ABSTRACT
Aiming at path planning and collision avoidance of multiple autonomous underwater vehicle (AUV) system under complex environment, an improved neural network algorithm based on biological inspired model is proposed. Firstly, establishing an improved bio-inspired neural network model, the two-dimensional working area is rasterized, and each grid and neuron are one-to-one correspondence, stipulating that the interest area and the obstacle area of the grid correspond to the excitatory and inhibition of neurons respectively, affecting the neurons activity in the whole working area by the transversal function of the adjacent neurons each other. Secondly, AUV plans a safe and collision-free path by comparing the size of the activity of neighbor neurons. Then, Aiming at the problem that AUV moves clinging to the edge of obstacles, adding lateral inhibitory effects of the obstacles on the neural network and greatly improving the safety and rationality of the path planning. Finally, changing the property of grid positions of each AUV in real time to realize collision avoidance between multi-AUV. Simulation experiments prove that the improved algorithm is valid about the path planning in this thesis and the large allowance collision avoidance problem in a complex environment with single-AUV and multi-AUV.

Keywords
Multi-AUV; Path planning; Bio-inspired model; Collision avoidance

1. INTRODUCTION
With the progress of science and technology, human desire for ocean exploration is more and more intense, autonomous underwater vehicle (AUV) has been widely applied in the process of ocean exploration. Due to the limited capacity and coverage of the single AUV, human gradually began to study the AUV networking observation in order to improve the working efficiency of AUV. And in the process of AUV ocean exploration, path planning [1-3] and collision avoidance is key technology and its purpose is, in the complex ocean environment, to design a path that can make AUV avoided the danger and to complete exploration mission efficiently. At present, there are a lot of research methods about AUV path planning, in the text [4], the bio-inspired neural network algorithm is introduced in the application of path planning, the characteristics of this algorithm is no learning, adaptive search and strong real-time performance. In the text [5], the bio-inspired neural network algorithm is further improved, this algorithm can adaptively plan a collision free path, but its collision avoidance design does not consider the obstacle influence on the surrounding area, causing the AUV to move along the edge of the obstacles. In the text [6], the bio-inspired algorithm is applied to the task assignment and target hunting of multi-AUV. This method is able to capture targets successfully, but it ignores the collision avoidance among AUV, which may occur the collisions with each other in the mobile process of multi-AUV.

Based on this, this paper, on the basis of the existing bio-inspired neural network algorithm, uses two-dimensional environment of the static and dynamic obstacles and adds the application of multi AUV and proposes a new path planning method which can achieve collision avoidance among multi-AUV and a large allowance for avoidance between AUV and obstacles.

This paper is organized as follows. In Section 2, the model construct, improved bio-inspired neural network model, path planning strategy, multi-AUV collision avoidance strategy and the stability proof of the model are presented. The simulation experiments for various situations are given in Section 3. Finally, the conclusion is given in Section 4.

2. PATH PLANNING ALGORITHM BASED ON IMPROVED BIO-INSPIRED NEURAL NETWORK
2.1 Model Construct
In this paper, the goal of the algorithm is to project a safe and effective path for AUV to avoid all the obstacles of the whole working area in a large allowance condition in a static or dynamic complex working environment. Assuming that the AUV is
searched in a fixed depth level or the path planning problem in this paper is expanded in a two-dimensional plane. The horizontal area \( W \) is discretized into size-fixed grids \([7-9]\). The whole area \( W \) is divided into the Key area, Forbidden area and General area, and the grid is divided into three names, namely, Interest area, Obstacle area and Blank area. Its attributes are defined as:

\[
p = \begin{cases} 
1 & \text{grid for the interest area} \\
-1 & \text{grid for the obstacle area} \\
0 & \text{grid for the blank area}
\end{cases}
\]

The discrete grids of the working area \( W \) make one-to-one correspondence with the neurons, then the neurons have different neural activity for the different properties of grids, the interest area of grid corresponds to the stimulation area of neurons, the obstacle area of grid corresponds to the inhibition of neurons, the blank area of grid corresponds to the general area of the neurons. The activity values of the interconnected neurons have an influence, which makes the active value of the whole area different. This feature provides a method for AUV’s motion and path planning in the working area \( W \).

