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An Improved Spinal Neural System-Based Approach for Heterogeneous AUVs Cooperative Hunting

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Abstract Cooperative hunting by a multi-AUV system in unknown 3D underwater environment is not only a research hot spot but also a challenging task. To conduct this task, each AUV needs to move quickly without obstacle collisions and cooperate with other AUVs considering the overall interests. In this paper, the heterogeneous AUVs cooperative hunting problem is studied, including two main tasks, namely the search and pursuit of targets, and a novel spinal neural system-based approach is proposed. In the search stage, a partition and column parallel search strategy is used in this paper, and a search formation control algorithm based on an improved spinal neural system is proposed. The presented search algorithm not only accomplishes the search task but also maintains a stable formation without obstacle collisions. In the cooperative pursuit stage, a dynamic alliance method based on bidirectional negotiation strategy and a pursuit direction assignment method based on improved genetic algorithm are presented, which can realize the pursuit task efficiently. Finally, some simulations are conducted and the results show that the proposed approach is capable of guiding multi-AUVs to achieve the hunting tasks in unknown 3D underwater environment efficiently.

Keywords Heterogeneous AUVs system · Cooperative hunting · Spinal neural system · Fuzzy rule · Genetic algorithm

1 Introduction

Autonomous underwater vehicle (AUV) is the key tool for the future exploration and exploitation of marine world and can complete various underwater operations, such as underwater objects search and submarine scientific research [2, 4, 19, 35, 42]. Multiple AUV system enables individuals to cooperate with each other to execute difficult tasks, offering greater advantage over a single AUV in terms of diversity, robustness, reliability and efficiency, so it is the inevitable development direction in the AUV research field [3, 8, 34].

This paper focuses on the cooperative hunting problem for heterogeneous AUVs system, which is a very important and challenging task in the field of multiple AUVs. A lot of work has been done for the cooperative hunting problem. For example, Cao et al. [5] proposed a multirobot hunting method based on a distributed control approach using local coordinate systems. Ni and Yang [22] studied the problem of real-time cooperative hunting by multirobots in unknown environments and proposed a bio-inspired neural network-based method. Song et al. [28] presented a mathematical model of multirobot cooperative hunting behavior. However, there are obvious differences between the hunting tasks for the ground mobile robot and the underwater robot. For example, the underwater

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environment is very complicated, which is three-dimensional (3D) and has more uncertainties [13, 37, 45]. In addition, environmental detection is difficult and communication bandwidth in underwater environment is limited [10, 44]. So, the general cooperative hunting approaches for the ground mobile robot cannot be used directly for multiple AUVs.

Many researches have been proposed to deal with various tasks in the cooperative hunting task. For example, Zhu et al. [43] proposed an improved self-organizing map and velocity synthesis method for the dynamic task assignment and path planning of multi-AUV system. Jung et al. [15] proposed a localization method of AUVs by exploiting visual measurements of underwater structures and artificial landmarks. Liu et al. [17] presented a collaborative path planning method for multi-AUVs under the influence of time-varying ocean currents, based on the dynamic programming algorithm. Those methods discussed above made the foundations for the multi-AUV hunting task. However, few of those methods above considered the cooperative hunting task as a whole, and the complexity of the hunting task in the unknown underwater environment is ignored.

The method of cooperative hunting for multiple AUVs should consider not only the safety of the AUVs, but also the cooperative efficiency [7, 14, 39]. To deal with the problem of the cooperative hunting for multiple AUVs in unknown 3D environment, some methods have been proposed. For example, Huang et al. [14] proposed a multi-AUV cooperative hunting algorithm based on bio-inspired neural network in 3D underwater environment with obstacles. Abreu et al. [1] presented a coverage path planning technique for search operations which takes into account the vehicle's position and detection performance uncertainties. However, there are still some shortcomings in the existing methods that should be solved, such as the low efficiency of the target search in the complex 3D underwater environment, and the complex computation in the cooperative pursuit method.

There are two main tasks in the cooperative hunting for multiple AUVs, namely the target search and pursuit, in which target search is the prerequisite for the hunting task [4, 40]. There are two kinds of target search methods, according to the target information. One is based on known information of target prior distribution, such as heuristic search methods [9, 32]. The other is based on completely unknown target information, such as the region search methods [23]. In the target pursuit stage, a pursuit alliance should be set up firstly when there are several targets. The adaptivity of the method to construct an alliance is very important for the overall efficiency of the cooperative hunting task.

Recently, more and more researchers focused on the bio-inspired methods, which is a hot area of research in multi-AUV control field [20]. For example, Sun et al. [29] presented a bio-inspired cascaded control approach for three-dimensional tracking control of unmanned underwater vehicles. Phillips et al. [24] developed an analytical model based on a similar mechanism used by fish to predict which flow frequencies excite the natural vibration modes of a flexible cylinder. Liu et al. [16] proposed a bio-inspired geomagnetic navigation model based on course constraint strategy under anomalies field disturbing for AUV. In this paper, to overcome the problems and complete the cooperative hunting task efficiently, a novel bio-inspired intelligent method is proposed, which is based on an improved spinal neural system [20, 27].

In the proposed approach, a novel search method is firstly proposed, where the search area is divided into many parts based on the underwater operation depth, and a column parallel search strategy is used to cover the search area orderly. To keep search formation of multi-AUV system, a formation control method based on the spinal neural system is proposed in this study. After retrieving the target information, a dynamic alliance for the target pursuit is determined using a bidirectional negotiation strategy. Then, an improved genetic algorithm is used to assign the pursuit direction for each AUV toward the target. The cooperative hunting method in this paper takes full consideration of the obstacles, making the pursuit task more in line with the actual situation and improving the practicality of the method.

The main contributions of this paper are summarized as follows. (1) A cooperative hunting task in 3D unknown underwater environment is presented, which is completed by two different types of heterogeneous AUVs. (2) A biologically inspired spinal neural system-based method is proposed for this task, which is an integration of several methods. (3) The ability of the spinal neural system-based method is improved, considering various actual situations in the hunting task. (4) Some simulations were conducted in 3D underwater environments, where various situations of the hunting task in real underwater environments were simulated, such as the obstacles in water, underwater mountains and damage of AUVs.

This paper is organized as follows. Section 2 presents the problem statement. The proposed cooperative hunting method for multiple AUVs based on spinal neural system is given in Sect. 3. Section 4 gives the simulation studies and the result analysis. The performance of the proposed approach is discussed in Sect. 5. Finally, conclusions are given in Sect. 6.

2 Problem Statement

In this paper, the heterogeneous AUVs cooperative hunting problem in unknown 3D environment is studied, and a cooperative hunting approach based on an improved spinal neural system is proposed. In this study, the environment information and the location of the target are completely unknown at the beginning of the hunting task, but each AUV is considered as an omnidirectional robot, having a 360° visual capability and the abilities to communicate with other AUVs, recognize each other, identify the target, detect obstacles and determine their locations in real time.

In the hunting task (denoted by Ψ) studied in this paper, a heterogeneous AUVs system (denoted by Ω_H) is used, where the AUV for search (denoted by A_{Si}) is different from the AUV for pursuit (denoted by A_{Pi}). The search AUV is assumed to have some more advanced sensors for target detection, and bigger energy storage capacity, which can complete the search task efficiently and more quickly. The pursuit AUV is assumed to have some special abilities (such as good mobile abilities and higher intelligence for cooperation), which is suitable for pursuit. It means that AUVs are identical for the same tasks, but heterogeneous for different tasks.

