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Dynamic Task Assignment for Multi-AUV Cooperative Hunting

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ABSTRACT

For cooperative hunting by a multi-AUV (multiple autonomous underwater vehicles) team, not only basic problems such as path planning and collision avoidance should be considered but also task assignments in a dynamic way. In this paper, an integrated algorithm is proposed by combining the self-organizing map (SOM) neural network and the Glasius Bio-Inspired Neural Network (GBNN) approach to improve the efficiency of multi-AUV cooperative hunting. With this integrated algorithm, the SOM neural network is adopted for dynamic allocation, while the GBNN is employed for path planning. It deals with various situations for single/multiple target(s) hunting in underwater environments with obstacles. The simulation results show that the proposed algorithm is capable of a cooperative hunting task with efficiency and adaptability.

KEY WORDS: multiple autonomous underwater vehicles (Multi-AUV), cooperative hunting, dynamic task assignment, self-organizing map (SOM) neural network, Glasius Bio-Inspired Neural Network (GBNN).

1 INTRODUCTION

COOPERATIVE hunting aims to surround detected targets by autonomous underwater vehicles (AUVs) in a certain pattern. Cooperative hunting methods are similar to pattern formation using swarm AUVs, which is often concerned with the formation of a complex shape (Millan et al., 2014; Cai, 2013). Multi-AUV hunting has attracted much attention as a good verification of cooperation and coordination of a multi-AUV system. Some significant achievements have been obtained in the exploration field (Huang et al., 2016; Zhu et al., 2015; Huang et al., 2013; Zhang et al.,2016; Shen et al.,2017) For example, Huang et al. (2013) proposed a loose-preference rule for cooperative hunting by swarm robotic systems. Zhang et al. (2016) used a reinforcement learning method with animal behavior to conduct research on the hunting problem. For multiple robots, a Lyapunov-based cooperative hunting method was proposed in Shen et al. (2017). The results of this paper showed that the robot group can effectively track and trap the target simultaneously. Robin et al. (2016) proposed a transverse synthesis, which solves the decision problem that target detection and tracking encompasses.

However, all of the above articles concentrate on known environments for a cooperative robot hunting task. In reality, working environments for robots are often unknown. In order to deal with a multi-robot hunting task in unknown environments, Zhang et al. (2014) proposed a self-organizing method based on a simplified virtual-force model for nonholonomic mobile swarm robots hunting in an unknown dynamic environment. This robust approach can make the group of robots maintain a good hunting formation in unknown dynamic obstacle environments and attain good performance in obstacle avoidance and flexibility. Recently, research has focused on the hunting problem with multiple evaders. Ni and Yang (2011) presented a multi-robot collaborated hunting algorithm based on a bio-inspired neural network in real-time in unknown environments. In the proposed approach, the pursuit alliances can dynamically change, and the robot motion can be adjusted in real-time to pursue the evader cooperatively to guarantee that all the evaders can be caught efficiently. The proposed approach can deal with various situations, e.g., when some robots break down, the environment has different boundary shapes. The results show that this algorithm is feasible and effective. Ishiwatari et al. (2014) proposed a new method in which multiple robots cooperatively hunt for a target using mobile

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agents. The mobile agents traverse mobile robots through migrations while collecting information about the target. Since each robot just needs to establish a connection with another robot for migration of a mobile agent, our method reduces the total communication cost of the system. However, the previous four papers did not consider map-building comprehensively, and obstacle avoidance was not usually considered in the literature (Avinesh et al., 2016).

Recently, researchers approached the hunting process with simple obstacles. Huang et al. (2016) proposed a multi-AUV cooperative hunting algorithm based on a bio-inspired neural network for 3-D underwater environments with obstacles. The simulation results demonstrate the effectiveness of the proposed algorithm. Pan et al. (2008) applied the improved reinforcement algorithm to the multi-robot hunting problem. However, in these studies, the hunting target was often static and not fully consistent with real environments.

