Frontiers of Information Technology & Electronic Engineering
www.jzus.zju.edu.cn; engineering.cae.cn; www.springerlink.com
ISSN 2095-9184 (print); ISSN 2095-9230 (online)
E-mail: jzus@zju.edu.cn

Multi-AUV SOM task allocation algorithm considering initial orientation and ocean current environment*

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Received Sept. 18, 2018; Revision accepted Feb. 1, 2019; Crosschecked Mar. 14, 2019

Abstract: There is an ocean current in the actual underwater working environment. An improved self-organizing neural network task allocation model of multiple autonomous underwater vehicles (AUVs) is proposed for a three-dimensional underwater workspace in the ocean current. Each AUV in the model will be competed, and the shortest path under an ocean current and different azimuths will be selected for task assignment and path planning while guaranteeing the least total consumption. First, the initial position and orientation of each AUV are determined. The velocity and azimuths of the constant ocean current are determined. Then the AUV task assignment problem in the constant ocean current environment is considered. The AUV that has the shortest path is selected for task assignment and path planning. Finally, to prove the effectiveness of the proposed method, simulation results are given.

Key words: Autonomous underwater vehicles; Self-organizing neural networks; Azimuths; Ocean current
https://doi.org/10.1631/FITEE.1800562 **CLC number:** TP249

1 Introduction

Autonomous underwater vehicles (AUVs) are used by humankind to explore the oceans and widely used in lake salvage, marine scientific investigation, deep sea search, and military defense (Erol et al., 2007; Paull et al., 2014; Smith et al., 2014; Nouri et al., 2016). Multi-AUV systems draw much interest in recent years due to their outstanding robustness and highly efficient coordination. In AUV applications, task assignment and path planning of a multi-AUV system has become a research hotspot (Zhu et al., 2013, 2018b; Huang et al., 2014; Cao and Zhu, 2015; Zadeh et al., 2016). Multi-AUV system task assignment and path planning is based on a certain algorithm to control the AUVs, and each AUV navigates along the optimal path under certain conditions to reach the destinations. Task assignment refers to assigning an AUV with the least energy consumption to the target point. Path planning technology refers to the path planning method for a single AUV after global task assignment. The fundamental problem is how to divide the whole task into several subtasks; thus, AUVs can move to their designated targets along the optimized paths while guaranteeing the least total consumption of a multi-AUV system.

There are some studies on task assignment of robots. *K*-means clustering (Elango et al., 2011) was used in multi-robot task allocation systems. The algorithm clusters the targets into groups; thus, AUVs can access the groups to complete the corresponding task. Conventional task allocation strategies include market mechanisms (Akkiraju et al., 2001; Sotzing and Lane, 2010; Wang and Feng, 2011; Redfield,

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* Project supported by the National Natural Science Foundation of China (Nos. U1706224, 91748117, and 51575336) and the Creative Activity Plan for Science and Technology Commission of Shanghai, China (Nos. 18JC1413000, 18DZ1206305, and 16550720200)

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2013). The multi-robot system is considered as an economy method and each robot is considered as an agent in a market-based system. A market mechanism algorithm maximizes the individual and overall profits with the minimum total consumption. To balance the consumption, the algorithm causes each robot to continuously calculate and compare the consumption of the visits to the designated target. The algorithm has been applied to AUVs' task assignment, but the algorithm cannot guarantee the optimization of task assignment when the number of destinations is unknown.

Due to the similarity between self-organizing map (SOM) neural networks and multi-task assignment, an SOM approach was applied to path planning and task assignment of the multi-robot system (Yu and Zhu, 2017; Zhu et al., 2018c). The algorithm is used mainly for dynamic classification of input vectors. After using the algorithm for multi-task assignment, the targets are automatically assigned to the appropriate robot. SOM was naturally proposed by Zhu and Yang (2006), Huang et al. (2012), and Zhu et al. (2012) to solve the task assignment problem in a multi-AUV system. The algorithm effectively resolves the problem of the number of AUVs and the number of unknown targets. Then the velocity synthesis approach combined with an SOM is applied to plan the shortest path for each AUV to visit the corresponding target in a dynamic environment. The algorithm allows each AUV to reach the target along the shortest path while guaranteeing the least total consumption of a multi-AUV system. However, these approaches based on the SOM require an ideal two-dimensional (2D) workspace with no azimuths or ocean currents, which is quite unrealistic in real-world applications. In a constant ocean current, AUVs that have different azimuths at the initial time and different maximum thrusts in the vertical and horizontal directions in a three-dimensional (3D) environment are not considered in the above SOM-based task assignment and path planning approaches of a multi-AUV system. For example, the selection of a winning neuron (Zhu et al., 2018a) depends on the Euclidean distance between AUVs and targets. There is a case where the Euclidean distance between AUVs and targets is the shortest but the initial azimuths of the AUVs are opposite to targets. When it is allocated to a target, it in fact navigates a longer distance, and because of the initial azimuths of AUVs, it consumes more energy. To reduce the energy consumption of AUVs, the selection of a winning neuron is changed in this study. In addition, the velocity synthesis approach proposed by Huang et al. (2012) is used to allocate tasks for AUVs. There is a case where the initial azimuths of AUVs make it impossible to turn to the sum direction during iteration; thus, a turning direction is proposed in this study.