The workflow of the cooperative hunting task by the heterogeneous AUVs system is as follows: (1) The search task is conducted by the search AUVs, till the designated area is completely covered and all the targets in this area are found. (2) All the targets are marked and their information is sent to the pursuit AUVs. (3) The pursuit AUVs form dynamic alliances and conduct the pursuit task based on the target information. (4) When all the targets are caught, the hunting task is completed. The workflow of the hunting task is shown in Fig. 1, and the solutions for the three main procedures will be introduced in the next section.

Remark The main objective of this paper is to study the cooperative hunting by a multi-AUV system. The concrete technologies, such as fault diagnosis, environment detection and underwater communication, are not introduced in this study, which have been focused in other literature [11, 36, 38].

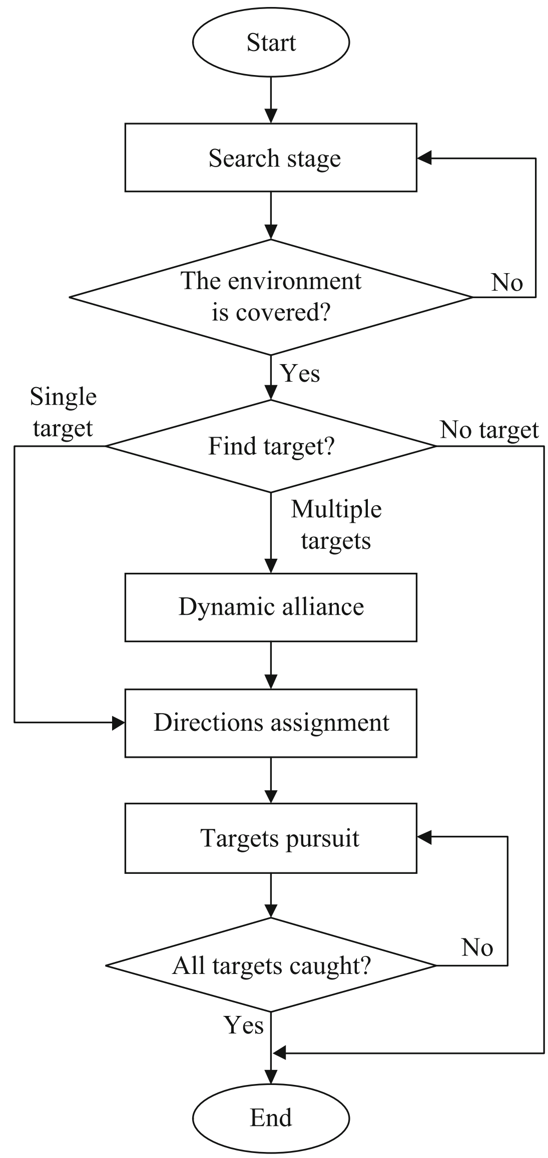

Fig. 1 The workflow diagram of the hunting task in this study

3 Proposed Approach

In order to complete the cooperative hunting task for heterogeneous AUVs system in an unknown 3D underwater environment, some key problems should be solved efficiently, including the formation control in the search stage, the dynamic alliance construction and the pursuit direction assignment. In this paper, an integrated approach based on an improved spinal neural system is proposed, which is presented in details as follows.

3.1 Spinal Neural System-Based Formation Control for Multi-AUV Search

In the search stage, how to improve the search efficiency and the search success rate are the key issues. According to obstacle distribution in underwater environment and the kinetic characteristic of AUVs, the partition search strategy based on the underwater depth (as shown in Fig. 2) is used in this paper, where the search area is divided as follows:

$$\text{Area}_i = d_i \text{ to } d_{i+1}, \quad i = 1, 2, \ldots, N \tag{1}$$

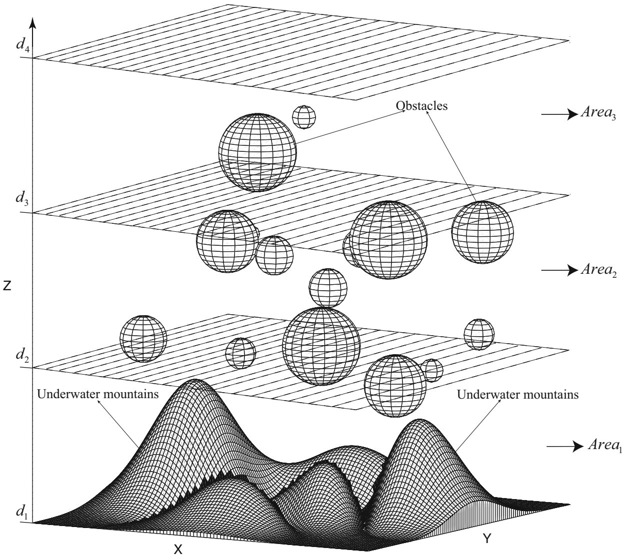

Fig. 2 The partition search strategy based on the underwater operation depth

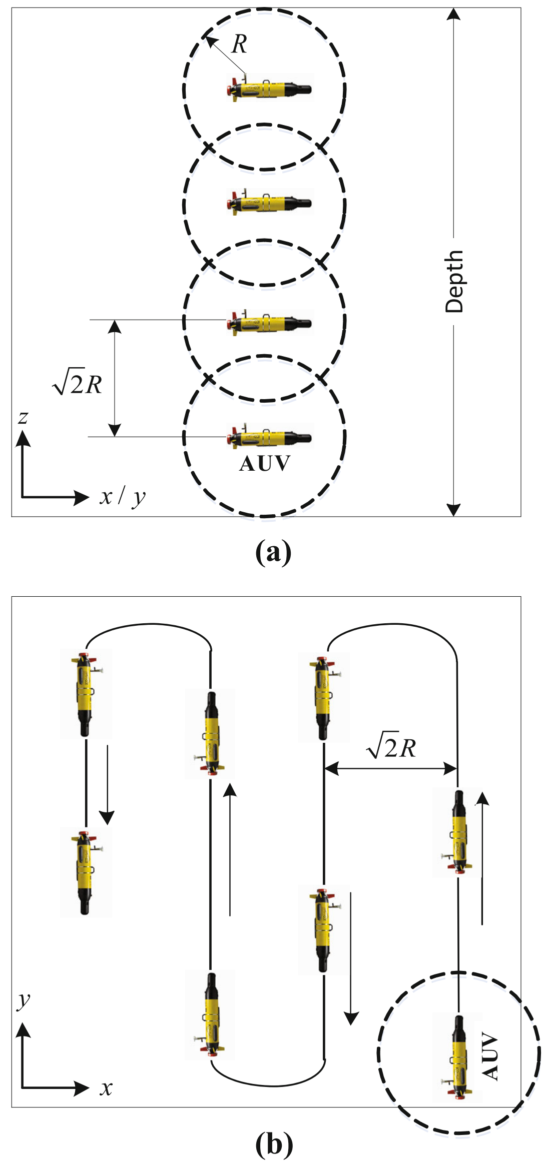

Fig. 3 The column parallel search strategy: **a** multi-AUV column formation observed from the x–z or y–z plane; **b** the AUV predetermined search path observed from the x–y plane

where Area$_i$ denotes the ith subarea, d_i is depth and N is the total number of subareas, which is decided by the detection ability of AUV and the depth of the environment.

In order to minimize the number of AUVs and expand the search range, the AUV does not only need to avoid obstacles, but also it should maintain a certain formation with other AUVs [12]. So, a column parallel search strategy is used in this study (see Fig. 3). The formation control is very important for improving the search success rate. In this study, an improved spinal neural system inspired method is used for the formation control. The main reason of using this spinal neural system inspired method is that it has both the advantages of behavior-based methods and the empirical methods [18, 26, 27].