To tackle the shortcomings discussed above, Belkhouche et al. (2005) focused on the problem of hunting an unpredictably moving prey using a group of robots. In this paper, for obstacles and cooperative collision avoidance, a collision cone approach was used. Zhu et al. (2015) proposed an algorithm based on a bio-inspired neural network model applied in a hunting task. This algorithm can provide rapid and highly efficient path planning in unknown environments with obstacles and non-obstacles. In order to solve obstacle avoidance in multi-robot hunting, Uehara et al. (2017) proposed a new PSO (particle swarm optimization)-based approach, enabling particles' search and capture of the target while getting around obstacles. In this approach, each robot records its moving trace in a fixed period. Once a robot is blocked by obstacles and cannot proceed, it creates a mobile software agent that migrates to other robots around it through Wi-Fi. In Sajjad et al (2017), a limit cycle-based algorithm using a neural oscillator with phase differences was proposed. Using the proposed algorithm, a group of robots is intended to move towards the target in such a way that the robots surround it. While moving to the target, self-collision between the robots is avoided. Moreover, collision avoidance with static obstacles, as well as dynamic targets, is realized. The robots reach the target at a desired distance, keeping uniformly distributed angles around the target. However, these algorithms do not consider task assignment of the multi-robot/multi-AUVs; the limitations in terms of coordination, robustness and effectiveness of a robot team mean that these methods cannot be fully applicable for a multi-AUV cooperative hunting problem in underwater circumstances.

In this paper, we study an algorithm for cooperative hunting of multi-AUVs in underwater environments. To improve cooperation efficiency and reduce energy consumption, an integrated strategy is proposed by combining a self-organizing map (SOM) neural network and Glasius Bio-Inspired Neural Network (GBNN) for hunting targets in underwater environments. As for the general design, because of similar characteristics between the multi-AUV system and a SOM neural network, the SOM algorithm can be used in multi-AUV task assignments. In cases of no prior knowledge about the dynamic environments, and without any learning procedures, GBNN is developed to plan AUVs' hunt paths. By combining the two algorithms, it is expected to avoid the conflict between AUVs and reduce energy consumption of the whole work system.

The advantages of this approach can be summarized as follows. 1) This approach is a combination of two methods and thus gives full play to the merits of both for cooperative hunting. 2) When the GBNN algorithm deals with different situations, it does not need a large number of function evaluations and parameter (A, B, D, μ and R) adjustments. To work for real-time cooperative searching and tracking, the proposed approach can be extended to real-world applications easily. 3) While the SOM-based approach has been applied for a multi-AUV system to deal with task assignments, it could be developed to perform collision avoidance.

The rest of the paper is organized as follows. In Section II, the problem statement is given. Section III presents the SOM- and GBNN-based integrated approach. The simulation experiments for various situations are given in Section IV. Finally, Section V presents the conclusion.

2 PROBLEM STATEMENT

IN this paper, a cooperative hunting task of multi-AUVs in underwater environments is studied. The multi-AUV system is unfamiliar with the underwater environments beforehand. Figure 1 shows the underwater environments randomly distributed with obstacles, AUVs and target. Its hunting process involves two phases, as shown in Figure 2. First, to reduce energy consumption and improve cooperation efficiency, only some of the AUV team members are assigned with hunting tasks. Second, the task performers should avoid obstacles while finding as short a path as possible. Figure 3 shows the conditions where the target is successfully surrounded by hunting AUVs. All targets, once surrounded, are regarded as being hunted, and the hunting task ends.

3 PROPOSED ALGORITHM

IN order to achieve the cooperative hunting task in unknown environments by multi-AUVs, two key problems need to be solved. The first is how to do the allocated tasks dynamically. The other is how to do cooperative hunting efficiently. Other problems that need solutions include how to realize collision avoidance. In this paper, an integrated approach based on a SOM neural network and GBNN is proposed. The