An improved SOM approach is proposed for a multi-AUV system that has different initial azimuths in a constant ocean current. The contributions of the improved SOM algorithm can be summarized as follows: (1) Competitive neurons consider initial orientation of each AUV in a constant ocean current; (2) The Euclidean distance between the post-steering competitive neurons and input neurons is considered in a constant ocean current. The improved SOM algorithm enables the AUV to visit the target while guaranteeing the least consumption. The improved SOM algorithm may be used in other fields where the task allocation problems share certain similarities, such as unmanned aerial vehicles (UAVs) (Sujit et al., 2005; Sujit and Beard, 2007).

2 Problem of multi-AUV system

The main problem of the multi-AUV system is how to divide the whole task into several subtasks; thus, the AUVs can move to their designated targets along the optimized paths while guaranteeing the least total consumption of a multi-AUV system. A schematic of the constant ocean current workspace with AUVs and targets is illustrated in Fig. 1. It is assumed that AUVs and targets are randomly distributed in a constant ocean current workspace. We evaluate the AUV consumption by the navigated distance from its starting position to its destination.

The actual underwater working environment is described by the velocity and direction of an ocean current. The ocean current in an underwater environment is a process that changes over time. Due to the subtle changes in ocean currents per unit time, the subtle changes have little effect on the assignment of AUVs in underwater working environments. Therefore, the task assignment of AUVs can be considered with a constant ocean current. By measuring the

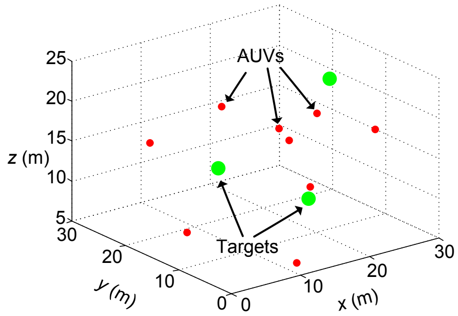

Fig. 1 Multi-AUV system with AUVs and targets randomly distributed

ocean current in a certain period of time, the average ocean current is obtained, and then the average ocean current is used as the constant ocean current in the underwater working environment.

To minimize the battery energy consumption, each AUV in the model will be competed, and the shortest path under the kinematic constraints and different azimuths will be selected for task assignment and path planning in a constant ocean current. First, the initial position and orientation of each AUV are determined. The velocity and azimuths of the constant ocean current are determined. Then the AUV task assignment problem under kinematic constraints, different azimuths, and constant ocean current environment is considered. The AUV that has the shortest path is selected for task assignment and path planning.

3 Multi-AUV task allocation and path planning algorithm based on an SOM

3.1 Traditional SOM task assignment algorithm

SOM neural network was first proposed by Kohonen et al. (2000). In recent years, this algorithm has become a valuable tool to intelligently control a multi-AUV system. Due to the similarity between SOM neural network and multi-task assignment, an SOM approach is applied to path planning of the multi-AUV system. As a self-organizing system can change its basic structure, a multi-AUV system can update all weight values according to the dynamic environment. The SOM algorithm applies a competitive learning principle to make the neighbor neurons tend to have similar weight vectors. With the cooperation and competition, a multi-AUV system can automatically control AUVs to achieve task locations. The neural network model, which is divided into two layers, is shown in Fig. 2. The first layer (input layer) is a single-dimensional neuron that represents the center of the target. The second layer (competitive layer) is a 2D neuron that represents the AUVs' locus. As shown in Fig. 2, the input layer gathers information from each neuron in the output layer through the weight vector initialized by the AUVs' coordinates. The competitive layer is the output layer. The output layer analyzes and compares input patterns to find rules and then classifies them. Target locations are inputted to the input layer one by one, and the competition iterations are acquired.

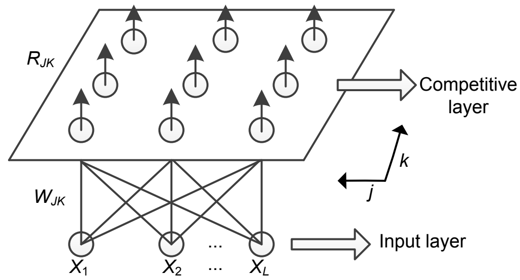

Fig. 2 SOM neural network structure in 3D workspace

SOM divides the entire issue into sub-problems including the rule of winner selection, the neighborhood function definition, and the rule of weight update. Fig. 3 shows the flow chart of the multi-AUV SOM neural network task assignment algorithm. As shown in Fig. 3, the SOM neural network is initialized, the target points are selected as the input neurons, and the AUVs' loci are selected as the output neurons. The SOM-based method is used to select the AUVs that are the winners for target positions.