### 2.2 Path Planning Algorithm

#### 2.2.1 Improved Bio-Inspired Neural Network Model

Bio-inspired neural network model is put forward by Hodgkin and Huxley in 1952, it is a kind of method based on cell circuit to describe thin film voltage \([10]\), Grossberg \([11]\) summary and improved the model. Yang \([12]\) applies bio-inspired neural network model to the path planning problem, which provides a new idea for the path planning problem. The improved model as:

\[
d_{xi} = -Ax_i + (B - x_i)S_i^x - (D + x_i)S_i^y
\]

Where \( x_i \) represents the activity value of the neuron \( i \) in the neural network. \( A, B, D \) respectively represent the passive decay rate, the upper limit of nerve stimulation and the lower limit of the neural inhibition, and the variable \( S_i^x \) and \( S_i^y \) respectively represent the inhibitory input and the excitatory input of the neuron \( i \).

In the proposed neural network model, the excitatory input \( S_i^x \) is caused by the interest area and near neurons, the inhibitory input \( S_i^y \) is from the obstacle area and its near neurons, so the shunting equation of the neuron \( i \) in the neural network as:

\[
d_{xi} = -Ax_i + (B - x_i) \left( [I]^+ + \sum_{j=1}^{N} w_{ij} [x_j]^+ \right)
- (D + x_i) \left( [I]^+ + \sum_{j=1}^{N} w_{ij} [x_j]^+ \right)
\]

Where \( N \) represents the total number of neural network neurons, \( [I]^+ + \sum_{j=1}^{N} w_{ij} [x_j]^+ \) and \( [I]^+ + \sum_{j=1}^{N} w_{ij} [x_j]^+ \) respectively represent the inhibitory input \( S_i^y \) and the excitatory inputs \( S_i^x \). The function \( [I]^+ \) is a nonlinear function defined as \([I]^+ = \max(I, 0)\), and \( [I]^+ \) is defined as \([I]^+ = \max(-1, 0)\). The external input \( I_i \) of the neuron \( i \) in the neural network is defined as:

\[
I_i = \begin{cases} 
\frac{1}{C + d(p_i - p_o)} & \text{piont } i \text{ is the interest area} \\
C & \text{piont } i \text{ is the obstacle area} \\
0 & \text{piont } i \text{ is the other area}
\end{cases}
\]

Where \( C \) is a positive integer and \( p_o \) represents the center coordinates \((x_o, y_o)\) of the interest area, \( p_i \) expresses the coordinates \((x_i, y_i)\) of the neuron \( i \) in the interest area and \( d(p_i - p_o) \) is the Euclidean distance from the neuron \( i \) to the neuron \( e \). \( d(p_i - p_o) = \sqrt{(x_i - x_o)^2 + (y_i - y_o)^2} \). Therefore, the closer the interest area is, the greater the activity value is. The closer to the obstacle area, the smaller the activity value is, \( w_{ij} \) is the lateral connection weights between the neuron \( i \) and the neuron \( j \), which is defined as:

\[
w_{ij} = f(d(p_i - p_j))
\]

\( f(m) \) is a monotone decreasing function, which is defined as:

\[
f(d(p_i - p_j)) = \begin{cases} 
\frac{r}{d(p_i - p_j)} & 0 \leq d(p_i - p_j) \leq r \\
0 & d(p_i - p_j) > r
\end{cases}
\]

Where \( r \) is a normal number, indicating that the neuron \( i \) can stimulate the maximal range of peripheral neurons. In this paper, setting \( r = \sqrt{2} \) and \( k \) represents the number of neurons that are transversely connected with neuron \( i \), \( sok = 8 \). In this model, when the values are different when considering the inhibition and stimulation of neurons, the value of \( \varepsilon \) is different and when and the neuron \( i \) is inhibition, the value of \( \varepsilon \) is small in order to reduce the effect of the obstacle on the activity values of the surrounding neurons. It not only ensures the negative activity values of the surrounding area, but also does not affect the activity of neurons outside the obstacles in a certain range, thus making the activity value of the whole working area more reasonable. The differential equation of the activity output value of the neuron \( i \) can be further simplified to:

\[
d_{xi} = -Ax_i + (B - x_i) \left( [I]^+ + \sum_{o<|j|<\sqrt{2}} w_{ij} [x_j]^+ \right)
- (D + x_i) \left( [I]^+ + \sum_{o<|j|<\sqrt{2}} w_{ij} [x_j]^+ \right)
\]

