooperative hunting, in addition, a virtual besieging range is combined into the algorithm, and it is demonstrated that a rational virtual range with shortest hunting time always exits. To decide the action (speed and direction) selected by hunters, Ishiwaka *et al*. [27] and [28] Sauter *et al*. [28] proposed a reinforcement learning (RL) algorithm in the study of hunting game. RL is applied to model the behavior of hunters, and hunters are able to learn the hunting strategy by this method. The simulation result demonstrates that RL is appropriate for hunting behavior model in most situations but may fail in some complex environments. Song *et al*. [29] studied on multi-robot cooperative hunting behavior and put forward a mathematical model to it. In fact, the output of the model has a steady state, but it assumes hunting for a target is fulfilled when four robots detect it so that does not discuss the important pursuit process.

Inspired by the good performance of bio-inspired network in managing many complex systems, Ni *et al*. [30] made use of bio-inspired neural network (BNN) for real-time cooperative hunting in unknown environment. The result shows the proposed approach can lead the robots to finish the real-time hunting efficiently, and the situation that some robots are broken in the hunting process is discussed too. However, the strategy of the evader to escape from capture is not discussed. Moreover, BNN utilized in the path planning of robots, has the shortcomings such as high computational complexity, long path planning time etc.

All the strategies discussed above are studied on the ground-hunting problem. There are few researches on the underwater hunting problem. Hunting in the ocean is different from the ground hunting since the problem to be solved is a three-dimensional (3-D) problem so that each AUV has six degrees of freedom. Nguyen and Hopkin [31] and Williams [32] modeled the mine hunting of AUV, and applied the complete coverage approach to fulfill the hunting. However, the hunted targets are static and have no intelligence. Zhu and Huang [33] studied the multiple AUVs hunting problem with the BNN model. The distance-based negotiation method is put forward to allocate hunting task. Simulation is completed in both 2-D and 3-D environment. The proposed algorithm can deal with various situations automatically and catch the target efficiently. However, sometimes it falls into conflict state. Later Cao *et al*. [34], Lv *et al*. [35], and Zhu *et al*. [36] proposed a method named location forecasting to solve the conflict. Hunting AUVs will check before their action. The algorithm is compared with the artificial potential field method, and the algorithm can deal with hunting tasks with less sailing distance than the artificial potential field method. However, in the studies [33]–[36] hunting team is formed with negotiation, which may be irrational sometimes. Underwater environment is a unique situation, and communication is narrow and prone to error. It seems that the underwater environment cannot provide the communication requirement of negotiation too.

Most studies are about hunting problem of homogeneous AUVs. So far, there is almost no research on the hunting problem of inhomogeneous multi-AUV and intelligent evaders. Some researches about task allocation during hunting have been completed, but lacks of research on the task allocation in the inhomogeneous multi-AUV hunting problem. What is more, many researches do not discuss on the problem that the evaders have some strategy to escape. In military applications, the multi-AUV hunting system often needs to capture invaders with certain intelligence such as microrobot fishes, and their intelligence will help them to escape. In practical, AUVs in the hunting team are often of different type and possess distinct ability such as different sailing speed or different safety distance, and the evader could have certain intelligence to escape too.

This study focuses on the problem of inhomogeneous AUVs hunting for intelligent evaders in dynamic underwater environment. Firstly, a novel competition method, which is suitable for task distribution among inhomogeneous AUVs with different speeds, is applied to distribute hunting tasks. Hunting AUVs compete for the evaders with their distance to the evaders and their safety distance as well as velocity. Dual competition strategy based on estimated hunting time is put forward. The evader with the least time to a hunting group will be chosen as an easiest hunted target and should be captured first. At the same time, a team of AUVs with the least time to capture the evader is formed into a dynamic alliance.

After forming the hunting alliance, a hybrid path planning approach is proposed in order to begin hunting as soon as possible. The approach combines GBNN and belief function path planning method. On the one hand, GBNN requires no prior knowledge and no learning procedures. On the other hand, belief function can affect the path of AUV locally to make a more reasonable trajectory. In addition, it is suitable for both static and dynamically varying environment. This study is different from many researches that the intelligence of evader is further discussed too, which makes the hunting harder and more complex. The proposed task allocation and path planning approach is computationally stable in the study. It can cope with the cooperative hunting of multi-AUV for intelligent evaders efficiently as well as improve hunting efficiency.

In the rest of this paper, the hunting problem is described in section II. The escaping strategy of evader is further discussed in section III. Later, the strategy to tackle with the cooperative hunting of inhomogeneous AUVs is put forward in section IV. Simulation studies are presented in section V. At last, the algorithm is summarized in section VI.

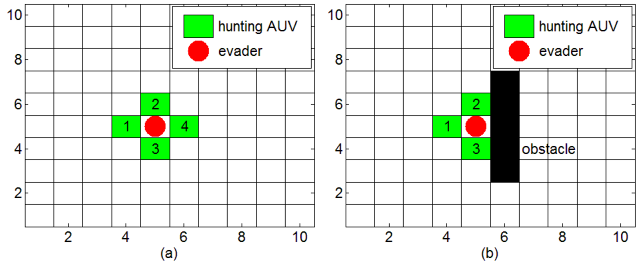

FIGURE 1. Successful hunting in 2-D environment.

II. PROBLEM STATEMENT

Grid map is used in the study of the cooperative hunting problem. As shown in Fig. 1(b), the environment is discretized, the black region stands for obstacle, and the blank region means a free space. The hunting problem of multi-AUV is described as follows. There are n hunting AUVs and m evaders in the environment. In the process of hunting, hunting AUVs move towards the evader, while the evader changes its direction to escape. Hunting is achieved after successful capture, when hunting AUVs round up the evader close enough and evenly distributes around the evader. The number of hunting AUV in a 2-D hunting group to encircle an evader is four, and it needs six hunting AUVs to capture an evader successfully for the 3-D underwater environment. If there is an obstacle around the evader to help with the capture, the number can be reduced correspondingly as shown in Fig. 1. As the overall hunting problem contains three stages and is too comprehensive to discuss all the stages in detail in a limited space, this paper will focus on the formation of hunting alliance and path planning to surround the evaders. The approach to search for evaders has been discussed in our earlier studies [10], [38], [39] and will not discuss in detail in this paper.

In the stage of forming hunting alliance, AUVs need to be divided into several groups, and the division is ought to improve the efficiency of hunting such as reducing hunting time or distance. Therefore, the ability of each AUV has to be highly considered. The inhomogeneous AUVs may have different sensing range, thrusters and energy. Among these abilities, sensing range mainly affects the result of AUVs to search for evaders. Since this study will not have a detailed discussion on the searching stage, it concentrates on the differences of thrusters and energy, which is mainly reflected in the sailing speed and safety distance. Once hunting alliance is formed, AUV needs to plan a safe path quickly and as short as possible to capture the evader. Because the evader also possesses intelligence, it may run away while being hunted. If there is any time delay for AUV to plan a path to capture the evader, it will be difficult in the fulfillment of the hunting task.