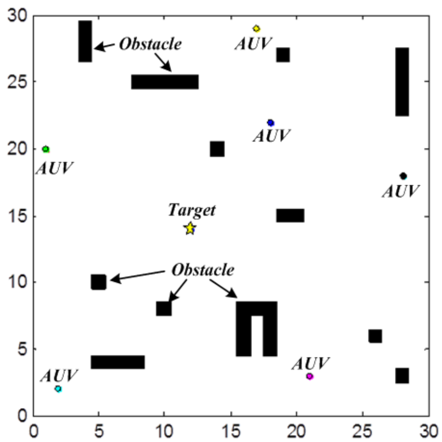


Figure 1. Underwater hunting environments

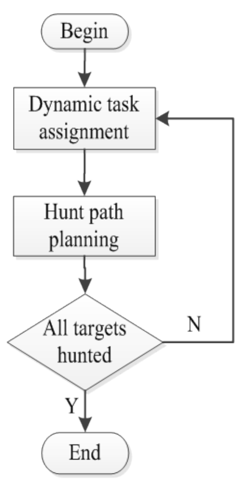


Figure 2. Flowchart of multi-AUV target hunting

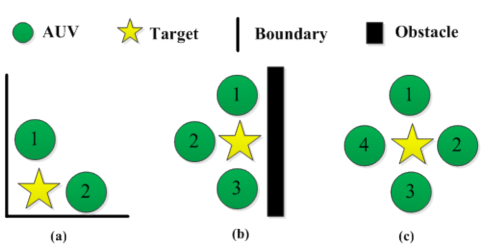


Figure 3. Target is hunted by AUVs in three conditions: (a) Hunted state in corner (b) Hunted state with help of obstacles (c) Hunted state by four hunting AUVs

SOM neural network is used to solve the task assignment problems while the pursuing target strategy for the hunting task is achieved by a GBNN.

3.1 Multi-AUV dynamic task assignment

The SOM neural network model with two layers is present in Figure 4. When the SOM neural network is used in a multi-AUV task assignment, the first layer is the input layer, including Q neurons which represent the Cartesian coordinates of the target; parameters (x_i, y_i) form one input neuron. The second layer is the output layer that involves AUV's coordinates. Each neuron of the output layer connects to the neurons in the input layer. The strength of each output neuron is given by a 2-D weight vector, which is initialized as the initial AUV's coordinate. Subspaces are input to the network one by one until the last target is input. The iterations end until all targets have been assignment AUV (Zhu et al., 2013).

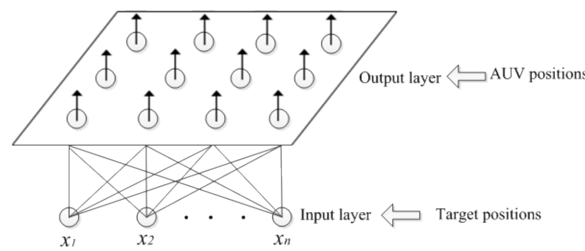


Figure 4. Structure of the SOM neural network

We divide the overall problem into some sub-problems including the rule to select, for the winner, the definition of the neighborhood function and the rule to update weights. First, the SOM algorithm is applied to determine which AUVs are the winners for targets. Then, the neighborhood function determines which AUVs are the neighbors of the corresponding winners, meanwhile, figures out the moving speed for winners as well as neighbors (Cao and Zhu, 2017; Kohonen, 1982).

A. Winner selection rules

The winner is determined by the following expression (Zhu and Yang, 2006):

$$[P_j] \Leftarrow \min\{D_{ij},\ i=1,2,...,I;\ j=1,2,...,J\}\ , \tag{1}$$

where $[P_j]$ denotes that the j-th neuron f is the selected winner to the i-th input neuron. D_{ij} is a value related to Euclid distance between the correlated two neurons. Selecting the winner depends on how to define and calculate D_{ij} during iterations. First, an equation is given to interpret the Euclidean distance between two neurons (Hendzel, 2005):

$$D_{ij} = |T_i - R_j| = \sqrt{(x_i - w_{jx})^2 + (y_i - w_{jy})^2}\ . \tag{2}$$

$T_i = (x_i, y_i)$ is the coordinate of the i-th input neuron in the 2-D coordinate system, which also donates the location of the subspaces. $R_j = (w_{jx}, w_{jy})$ is the coordinate of the output neurons, representing the location of a certain AUV at a certain time.

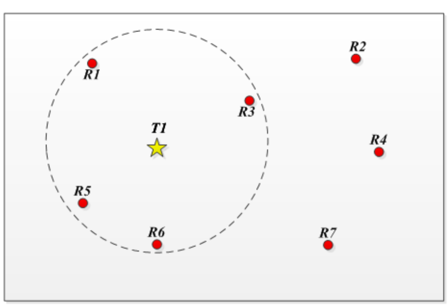
B. Neighborhood updating rules

After the winner is selected, the next step is to design the neighborhood function and compute weights of winner and neighbors. The neighborhood is designed to a sphere with radius λ where the center is the winner node. The neighborhood function determines the attractive strength of the input data on the winner as well as its neighbors. The influence on selected neurons is diminishing as the distances between the neighbor neuron and the winner increase. The neighbors of the winner are determined according to the following equation (Reeve and Hallam, 2005; James and Erion, 2017):