In the application of obstacle avoidance, the traditional algorithm based on bio-inspired neural networks often occurs one condition that AUV moves clinging to the edge of obstacles, the main reason for this result is that only considering the excitation of the target location to the neural network and ignoring the lateral inhibitory of the obstacles in the whole neural network. In this paper, the lateral inhibitory effects of the obstacles on the neural network are added, and the effective range of the target points and obstacles on the activity of the neurons in the working area are adjusted by setting the value of \( \varepsilon \), and then ensuring that the effect of the target point on the activity of the neurons in the area is far greater than the one of the obstacles, thus making an effectively plan that can make AUV motive with sufficient safe allowance in the area away from the obstacles, while improving the applicability of the model.

#### 2.2.2 Path Planning Strategy

Using the formula (4) to calculate the activity value of each neuron and stipulate the next motive position of each AUV in the coordinate position corresponding to the maximal activity value of the neighbor neuron. As AUV moves, the neuron activity of the whole working area is constantly updated in order to plan a reasonable path. Supposing that the current position of AUV is \( p_c \) and the next motive position is \( p_n \) in the working area \( W \),

\[
p_n = \arg\max_{p_n \in \mathcal{U}(p_c, r)} x_{p_n}
\]

Where \( \mathcal{U}(p_c, r) \) is the grids that distance \( p_c \) less than \( r \), \( x_{p_n} \) indicates the activity value of \( p_n \).

#### 2.2.3 Multi-AUV Collision Avoidance Strategy

In the multi-AUV path planning, the traditional bio-inspired neural network ignores that the current position of AUV at every
moment should be considered as an obstacle and may lead to a collision between AUVs. This paper proposes a more perfect multi-AUV path planning algorithm for this problem.

This paper selects 3 AUVs to move in the working area and records the current coordinates, they are respectively \((x_1, y_1), (x_2, y_2), (x_3, y_3)\). The implemented methods of collision avoidance as follow:

Setting the property of current coordinates of the AUV1 as the blank area and the corresponded neuron activity as 0. Updating the activity values of the whole neuron. Selecting the next motive position of the AUV1 at next time according to the formula (5), then setting the property as an obstacle, and calculating the activity value of the neurons through the formula (4). Then implementing same operation to AUV2, AUV3 respectively. Moving these three AUVs and assigning the coordinates of the three AUVs at the next moment to the current coordinates, then looping until AUV reaches the target area.

By this method, the next location of the AUV is set as an obstacle, and then updating its activity. While the rest of the AUVs move the location at the next time in the path planning, it can avoid the collision between the AUVs, because the activity of the neighbor neurons is larger than the neuron activity of the obstacle and then avoiding the multi-AUV moving to the same position at the same time.

2.2.4 The Stability Proof of the Model

Definition: 
\[ z_i = x_i - B \]

Get:
\[ x_i = z_i + B \]  \hspace{1cm}  (6)
\[ \frac{dz_i}{dt} = \frac{dx_i}{dt} \]  \hspace{1cm}  (7)
\[ x_j = z_j + B \]  \hspace{1cm}  (8)

Get from sorting out:
\[ \frac{dz_i}{dt} = -z_i \left( \frac{1}{z_i} (AB + (D + B)I_z) + z_i (A + [I_z] + [I_z]) \right) \]
\[ \sum_{0<i<j} (-w_{ij}) \left( (z_j + B)^+ + \frac{(z_i+D+B)}{z_i} (z_j + B)^- \right) \]  \hspace{1cm}  (9)