According to the requirements, competition strategy based on estimated hunting time is proposed. The strategy will give priority to distribute a hunting AUVs' team to capture the easiest hunted evader. If an evader has the least estimated time to capture, it will be considered as the easiest hunted evader. Then the second easiest one and so forth. Later, the path planning algorithm combining GBNN and belief function method is applied to round up the evader. AUV will take its hunting step immediately, and can avoid obstacles until rounding up the evader.

III. EVASION STRATEGY OF EVADER

It is assumed that the evader has a perception range. When the hunting AUV does not enter the perception range of the evader, it moves in a random direction. Once the evader detects hunting AUVs, it will take escaping strategy. Two different escaping situations will be discussed as follows.

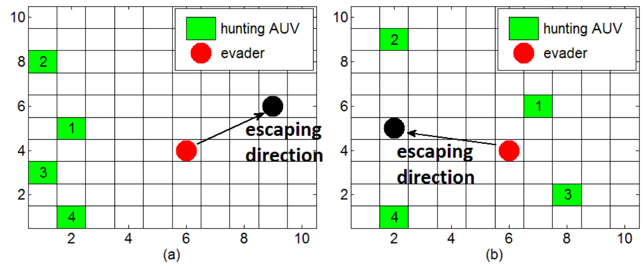

FIGURE 2. Escaping direction of evader.

A. HUNTING CIRCLE HASN'T BEEN FORMED

The first situation is that AUVs haven't formed a hunting circle as shown in Fig. 2(a). In this situation, the evader will turn its direction against hunting AUVs. The target point of evader is changed as (1).

$$e_{it} = e_i + \sum\nolimits_{j=1}^{k} (e_i - w_j)/redFact \tag{1}$$

e_{it} is the target point of the i-th evader, which will make evader change its direction. e_i means current position of this evader, and k is the number of hunting AUVs within the detection region of evader. w_j is the location of the j-th AUV. Because values of target point may exceed the size of the simulation environment, $redFact$ is a changeable coefficient introduced to keep the target point in the region of the environment.

B. HUNTING CIRCLE HAS BEEN FORMED

If the evader has been in the siege, it will take its direction to the midpoint of two neighbor AUVs with a largest distance as shown in Fig. 2(b).

For the 3-D situation, hunting circle formed or not is checked by projection. Locations of AUVs and evader are projected onto X-Y, X-Z and Y-Z planes. In case that hunting circle is not formed in one of these planes, 3-D hunting circle is not formed either. Evader will take similar escaping strategy in the 3-D case. If hunting circle is not formed, the evader will run against the AUVs, otherwise, it will take the midpoint between two neighbor AUVs with the largest distance as the escaping direction.

IV. PROPOSED ALGORITHM

In the hunting, AUVs should search for evaders first. After any evader is found, a dynamic hunting alliance will be

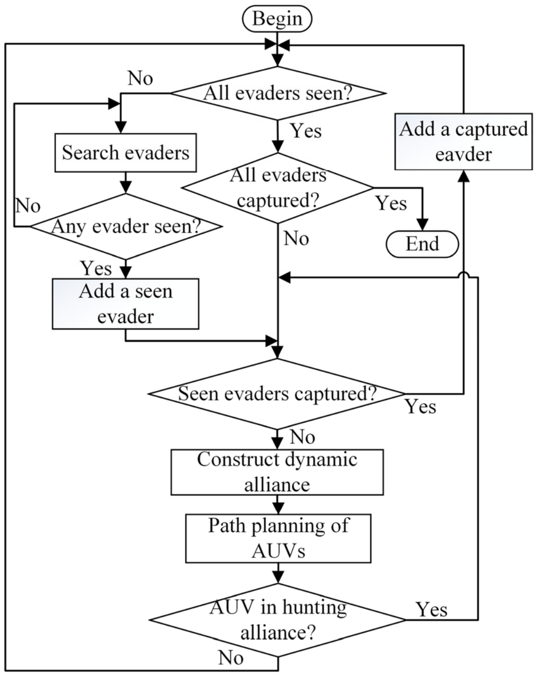

FIGURE 3. Flowchart of hunting process.

formed among AUVs. The AUV, which is not in the dynamic alliance, will search for other evaders. Hunting AUVs in the team will plan a path to capture the seen evader by the combined path planning algorithm. After all the evaders are seen and captured, the hunting ends. The flow chart is shown in Fig. 3.

Hunting alliance formed among inhomogeneous multi-AUV and path planning to round up the evader are two keen problems of this paper. The influence factors such as different speed and safety distance of AUVs should be taken into consideration in the hunting process. Because the evader will try their best to escape, there are other problems to be solved including how to avoid run-away of the intelligent evader and obstacle avoidance.

A. STRATEGY OF INHOMOGENEOUS AUVs' DYNAMIC ALLIANCE

n inhomogeneous AUVs are supposed to hunt m evaders. Positions of evaders and AUVs are expressed as matrixes E and W respectively, and every row in the matrixes is the coordinate point of AUV or evader. In the 2-D hunting problem, z_j $(j = 1, 2 \ldots \mathrm{m})$ and w_{iz} $(i = 1, 2 \ldots \mathrm{n})$ are set to zero.

$$E = \begin{bmatrix} x_1 & y_1 & z_1 \\ \vdots & \vdots & \vdots \\ x_m & y_m & z_m \end{bmatrix} \tag{2}$$

$$W = \begin{bmatrix} w_{1x} & w_{1y} & w_{1z} \\ \vdots & \vdots & \vdots \\ w_{nx} & w_{ny} & w_{nz} \end{bmatrix} \tag{3}$$

D_{we} in (4) is the distance matrix containing distances from each AUV to all the evaders. M_1 is a three rows and m columns matrix, and M_2 has n rows and three columns. The elements in matrixes M_1 and M_2 are all one. E^{T} means a transposed matrix of E. Symbols $W^{2}_{.}$ and $(E^{\mathrm{T}})^{2}_{.}$ stand for dot square of matrixes W and E^{T}. Therefore, the i-th row vector in D_{we} indicates the distance from the i-th AUV to all the evaders from no.1 to m.

$$D_{we} := \sqrt{W^{2}_{.} \cdot M_1 + M_2 \cdot (E^{\mathrm{T}})^{2}_{.} - 2 \cdot W \cdot E^{\mathrm{T}}} \tag{4}$$

For inhomogeneous AUVs, they have different batteries and thrusters. These differences are largely in the safety distance and the speed. Here, the distance that an AUV can sail very safely with its limited energy is called the safety distance. In consideration of safety distance, if the total sailing distance of an AUV to the evader will go beyond the safety distance, the distance from this AUV to the evader will be set to be ∞.

$$d_{wiej} = \begin{cases} d_{wiej} & \mathit{if}\ d_{wiej} \le c_{safei} \\ \infty, & \mathit{otherwise}. \end{cases} \tag{5}$$

d_{wiej} is the distance from the i-th AUV to the j-th evader, which is the i-th row and j-th column value of the matrix D_{we}, and c_{safei} is the safety distance of the i-th AUV, $i = 1, 2 \ldots n$, $j = 1, 2 \ldots m$. To acquire the estimated hunting time, the velocity of each AUV divides the distance from hunting AUVs to the evaders in (6). Vel is a velocity matrix contains velocity value of each AUV, and it is compiled with the same size as D_{we}. Each row of the velocity matrix is the velocity of the i-th AUV.

$$t_{we} := (D_{we})./Vel \tag{6}$$

In the strategy, AUVs carry out a competition to determine the hunting sequence of evaders at first. Then AUVs with the least estimated hunting time will be distributed into the team to capture the corresponding evader. While capturing, the evader tries to run away. This may cause change of AUV with the least hunting time, and will lead to change the hunting team. Therefore, the alliance is dynamic and changing with the environment. The alliance forming algorithm is summarized in Algorithm 1.

