

The Path Planning of AUV Based on D-S Information Fusion Map Building and Bio-inspired Neural Network in Unknown Dynamic Environment

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Abstract In this paper a biologically inspired neural dynamics and map planning based approach are simultaneously proposed for AUV (Autonomous Underwater Vehicle) path planning and obstacle avoidance in an unknown dynamic environment. Firstly the readings of an ultrasonic sensor are fused into the map using the D-S (Dempster-Shafer) inference rule and a two-dimensional occupancy grid map is built. Secondly the dynamics of each neuron in the topologically organized neural network is characterized by a shunting equation. The AUV path is autonomously generated from the dynamic activity landscape of the neural network and previous AUV location. Finally, simulation results show high quality path optimization and obstacle avoidance behaviour for the AUV.

Keywords AUV (Autonomous Underwater Vehicle), Map Building, D-S Information Fusion, Path Planning, Biologically Inspired Neural Dynamics, Neural Network, Obstacle Avoidance

1. Introduction

The basic feature of an autonomous mobile robot is its capability to operate independently in unknown or partially known environments. The autonomy implies that the robot is capable of reacting to static obstacles and unpredictable dynamic events that may impede the successful execution of a task [1]. To achieve this goal, solutions need to be developed in map building, path planning and navigation. In the paper, map building with particular reference to modelling the ultrasonic sensor information and probabilistic in map construction is discussed. Path planning is a fundamentally important issue in robotics. Similarly to an autonomous mobile robot, point-to-point AUV path planning in a two-dimensional environment requires the AUV to pass through partially known areas in the workspace.

The performance of the AUV in navigating in an unknown environment depends strongly on the accuracy

of its perception capabilities. The system needs to gather a large amount of sensory information and to integrate it into a proper representation of the environment. The traditional paradigm for covering spatial information is based on the use of a two-dimensional tessellation called an occupancy grid. It was first introduced by Moravec and Elfes [2] and it is widely used in mobile robot navigation. In principle, occupancy grids store qualitative information about which areas of the robot's surroundings are empty and which areas are occupied by obstacles.

Map building using ultrasonic sensors has been addressed by many researchers and a substantial body of modelling and experimental work has been presented in [3-7]. Ultrasonic range-finders are common in mobile robot navigation due to their simplicity of operation and high working speed. The sensor provides the relative distance between the robot and surrounding obstacles located within its radiation cone. The time elapsed between the transmission of a wave and the reception of its echo allows the computation of a range reading. This means that an obstacle may be located somewhere on the arc of a radius within the sensor beam. However, the sensor is prone to several measuring errors due to various phenomena, for example, the wide radiation cone, the low angular resolution and the specular properties of the environment. As a consequence, the sensing process is affected by a large amount of uncertainty. In order to handle uncertainty during the occupancy grid building process, the formulation fusion approach is used to process sonar data and build the map.

The building of an occupancy map is well suited to path planning, navigation and obstacle avoidance because it explicitly models free space [8]. The Bayesian approach [9] has traditionally dominated the probabilistic sensor fusion in building occupancy maps. To quantify the sensor uncertainty, all conditional probabilities must be specified. Because of the difficulty of completing the model, the conditional probabilities are usually approximated, which causes difficulties in building a reliable map. The Bayesian is certainly not the only method that has been engaged to solve the problem of data fusion. Fuzzy maps have been applied to this problem with better results than the Bayesian approach, as reported by Gabino [10], as have more methods such as histogram grids [11] and the D-S (Dempster-Shafer) formulation fusion approach [12]. Daniel applied the D-S theory to full three-dimensional mapping of indoor environments, employing stereo vision as the measuring sensor. In the paper, the D-S approach is used to process a series of sonar data from an unknown environment.

Path planning is one of the key issues in mobile robots and it is traditionally divided into two categories: global

path planning and local path planning. In global path planning, prior knowledge of the workspace is available. Local path planning methods use ultrasonic sensors, laser range finders to perceive the environment in which planning is performed. In the paper, the workspace for the path planning of the AUV is assumed to be unknown, so it may have stationary or non-stationary obstacles.