The basic work mechanism of this spinal neural system is as follows: The spinal neural system obtains the input environmental information of the sensory organs and reacts after fusion, and then, the simple fundamental movements (such as jump, claws and other acts) are stimulated. This method simplifies the fusion of perceptual information and the rules of behavior decision, so it can make a decision efficiently, which is suitable for the formation control of multi-AUV system in the complex unknown underwater environment.

In this spinal neural system-based method, there are three procedures, namely sensor data fusion, behavior mapping of spinal nerve fields and fuzzy control. Here, the sensory data are assumed to be correct enough, so the sensor data fusion is not introduced in this study. (The details can be seen in [27].) The mapping between the input information and the spinal neural system process is shown in Fig. 4.

As shown in Fig. 4, the final decision in the proposed spinal neural system-based method is based upon the environment information F, the location information G and the team information H, to obtain the behavior B. The environment information F is obtained from the onboard sensors, which is marked by:

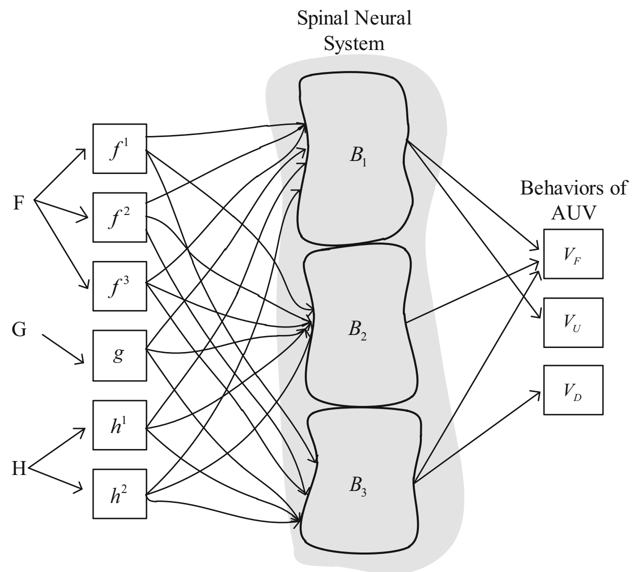

Fig. 4 The mapping between the input information and the behaviors based on the spinal neural system

$$f_i^1 = \begin{cases} 0, \text{ No obstacle up forward of } A_{\mathrm{Si}} \\ 1, \text{ Some obstacles up forward of } A_{\mathrm{Si}} \end{cases}$$
$$f_i^2 = \begin{cases} 0, \text{ No obstacle forward of } A_{\mathrm{Si}} \\ 1, \text{ Some obstacles forward of } A_{\mathrm{Si}} \end{cases} \tag{2}$$
$$f_i^3 = \begin{cases} 0, \text{ No obstacle down forward of } A_{\mathrm{Si}} \\ 1, \text{ Some obstacles down forward of } A_{\mathrm{Si}} \end{cases}$$

The location information G is the desired position of the ith AUV (A_{si}) to its real position, which is marked by:

$$g_i = \begin{cases} -1, & \text{It is in the front lower} \\ 0, & \text{It is in the right ahead} \\ 1, & \text{It is in the front upper} \end{cases} \tag{3}$$

The team information H is decided by the movement status of the neighboring AUV to the current AUV (A_{si}), which is denoted by:

$$h_i^k = \begin{cases} -1, & \text{It is moving down forward} \\ 0, & \text{It is moving forward} \\ 1, & \text{It is moving up forward} \end{cases} \tag{4}$$

where $k = 1, 2$, denotes the neighboring AUV above A_i and below A_i, respectively. If there is no any AUV above or below the current AUV, h_i^k is set as 0.

In this study, there are three cases of behavior B, namely moving up-forward, moving forward and moving down-forward:

$$B_1 = \{V_F, V_U\}, B_2 = \{V_F\}, B_3 = \{V_F, V_D\} \tag{5}$$

where V_F means moving forward, V_U means moving upward and V_D means moving downward.

In the spinal neural system-based method, the fuzzy control is used for the decision of the movement states of search AUVs [31], to realize the formation control. The fuzzy rules are listed in Fig. 5.

The search process of the proposed spinal neural system-based method is summarized as follows:

Step 1: Divide the 3D underwater environment to N subareas, and each subarea is assigned to a search group with M AUVs.

Step 2: The search group forms a column parallel search formation and plans a search path;

Step 3: Each AUV in the search group decides its movement using the spinal neural system-based method, based on current environment, positions of other AUVs and the search path.

Step 4: Each AUV begins to search in its own search area. If the environment is completely searched and all the targets are found, the search task is end, otherwise, go to Step 3.

3.2 Dynamic Alliance Based on Bidirectional Negotiation Method

When the search stage ends, the information of all the targets will be sent to the pursuit AUVs and the pursuit stage begins. Before pursuit task begins, each target should be assigned to a pursuit team, which is a dynamic alliance problem. In this study, a multi-AUV dynamic alliance assignment strategy based on the bidirectional negotiation method is proposed.

In the proposed dynamic alliance assignment strategy, not only the distance from AUV to target is taken into account, but also the number of pursuit AUVs for each target and the balance among all the teams are considered.

Rule Base
(1) If $f^1 == 0$ & $f^2 == 1$ & $f^3 == 1$, Then $B = \{V_F, V_U\}$
(2) If $f^1 == 1$ & $f^2 == 0$ & $f^3 == 1$, Then $B = \{V_F\}$
(3) If $f^1 == 1$ & $f^2 == 1$ & $f^3 == 0$, Then $B = \{V_F, V_D\}$
(4) If $f^1 == 1$ & $f^2 == 1$ & $f^3 == 1$ & $h^1 \neq -1$, Then $B = \{V_F, V_U\}$
(5) If $f^1 == 1$ & $f^2 == 1$ & $f^3 == 1$ & $h^1 == -1$, Then $B = \{V_F, V_D\}$
(6) If $f^1 == 0$ & $f^2 == 0$ & $f^3 == 1$ & $h^1 == 1$, Then $B = \{V_F, V_U\}$
⋮ ⋮ ⋮ ⋮ ⋮
(12) If $f^1 == 0$ & $f^2 == 1$ & $f^3 == 0$ & $h^2 == 0$ & $g == -1$, Then $\{V_F, V_D\}$
(13) If $f^1 == 0$ & $f^2 == 1$ & $f^3 == 0$ & $h^2 == 0$ & $g \neq -1$, Then $\{V_F, V_U\}$
⋮ ⋮ ⋮ ⋮ ⋮
(17) If $f^1 == 0$ & $f^2 == 0$ & $f^3 == 0$ & $h^1 == 1$ & $h^2 == -1$, Then $B = \{V_F\}$
(18) If $f^1 == 0$ & $f^2 == 0$ & $f^3 == 0$ & $h^1 == -1$ & $h^2 == 1$, Then $B = \{V_F\}$
(19) If $f^1 == 0$ & $f^2 == 0$ & $f^3 == 0$ & $h^1 == 1 \vert\vert h^2 == 1$, Then $B = \{V_F, V_U\}$
(20) If $f^1 == 0$ & $f^2 == 0$ & $f^3 == 0$ & $h^1 == -1 \vert\vert h^2 == -1$, Then $B = \{V_F, V_D\}$

Fig. 5 The proposed rule base for the spinal neural system-based method

An example of the dynamic alliance assignment method based on the proposed strategy is shown in Fig. 6.