The winner selection rule is expressed as (Zhu et al., 2013)

$$[P_j] \Leftarrow \min\{D_{kjl}, k=1,2,...,K, j=1,2,...,J, l=1,2,...,L\}, \tag{1}$$

where $[P_j]$ denotes that the j^{th} neuron from the k^{th} group is the selected winner to the l^{th} input node, and D_{kjl} the relevant Euclidean distance between two correlated neurons. The winner selection depends on how we define and calculate D_{kjl} during iterations. The Euclidean distance between two neurons is defined as

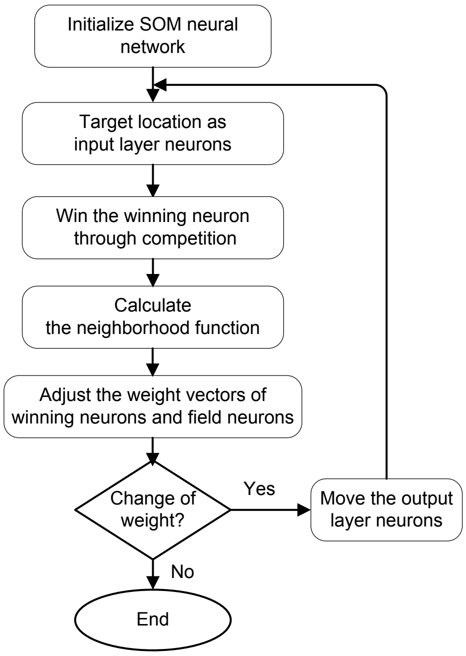

Fig. 3 SOM algorithm flow chart

$$\|T_l - R_{jk}\| = \sqrt{(x_l - w_{jkx})^2 + (y_l - w_{jky})^2 + (z_l - w_{jkz})^2}, \tag{2}$$

where $T_l=(x_l, y_l, z_l)$ is the coordinate of the l^{th} input neural node in a 3D system, which is known as the "location of the target." $R_{jk}=(w_{jkx}, w_{jky}, w_{jkz})$ is the specific AUV location of the output neuron. Because of insufficient power, the workload for each AUV should be taken into consideration to guarantee that all of the AUVs can make the best use of power and simultaneously avoid vehicle breakdowns on the way to targets when they run out of power. A parameter to control the workload of each AUV is defined as

$$W = (P_j - \overline{W})/(S + \overline{W}), \tag{3}$$

where P_j is the actual distance moved by the AUV, S the safe distance that a single AUV can travel, and $\overline{W}$ the average distance moved by a team of AUVs in a certain task. Then the weight distance D_{kjl} is expressed as

$$D_{kjl} = \begin{cases} |T_l - R_{jk}|, & 0 \le P_j < S, \\ |T_l - R_{jk}|(1+W), & S \le P_j < S_{\max}, \\ \infty, & P_j \ge S_{\max}, \end{cases} \tag{4}$$

where $S_{\max}$ is the maximum distance that a single AUV can navigate. Obviously, if $P_j \ge S_{\max}$, the AUV cannot arrive at the appointed destination. Then the AUV should terminate its task and return.

Three different cases are presented to describe the calculation progress of neural weight distance D_{kjl}. In case one, where the moving distances are shorter than the safe distances, the winner is easy to find and the workload balance can ensure the completion of the overall task with the least total and individual consumption. In case two, where the AUV's moving distance is longer than the safe length, the workload equitable measurements will be executed to deal with the energy problem. In case three, where the AUV's traveling distance is longer than the maximum length that a single AUV can afford in a mission, there is a risk for the AUV to run out of energy. In case three, D_{kjl} will be set to ∞, indicating that the AUV will never be recognized as a winner.

The traditional SOM neural algorithm selects winning neurons corresponding to the distance between the AUV and the target point. Then the neighborhood function chooses the winner neighbors of AUVs and figures out the moving speed of winners and neighbors. Finally, AUVs will reach target locations by updating the weight vector of winner AUVs in the constant ocean current. When all target locations have been visited, iterations are completed. For details, he/she can refer to Zhu et al. (2013).

3.2 Improved SOM task allocation and path planning algorithm

3.2.1 Improved SOM task allocation and path planning algorithm in 2D plane

Ocean current in the actual underwater working environment is important. The improved algorithm considers that the AUV in the actual working environment has a constant ocean current, different azimuths at the initial moment, and different Euclidean distances between input neurons and competitive neurons. Winning neurons are selected by considering the velocity and azimuths of the constant ocean current, the turning distance of the AUV at the initial moment, and the distance between the turning AUV and target point. The neighborhood function of the winning neuron is calculated. The neighborhood function chooses winner neighbors of AUVs and figures out the moving speed of winners and neighbors. The weights of field neurons and winning neurons are adjusted and kept updating until the AUV reaches the destination. Input vectors are $\boldsymbol{X}$=(x_1, x_2, ..., x_N) and $\boldsymbol{V}$, where N is the number of input neurons, $\boldsymbol{V}$ the constant ocean current, and x_N the coordinate of the N^{th} target point in the Cartesian coordinate system. The output layer includes $K\cdot J$ neurons (R_{11}, ..., R_{1J}, ..., R_{K1}, ..., R_{KJ}), and $\boldsymbol{R}_{KJ}$=(W_{KJX}, W_{KJY}) is the weight vector of the J^{th} neuron (AUV) from the K^{th} group, indicating the position of the AUV in the 2D plane.