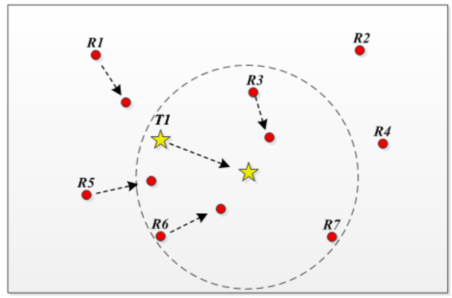
$$f(d_m, g) = \begin{cases} e^{-d_m^2/g^2(t)}, d_m < \lambda \\ 0, \qquad d_m \geq \lambda \end{cases}. \tag{3}$$

$d_m = |N_m - N_j|$ is the distance between the m-th output neuron and the winner. λ is set to a constant value denoting neighborhood range. The function $g^2(t) = (1-\partial)^t g_0$ is nonlinear, where t represents the number of iterations. ∂ is the update rate determining the calculation time, and $\partial < 1$ is constant. The computation time is diminishing as the parameter ∂ increases.

As shown in Figure 5, there are seven AUVs and one target ready for task assignment in underwater environments. According to the principle of SOM, the target should be taken as input neuron of the SOM neural network and AUVs' positions as the output neuron. As per Section 2, rounding up a target requires four AUVs. In other words, each input should correspond to four outputs, i.e., each target should be allocated with four AUVs. By the competition rules in formula (1), (2) and (3), *R1*, *R3*, *R5* and *R6* are allocated respectively to *T1* in the initial stage (Figure 5 (a)). Within the hunting process, the target may change the AUV that it is pursuing if another AUV is found near than the first AUV. The result in Figure 5(b) shows that SOM dynamically allocated tasks in the hunting process. At the initial stage, an alliance (*R1*, *R3*, *R5* and *R6*) cooperate to pursue the target *T1*. After a period of time, *R7* is closer to the target *T1* than *R1*. At this time to reallocate tasks, *R3*, *R5*, *R6* and *R7* are allocated to *T1*.



(a)



(b)

Figure 5 Process of multi-AUV task assignment (a) initial state (b) dynamic task assignment state

3.2 Pursuing strategy based on GBNN

The search target is determined by the GBNN in underwater environments. The GBNN algorithm in this paper is a kind of discrete Hopfield-type neural network. Firstly, the GBNN is built according to underwater environments (Figure 6). In this model, each individual neuron is connected with adjacent ones to form a network for their transmission of activity.

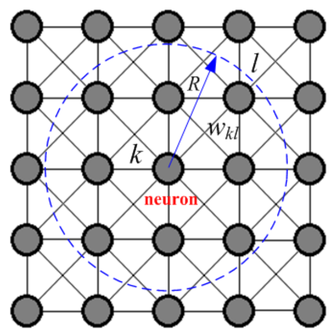


Figure 6. GBNN model

In the proposed model, the excitatory input results from the target and lateral neural connections, while the inhibitory input results from the obstacles only. Each neuron has local lateral connections to its neighboring neurons. The neuron responds only to the stimulus within its receptive field (Cao et al., 2016). In the proposed model, the collision-free AUV motion is planned in real-time based on the dynamic activity landscape of the neural network. The dynamics of this discrete time neural network is described as the following equations (Luo et al., 2014; Oliveira and Fernandes, 2016).

$$x_k(t+1) = g(\sum_{l \in S_l} \omega_{kl} x_l(t) + I_k) \tag{4}$$

$$\omega_{kl} = \begin{cases} e^{-\gamma|k-l|^2}, & |k-l| \le r \\ 0, & |k-l| > r \end{cases}, \tag{5}$$

where ω_{kl} are symmetric connection weights between the k-th neuron and the l-th neuron; $|k-l|$ is the Euclidian distance from the k-th neuron to the l-th neuron; $g(\cdot)$ is the transfer function; γ and $\gamma > 0$ are constants; The external input I_k to the k -th neuron is defined as $I_k = E$, if it is a target; $I_k = -E$, if it is an obstacle position; $I_k = 0$, otherwise, where $E >> 1$ is a positive constant.

$$I_i = \begin{cases} E, & \textit{if it is a target} \\ -E, & \textit{if it is an obstacle} \\ 0, & \textit{otherwise} \end{cases} \tag{6}$$

Transfer function $g(\cdot)$ may be any monotonically increasing function (Glasius et al., 1995; Glasius et al., 1996). A piecewise linear function is selected as the transfer function as follows.

$$g(x) = \begin{cases} 0, & x < 0 \\ \beta x, & x \in [0,1] \\ 1, & x > 1 \end{cases}, \tag{7}$$

where $\beta > 0$ is a positive constant.