The AUV chooses the desired pursuit target according to the target location and its own situation firstly; this is the choice process. For example, AUV1 (A_1) chooses target2 (T_2), A_4 chooses T_1, etc. (see Fig. 6a). After the choice process of AUVs, the targets begin to choose AUV. As shown in Fig. 6b, five AUVs are chosen by their desired targets, except A_2. So, it is time for the other round of the choice. The AUV that is abandoned by its desired target can choose a new desired target, and then, it will also be chosen again. After several rounds of this bidirectional negotiation selection, the dynamic alliance is established (see Fig. 6c). This kind of strategy is simple and efficient. The pseudocode of the proposed bidirectional negotiation method for the dynamic alliance is shown in Fig. 7.

Remark Based on the proposed bidirectional negotiation strategy, each AUV in the alliance will decide its pursuit target automatically, when the situations of other AUVs, the environment and the target change. Hence, the proposed dynamic alliance assignment strategy is distributed. This performance is very important for the multi-AUVs cooperation in complex underwater environment, which has lots of uncertainties.

3.3 Pursuit Direction Assignment Method Based on Genetic Algorithm

The final and important stage is to round up the target, after the dynamic alliance is established. So, each AUV in the same alliance should be assigned a pursuit direction to the target to achieve the pursuit task efficiently, which is an optimal solution search problem [30, 41]. In this paper, the AUV is not explicitly assigned a pursuit location coordinate, but distributed a direction (direction is expressed by an angle of altitude θ and azimuth ϕ). After these directions are determined, AUV adjusts the pursuit location coordinate according to the distance between AUV and target during the pursuit process.