Fig. 4 shows the initial moment steering problem considering the kinematic constraints. Angle=(θ_1, θ_2, ..., θ_J) is the initial direction angle of the AUV, where J is the number of AUVs. θ_J, which is the direction angle of the J^{th} AUV at the initial moment, is the angle between x-axis and the AUV at the initial moment. V_{angle}, which is the direction angle of the constant ocean current, is the angle between x-axis and constant ocean current at the initial moment. The angle between the target point and the AUV is expressed as α=(α_1, α_2, ..., α_J), and α_J is the angle between x-axis and black dotted line, which connects the AUV and target point at the initial time. V_{add} is the direction angle of V_{angle} and θ, defined as

$$\begin{aligned} V_{\text{add}} &= V_{\text{angle}} + \theta \\ &= \arctan \frac{R_{\text{V}} \sin V_{\text{angle}} + R \sin \theta}{R_{\text{V}} \cos V_{\text{angle}} + R \cos \theta}, \end{aligned} \tag{5}$$

where R_{V} represents the speed of constant ocean current and R the speed of the AUV. Define γ as follows:

$$\gamma = V_{\text{add}} - \alpha. \tag{6}$$

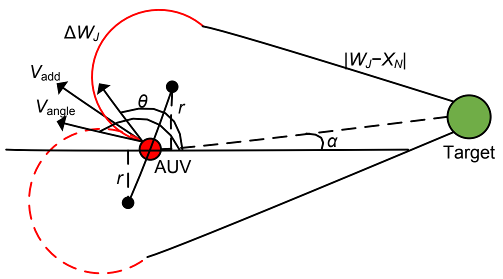

Fig. 4 Initial moment steering problem considering kinematic constraints
Green dot indicates the target point and red dot indicates the AUV. References to color refer to the online version of this figure

An AUV has two turning paths, which are the red dashed line and the red solid line in Fig. 4. The AUV is steered in the decreasing direction of $|\gamma|$ until γ=0. The actual path navigated by the AUV is the red solid line plus the black line in Fig. 4. $\boldsymbol{W}$=(w_1, w_2, ..., w_J) represents the coordinate of the AUV in the 2D plane. ΔW_J indicates the distance navigated by the J^{th} AUV when γ=0. Parameter P controls the navigation load balancing among AUVs (Yu and Zhu, 2017), and can be expressed as

$$P = (C_j - S)/(C + S), \tag{7}$$

where S represents the average navigating distance of each AUV in a multi-AUV system when completing a certain global task, and C the safe distance that the AUV can navigate without considering running out of energy. C_J (see the red and black lines in Fig. 4), representing the actual navigating distance of the J^{th} output neuron (AUV), is defined as

$$C_J = |W_J - x_N| + \Delta W_J. \tag{8}$$

Then the weight distance D_{KJN}, i.e., the turning distance of the J^{th} competitor neuron (AUV) from the K^{th} group when considering the initial orientation angle plus the Euclidean distance between the turning competing neuron (AUV) and the N^{th} input neuron (target point), is defined as

$$D_{KJN} = \begin{cases} C_J, & 0 \le C_J < C, \\ C_J(1+P), & C \le C_J < C_S, \\ 0, & C_S \le C_J, \end{cases} \tag{9}$$

where C_S is the maximum distance that the AUV can navigate. The method fully considers the velocity and azimuths of constant ocean current, the orientation angle of competitive neurons (AUV) at the initial moment, the Euclidean distance between turning AUVs (competitive neurons) and target points (input neurons), and navigation load balancing. The winner (AUV) selection depends on D_{KJN} during iterations. The AUV with the smallest D_{KJN} is the winning neuron. The neighborhood function of the winning neuron is calculated and the neighboring winning neurons are updated. Then weights are continually adjusted until they reach the destinations.

3.2.2 Improved SOM task allocation and path planning algorithm in 3D plane

The AUV, which has different azimuth angles at the initial moment and an independent propeller in the vertical and horizontal directions, navigates in the actual underwater working environment where there is an ocean current. The maximum thrust that can be generated by the vertical and horizontal propellers is related to the maximum steering angle of the AUV. The horizontal and vertical thrusters of the AUV are independent. The AUV navigation in the 3D plane is divided into vertical and horizontal plane motions.

Fig. 5 shows the simplified model considering the initial angle. Fig. 6 shows the model considering the angle of the constant ocean current.

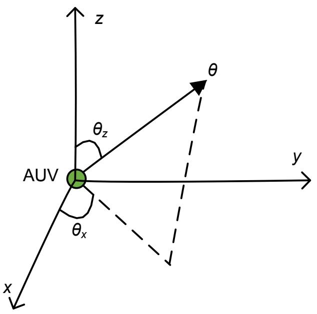

Fig. 5 Simplified model considering the initial angle
Green dot represents the AUV. θ represents the initial direction angle of the AUV, θ_x the angle between x-axis and the projection of the AUV on the x-o-y surface, and θ_z the angle between z-axis and θ. References to color refer to the online version of this figure

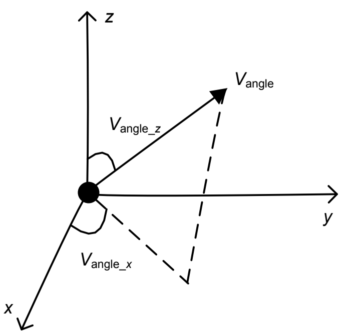

Fig. 6 Model considering the angle of the constant ocean current
Black dot represents the constant ocean current. V_{angle} represents the direction angle of the constant ocean current, $V_{\text{angle\_}x}$ the angle between x-axis and the projection of the constant ocean current on the x-o-y surface, and $V_{\text{angle\_}z}$ the angle between z-axis and V_{angle}. References to color refer to the online version of this figure