There are some learning based models for motion planning of mobile robots for unknown environments. For example, Gambardella [13] proposed a learning method for path planning in a robot in a cluttered workspace where the dynamic local minima can be detected, and it can avoid the local minima by learning, such as in deadlock situations. Svestka [14] proposed a probabilistic learning approach to motion planning of a mobile robot, which involves a learning phase and a query phase and uses a local method to compute feasible paths for the robot. Fujii [15] proposed a multilayer reinforcement learning model for path planning of multiple mobile robots. However, the planned robot motion using learning based approaches is not efficient and is computationally expensive, especially in its initial learning phase. There have been some neural network based approaches to path planning. For example Yang and Luo [21-22] proposed a neural network model for complete coverage path planning in non-stationary environments. However, the current knowledge of the non-stationary environment was assumed to be completely known in the literature [22].

In this paper, map building and path planning algorithms are proposed for an AUV in an unknown environment. A local map composed of square cells is built by the D-S formulation fusion of sonar data during AUV navigation. The state space of the topologically organized neural network is the 2D workspace of the AUV map. The dynamics of each neuron is characterized by a shunting equation derived from Hodgkin and Huxley's membrane model for a biological nervous system [21]. There are only local lateral connections among neurons. Thus, the computational complexity depends linearly on the neural network size. The varying environment is represented by the dynamic activity landscape of the neural network. The AUV path is directly planned from the dynamic neural activity landscape and previous AUV position without any prior knowledge of the changing environment. Since the neural connection weights are set in the model design and can be chosen in an extensive range, there is no need to find an optimal connection weight among neurons. Thus, there are no learning procedures in the proposed neural network and no need for any templates in an unknown environment during the navigation.

This paper is organized as follows. The environment model, the ultrasonic sensor model, the establishment

and conversion of coordinates and the D-S information fusion to build the map in unknown environments for an AUV are presented and the simulation results of map building are given in Section 2. In Section 3, the biological inspiration and the neural network model used to plan the path for the AUV are described and the simulation results in static and changing environments are presented. Finally, in Section 4, several important properties of the D-S evidence and the biological inspiration approach using path planning for the AUV are concluded.

2. Map Building

As mentioned above, the building of an occupancy map is well suited to path planning, navigation and obstacle avoidance because it explicitly uses free space. An occupancy grid is essentially a data structure that indicates the certainty that a specific part of space is occupied by an obstacle. It represents an environment as a two-dimensional array. Each element of the array corresponds to a specific square on the surface of the workspace and its value shows the certainty that there is some obstacle there. When new information about the workspace is received, the array is adjusted on the basis of the nature of the information.

In the paper, the sonar data are interpreted by D-S evidence theory and used to modify the map using Dempster's inference rule. Whenever the AUV moves, it catches new information about the environment and updates the old map. More specifically, to build an occupancy map of the environment, a grid is constructed to represent the whole space. Every discrete region of the map (each cell) may be in two states: Empty or Occupied. A series of range readings of data collected at known sensor locations is available. In principle, the task of the map building system is to process the readings data in order to assess, as accurately as possible, which cells are occupied by obstacles and which cells are empty and thus suitable for AUV navigation.

2.1 Environment Modelling

To build an occupancy map of the environment, in the paper we construct a grid representing the whole space. Every discrete region of the map (each cell in the grid) is characterized by two states: Empty and Occupied. The implemented approach finds its formulation through the use of the D-S theory of evidence. In this case, the goal of the occupancy grids' building procedure is to determine the support for the states E and O , corresponding to the possibilities that the cell is Empty or Occupied. Thus, defining the set of discernment by $\Theta = \{O, E\}$ and the set of states by

$$\Lambda = 2^\Theta = \{\emptyset, E, O, \{E, O\}\} \quad (1)$$

The whole grid is defined by U and any grid in the workspace is represented by $U(i, j)$. The state of each cell $U(i, j)$ is described by assigning basic probability $m_{i,j}$ to each label in Λ . However, it is known that for each cell $U(i, j)$ in the grid

$$m_{i,j}(\emptyset) = 0 \quad (2)$$

and

$$\sum_{A \in \Lambda} m_{i,j}(A) = m_{i,j}(\emptyset) + m_{i,j}(E) + m_{i,j}(O) + m_{i,j}(\{E, O\}) = 1 \quad (3)$$

Considering this linear dependence and assuming $m_{i,j}(\emptyset) = 0$, it is sufficient to store $m_{i,j}(E)$ and $m_{i,j}(O)$ only to fully represent the state of the system. Every cell in the map is first initialized

$$m_{i,j}(O) = m_{i,j}(E) = 0 \text{ and } m_{i,j}(\{E, O\}) = 1 \quad (4)$$

which represents total ignorance about the state of each cell.