Algorithm 1: The proposed dynamic alliance method

```
(1) Initialize: A_i, i = 1,2,..., NumA ; T_j, j = 1,2,..., NumT
    % Initialize the information of AUVs and targets;
(2) Calculate: tempActive(i, j) = |P(A_i) - P(T_j)|
    %Calculate the distance of each target to every AUV;
(3) If E(tempActive(i, j)) > C(A_i), tempActive(i, j) = MaxV
    % E(·) is a function to judge the energy consumption of AUV and C(·) is
    a function to get current energy of AUV;
(4) The AUVs choose the target:
      for i = 1 : NumA
        while flagA_i = 0
          row = find(tempActive(i,:) == min(tempAcitve(i,:)));
          if flagT_row = 0
            flagA_i = row; teamT_row = teamT_row + 1;
          else tempActive(i, row) = maxActive;
          end
        end
      end
(5) The targets choose AUV based on the choice of AUV:
      for j = 1 : NumT
        while teamT_j < teamT
          minActice = maxValue + 1; minA = 0;
          for k = 1 : NumA
            if flagA_k == i & tempActive(k, j) < minActive
              minActive = tempActive(k, j); minA = k;
            end
          end
          flagA_minA = -1; teamT_j = [teamT_j, minA];
        end
        flagA(find(flagA > 0)) = 0;
      end
(6) If there are some AUVs with enough energy left, go to (4), otherwise the
    bidirectional negotiation process is end and the dynamic alliance is
    constructed.
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Fig. 7 The pseudocode of the proposed bidirectional negotiation method for the dynamic alliance

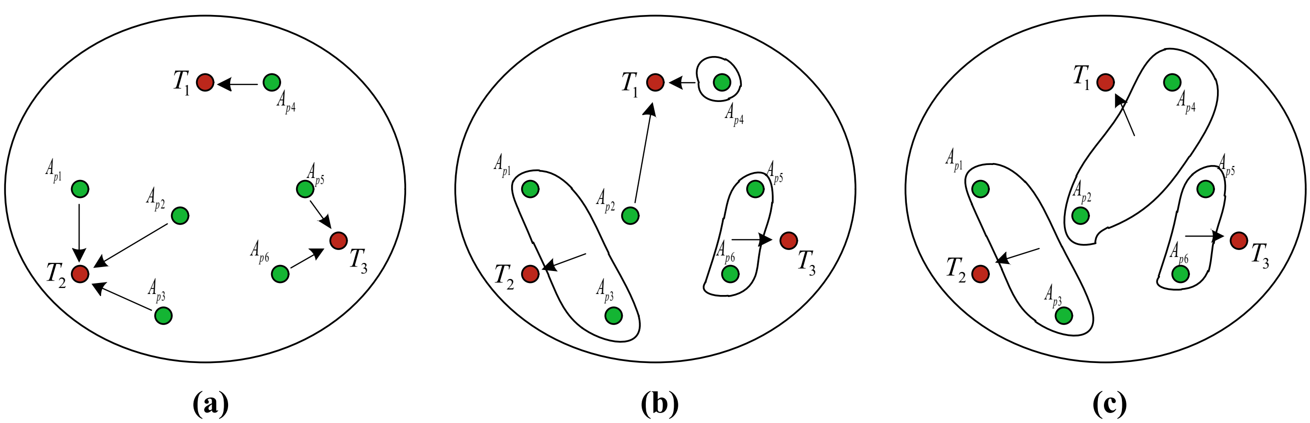

Fig. 6 An example of the proposed bidirectional negotiation dynamic alliance assignment strategy: **a** AUVs choose pursuit targets; **b** targets choose pursuit AUVs; **c** the results of dynamic alliance assignment

In this paper, a target pursuit direction assignment method based on an improved genetic algorithm (GA) is proposed. In the proposed method, the length of the chromosome of GA-based method can change adaptively with the number of members in the alliance, and a new fitness function is presented, which will be introduced in detail as follows.

(a) The coding scheme with adaptive length chromosome: The primary task of using GA for optimal search is the coding problem. In this study, solution of the optimal pursuit directions assignment problem is a sequential set of the corresponding directions for each AUV. So the chromosome length should be equal to the AUV number (denoted by *NumA*). Because the number of AUVs in each alliance is not same and may be changed during the pursuit task, the length of the chromosome needs to be adjusted adaptively based on the number of AUVs, which is expressed as:

$$p = \{(\theta_{i,1}, \phi_{i,1}), (\theta_{i,2}, \phi_{i,2}), \ldots, (\theta_{i,NumA}, \phi_{i,NumA})\} \tag{6}$$

where p is the chromosome used in the proposed GA-based method.

(b) Fitness function: The fitness function is used to test the fitness value of each solution. In this direction assignment task, the fitness function should consider the following factors: (1) Whether there are any obstacles on the temporary pursuit location. (2) Whether the pursuit directions are distributed evenly around the target. (3) Whether the sum of the distances of each AUV to the pursuit location is as small as possible. According to these factors above, a new fitness function $f(p)$ is presented:

$$f(p) = b(p)\left(\frac{wCir}{gapVarCir(p) + 1} + \frac{wDis}{totalDis(p) + 1}\right) \tag{7}$$

where $b(\cdot)$ is used to judge whether there is an obstacle; $gapVarCir(\cdot)$ is a function to calculate the distribution degree of directions; *wCir* is the weight of the distribution; *wDis* is the weight of distance; and $totalDis(p)$ is a function to calculate the sum of distances between the current position of AUV and the target.

(c) Genetic operators: In this paper, the genetic operators of the genetic algorithm are improved: (1) The mutation operator is changed to the internal mutation operator and the external mutation operator. The internal mutation operator is a mutation in different parts of a chromosome, and the external mutation operator is a mutation in different chromosomes. Namely, the internal mutation operator is to randomly change some genes of one chromosome, and the external mutation operator is to randomly replace one chromosome by a new one (see [25] and [33] for details). (2) The population migration operator is used. A part of the new individuals is produced into the population according to the probability of migration, taking the place of individuals with low fitness, increasing the diversity of the population greatly, avoiding premature convergence into the local extreme. In the selection process, a roulette selection strategy is used [6, 25], where the higher the fitness value is, the higher the selection probability is. The probability $P(p_i)$ of the ith individual p_i chosen to the next generation is calculated by