In a word, inhomogeneous AUVs usually have distinct abilities. The original algorithm only thinks of distances from AUVs to evaders, so hunting alliance established may be inefficient. The proposed hunting alliance algorithm considers AUVs' different speed ability and achieves the hunting with less energy. Furthermore, in order to avoid any AUV running out of energy, preventive measure has been taken.

B. COMBINED ALGORITHM FOR PATH PLANNING WHILE CHASING

After the dynamic hunting alliance formed, path planning to chase and then encircle the evader is the next step.

Algorithm 1 Hunting Alliance Forming Algorithm

Input: t_{we}: estimated hunting time, TeamNum: max team numbers hunting AUVs can form, Num: AUVs' number needed in a team, 2-D hunting: Num=4, 3-D hunting: Num=6; NumEvader: the number of evaders

Output: evaderIndex: the evaders' hunting sequence (row vector), AUVIndex: AUVs hunting alliance for each evader (matrix);

(1) Initialize: j=1, evaderIndex = zero vector with TeamNum elements, AUVIndex = zero matrix with TeamNum rows and Num columns

(2) While j<=NumEvader and j<=TeamNum

% sort the hunting time

[sortedTime, winners]=Sort($t_{we}$$t_{\mathrm{we}}$)

for i=1 to NumEvader

% get the first Num rows of sortedTime

teamSortedTime(:,i)=sortedTime(1:Num,i)

End For

teamTotalTime=sum(teamSortedTime)

[∼,winnerIndex]=sort(teamTotalTime)

% Fetch the index of evader with the least hunting time evaderIndex (1,j) = winnerIndex (1,1);

% Distribute AUVs to hunt the evader

AUVIndex(j,:) = winners(1: Num, evaderIndex (1,j));

% prevent winning evader win competition again

t_{we} (:,evaderIndex (1,j)) = colBigValue;

End While

1) GBNN MODEL

Glasius BNN model (GBNN: Glasius Bio-inspired Neural Network) was published by Glasius *et al.* [37] in 1995. In the algorithm, obstacles have only local effect. The activity of target will propagate to guide the AUV to reach it. Moreover, the model requires no prior knowledge and no learning procedures, which is suitable for static and dynamic varying environment. The GBNN model is established to represent the underwater working environment. The 2-D neural network of GBNN is shown in Fig. 4(a) and the 3-D neural network of GBNN is shown in Fig. 4(b). There is a neuron for each grid on the map. Neurons connect with each other, and their receptive field is in a circular region with a radius of R. It is a discrete-time Hopfield-type neural network model, which is described as (7).

$$x_i(t+1) = f\left(\sum\nolimits_{j\in S_i}(w_{ij}\cdot x_j(t)) + I_i\right) \tag{7}$$

$$w_{ij} = \begin{cases} e^{-\gamma\cdot dist(p_i-p_j)} & if\ dist(p_i-p_j)\le R \\ 0, & otherwise \end{cases} \tag{8}$$

$$I_i = \begin{cases} v, & grid\ i\ is\ target \\ -v, & grid\ i\ is\ occupied \\ 0, & else \end{cases} \tag{9}$$

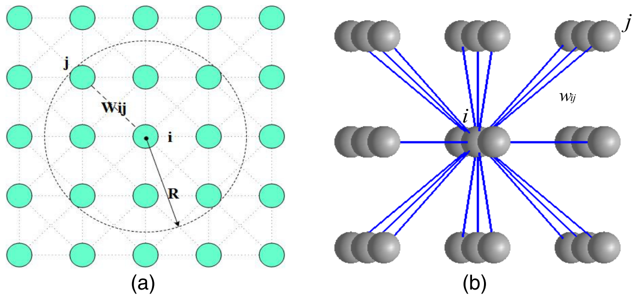

FIGURE 4. GBNN neural network. (a) 2-D neural network. (b) 3-D neural network.

$$f(x) = \begin{cases} 1, & x\ge 1 \\ \beta\cdot x, & 0<x<1 \\ 0, & else \end{cases} \tag{10}$$

$x_i(t+1)$ in (7) is the neural activity of the i-th grid, and $x_j(t)$ is the neural activity of the j-th grid a time step ago. w_{ij} is symmetric connection weight that can be computed by (8), and $dist(p_i - p_j)$ is the Euclidean distance from the neuron i to j. R is the radius shown in Fig. 4(a). External input I_i expresses the information about the target and occupied grid and is given by (9), where $v \gg 1$. The grids occupied by mountain, obstacles, AUVs as well as evaders on the map are occupied units. f(x) is a piecewise linear transfer function as expressed in (10), and $\beta < 1$.

2) BELIEF FUNCTION METHOD

It takes the direction of the target and the obstacles into consideration while planning path by the belief function method, and has the advantages of quick response, small calculation and certain obstacle avoidance ability.

In the belief function method, the occupied unit is indicated in (12). For an occupied unit, the equation will make the belief function value at this unit less than zero. The belief function value of the j-th unit is defined as (11), where $b(j)$ represents the overall belief function value of the j-th unit.

$$b(j) = c\cdot(N_j + D_j) + G_j \tag{11}$$

$$G_j = \begin{cases} 0, & free\ unit \\ -1, & occupied\ unit \end{cases} \tag{12}$$

$$N_j = \cos(\Delta\theta) \tag{13}$$

$$D_j = e^{-dist(p_t-p_j)/mw} \tag{14}$$

N_j in (11) is a directional function and is calcuted by (13), where $\Delta\theta$ is the angle between two vectors from AUV to the j-th unit and to the target separately. D_j is a distance function to control AUVs sailing nearer to the target and represents in (14). $dist(p_t - p_j)$ is the Euclidean distance between the location of the target and the j-th grid and mw is the environment size to keep the $dist(p_t - p_j)/mw$ in the region of [0, 1], therefore D_j is in [0.3679, 1].

3) COMBINED ACTIVITY FOR PATH PLANNING

Total activity of each grid unit is described as

$$y_i(t+1) = x_i(t+1) + e^{-(m+t)}\cdot b(i) \tag{15}$$

Here the neural activity of GBNN is combined with the belief function value. $y_i(t+1)$ is the combined activity of the i-th grid, $x_i(t+1)$ and $b(i)$ are the neuron activity of GBNN and belief function respectively, m is an initial value, and the time item in the exponential function can make the influence of belief function value decrease over time. The AUV will sail to the grid closed to it with the biggest total neural activity.

$$\begin{aligned} Path &= P_n | y_{P_n} = \max\{y_i, i = 1, 2, \ldots, k\}, \\ P_p &= P_c, \quad P_c = P_n \end{aligned} \tag{16}$$

y_i is the total activity of the grids besides current position of AUV. For the 2-D path planning, k equals eight and equals twenty-six in the 3-D situation. P_p, P_c and P_n are the previous, current and next position of AUV.