2.2 Sensor Modelling

The ultrasonic sensor [16] is a very common device that can detect distances within its radiation cone (consider 30° the width of the radiation cone) and is used for map building. A single reading provides the information that one or more obstacles are located somewhere along the 30° arc of circumference of the radius R (Figure 1). Hence, there is evidence that cells located in the proximity may be 'occupied'. On the other hand, cells well inside the circular sector of radius R are likely to be 'empty'. To model this knowledge, in this paper the D-S theory of evidence is used. The evidence is obtained by projecting the raw ultrasonic sensor responses onto the evidence grid through the sonar profile model. This profile sonar model is a function of the angle and the sonar range reading, as shown in Figure 2.

- (a) Profile for the range.
- (b) The partition of the ultrasonic sensor model.
- (c) Profile for the angle

The model converts the range information into probability values. For modelling the general behaviour of the sonar sensors in angular and range resolution, independently of the selected approach, the model [6] in Figure 2 is given by Eqs. (5)-(10).

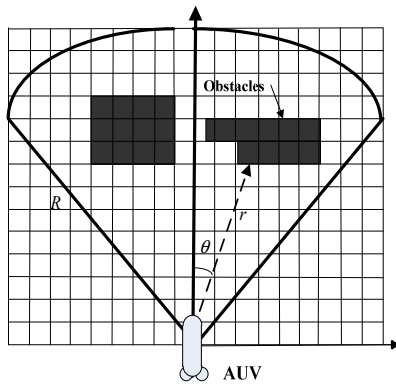


Figure 1. The sensor beam on a rectangular grid

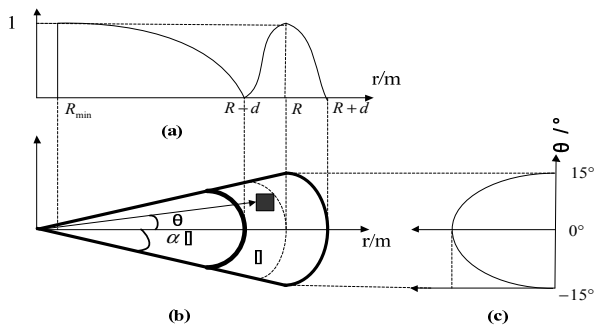


Figure 2. The ultrasonic sensor model

In region I, where $R - d \leq r \leq R + d$:

$$m(O) = \frac{\left(\frac{\alpha - |\theta|}{\alpha}\right)^2 + \left(\frac{d - |R - r|}{d}\right)^2}{2} \quad (5)$$

$$m(E) = 0 \quad (6)$$

$$m(\{O, E\}) = 1.00 - m(O). \quad (7)$$

In region II, where $R_{\min} \leq r \leq R - d$:

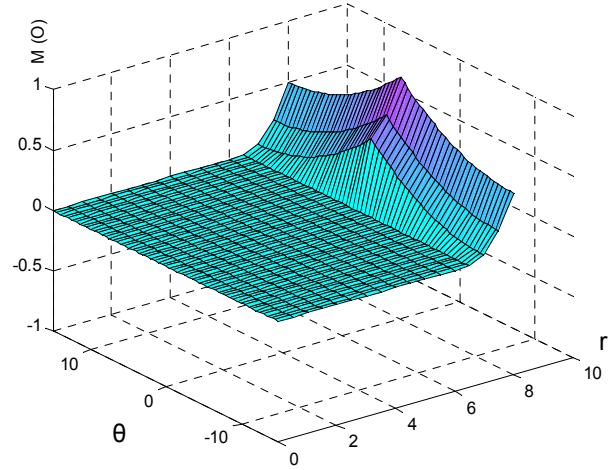
$$m(O) = 0 \quad (8)$$

$$m(E) = \frac{\left(\frac{\alpha - |\theta|}{\alpha}\right)^2 + \left(\frac{R - r - d}{R - d}\right)^2}{2} \quad (9)$$