By the following substitutions:
\[ a_i(z_i) = -z_i \]  \hspace{1cm}  (10)
\[ b_i(z_i) = \frac{1}{z_i} (AB + (D + B)I_z) + z_i (A + [I_z] + [I_z]) \]  \hspace{1cm}  (11)
\[ c_{ij} = w_{ij} \]  \hspace{1cm}  (12)
\[ d_i(z_j) = (z_j + B)^+ + \frac{(z_i+D+B)}{z_i} (z_j + B)^- \]  \hspace{1cm}  (13)

Get:
\[ \frac{dz_i}{dt} = a_i(z_i)(b_i(z_i) - \sum_{j=1}^{8} c_{ij} d_i(z_j)) \]  \hspace{1cm}  (14)

The previous description can deduce \( d_i(z_j) = 1 \) at \( z_j \geq -B \).

Next, analyzing the path planning problem of single AUV in complex environment.

3.1 Path Planning of Single-AUV

3.1.1 Path Planning of Single-AUV in Static Environment

In this section, the path planning of a single AUV is considered to achieve large allowance collision avoidance in a static environment. In order to verify the effectiveness of this algorithm, the path planning results of traditional algorithm are compared with the ones in this algorithm. Designing single AUV from coordinate position \((2, 2)\) to search target location \((70, 70)\) in the working area, in which there are two pieces of obstacles, respectively enclosed by coordinates positions \((7, 7), (7, 13), (13, 13), (13, 7)\) and coordinate positions \((47, 47), (47, 53), (53, 53), (53, 47)\). In Figure 2, its search path is shown according to the traditional bio-inspired algorithm to solve this problem, the AUV
clinging to the lower edge of the obstacle area coordinate position (10, 10) doing search. Because the safety allowance is 0 between AUV motion trajectory and obstacles, it may cause collision of AUV and obstacle and an incalculable consequence in the actual environment, the main reason of this result is that the neuron activity is extremely low corresponding to obstacle position or the neurons activity value surrounded by the obstacles is too high, the AUV moves along the edges of the obstacle or the position where activity value is high.

Figure 2. The obstacle avoidance effect of the traditional biologic heuristic model

In order to improve the safe allowance of AUV and obstacles, and solve the problem of AUV collisions with obstacles, this paper considers the lateral inhibitory of the obstacle’s activity value to the surrounding area’s active value within a certain range into the algorithm, taking impact factor $\varepsilon = 1 \times 10^{-18}$. After improving the algorithm, the search path of single AUV in a static environment is shown in Figure 3. The neighbor neuron activity value of obstacle at the coordinate position (10, 10) is shown in Table 1, the second column is the activity value after the algorithm improvement and the third column is the activity value before the algorithm improvement. The simulation result shows that the AUV path trajectory usually keep 40 meters allowance with obstacles, the nearest allowance also keep 20 meters, the autonomous planning path of AUV is far away from the obstacle, so as to improve search security.

| Coordinate position | The activity value after the algorithm improvement | The activity value before the algorithm improvement |
|---------------------|-----------------------------------------------|-----------------------------------------------|
| (6,6)               | -7.2132884035e-35                            | 2.7668373226e-77                             |
| (6,7)               | -1.1375695422ce-34                           | 2.9982344180e-76                             |
| (6,8)               | -1.8582081510e-34                           | 1.1914714932e-74                             |
| (6,9)               | -1.8572834670e-34                           | 5.2508443204e-73                             |
| (6,10)              | -1.8557197909e-34                           | 2.090812096e-71                              |
| (6,11)              | -1.8532695978e-34                           | 1.0509421415e-69                             |
| (6,12)              | -1.8485280144e-34                           | 3.8219816867e-68                             |
| (6,13)              | -1.1269244256e-34                           | 3.9249225528e-66                             |
| (6,14)              | -7.1357309653e-35                           | 3.2766404874e-65                             |

3.1.2 Path Planning of Single-AUV in Dynamic Environment

The following analysis of the proposed algorithm is based on the application effect of the single-AUV path planning under the dynamic changing environment. Assuming that the number and position of the static obstacles remains unchanged in the working area, and the start coordinates of AUV also remains unchanged. Figure 2 is the path planning result of the coordinates (60, 60) without obstacles. When AUV moves to around this position and appears a bar obstacles enclosed by coordinates (58, 47), (58, 53), (62, 53) and (62, 47), the path based on the traditional bio-inspired neural network algorithm planning is shown in Figure 4. The minimum of safe allowance between AUV planning path and dynamic obstacle is zero.