The proposed network characterized by equation (4) guarantees that the positive neural activity is able to be propagated to all the state space, but the negative activity only stays locally. Therefore, the target globally attracts the AUV, while the obstacles only locally avoid the collision. The activity landscape of the neural network dynamically changes due to the varying external inputs from the targets and obstacles and the internal activity propagation among neurons. The optimal AUV path is planned from the dynamic activity landscape and the previous AUV location. The AUV will move to the neuron with maximal neural activity. After the current location reaches its next location, the next location becomes a new current location. The current AUV location adaptively changes according to the varying environments. The activity landscape of the neural network dynamically changes due to the varying external inputs from the target and obstacles and the internal activity propagation among neurons. For energy and time efficiency, the AUV should travel the shortest path and make the least turns in moving directions. For a given current robot location, denoted by , the next robot location is obtained by Lc (Luo et al., 2014)

$$Ln = \arg\max_{m,n}(x(m,n)) \in \{N_s \mid (m,n)\}, \tag{8}$$

where S is the number of neighboring neurons of the Lc -th neuron (S =8), i.e., all the possible next locations of the current location Lc . Variable $x(m,n)$ is the neural activity of the l-th neuron.

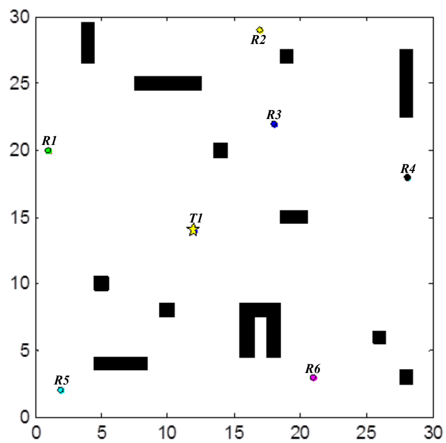
In the hunting task, the neural activity landscape will never reach a steady state as in the underwater environments. The AUV keeps moving toward the neuron location with the maximum activity in the AUV detection region. In the proposed model, due to the very large external input constant E, the target and obstacles keep staying at the peak and valley of the activity landscape of the neural network, respectively. Thus, the AUV should be able to hunt the target efficiently with obstacle avoidance until the hunting task ends. In this manner, the AUVs can realize cooperative hunting efficiently and naturally. It is a main difference between the proposed algorithm and other algorithms for cooperative hunting.

4 SIMULATION STUDIES

TO demonstrate the effectiveness of the proposed algorithm, several different cases, including hunting for single and multiple targets, were implemented on the software platform of MATLAB R2011a. Simulations were carried out with different models of underwater environments, with targets randomly distributed. The assumptions are as follows. 1) All the AUVs and targets are assumed as points without any shapes. 2) The AUV velocity is set at a value more than the target velocity. Because the target has the same intelligence of AUVs except cooperation, it will be difficult to catch the target if the target is faster than the AUV's velocity. 3) AUV members are not informed in advance of their working environments other than the total number of targets and boundaries of the underwater work areas.

4.1 *Hunt single target*

In order to test the basic performance of the proposed approach, the first simulation is conducted. In this simulation, there is just one target, six AUVs, and some obstacles. The areas of the environments are 30×30 . In this case, obstacles and static targets are randomly distributed in the work area (shown as in Figure 7(a)). The initial coordinates of the target is (12,14), and the initial coordinates of the 6 AUVs are (1,20), (21,3), (18,22), (2,2), (17,29) and (28,18). According to the proposed algorithm, a target should require four AUVs to hunt. Through calculation from formula (1)-(3) by SOM, winners *R1*, *R3*, *R5* and *R6* are assigned to target *T1*. Since *R2* and *R4* fail in the competition, they will not join in the pursuing task but keep still. After completion of the task assignment, GBNN automatically plans a collision-free pursuing path for each hunter according to formula (5)-(9). As shown in Figure 7 (b), target *T1* which moves at random in the whole work area is hunted by AUV *R1*, *R3*, *R5* and *R6*. From Figure 7, we find that 4 AUVs have been assigned with pursuing tasks while the other two AUVs remain stationary. This proves that the proposed algorithm not only works with high efficiency but also saves energy for the whole work team.