Fig. 7 shows the initial moment steering problem considering kinematic constraints on the x-o-y plane current. The initial direction angle of the AUV is known. $V_{\text{add\_}x}$ represents the vector direction angle of $V_{\text{angle\_}x}$ and θ_x, defined as

$$\begin{aligned} V_{\text{add\_}x} &= V_{\text{add\_}x} + \theta_x \\ &= \arctan\frac{R_{\text{V}} \sin V_{\text{angle\_}z} \sin V_{\text{angle\_}x} + R_x \sin\theta_x}{R_{\text{V}} \sin V_{\text{angle\_}z} \cos V_{\text{angle\_}x} + R_x \cos\theta_x}. \end{aligned} \tag{10}$$

According to the AUV horizontal thruster, R_x represents the speed of the AUV on the x-o-y surface. Define γ_x as

$$\gamma_x = V_{\text{add\_}x} - \alpha. \tag{11}$$

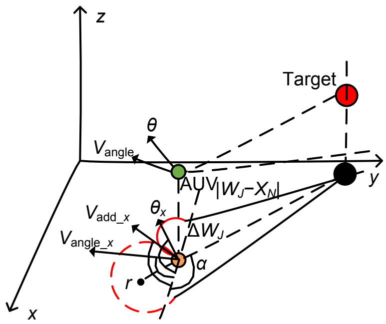

Fig. 7 Initial moment steering problem considering kinematic constraints on x-o-y plane current
Green dot represents the AUV, red dot represents the target dot, blue dot represents the projection of the AUV on the x-o-y surface, and black dot represents the projection of the target dot on the x-o-y surface. References to color refer to the online version of this figure

According to the AUV's horizontal thruster, the maximum steering angle of the AUV on the x-o-y plane and the steering radius are given. The AUV is steered in the decreasing direction of $|\gamma_x|$ until γ_x=0. The analysis method for the blue point navigation path is the same as that for 2D plane path planning. γ_z is defined as

$$\gamma_z = \frac{|T_z - R_z|}{R_{\text{V}} \cos V_{\text{angle\_}z} + R_{\text{VT}}}, \tag{12}$$

where T_z represents the z coordinate of target and R_z the z coordinate of AUV. According to the AUV's vertical thruster, R_{VT} represents the speed of the AUV on the z-axis. To ensure the normal navigation of the AUV, R_{VT} must be greater than $R_{\mathrm{V}}\cos V_{\mathrm{angle}\_z}$. The AUV is navigated until $\gamma_x=1$. ΔW_J indicates the actual navigated distance by the J^{th} AUV when $\gamma_x=0$ on the x-o-y plane. ΔW_J is the red solid line in Fig. 7. Parameter P controls the navigation load balancing among the AUVs (Yu and Zhu, 2017), and can be expressed as

$$P=(C_J-S)/(C+S), \tag{13}$$

where S represents the average navigating distance of each AUV in a multi-AUV system when completing a certain global task. C is the safe distance that AUV can navigate without considering running out of energy. C_J is defined as

$$C_J=|W_J-X_N|+\Delta W_J+|T_z-R_z|, \tag{14}$$

where C_J represents the actual navigating distance of the J^{th} output neuron (AUV), and C_{S} is the maximum distance that the AUV can navigate. Then the weight distance D_{KJN} is defined as

$$D_{KJN}=\begin{cases} C_J, & 0\le C_J<C,\\ C_J(1+P), & C\le C_J<C_{\mathrm{S}},\\ 0, & C_{\mathrm{S}}\le C_J. \end{cases} \tag{15}$$

By constantly adjusting the horizontal and vertical propellers, the AUV keeps moving closer to the target point and steering until the AUV and constant ocean current combine the speed direction of navigation points with the target point. Winning neurons (AUVs) are selected by considering the velocity and azimuths of constant ocean current, the turning distance of the AUV at the initial moment, and the distance between turning AUVs and target points. The AUV with the smallest weight distance D_{KJN} is the winning neuron. Then update the neighborhood of winning neurons, constantly adjusting weights until winning neurons reach the destinations.

4 Simulation results

To prove the effectiveness of the proposed method in multi-AUV system task assignment under constant ocean current, the following simulation results are given.

4.1 2D plane simulation results

4.1.1 Number of AUVs exceeding the target number

According to the improved competition principle of the self-organizing neural network algorithm, seven AUVs are assigned to the corresponding nearest targets after considering the initial angle and constant ocean current. Then the optimal path is planned for AUV mission according to the weight update rule. Fig. 8 shows the task assignment solution in a multi-AUV system when the number of AUVs exceeds the target number. As shown in Fig. 8, there is a constant ocean current in the workspace. Assume that the constant ocean current speed is 0.04 m/s and the AUV running speed is 0.08 m/s. Then the ratio of the AUV running speed to the constant ocean current speed is 2. The angle between ocean current and the x-axis is −10°. As for R1, the angle between R1 and the x-axis is θ_1, and θ_1 is −120°.