$$P(p_i) = \frac{f(p_i)}{\sum_{i=1}^{\mathrm{PopSize}} f(p_i)} \tag{8}$$

After the pursuit direction for each pursuit AUV is decided, the round-up position for each pursuit will be calculated. In this study, the round circle concentration strategy (namely the radius of the circle concentration will be reduced with the movement of the AUVs) is used. Then the intersection point of the pursuit direction and the round circle is the next round-up position for the certain pursuit AUV. Finally, the AUV will navigate to this position using some navigation methods. In this study, a bio-inspired neural network-based method is used for the AUV real-time path planning (which can be seen in our previous work [21] for details).

The whole workflow of the proposed method in the cooperative hunting task is summarized as follows:

Step 1: Divide the 3D underwater environment and the search AUVs begin the search stage based on the spinal neural system;

Step 2: If the environment is completely searched, the dynamic alliances for the pursuit AUVs are constructed by the bidirectional negotiation method;

Step 3: Each AUV in the dynamic alliance is assigned a pursuit direction based on the proposed GA-based method and begins the pursuit stage;

Step 4: Each AUV is navigated to the target based on its pursuit direction, by using the real-time path planning method;

Step 5: If all the targets are caught, the hunting task is end.

4 Simulation Studies

To test the effectiveness of the proposed method for the heterogeneous AUVs cooperative hunting in unknown 3D dynamic environment, some simulations are carried out by a computer with 4G RAM and i5-4460S 2.9 GHz CPU at the platform of MATLAB. To simplify the realization, the assumptions in this study are as follows: (1) The AUVs and targets are assumed as points without any shapes. (2) The target is assumed to have some simple intelligence to avoid being caught by the AUV system. (3) The AUV velocity is greater than the target velocity, otherwise it will be difficult to catch the targets. (4) The minimum number of the pursuit AUVs used to catch one target is 4. The parameters in all the simulations are the same and given in Table 1. The initial positions of the search AUVs are $A_{s1} = (10, 10, 16)$, $A_{s2} = (10, 10, 32)$, $A_{s3} = (10, 10, 48)$, and $A_{s4} = (10, 10, 64)$.

Remark (1) The shape of the AUV is a very important factor that should be considered in the control of actual AUVs. To deal with this problem, the obstacles are enlarged properly in the simulations. (2) The orientation angle of the AUV is just the movement direction in this study. (3) If the number of the usable pursuit AUVs in the system for one target is less than 4, the task is failed.

4.1 Single Target Simulation

In this simulation, there is only one target in the environment. Firstly, the search AUVs start to search from their initial positions with a uniform column (shown in Fig. 8a). The search process of the AUVs is shown in Fig. 8b. To show the multiple AUVs formation control in the cooperative search process, a Y-plane screenshot of the search trajectories of the AUVs is shown in Fig. 8c (where $Y = 58$). The results in Fig. 8 show that the search AUVs can adjust the search formation adaptively based on the information of obstacles and the distance between neighboring AUVs, and finally find the target efficiently. The coordinate of the target is $T_1 = (50, 55, 15)$, which will be sent back to the pursuit AUV system immediately.

Since there is only one target, just one alliance is needed for the pursuit task. After the alliance is set up, six AUVs are assigned to the pursuit task. The initial positions of the 6 pursuit AUVs are $A_{p1} = (10, 10, 5)$, $A_{p2} = (30, 20, 15)$, $A_{p3} = (15, 75, 15)$, $A_{p4} = (15, 90, 30)$, $A_{p5} = (80, 15, 20)$, $A_{p6} = (85, 65, 20)$ (see Fig. 9a). Firstly, each pursuit AUV will obtain a pursuit direction calculated by the proposed GA-based method and then start to pursue the target (see Fig. 9b). The target will run toward the area of no hunters when the pursuit AUVs come into the detection range of the target (see Fig. 9c). Despite this, the target is caught by pursuit AUVs from all directions at the position (57, 62, 32) (shown in Fig. 9d). In this simulation, the number of steps to catch the target is 551, and the total response time of the spinal neural system-based method is 0.0915 s. So the response efficiency of the formation controller is 0.0332 (ms/step). The result indicates that the response speed of the spinal neural system-based method is fast, which is very important for the cooperative hunting task.