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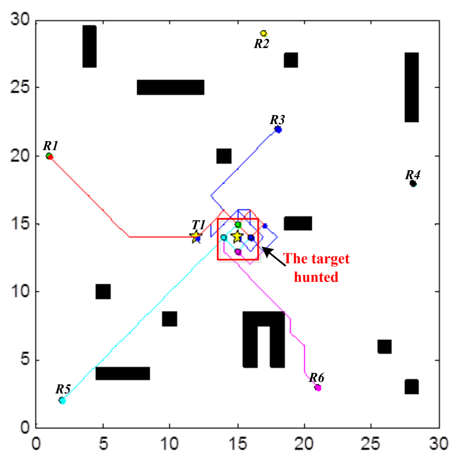
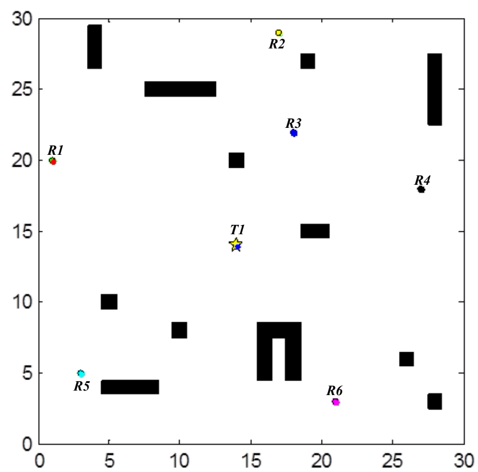


(b)

Figure 7 Hunting process of the first simulation: (a) initial locations, (b) final trajectories

In addition, dynamic task assignment in the hunting process is considered in the experiment. This simulation involves one target, four AUVs, and several obstacles. Figure 8(a) shows the initial distribution of them. At the beginning of the hunting task, winners *R1*, *R3*, *R5* and *R6* are assigned to target *T1* through calculation from formula (1)-(3) by SOM. *R2* and *R4*, the failures in the competition, are excluded from the pursuing task and keep still (Figure 8 (b)). As the target moves southeast, after a period of time, the distances between it and each AUV will change. According to the principle of dynamic task assignment, each AUV will be re-allocated with tasks. By formula (1)-(3) by SOM, *R3*, *R4*, *R5* and *R6* gain their pursuing task while *R1* and *R2* keep still (Figure 8(c)). Then, the target impact the entire work area through neural transmission, the activity of each neuron can be derived from the shunting equation (4). When a winner AUV makes a selection of its path, it compares the activity value of the neuron of its current location with its neighbors and chooses the one with the highest value as the next step. With the GBNN, the targets and obstacles are excitation and inhibitory of the neural network, respectively. By repeating this performance, AUVs keep moving towards their targets by rounding obstacles to avoid collision. As shown in Figure 8(d), target *T1* is hunted by AUV *R3*, *R4*, *R5* and *R6*. This shows that the proposed algorithm realizes hunting for a single target.



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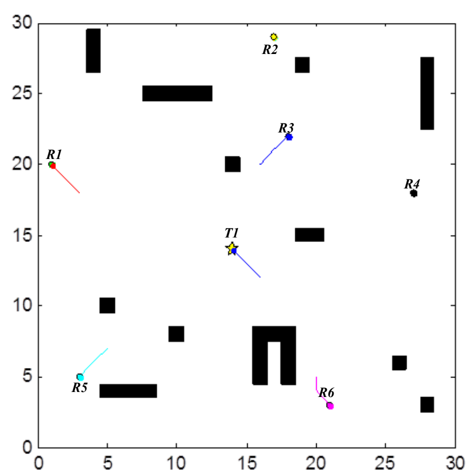