Figure 4. AUV bypasses dynamic obstacles of the traditional model

The improved algorithm of obstacle avoidance considers the lateral inhibitory of the obstacles to the surrounding area, When AUV moves to near the coordinates (51, 62) and appears a square obstacle enclosed by coordinates (53, 64), (53, 70), (57, 70), (57, 64). Each motion coordinates of the AUV and the corresponding neuron activity values of the surrounding area shown in Table 2. The activity value of the 10m area on the edge of the obstacle is always less than the activity value of the edge 20m region when the dynamic obstacle appears, avoiding the AUV moving clinging to the obstacle, which reflects the inhibition effectiveness of the obstacle area on the activity of the peripheral neurons. As the

Figure 3. The obstacle avoidance effect of the improved biologically heuristic model
AUV moves toward the target, the activity of the neuron in the location of AUV gradually becomes large, which proves the excitation effectiveness of the target area to the neurons of the whole working area. The final planning path, as shown in Figure 5, when a dynamic obstacle is encountered, AUV can bypass the obstacles in time and replan a path to the target point directly and the minimal allowance of the AUV trajectory and the dynamic obstacle is 20 meters, which greatly improves the safety and rationality of the path planning.

![Figure 5. AUV bypasses dynamic obstacles of the improved model](image)

### Table 2. Activity values of neurons surrounding area of AUV

| Current position | (51,62) | (52,61) | (53,61) | (54,62) |
|------------------|---------|---------|---------|---------|
| Pc (x-1,y-1)     | 2.161e-06 | 1.398e-05 | 5.699e-05 | 0.00013 |
| Pc (x-1, y)      | 3.873e-06 | 1.697e-05 | 4.067e-05 | 0.00025 |
| Pc (x-1, y+1)    | 3.346e-06 | 8.789e-06 | 6.383e-05 | 0.00015 |
| Pc (x,y-1)       | 1.639e-05 | 5.922e-05 | 0.0002 | 0.00096 |
| Pc (x, y)        | 6.106e-06 | 2.587e-05 | 9.713e-05 | 0.00031 |
| Pc (x,y+1)       | 1.410e-05 | 6.759e-05 | 0.00026 | 0.00061 |
| Pc (x+1,y-1)     | 6.388e-05 | 0.000213 | 0.0007 | 0.00312 |
| Pc (x+1,y)       | 6.385e-05 | 0.000255 | 0.0009306 | 0.00317 |
| Pc (x+1,y+1)     | 4.449e-05 | 0.000253 | 0.0009307 | 0.00214 |
| Next position    | (52,61) | (53,61) | (54,62) | (55,62) |

### 3.2 Path Planning for Multi-AUV

The single-AUV is limited by the energy consumption, the work efficiency is not high enough, and the multi-AUV [14-15] cooperative work will greatly improve the efficiency. This section will introduce the specific implementation of collision avoidance of the algorithm in the multi-AUV path planning. In this paper, the working area of AUV is 1000m × 1000m. In real conditions, the range of underwater acoustic communication is 2km, so this paper stipulates that real-time communication and transmit data can realize between multi-AUV.

#### 3.2.1 Path Planning of Multi-AUV in Dynamic Environment

First analyzes the path planning ability of the proposed algorithm in a dynamic environment. The activity values of the whole working area are shown in Figure 6, and the Z axis indicates the size of the neuron activity value. From the diagram, the activity values are all between -1 and 2, which corresponds to the ones from the previously proposed model.