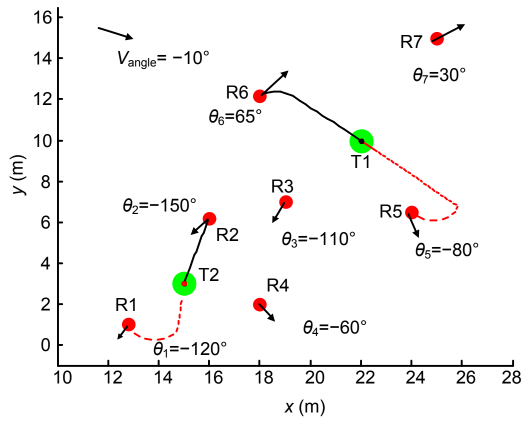

Fig. 8 Task assignment solution in a multi-AUV system when the number of AUVs exceeds the target number
Green dots represent targets, red dots represent AUVs, the black line indicates the moving path of the AUV in the improved algorithm, and the red dotted line indicates the moving path of the AUV in the traditional algorithm. References to color refer to the online version of this figure

Fig. 9 shows the actual navigation distance of the AUV group to the target with a constant ocean current. The traditional SOM neural algorithm selects winning neurons corresponding to the distance between the AUV and target point. The improved SOM method considers the constant ocean current and the fact that

AUVs have different azimuth angles at the initial time. In the traditional self-organizing algorithm, when the task is assigned to T1, the winning neuron is R5, and the actual distance from R5 to the target point is 7.1919 m. The winning neuron in the improved self-organizing algorithm is R6. The distance that R6 actually navigates to the target is 5.1420 m. In contrast, R6 actually navigates a shorter distance and is more effective than R5. In the traditional self-organizing algorithm, when the task is assigned to T2, the winning neuron is R1, and the actual distance from R1 to the target point is 4.4448 m. The winning neuron in the improved self-organizing algorithm is R2. R2 actually navigates to the target point over a distance of 4.2986 m. In contrast, R2 actually navigates a shorter distance and is more effective than R1. The sum navigating distances of the AUV group for T1 and T2 are 11.6367 m and 9.4406 m in the traditional self-organizing algorithm and the improved self-organizing algorithm, respectively. The improved algorithm saves 18.87% of the total navigation length compared with the traditional algorithm. As shown in Fig. 9, the improved algorithm saves energy for the AUV group.

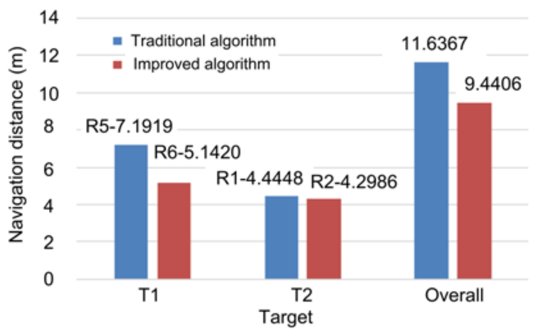

Fig. 9 Actual navigation distance of the AUV group to the target with constant ocean current when the number of AUVs exceeds the target number
References to color refer to the online version of this figure

Fig. 10 is an extension of Fig. 8. Each path of the AUV is illustrated in Fig. 10. The actual navigation distance of R1 is 14.073 m. The distance that R2 actually navigates to the target is 8.3181 m. The actual navigation distances that R3–R7 actually navigate to the target are 5.5634, 11.0994, 7.1919, 5.1420, and 7.9419 m, respectively. The winner neuron is R5, for which the Euclidean distance between the AUV and the target point is the shortest in the traditional algorithm. The winner neuron is R6 in the improved algorithm. According to the theory in Section 3, the improved algorithm selects the shortest AUV navigation distance. The shortest navigation distance is R6 (Fig. 10).

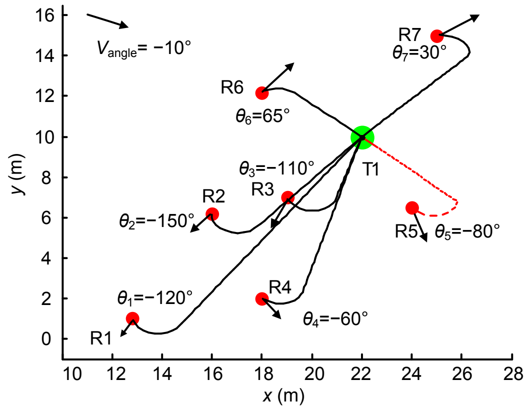

Fig. 10 Task assignment solution in a multi-AUV system for a single target

Considering the constant ocean current and direction angle of the AUV at the initial moment, the AUV not only smoothly traverses to the target, but also has the shortest navigation path. AUVs that have not been assigned to a mission remain intact throughout mission assignment and path planning, saving even more energy for the AUV system.

4.1.2 Number of AUVs equaling the target number

The proposed approach is applied to a case where the number of AUVs is equal to the number of targets (Fig. 11). In the multi-AUV system's workspace, there are three AUVs that need to access three randomly distributed targets. As for R1, the angle between R1 and the x-axis is θ_1 (θ_1 is 150°). The angles for R2 and R3 are shown in Fig. 11. The traditional SOM neural algorithm selects winning neurons corresponding to the distance between the AUV and target point. R3 is closest to T1. The Euclidean distance between R2 and T3 is the shortest. R1 is closest to T2. According to the competition principle of the self-organizing neural network algorithm in the improved algorithm, three AUVs are assigned to the corresponding nearest targets after considering constant ocean current and initial angle. Then the optimal path is planned for the AUV mission according to the weight update rule. Fig. 11 shows the task assignment solution in a multi-AUV system when the number of AUVs is equal to the target number. There is a constant ocean current in the workspace. The angle between ocean current and the x-axis is −60°.