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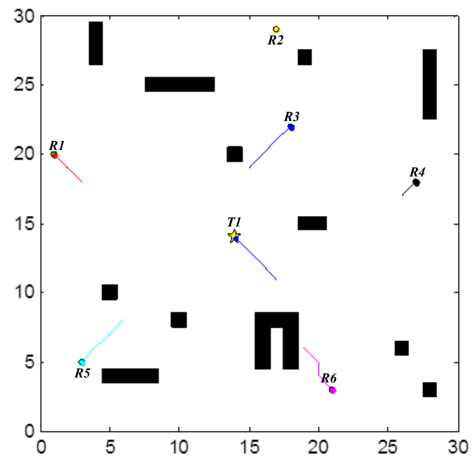

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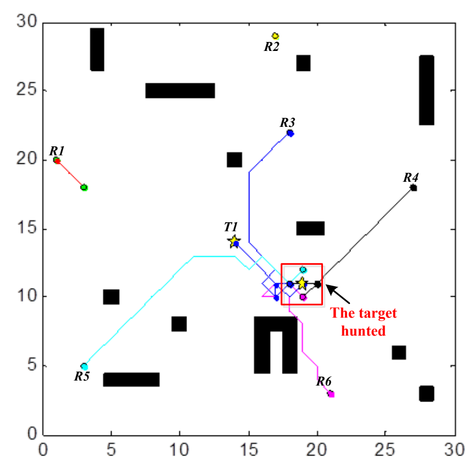
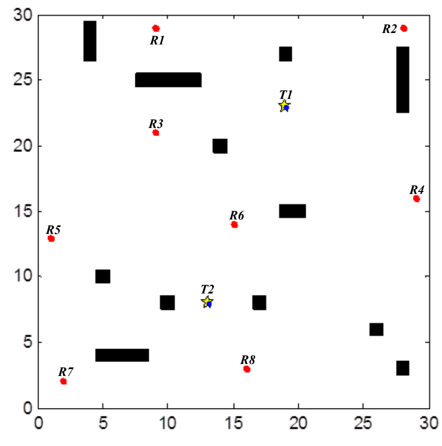
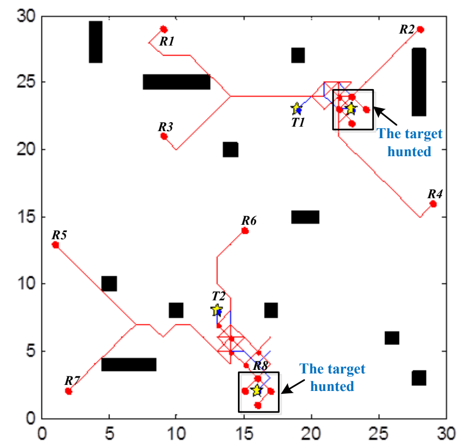


(d)

Figure 8. Hunting process of the second simulation: (a) initial locations, (b) at the 3rd step, (c) at the 4th step, (d) final trajectories



(a)



(b)

Figure 9. Hunting process of the multiple targets: (a) initial locations, (b) final trajectories

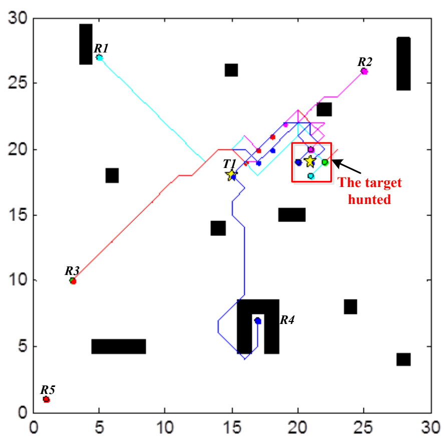
4.2 Hunt multiple targets

The second simulation is conducted to test the dynamic cooperation when multiple targets are needed to be caught. For easy analysis, it is assumed that there are two targets and eight AUVs, both of which are randomly distributed in the work area. The initial locations of *T1* and *T2* are (13, 8), and (19, 23), respectively, as shown in Figure 9(a). Through the task assignment, *R1*, *R2*, *R3* and *R4* are assigned to target *T1*, and the other four AUVs (*R5*, *R6*, *R7* and *R8*) cooperate to pursue target *T2*. All the AUVs are guided by the activity of the neural network for their own pursuing targets. Eventually, both the targets are hunted. Figure 9(b) shows the final trajectories of this hunting. Similarly, the simulation result shows effective cooperative hunting for multiple dynamic targets.