The neural activity propagation of GBNN model works a bit like wave propagation in a lake. If wave starts in the middle of the lake, it takes some time to spread to the shore side. The broader the lake is, the longer the spread will be. The single GBNN model needs some time to propagate the neural activity at the target's grid to the position of AUV. The combined algorithm applies belief function as a local effect, and this effect is relatively large when the AUV is far away from its target because of the small GBNN activity value at that place. It can eliminate the time delay for the propagation of GBNN model. As time goes up and AUV goes near to its target, GBNN will take charge of the AUV. The neural activity of GBNN at the obstacle unit is equal to zero, and that of belief function method is less than zero. However, the neural activity of free unit on the direction to get closer to the target is higher than zero and increases as the distance to the target decreases. Therefore, even if the target or the obstacle is dynamic, the combined approach will ensure the activity of the obstacle less than that of the free unit. That is to say, the activity propagates from the target to the AUV gradually, and has a relatively small value at the obstacle unit. In conclusion, the AUV, which takes the next step with the biggest total neural activity, will reach the target with obstacle avoidance.

V. SIMULATION STUDY

In order to verify the feasibility and effectiveness of the proposed algorithm, simulation experiments are carried out on the platform Matlab. In this section, experiments will be conducted in the 2-D hunting with the proposed algorithm first, and then the results will be compared with other algorithms. At last, a cooperative hunting of inhomogeneous AUVs in 3-D underwater environment is also finished. The computer to run the simulation program is a computer with Windows 10, Intel(R) Core(TM) i7-6700HQ CPU @ 2.6GHz, and 8 G memory.

Remark: (1) Although the AUV and evader are thought as mass points in this paper, the obstacles are enlarged for one grid unit in size to consider their shape in real situation. (2) It is supposed that the AUV is able to turn its moving direction immediately without any delay.

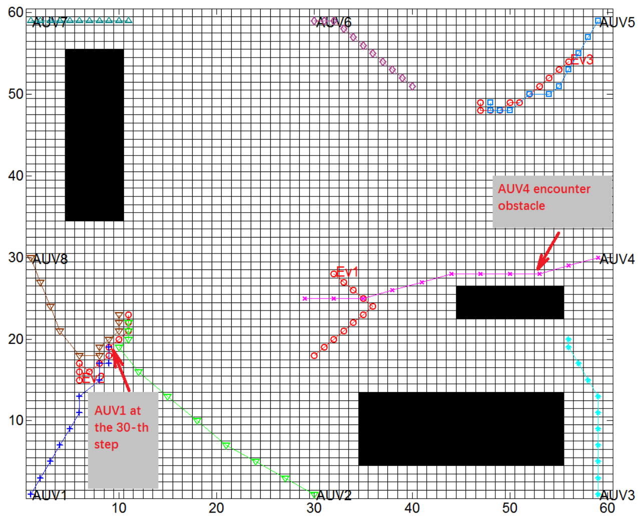

FIGURE 5. Cooperative Hunting of inhomogeneous AUVs with proposed algorithm at the 30 th step.

A. 2-D SIMULATION DESIGN

In the simulation, eight AUVs will hunt for three evaders. Evaders are named as Ev1, Ev2, and Ev3, and AUVs are called as AUV1, AUV2 … to AUV8. Hunting environment is an area with 60×60 grids. Evaders try to run away when the hunting AUVs enter into its perception range with a diameter of 10. The evaders' speed is often less than or equal to the speed of AUV. As our lab's AUV configuration, some AUVs have lower speed that may be the same as evader's, and some of them are faster. We set AUV1, AUV3, and AUV5 with a speed of two and the speed of AUV2, AUV4, and AUV8 is three. Other AUVs' speed is the same as the evaders. Therefore, evaders and some AUVs can move one grid once, but AUVs with higher speed may move more grids at a time. Regularly, faster AUV carrying more batteries can run farther. The AUVs with a speed of one have a safety distance of 120, and the AUVs with a speed of two can sail for 180, as well as the energy of the fastest AUVs can support them for a distance of 220.

1) HUNTING OF INHOMOGENEOUS AUVs WITH PROPOSED ALGORITHM

At the initial state, three evaders are randomly generated and locate at the units (32, 28), (6, 15) and (56, 54), and they go in a random direction too. AUVs stay on the border of the map getting ready to capture these evaders. In the experiment, the parameters are set as $\beta = 0.01$, $\nu = 200$, $\gamma = 3$, $R = 1.8$, $c = 0.1$, $m = 10$. The hunting process is shown in the figures of Fig. 5 and Fig. 6. On the figures, the black regions stand for obstacles, and the hunting step increases by one for each evader's movement.

Fig. 5 shows the status of the first thirty steps. Eight AUVs are divided into two teams. One of the teams comprises AUV1, AUV2, AUV4, and AUV8 to hunt for Ev2. The other team contains the rest of AUVs pursuing Ev3. Evaders will

TABLE 1. **Combined activities of Auv4 from Unit (53, 28) to Unit (50, 28).**

y Activity x	25	26	27	28	29	30	31
50	-9.73E-08	-9.64E-08	-9.58E-08	**1.63E-08**	1.48E-08	1.28E-08	1.10E-08
51	-9.87E-08	-9.74E-08	-9.61E-08	1.62E-08	1.38E-08	1.09E-08	8.89E-09
52	-1.01E-07	-9.98E-08	-9.75E-08	1.61E-08	1.09E-08	7.48E-09	5.87E-09
53	-1.04E-07	-1.04E-07	-1.04E-07	**5.18E-09**	2.26E-09	2.23E-09	2.20E-09
54	-1.08E-07	-1.10E-07	-1.13E-07	-5.78E-09	-4.67E-09	-2.41E-09	-1.17E-09
55	-1.11E-07	-1.13E-07	-1.16E-07	-5.86E-09	-6.03E-09	-4.77E-09	-3.50E-09
56	-1.13E-07	-1.15E-07	-1.17E-07	-5.94E-09	-6.32E-09	-5.76E-09	-4.87E-09

TABLE 2. **Combined activities of Auv1 from Unit (9, 19) to Unit (10, 21).**

y Activity x	19	20	21	22	23	24	25
8	3.91E-13	7.60E-13	7.12E-12	1.36E-12	6.56E-12	6.49E-13	1.61E-14
9	**7.47E-13**	1.36E-11	6.16E-10	1.24E-08	1.23E-09	1.24E-08	6.15E-10
10	7.00E-12	2.32E-12	**1.24E-08**	2.26E-12	2.48E-05	0.0004978	2.48E-05
11	1.31E-12	3.77E-11	1.35E-09	3.71E-08	0.000498	0	0.0004979
12	6.38E-12	1.26E-10	1.24E-08	2.48E-07	0	0	**1**