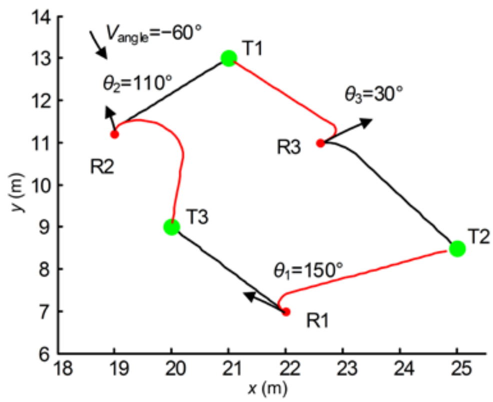

Fig. 11 Task assignment solution in a multi-AUV system when the number of AUVs is equal to that of targets
Green dots represent targets, red dots represent AUVs, the red line indicates the moving path of AUVs in the traditional algorithm, and the black line indicates the moving path of AUVs in the improved algorithm. References to color refer to the online version of this figure

Fig. 12 shows the actual navigation distance of the AUV group to the target with a constant ocean current. In the traditional self-organizing algorithm, when the task is assigned to T1, the winning neuron is R3, and the actual distance from R3 to the target point is 3.8991 m. The winning neuron in the improved self-organizing algorithm is R2. R2 actually navigates to the target point with a distance of 3.6886 m. In contrast, R2 actually navigates a shorter distance and is more effective than R3. In the traditional self-organizing algorithm, when the task is assigned to T2, the winning neuron is R1, and the actual distance from R1 to the target point is 4.5323 m. The winning neuron in the improved self-organizing algorithm is R3. R3 actually navigates to the target point with a distance of 4.2958 m. In contrast, R3 actually navigates a shorter distance and is more effective than R1. In the traditional self-organizing algorithm, when the task is assigned to T3, the winning neuron is R2, and the actual distance from R2 to the target point is 3.8478 m. The winning neuron in the improved self-organizing algorithm is R1. R1 actually navigates to the target point with a distance of 3.6819 m. The sum navigating distances of the AUV group for T1, T2, and T3 are 12.2792 m and 11.6663 m in the traditional self-organizing algorithm and the improved self-organizing algorithm, respectively. The improved algorithm saves 5% of the total navigation length compared with the traditional algorithm.

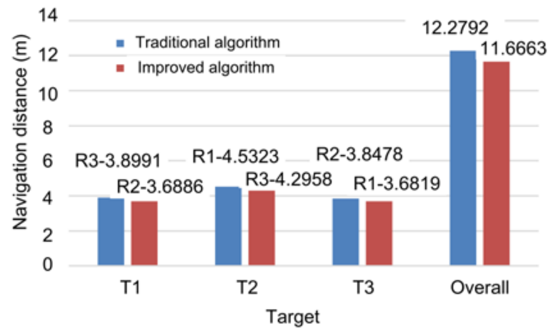

Fig. 12 Actual navigation distance of the AUV group to the target with constant ocean current when the number of AUVs is equal to that of targets
References to color refer to the online version of this figure

4.2 3D plane simulation results

Fig. 13 shows the task assignment solution in a multi-robot system when the number of AUVs exceeds the target number. In the workspace, there are nine AUVs that need to access three targets. There are more AUVs in the 3D plane than the number of target points to visit and some AUVs are not assigned to the target. There is a constant ocean current in the workspace. The angle between R1 and the x-axis is 100°. The angle between R1 and the z-axis is 3°. The angle between ocean current and the z-axis is 5°. The angle between ocean current and the x-axis is 10°. According to the competition principle of the self-organizing neural network algorithm, nine AUVs are assigned to the corresponding nearest targets after considering the initial angle and constant ocean current. Then the optimal path is planned for the AUV mission according to the weight update rule.

Fig. 14 shows the actual navigation distance of the AUV group to the target with a constant ocean current. The traditional SOM neural algorithm selects winning neurons corresponding to the distance between the AUV and target point. The improved SOM method considers a constant ocean current and the fact that AUVs have different azimuth angles at the initial time. In the traditional self-organizing algorithm, when the task is assigned to T1, the winning neuron is R7, and the actual distance from R7 to the target point is 9.5774 m. The winning neuron in the improved self-organizing algorithm is R5. R5 actually navigates to the target point with a distance of 8.7547 m. In contrast, R5 actually navigates a shorter distance and is more effective than R7. In the traditional self-organizing algorithm, when the task is assigned to T2, the winning neuron is R2, and the actual distance from R2 to the target point is 8.4287 m. The winning neuron in the improved self-organizing algorithm is R1. R1 actually navigates to the target point with a distance of 8.1031 m. In contrast, R1 actually navigates a shorter distance and is more effective than R2. In the traditional self-organizing algorithm, when the task is assigned to T3, the winning neuron is R3, and the actual distance from R3 to the target point is 11.7361 m. The winning neuron in the improved self-organizing algorithm is R9. R9 actually navigates to the target point with a distance of 9.1308 m. In contrast, R9 actually navigates a shorter distance and is more effective than R3. The constant ocean current plays a positive role in AUV path planning.