![Figure 6. Distribution of activity values of neurons in working area](image)

When multiple AUV moves, an obstacle suddenly appears nearby, the proposed algorithm can successfully avoid dynamic obstacles and plan a new safe path. The starting coordinates of the three AUVs are (25, 20), (40, 20), (20, 45), and the target location is a square area centered at (80, 75) with a length of 20. There are three obstacles in the working area before the dynamic obstacle is encountered, the multi-AUV successfully avoids the obstacles of coordinates (60, 50) and (40, 50) and always moves toward the direction of the target location, as shown in Figure 7. When moving to the coordinates (70, 60), a dynamic obstacle suddenly occurs, this causes the activity value nearby being changed, and then the AUV replan the mobile path in the local area. From Figure 8, AUV can bypass the dynamic obstacle area and replan a path toward the target area when the obstacle is suddenly encountered.

![Figure 7. The AUV path before the occurrence of a dynamic obstacle](image)
3.2.2 Path Planning for Multi-AUV Collision Avoidance

In the path planning problem of the multi-AUV, in addition to considering the collision between the AUV and the obstacles, the collision between AUV needs to be considered, and the AUV itself needs to be regard as an obstacle. The target location is a square area centered at (80, 75) with a length of 20. The multi-AUV search algorithm designed in this paper sets the next location of the AUV1 as an obstacle, so the activity value of the neuron in this location will become a negative one, which is smaller than the activity value of the neuron at the neighbor location. When the AUV2 plans path, the activity value of \( x_n \) is changed into negative one, and the AUV2 will choose other location in the near area as moving position for the next moment to avoid collisions among AUV. After AUV1 searches and leaves the coordinate position \( x_n \), the attribute of \( x_n \) is changed to blank so that the path planning of AUV in the near future can still go through the position. In Figure 9, the red path end represents the current position of AUV2 is the coordinates (72, 71), the light blue path end indicates the current position of AUV3 is the coordinates (72, 70), and Figure 10 is the larger image at this time.

The activity of neurons around AUV2 and AUV3 at this moment is like Table 3, the second column is the activity value of neurons around AUV2 and third one is the activity value of neurons around AUV3. The locations of the neurons with the largest neighbor activity of AUV2 and AUV3 are the coordinates (73, 70), the next moving coordinates of AUV2 and AUV3 both are coordinates (73, 70), AUV2 and AUV3 will collide. After the improvement of the proposed algorithm, when AUV2 reaches that point and its property is changed to obstacle, so \( I_i = -E \) and according to the definition of \( [I]^+ \), \( [I]^− \) we know \( [I]^+ = 0 \), \( [I]^− = E \), and substitutes it into formula (5), the corresponding activity value at the coordinates (73,70) becomes a negative number, the next moving position of AUV3 will be changed from the coordinates (73,70) to coordinates (73, 69) which is selected from an activity value around other points. In Figure 11, the proposed algorithm will avoid moving to the same location at the same time in the path planning process.

| Current position | Activity value of AUV2 | Activity value of AUV3 |
|------------------|------------------------|------------------------|
| (x-1,y-1)        | 0.33365982564          | 0.36519406427          |
| (x-1, y)         | 0.27675950305          | 0.33365982564          |
| (x-1, y+1)       | 0.33258791385          | 0.27675950305          |
| (x,y-1)          | 0.54744705811          | 0.14783007796          |
| (x, y)           | 0.59583169694          | 0.54744705811          |
| (x,y+1)          | 0.21947807118          | 0.59583169694          |
| (x+1,y-1)        | 0.95864537545          | 0.95830274948          |
| (x+1,y)          | 0.95855577696          | 0.95864537545          |
| (x+1,y+1)        | 0.94314566034          | 0.95455577696          |

Figure 8. The AUV path after the occurrence of a dynamic obstacle

Figure 9. The location of AUV2 and AUV3 at a certain moment

Figure 10. The larger image of AUV2 and AUV3
4. CONCLUSION
This paper proposes an improved bio-inspired neural network model algorithm, and proves the effectiveness of the path planning in the two-dimensional environment through the simulation experiment. By comparing with the traditional neural network model algorithm, it is proved that the algorithm can greatly improve the security allowance and the collision ability to avoid the obstacles in the path planning process. The experiment also proves that the algorithm has the avoidance ability of dynamic obstacle and the ability to avoid collision between AUVs in the process of multi-AUV path planning. It can plan a safe and efficient path.

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