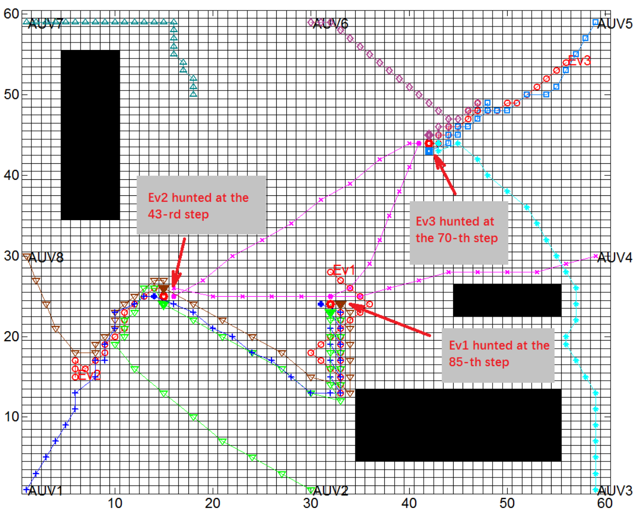

FIGURE 6. **Cooperative Hunting of inhomogeneous AUVs with proposed algorithm at the final step.**

run away while encountering hunting AUVs. AUV4 meets with an obstacle at the unit (53, 28). Table 1 shows the combined activities of AUV4 near the unit (53, 28). The activities of obstacle units are listed in the first three columns and are all less than zero. AUV4 can move three units once. Here it finds the biggest activity unit at the position (50, 28) within three units. AUVs can avoid obstacle with the combined algorithm from this analysis. At the 30-th step, AUV1 is at the position of (9, 19) and is going to (10, 21) as a next step. Table 2 explains the path planning of AUV1 at this step. In the range that AUV1 can reach, the unit (10, 21) possesses the biggest activity. From the table, it can be found that the round up site has an activity of one. The units occupied by other AUVs and evaders are treated as an obstacle and have an activity value less than or equal to zero, so AUV1 would not run into these units. With the guidance of neural activity, AUV1 can get closer to the roundup site gradually to fulfill the capture of Ev2.

Fig. 6 shows that Ev1, Ev2, and Ev3 are caught at position (32, 24), (15, 25), and (42, 44). After Ev2 is first captured, hunting alliance is reorganized. AUV3, AUV4, AUV5, and AUV6 are distributed to pursuit Ev3 and the rest of AUVs hunt for Ev1. Then the hunting group catches Ev3. At last, AUV1, AUV2, AUV4, and AUV8 form an alliance starting to capture Ev1 until success. The cost of AUVs and escaping distance of evaders are listed in the second column of Table 3.

2) HUNTING OF INHOMOGENEOUS AUVs BY HUNTING ALLIANCE FORMED BY DISTANCE-BASED COMPETITION

For the same situation stated above, the dynamic alliance algorithm based on distance is applied. As shown in Fig. 7, the AUVs also form dynamic hunting alliance but in a different way. AUV1, AUV2, AUV7, and AUV8 are going

TABLE 3. Cost and efficiency comparison of hunting simulation experiments by different algorithms.

	Proposed algorithm	Distance competition	Single GBNN model
AUV1's distance	76.57	108.61	83.64
AUV2's distance	78.44	113.87	104.31
AUV3's distance	51.08	94.71	59.29
AUV4's distance	98.34	98.72	59.01
AUV5's distance	33.67	51.93	95.12
AUV6's distance	30.63	38.87	61.60
AUV7's distance	24.83	24.83	27.80
AUV8's distance	63.23	42.70	93.62
AUVs' Average	**57.10**	**71.78**	**80.34**
Ev1's distance	34.38	40.21	70.04
Ev2's distance	18.31	30.21	42.21
Ev3's distance	26.73	29.21	75.36

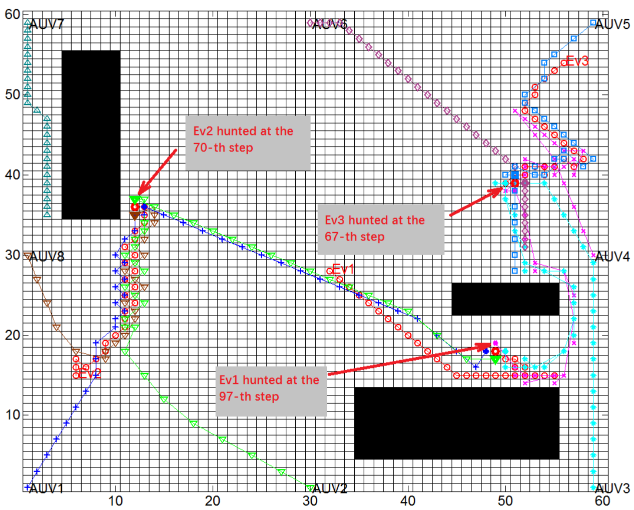

FIGURE 7. Cooperative Hunting of inhomogeneous AUVs with alliance forming algorithm based on distance competition.

to hunt for Ev2 at first. The other team contains rest of AUVs pursuing Ev3. Hunting can be completed with distance-based competition mechanism but costs more steps. The evaders are captured at the unit (49, 18), (12, 36), and (51, 39) respectively. Ev3 is firstly captured by AUV3, AUV4, AUV5, and AUV7. Then AUV1, AUV2, and AUV8 catch Ev2 with the help of obstacle. At last, AUV1, AUV2, AUV3, and AUV4 fulfill the hunting of Ev1. Since the hunting alliance formed only depend on distance, some AUVs in a hunting team have lower ability that makes the evader escape a longer distance. The cost of AUVs and escaping distance of evaders are listed in the third column of Table 3 for comparison.

3) HUNTING OF INHOMOGENEOUS AUVs BY SINGLE GBNN MODEL

The efficiency of the combined path planning algorithm will be compared with the single GBNN model in this section.

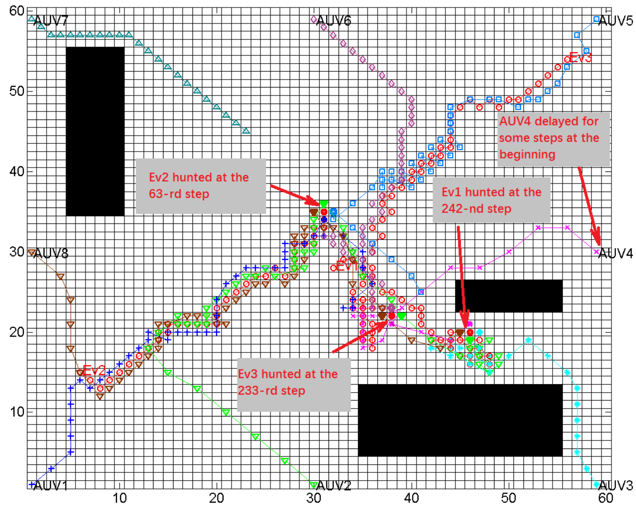

FIGURE 8. Cooperative Hunting of inhomogeneous AUVs with single GBNN model.