The sum navigation distances of the AUV group for T1, T2, and T3 are 29.7422 and 25.9886 m in the traditional self-organizing algorithm and the improved self-organizing algorithm, respectively. The improved algorithm saves 12.62% of the total navigation length compared with the traditional algorithm.

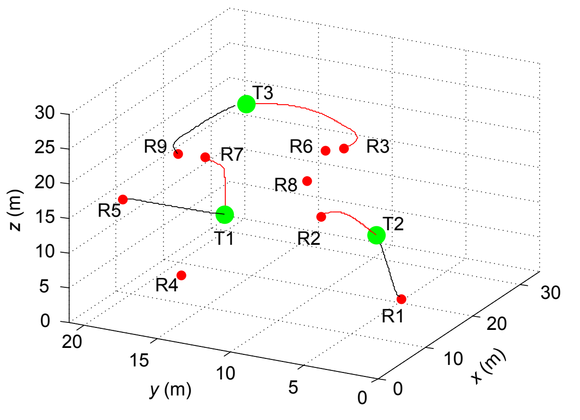

Fig. 13 Task assignment solution in a multi-robot system when the number of AUVs exceeds the number of targets
Green dots represent targets, red dots represent AUVs, the red line indicates the moving path of AUVs in the traditional algorithm, and the black line indicates the moving path of AUVs in the improved algorithm. References to color refer to the online version of this figure

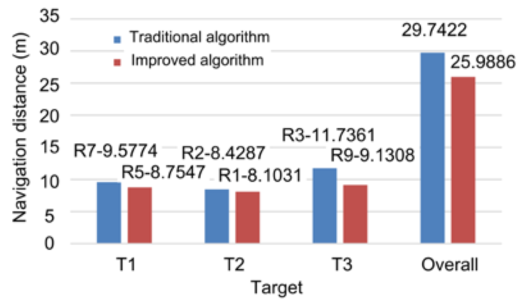

Fig. 14 Actual navigation distance of the AUV group to the target with constant ocean current when the number of AUVs exceeds that of targets in 3D plane
References to color refer to the online version of this figure

4.3 Comparison of simulation results between *k*-means and the improved algorithm

The *k*-means clustering is used in multi-robot task allocation systems. The algorithm clusters the targets into groups. AUVs can access groups to complete the corresponding task. In Fig. 15, there are three AUVs and seven targets. Targets are divided into three groups according to *k*-means clustering. R3 is allocated to T6 and T7. R2 is allocated to T3, T2, and T1. R1 is allocated to T4 and T5. All of the AUVs are allocated to targets. The total navigation distance is 47.64 m. In Fig. 16, the coordinates of AUVs and targets are the same as those in Fig. 15. R2 is allocated to T1, T6, and T7. R1 is allocated to T2, T3, T4, and T5. The total navigation distance is 39.88 m. The actual navigation distance of the improved algorithm is smaller than the actual navigation distance of the *k*-means algorithm. The improved algorithm saves more energy than the *k*-means algorithm.

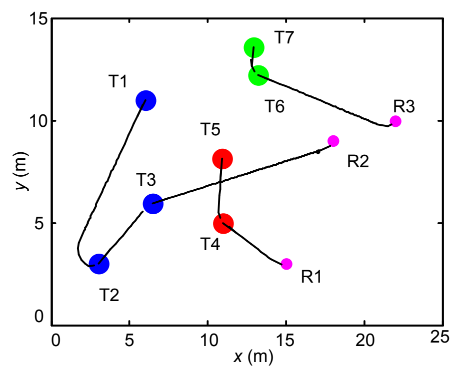

Fig. 15 Task assignment solution in a multi-robot system using the *k*-means algorithm
Pink dots are AUVs and other dots are targets. References to color refer to the online version of this figure

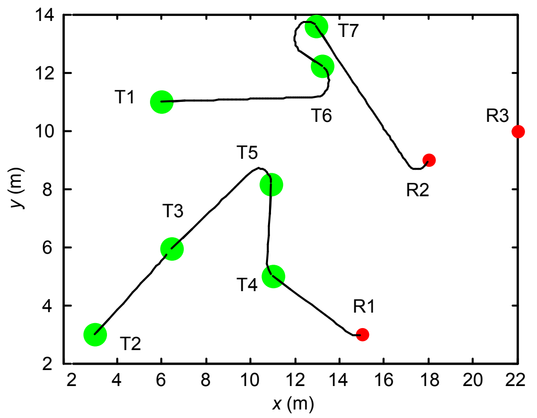

Fig. 16 Task assignment solution in a multi-robot system using the improved algorithm
Red dots are AUVs and green dots are targets. References to color refer to the online version of this figure

5 Conclusions

In this paper, the constant ocean current, kinematic constraints, and different azimuths at the initial time have been considered during multi-AUV task assignment and path planning. A novel SOM task assignment and path planning algorithm has been proposed. In the improved self-organizing map algorithm, an AUV not only successfully traverses to the target point, but also has the shortest navigation path and saves energy for the AUV group. This method can be extended to complex situations, such as moving obstacles.

Acknowledgements

We would like to thank Dr. Bing SUN for discussion.

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