Table 1 Parameters of the proposed method and the simulations

Parameters	Values	Remarks
M	4	Number of search AUVs
R	10	Detection range of AUV (m)
S	$100 \times 100 \times 70$	Size of environment (m^3)
PopSize	80	Size of population
Generation	100	Generation of population
CrossProb	0.6	Crossover probability
MutInProb	0.15	Internal mutation probability
MutOutProb	0.1	External mutation probability
SuppleProb	0.2	Migration probability

4.2 Multiple Targets Simulation

To test the performance of the proposed approach in multiple targets hunting task, this simulation is conducted. In this simulation, there are two targets, and the search results are shown in Fig. 10. As shown in Fig. 10, two targets are found successfully, and their positions are $T_1 = (40, 72, 15)$ and $T_2 = (70, 45, 20)$. After the search stage is completed, the target information is sent to the pursuit AUV system.

Because there are two targets found in the environment, two alliances should be constructed by the proposed bidirectional negotiation strategy firstly. In this simulation, the number of AUVs assigned to the pursuit task is 11, and their initial positions are $A_{p1} = (10, 10, 8)$, $A_{p2} = (30, 10, 15)$, $A_{p3} = (60, 15, 10)$, $A_{p4} = (15, 85, 12)$, $A_{p5} = (30, 95, 15)$, $A_{p6} = (10, 40, 10)$, $A_{p7} = (95, 20, 10)$, $A_{p8} = (80, 15, 18)$, $A_{p9} = (85, 65, 28)$, $A_{p10} = (5, 60, 24)$, $A_{p11} = (90, 90, 30)$, which are shown in Fig. 11a. Based on the alliance strategy, the pursuit alliances for the targets are T_1={A_{p3}, A_{p7}, A_{p8}, A_{p9}, A_{p11}} and T_2={A_{p1}, A_{p2}, A_{p4}, A_{p5}, A_{p6}, A_{p10}}, respectively.

If all the pursuit AUVs are working normally, the AUV in each alliance will catch its own target and not interfere with other AUVs. The results in this normal states are shown in Fig. 11. The two targets are caught at the position $T_1 = (30, 79, 26)$ and $T_2 = (58, 76, 51)$, respectively (shown in Fig. 11d). The simulation results show that the proposed cooperative hunting method for the heterogeneous AUVs is effective and practical.

4.3 AUV Damage Simulation

During the pursuit process, the AUV may break down due to some accident. To further test the performance of the proposed method in this state, a simulation is conducted, where all the initial conditions and the search process are the same as the simulation in Sect. 4.2, expect one pursuit

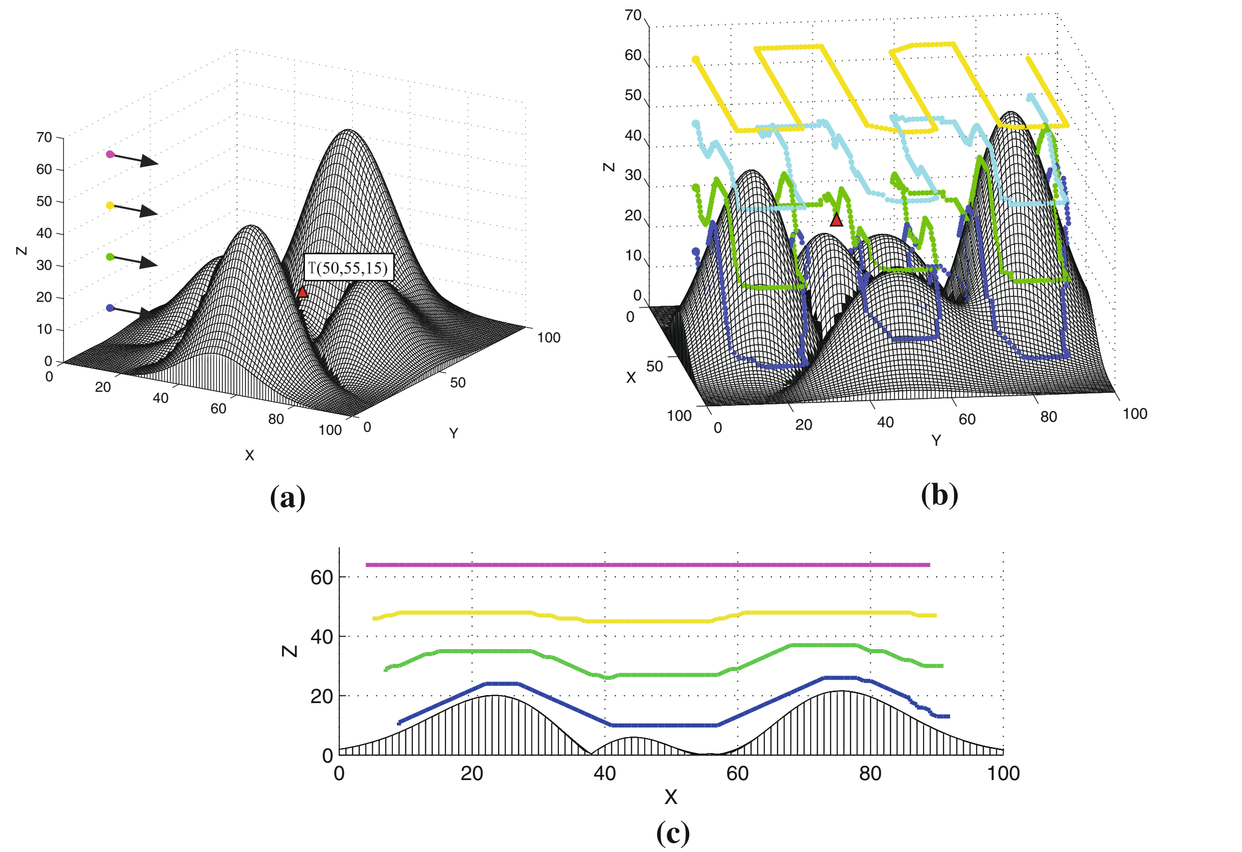

Fig. 8 The search process of single target: **a** initial positions and formation of search AUV, view = (31°, 18°); **b** search path and results, view = (75°, 32°); **c** the Y-plane screenshot of the search path, $Y = 58$

AUV will break down. The simulation results in this state are shown in Fig. 12.

In this simulation, the pursuit AUV A_{P8} in the alliance for target T_1 is assumed to fail at position (78, 43, 29) when the pursuit process is at the 30th step (see Fig. 12b). Because there are just four pursuit AUVs for target T_1, which cannot complete the task of target hunting efficiently, and the balance between the alliances for T_1 and T_2 is broken, the alliances for the two targets should be modified based on the real-time conditions. Then the bidirectional negotiation process starts, based on the information of the targets, the pursuit AUVs and the environment. In this simulation, the pursuit AUV A_{P2} goes to the first alliance. The two new alliances are $T_1 = \{A_{p2}, A_{p3}, A_{p7}, A_{p9}, A_{p11}\}$ and $T_2 = \{A_{p1}, A_{p4}, A_{p5}, A_{p6}, A_{p10}\}$, respectively (see Fig. 12c). Finally, the two teams catch the targets successfully at the position $T_1 = (44, 76, 47)$ and $T_2 = (75, 78, 53)$ (as shown in Fig. 12d). The simulation results show that even if the AUV failure occurs in the hunting process, the proposed algorithm can adjust the assignment as soon as possible and finally realize the multi-target hunting task.

5 Discussions

The results of the simulations in Sect. 4 show that the proposed method can achieve the heterogeneous AUVs cooperative hunting task effectively in an unknown 3D environment. The performances of the proposed method are discussed in this section.