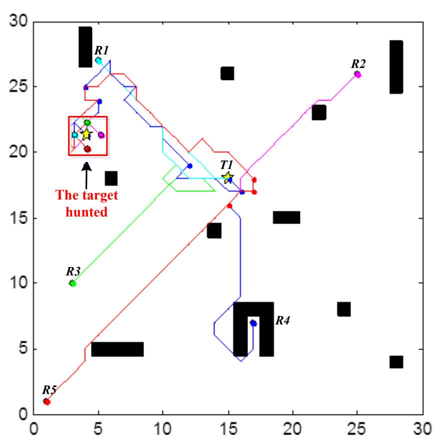
4.3 Comparison of different algorithms

The proposed algorithm is expected to improve efficiency for multi-AUV cooperative hunting in underwater environments compared with other commonly used algorithms, such as the bio-inspired neural network algorithm (Zhu et al., 2014; Ni and Yang, 2011). According to the principle of the bio-inspired neural network algorithm, the AUV's movement is determined by the dynamic activity landscape of the topologically organized neural network and the AUV's speed. In the hunting task, the neural activity landscape will never reach a steady state as in static environments. The AUV keeps moving toward the neuron location with the maximum activity in the AUV detection region. Figure 9 shows the hunting process with these two different algorithms.

This comparative simulation includes one target, five AUVs and several obstacles in work areas of 30×30. The initial locations of the targets are (15, 18). AUVs are randomly distributed with their coordinate points (3, 10), (25, 26), (17, 7), (5, 27) and (1, 1). Figure 10 (a)-(b) shows the hunting process with two different algorithms. According to the result of Figure 10, the proposed algorithm takes a shorter hunting path no matter whether for each AUV member or the whole multi-AUV team compared with the bio-inspired neural network algorithm. To analyze why this is so, the proposed algorithm can make a dynamic task assignment that chooses the fittest performers from the multi-AUV team according to SOM neural network, while always keeping the chosen ones stalking the target according to GBNN. In contrast, as the bio-inspired neural network algorithm lacks the function of task allocation, repetitive searches and longer pursuing paths are inevitable. The simulation results show that the proposed algorithm works with higher efficiency and adaptability compared with a bio-inspired neural network algorithm.



(a)



(b)

Figure 10. Hunting process with different algorithms: (a) the proposed algorithm, (b) the bio-inspired neural network algorithm

In order to further prove the effectiveness of the proposed algorithm, the mobile distance of the two algorithms for each AUV in the hunting process has been compared. In these conditions, two algorithms respectively complete 50 times simulations of five AUVs for one target. In each simulation, the target, AUVs and obstacles are randomly deployed. To make a clear distinction between the two algorithms, Figure 11 shows the mean and standard deviation statistics of mobile distance for each AUV in the hunting process. The result shows that the total mobile distance of the proposed algorithm is reduced by 35%, and the standard deviation statistics of the proposed algorithm is smaller. Therefore, the method proposed in this paper applied to the hunting process is much more efficient. For the power consumption problem, since this work is based on the design of path planning, the power consumption can simply be in linear correlation with the hunting path length. From this point of view, it is easy to conclude that the proposed algorithm is superior to bio-inspired neural network algorithm.

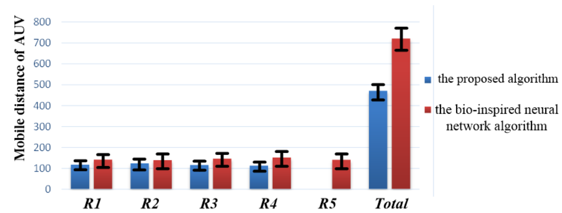


Figure 11. Comparison of hunting efficiency between the two algorithms

5 CONCLUSION

IN this paper, an integrated algorithm of self-organizing map neural network and Glasius Bio-Inspired Neural Network is introduced to deal with cooperative hunting by a multi-AUV team. On the one hand, the SOM neural network can be used in multi-AUV task assignments, which strengthens cooperation among multi-AUV team members. On the other hand, it makes full use of the advantages of GBNN without any preoccupied information about the workspace or any pre-learning as well as few parameter adjustments. Through the simulation experiments with targets of different states, it proves that the proposed algorithm is able to plan shorter search paths to enhance work efficiency and save energy. Despite these advantages, there are still practical problems to be addressed. These may include how AUVs should overcome the effects of ocean currents in underwater environments during their hunting process, and how to deal with 3-D environments when the target moves faster than its hunters under the proposed method. Further studies on how to solve these problems are needed.

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