The result of hunting with single GBNN model but constructing alliance based on the same time competition mechanism proposed in this study is shown in Fig. 8. The AUVs initially form the same dynamic hunting alliance as the hunting with the proposed algorithm. Because the evaders try to escape in the hunting, the round up sites are always changing. GBNN model needs some time for the activity at the original round up site to cut down and may mislead the AUV to make some useless steps. What is more, GBNN model may cause the AUV delay for some steps when the AUV is far away from its target. This is the time for the propagation of neuron activity, and AUV4 explains this problem. It delays some steps before the first step to chase Ev2. Therefore, Ev2 escapes for a long distance and then is distributed to other AUVs. Later it is caught by AUV1, AUV2, AUV5, and AUV8 at the unit (31, 35). After that, the hunting group including AUV2, AUV4, AUV6, and AUV8 captures Ev3 at the unit (38, 22). At last, AUV2, AUV3, AUV4, and AUV8 fulfill the hunting of Ev1 at the unit (46, 20). The total hunting step is 242, and single GBNN model takes more steps than other experiments stated above. The cost of AUVs and escaping distance of evaders are listed in the fourth column of table 3 for comparison too.

4) DISCUSSION

Simulation results of comparison experiments above are listed in table 3. Sailing distance of each AUV in the hunting process and their average distance are recorded as a cost comparison, and the escaping distance of evaders is listed for an efficiency comparison. As shown in table 3, the proposed algorithm can help the AUVs to capture the evaders with less cost and higher efficiency. It takes an average distance of 57.10 for the AUVs to catch all the evader successfully. However, that of hunting alliance algorithm based on distance competition and single GBNN model is 71.78 and 80.34 respectively. Reasons can be summarized as follows.

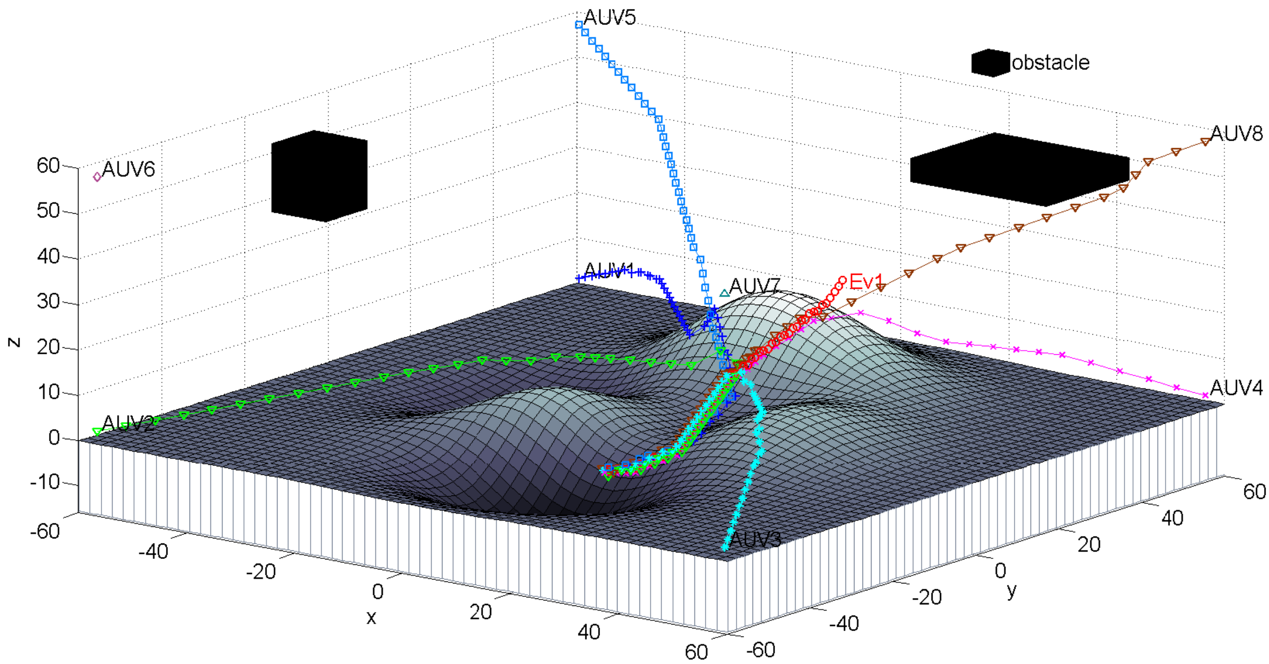

FIGURE 9. 3-D underwater hunting with proposed algorithm at the final (50-th) step, view(37.5, 30).

Firstly, AUVs with different ability should form several groups to chase the evaders in the hunting of evaders with inhomogeneous AUVs. Dynamic hunting alliance constructed with the algorithm proposed in the study can make the best use of each AUVs, which will shorten the hunting time. The proposed algorithm forms the hunting alliance with the consideration of AUVs' capacity. This can make every AUVs in a hunting team has almost equal ability. However, distance competition mechanism neglects the ability of AUVs, so that there may be AUVs of great difference in ability in a hunting team. Like the bucket effect, the ability of a team is restricted by the AUV with minimum ability. In conclusion, the time competition mechanism is more suitable for forming the hunting alliance among inhomogeneous AUVs.

Secondly, hunting should be as fast as possible. Combined with belief function, GBNN model can put all the AUVs in the hunting groups set about pursuing immediately after finding the evaders. The proposed algorithm can hunt all the dynamic evaders with a high efficiency and avoid some useless steps. It is superior to the single GBNN model in the solution of hunting problem. Belief function affects locally to bring a clear goal to AUVs while they are far away from targets. As hunting goes on, GBNN will plan the path for AUV to ensure success of the capture. At the obstacle unit, neural activity of GBNN is equal to zero and that of belief function algorithm is less than zero. Therefore, AUV can avoid obstacle on the way to the target.

From the comparison, the algorithm presented in this paper is superior to that based on distance competition mechanism and single GBNN model both in hunting cost and in efficiency.

B. HUNTING IN THE 3-D UNDERWATER ENVIRONMENT

Cooperative hunting of inhomogeneous AUVs in the underwater three-dimensional environment is introduced in this section. In fact, underwater environment is a vast 3-D environment. There are obstacles in the vast region. At the bottom of the environment, it has rolling mountains too. The environment is assumed as a cuboid with a length and width from -60 to 60, and a height between -16 and 60. At the bottom of the environment, there are simulated mountains. The deepest of this underwater environment is the valley of the mountain at the height of about -15. Howbeit the peak of the mountain is at the height of 20. The black blocks represents the obstacles.

1) UNDERWATER HUNTING OF INHOMOGENEOUS AUVs WITH PROPOSED ALGORITHM

There is an AUV in every corner of the environment. An evader locates at (20, 20, 30) at the initial state. The type of evader and AUV is the same as experiments in the 2-D situation. AUV needs to sail longer to catch an evader in the 3-D hunting, so the consideration of the safety distance is more important. Fig. 9 shows the result of this experiment at the view (37.5, 30). View (*az*, *el*) means the azimuth and elevation angles of the viewer are *az* and *el* degree.