In order to verify the success rate of the proposed spinal neural system-based search algorithm, it is compared with the general random search algorithm. The workflow of the random algorithm is that all the AUVs search the environment randomly without any search strategies [23]. Some comparison simulations are conducted, where the environment is the same as the first simulation in Sect. 4.1. If the number of the maximum search steps is 600, the proposed search strategy in 10 repetitive simulations can ensure a 100% success rate; however, the success rate of the random search algorithm is only 70%. In addition, the communication between the AUVs in the proposed algorithm is very small, where only the movement states of the neighboring AUV are needed. But the information of all the other AUVs should be communicated in the search system based on the random search algorithm. This

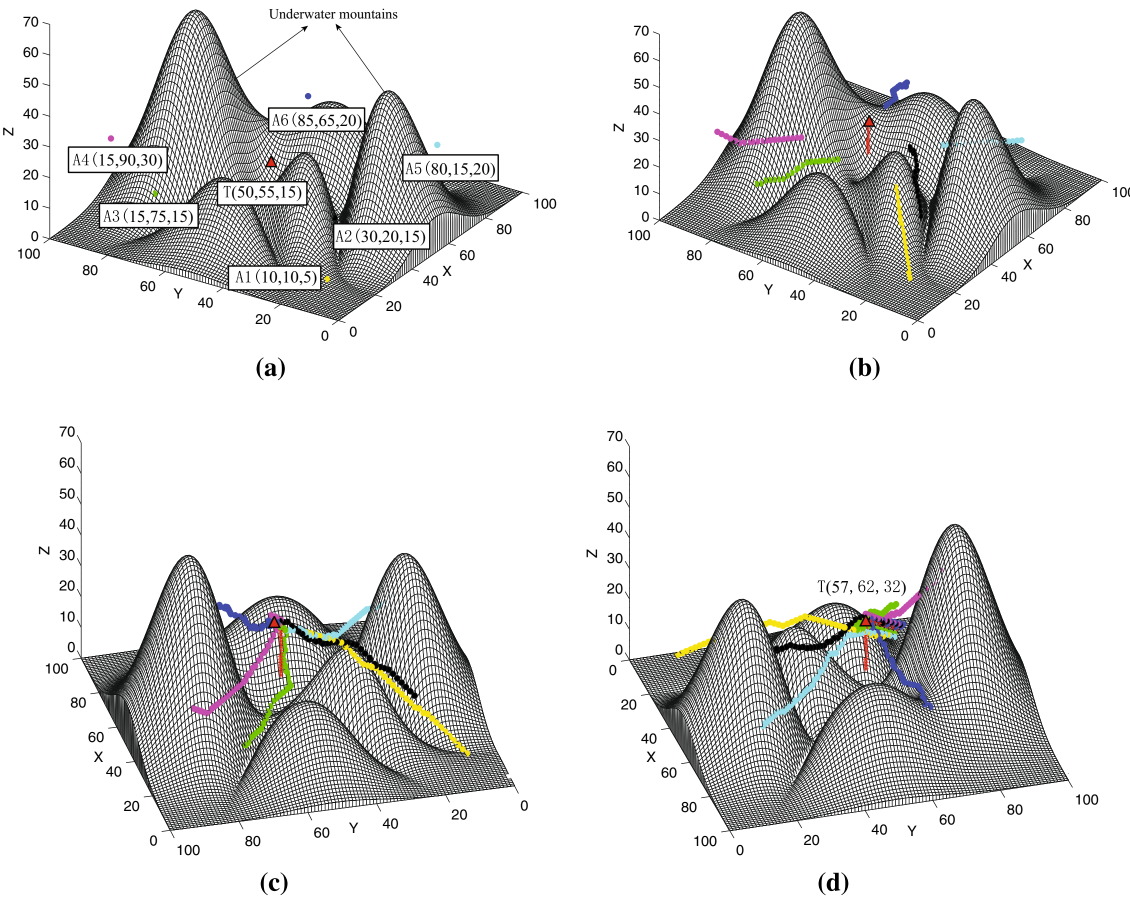

Fig. 9 Hunting process of single target: **a** initial positions and formation of hunting, view = (−57.5°, 26.4°); **b** at the 20th step, view = (−54.5°, 33.0°); **c** at the 38th step, view = (104.5°, 30.0°); **d** final trajectories, view = (73.5°, 30.3°)

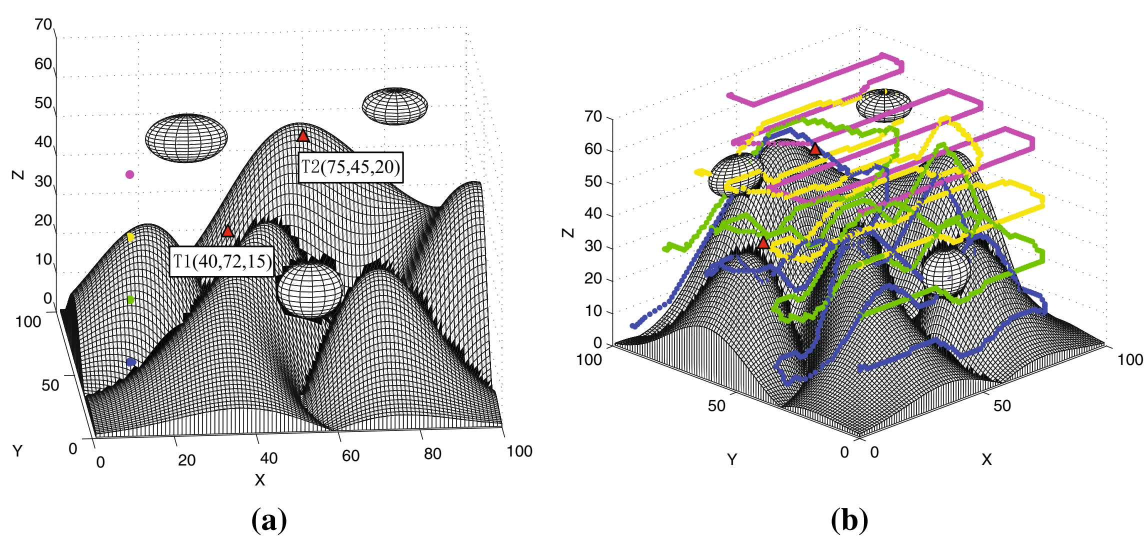

Fig. 10 Search process of multiple targets: **a** initial positions and formation of search AUVs, view = (−5°, 18°); **b** search path and result, view = (−45°, 22°)

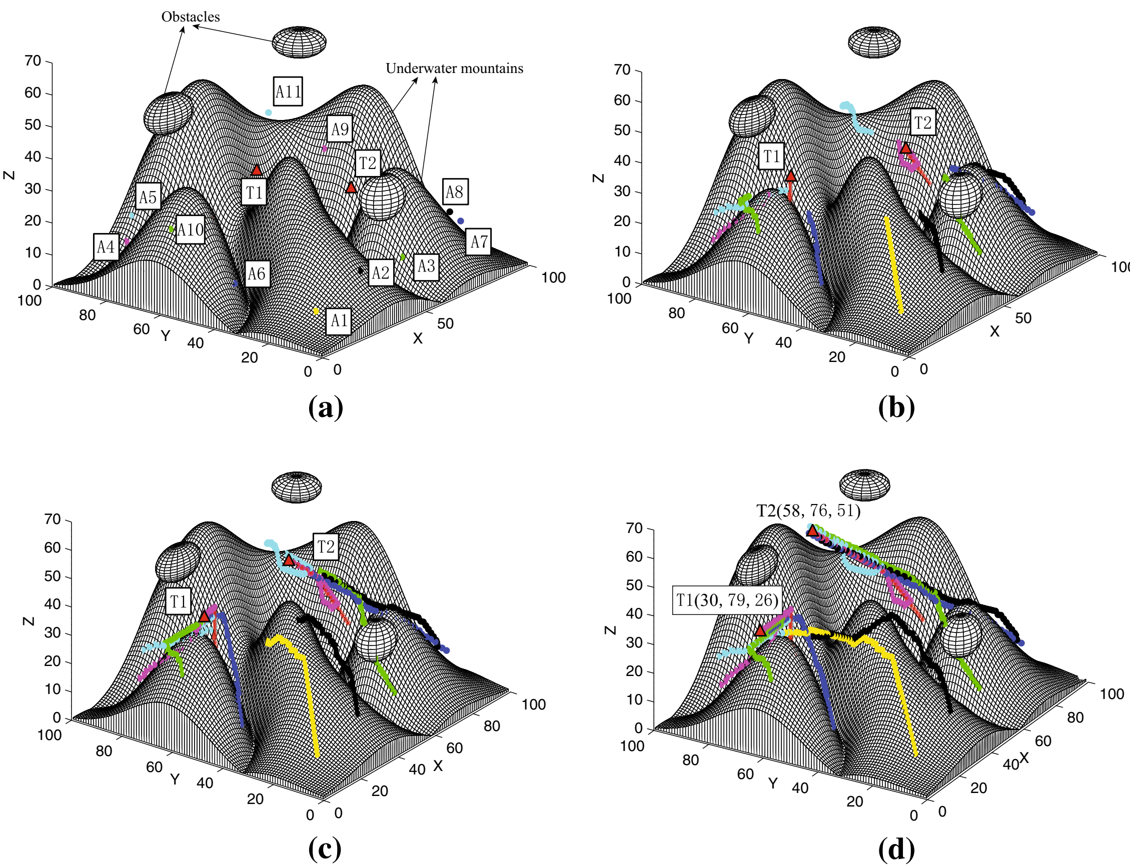

Fig. 11 Hunting process of multiple targets: **a** Initial positions and formation of hunting, view = (−52.5°, 20°); **b** at the 20th step, view = (−54.5°, 22.5°); **c** at the 40th step, view = (−53.5°, 25.5°); **d** final trajectories, view = (−59.5°, 25.5°)

performance of the proposed algorithm is very important for the AUV's task, because the communication is very difficult in the underwater environment.

To illustrate the advantage of the proposed pursuit direction assignment method based on the improved genetic algorithm, another comparison simulation is conducted, where the proposed method is compared to the fixed direction assignment strategy based on the negotiation method (see [22, 43] for details). To easily show the effectiveness of the pursuit direction assignment method, here the pursuit positions for each AUV are used to evaluate the pursuit direction assignment methods. The pursuit positions for AUVs based on the two methods are shown in Fig. 13, where there are six AUVs for the pursuit task, and their initial positions are $A_{p1} = (5, 2, 2)$, $A_{p2} = (7, 2, 2)$, $A_{p3} = (9, 2, 2)$, $A_{p4} = (11, 2, 2)$, $A_{p5} = (13, 2, 2)$, $A_{p6} = (15, 2, 2)$. The position of the target is $T_1 = (10, 10, 10)$. The evaluation results are listed in Table 2. The results in Fig. 13 and Table 2 show that both of the two methods can form a good round circle; however, the results obtained by the proposed method are more suitable, because each direction for the AUV is capable of forming a round circle, and the distance between all the AUVs and the pursuit positions is smaller than that of the fixed direction assignment strategy.

6 Conclusions

The heterogeneous multi-AUV cooperative hunting problem in an unknown 3D environment is studied in this paper, and a novel integrated method is proposed. In the proposed method, an improved spinal neural system-based method is presented for the multi-AUV search. In the pursuit stage, a bidirectional negotiation method is proposed to construct the dynamic alliance for multiple pursuit AUVs, and an improved GA-based method is used to realize the pursuit direction assignment. The proposed method can deal with the problems in the cooperative hunting task efficiently. The communication burden of the proposed method is less than other methods, and the adaptivity of the proposed method is high, which is very suitable for the cooperative hunting of multiple AUVs in the complex 3D underwater environment. In the future work, the real experiments for

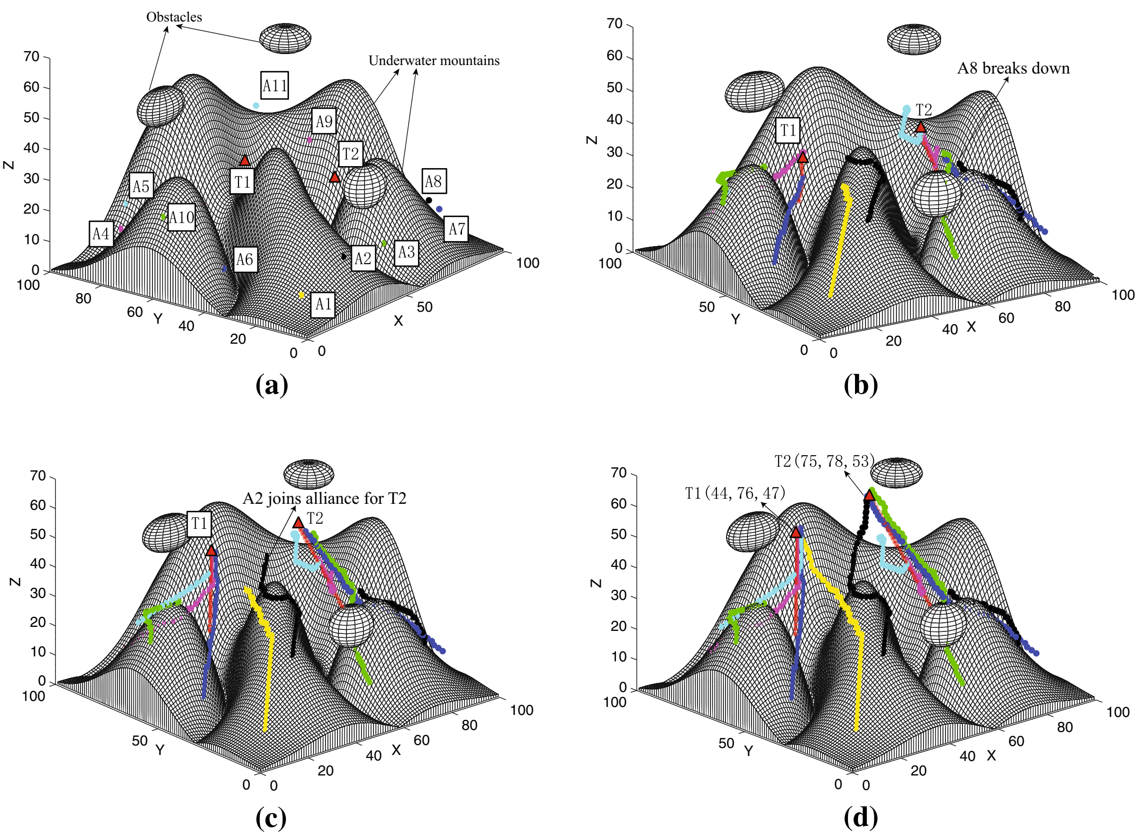

Fig. 12 Hunting process of multiple targets when the AUV damage occurs: **a** initial positions and formation of hunting, view = (−55.4°, 21.5°); **b** at the 30th step, view = (−33.5°, 18.0°); **c** at the 50th step, view = (−40.5°, 21.7°); **d** final trajectories, view = (−41.5, 19.7)

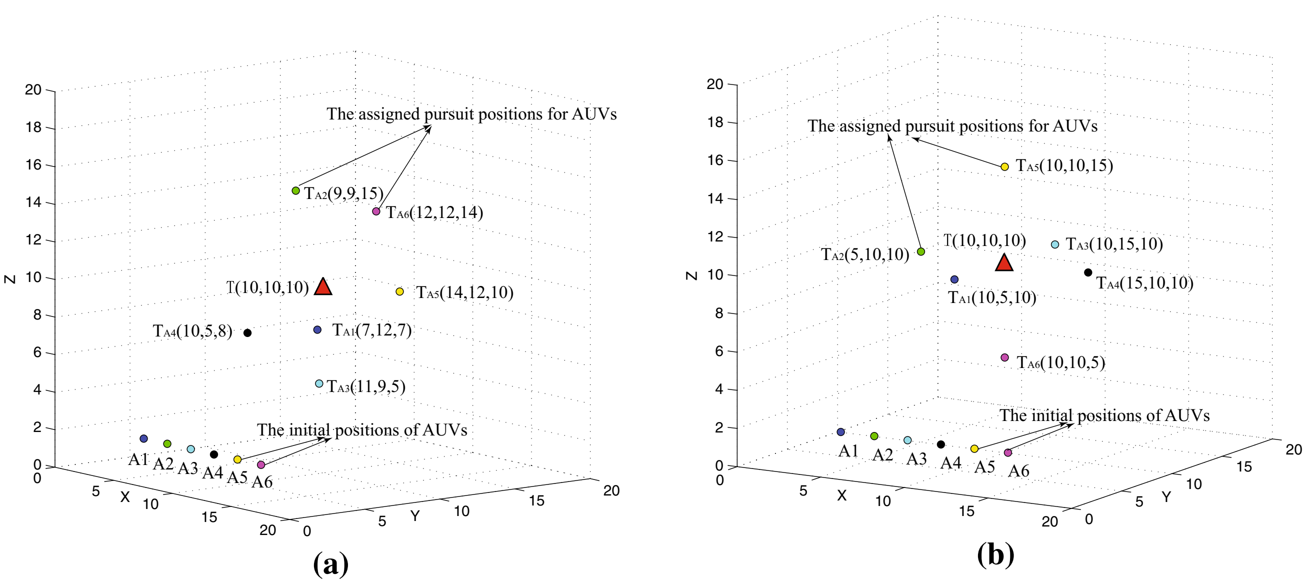

Fig. 13 The comparison simulation results of the two pursuit direction assignment strategies: **a** based on the proposed method; **b** based on the fixed directions

Table 2 The comparison results of the two pursuit direction assignment strategies

Assignment strategy	The distance between AUV and the respective target (m)						The total distances (m)
	A_{p1}	A_{p2}	A_{p3}	A_{p4}	A_{p5}	A_{p6}	
The proposed method	11.36	14.9	7.87	6.78	12.85	15.91	69.67
The fixed directions	9.9	11.49	15.3	12	15.56	9.9	74.14

multiple AUVs hunting will be conducted to test the practical performance of the proposed method. In addition, the bio-inspired method will be studied further, to present some more efficient methods for the applications in heterogeneous multiple AUVs.

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