Hunting is distributed to no. 1, 2, 3, 4, 5, and 8 AUVs by the time competition mechanism. The evader tries hard to run away. AUV8 avoids collision with obstacle, and AUV1 and AUV4 avoid collision with the sea mountain. AUV1 sails a distance of 139.76 to catch the evader, and the distance of AUV2, AUV3, AUV4, AUV5, and AUV8 is 136.66, 100.24, 119.71, 140.92 and 126.34 respectively. The evader

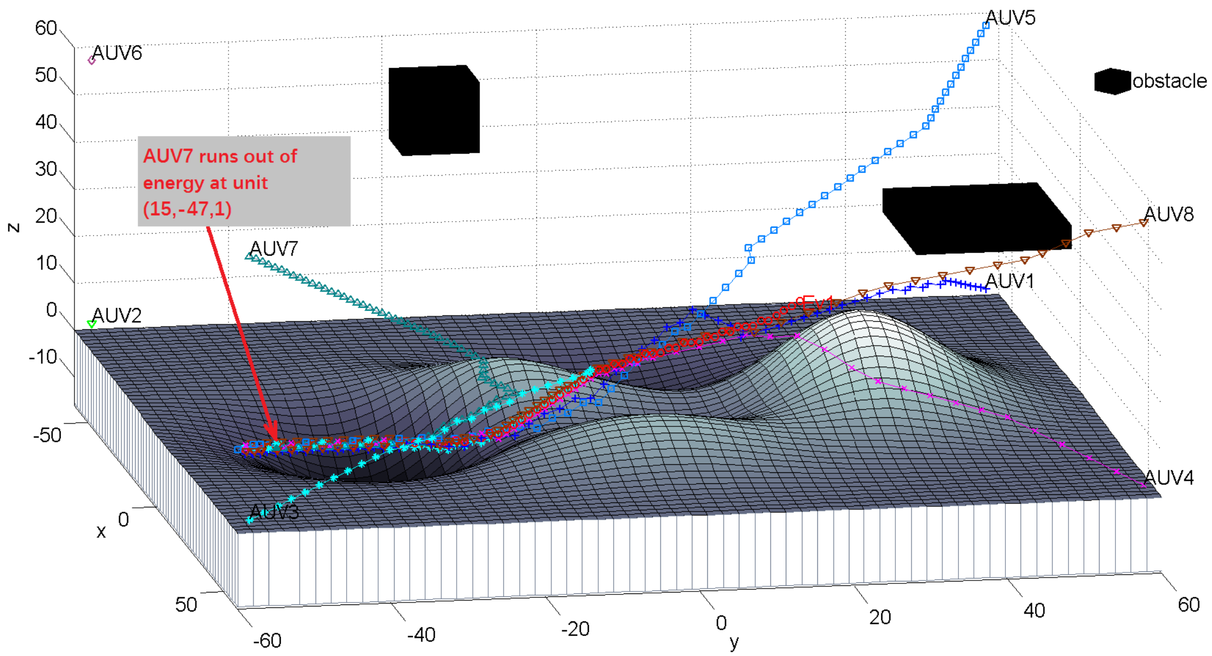

FIGURE 10. 3-D underwater hunting by distance-based competition mechanism at the 76-th step, view(80, 30).

is besieged in a globe with six AUVs at (15, −30, 1) at last with escaping distance of 64.91.

2) UNDERWATER HUNTING OF INHOMOGENEOUS AUVs BY HUNTING ALLIANCE FORMED ON THE BASIS OF DISTANCE COMPETITION

For the same 3-D situation stated above, hunting experiment is carried out by the distance competition mechanism. AUVs form the hunting team in a different way. As it is shown in Fig. 10, AUV7 replaces AUV2 in the hunting alliance. However, AUV7 moves slowest in the group and must try hard to catch up with the evader because its speed is just equal to that of evader's. Moreover, the safety distance of AUV7 is only 120. Hunting will fail if AUV7 runs out of energy in the pursuing. Fig. 10 shows this situation that AUV7 runs out of energy because the distance it sailed exceeds its safety distance. Therefore, because the original algorithm only considers the distance, it is unsuitable for hunting of inhomogeneous AUVs in underwater 3-D environment.

In the 3-D situation, original hunting alliance forming algorithm may construct an invalid hunting group. It may distribute the hunting task to an AUV with relatively low capacity. A team with an AUV of lower capacity behaves worse than in the 2-D situation. Because of the vast environment, the evader can run away more easily. Hunting group is unable to form a round up globe if one of the AUVs cannot catch up with the evader. Without the consideration of the safety distance of AUV, hunting may be failed too. The proposed algorithm distributes the task to a team of AUVs with better ability, and they can fulfill the task efficiently.

VI. CONCLUSION

In this paper, cooperative hunting task of inhomogeneous multi-AUV is studied. A time competition mechanism is proposed to construct dynamic hunting alliance. Then GBNN and belief function method are combined for a highly efficient path planning. The feasibility and effectiveness of the proposed algorithm are verified by simulation. The algorithm proposed is compared with original distance competition algorithm and single GBNN model. The results show that the proposed algorithm is more efficient. The single GBNN model works badly in such a fast dynamic environment as hunting, and it takes more distance to finish the hunting task. The distance-based hunting alliance algorithm is not good at the hunting alliance formation of inhomogeneous AUVs too. The proposed algorithm can reduce the hunting steps with less AUVs' total distance and evaders' escaping distance. At last, it is demonstrated that the algorithm can also fulfill the hunting in the 3-D underwater environment where the evader can run away more easily.

REFERENCES

[1] M. Sibenac, T. Podder, W. Kirkwood, and H. Thomas, "Autonomous underwater vehicles for ocean research: Current needs and state of the art technologies," *Marine Technol. Soc. J.*, vol. 38, no. 2, pp. 63–72, 2004.

[2] M. L. Corradini and G. Orlando, "A discrete adaptive variable-structure controller for MIMO systems, and its application to an underwater ROV," *IEEE Trans. Control Syst. Technol.*, vol. 5, no. 3, pp. 349–359, May 1997.

[3] D. R. Blidberg, "The development of autonomous underwater vehicles (AUV); A brief summary," *IEEE ICRA*, vol. 17, no. 5, pp. 209–212, 2008.

[4] J. A. Monroy, E. Campos, and J. A. Torres, "Attitude control of a micro AUV through an embedded system," *IEEE Latin Amer. Trans.*, vol. 15, no. 4, pp. 603–612, Apr. 2017.

[5] T.-H. Joung *et al.*, "A study on the design and manufacturing of a deep-sea unmanned underwater vehicle based on structural reliability analysis," *Ships Offshore Struct.*, vol. 4, no. 1, pp. 19–29, 2009.
[6] A. Farinelli, L. Iocchi, and D. Nardi, "Multirobot systems: A classification focused on coordination," *IEEE Trans. Syst., Man, Cybern. B, Cybern.*, vol. 34, no. 5, pp. 2015–2028, Oct. 2004.
[7] W. Xing, Y. Zhao, and H. Karimi, "Convergence analysis on multi-AUV systems with leader-follower architecture," *IEEE Access*, vol. 5, pp. 853–868, 2017.
[8] Q. W. Liang and T. S. L. Shi, "Reliability analysis for mutative topology structure multi-AUV cooperative system based on interactive Markov chains model," *Robotica*, vol. 35, no. 8, pp. 1761–1772, 2016.
[9] S. Yoon and C. Qiao, "Cooperative search and survey using autonomous underwater vehicles (AUVs)," *IEEE Trans. Parallel Distrib. Syst.*, vol. 22, no. 3, pp. 364–379, Mar. 2011.
[10] X. Cao, D. Zhu, and S. X. Yang, "Multi-AUV target search based on bioinspired neurodynamics model in 3-D underwater environments," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 27, no. 11, pp. 2364–2374, Nov. 2016.
[11] A. J. Healey and J. Kim, "Control and random searching with multiple robots," in *Proc. 39th IEEE Conf. Decision Control*, Sydney, NSW, Australia, Dec. 2000, pp. 340–345.
[12] B. Garau, M. Bonet, A. Alvarez, and S. Ruiz, "Path planning for autonomous underwater vehicles in realistic oceanic current fields: Application to gliders in the Western Mediterranean Sea," *J. Maritime Res.*, vol. 6, no. 2, pp. 5–22, 2009.
[13] A. J. Healey, "Application of formation control for multi-vehicle robotic minesweeping," in *Proc. IEEE CDC*, Orlando, FL, USA, Dec. 2001, pp. 1497–1502.
[14] D. Zhu, H. Huang, and S. X. Yang, "Dynamic task assignment and path planning of multi-AUV system based on an improved self-organizing map and velocity synthesis method in three-dimensional underwater workspace," *IEEE Trans. Cybern.*, vol. 43, no. 2, pp. 504–514, Apr. 2013.
[15] J. G. Bellingham, "New oceanographic uses of autonomous underwater vehicles," *Marine Technol. Soc. J.*, vol. 31, no. 3, p. 34, 1997.
[16] J. Li, Q. S. Pan, B. R. Hong, and M. H. Li, "Multi-robot cooperative pursuit based on association rule data mining," in *Proc. Int. Conf. Fuzzy Syst. Knowl. Discovery*, Tianjin, China, vol. 7. Aug. 2009, pp. 303–308.
[17] H. Jun and Q. Zhu, "A multi-robot hunting algorithm based on dynamic prediction for trajectory of the moving target and hunting points," *Acta Electron. Sinica*, vol. 39, no. 11, pp. 2480–2485, 2011.
[18] M. Wu, F. Huang, L. Wang, and J. Sun, "A distributed multi-robot cooperative hunting algorithm based on limit-cycle," in *Proc. Int. Asia Conf. Informat. Control, Autom. Robot.*, Feb. 2009, pp. 156–160.
[19] R. E. Korf, "A simple solution to pursuit games," in *Proc. 11th Int. Workshop Distrib. Artif. Intell.*, 1992, pp. 183–194.
[20] J. Li, Q. Pan, and A. B. Hong, "A new approach of multi-robot cooperative pursuit based on association rule data mining," *Int. J. Adv. Robotic Syst.*, vol. 6, no. 4, pp. 1169–1174, 2010.
[21] J. Denzinger and M. Fuchs, "Experiments in learning prototypical situations for variants of the pursuit game," in *Proc. Tech. Univ. Kaiserslautern, Fachbereich Inf. (ICMAS)*, Jun. 1996, pp. 48–55.
[22] R. Vidal, O. Shakernia, H. J. Kim, D. H. Shim, and S. Sastry, "Probabilistic pursuit-evasion games: Theory, implementation, and experimental evaluation," *IEEE Trans. Robot. Autom.*, vol. 18, no. 5, pp. 662–669, Oct. 2002.
[23] Y. C. Chen, H. Qi, and S.-S. Wang, "Multi-agent pursuit-evasion algorithm based on contract net interaction protocol," in *Proc. 1st Int. Conf. (ICNC)*, Changsha, China, Aug. 2005, pp. 482–489.
[24] H. Yamaguchi, "A cooperative hunting behavior by multiple nonholonomic mobile robots," in *Proc. IEEE Int. Conf. Syst., Man*, San Diego, CA, USA, vol. 4. Oct. 1998, pp. 3347–3352.
[25] H. Yamaguchi, "A cooperative hunting behavior by mobile-robot troops," *Int. J. Robot. Res.*, vol. 18, no. 9, pp. 931–940, 1999.
[26] Z. Cao *et al.*, "A distributed hunting approach for multiple autonomous robots," *Int. J. Adv. Robotic Syst.*, vol. 10, no. 1, p. 217, 2013.
[27] Y. Ishiwaka, T. Sato, and Y. Kakazu, "An approach to the pursuit problem on a heterogeneous multiagent system using reinforcement learning," *Robot. Auton. Syst.*, vol. 43, no. 4, pp. 245–256, 2003.
[28] M. Z. Sauter, D. Shi, and J. D. Kralik, "Multi-agent reinforcement learning and chimpanzee hunting," in *Proc. IEEE Int. Conf. Robot. Biomimetics (ROBIO)*, Guilin, China, Dec. 2009, pp. 622–626.
[29] Y. Song, Y. Li, C. Li, and X. Ma, "Mathematical modeling and analysis of multirobot cooperative hunting behaviors," *J. Robot.*, vol. 2015, no. 11, 2015, Art. no. 184256.
[30] J. Ni and S. X. Yang, "Bioinspired neural network for real-time cooperative hunting by multirobots in unknown environments," *IEEE Trans. Neural Netw.*, vol. 22, no. 12, pp. 2062–2077, Dec. 2011.
[31] B. Nguyen and D. Hopkin, "Modeling autonomous underwater vehicle (AUV) operations in mine hunting," in *Proc. OCEANS*, vol. 1. 2005, pp. 533–538.
[32] D. P. Williams, "On optimal AUV track-spacing for underwater mine detection," in *Proc. IEEE Int. Conf. Robot. Autom.*, Anchorage, AK, USA, May 2010, pp. 4755–4762.
[33] Z. Huang and D. Zhu, "A cooperative hunting algorithm of multi-AUV in 3-D dynamic environment," in *Proc. 27th Chin. Control Decision Conf. (CCDC)*, Qingdao, China, May 2015, pp. 2571–2575.
[34] X. Cao, Z. Huang, and D. Zhu, "AUV cooperative hunting algorithm based on bio-inspired neural network for path conflict state," in *Proc. IEEE Int. Conf. Inf. Autom.*, Lijiang, China, Aug. 2015, pp. 1821–1826.
[35] R. Lv, W. Gan, B. Sun, and D. Zhu, "A multi-AUV hunting algorithm with ocean current effect," in *Proc. IEEE Int. Conf. Cyber Technol. Autom., Control, Intell. Syst. (CYBER)*, Shenyang, China, Jun. 2015, pp. 869–874.
[36] D. Zhu, R. Lv, X. Cao, and S. X. Yang, "Multi-AUV hunting algorithm based on bio-inspired neural network in unknown environments," *Int. J. Adv. Robotic Syst.*, vol. 12, no. 1, p. 166, 2015.
[37] R. Glasius, A. Komoda, and S. C. A. M. Gielen, "Neural network dynamics for path planning and obstacle avoidance," *Neural Netw.*, vol. 8, no. 1, pp. 125–133, 1995.
[38] X. Cao and A.-L. Yu, "Multi-AUV cooperative target search algorithm in 3-D underwater workspace," *J. Navigat.*, vol. 70, no. 6, pp. 1293–1311, 2017.
[39] D. Zhu, X. Cao, B. Sun, and C. Luo, "Biologically inspired self-organizing map applied to task assignment and path planning of an AUV system," *IEEE Trans. Cogn. Develop. Syst.*, to be published, doi: 10.1109/TCDS.2017.2727678.

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