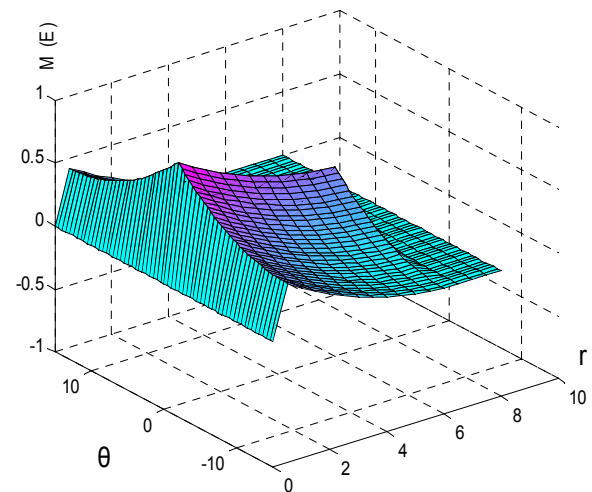
$$m(\{O, E\}) = 1.00 - m(E). \quad (10)$$

where R is the range response from the ultrasonic sensor, $\alpha = 15^\circ$ is the half open beam angle of the sonar cone, θ is the angular distance to the beam axis and r is the distance from sensor to obstacle, so (r, θ) represents

the coordinate of a point inside the sonar cone. $d = 1.5\text{m}$ is the range error and it distributes the evidence in Region I. The 3D profiles of the ultrasonic sensor model for Eqs. (5)-(10) are depicted in Figure 3.



(a) Model for Occupied cells



(b) Model for Empty cells

Figure 3. The 3D profiles of the sensor models used to interpret range data in the evidence theory

2.3 The Establishment and Conversion of Coordinates

The ultrasonic sensor studied in this article is a forward-looking multi-beam transmitter. To obtain the distance from sensor to obstacle, the ultrasonic sensor scanning the surrounding environment is based on a certain resolution scanning, so the raw data it gets are discrete data. If the scattering angle of ultrasonic sensor is α , every point within the radiation sector is represented by a certain distance r and the scan angle θ , indicating the form of (r, θ) as shown in Figure 1. Clearly, the polar coordinate of the AUV needs to be changed to an inertial

coordinates map. Figure 4 shows an example of the establishment and conversion of coordinates. If (X, Y) are selected as the inertial coordinate system, the data of obstacles obtained from ultrasonic sensor are converted to the AUV's inertial coordinate by the following equations.

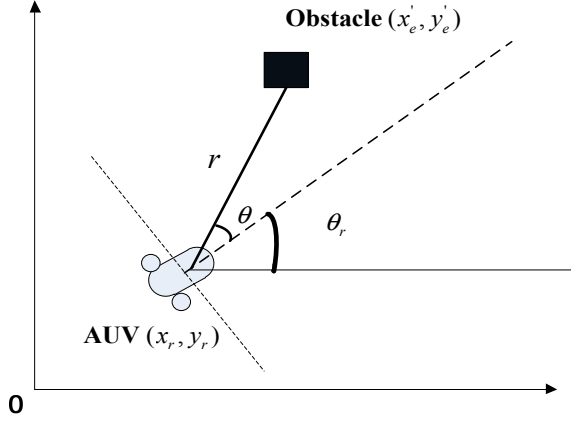


Figure 4. Schematic diagram for AUV

When an obstacle is set as (r, θ) , the conversion is given by

$$\begin{cases} x_e' = x_r + r \cdot \cos(\theta + \theta_r) \\ y_e' = y_r + r \cdot \sin(\theta + \theta_r) \end{cases} \quad (11)$$

where x_e' and y_e' are the coordinates of the obstacle in the inertial coordinate system and (x_r, y_r, θ_r) are the inertial coordinates and the direction angle of AUV, respectively.

Furthermore, by transforming the inertial coordinate (x_e', y_e') of an obstacle into the inertial grid coordinate (x_e, y_e) , its physical meaning is that any position within a grid is expressed as the location of the centre of the grid. Define the size of a grid as $1 \times 1\text{m}$ and $w=1$. The conversion relationships are described as:

$$\begin{cases} x_e = \left\lfloor \frac{x_e'}{w} \right\rfloor \bullet w + \left(\frac{w}{2} \right) \\ y_e = \left\lfloor \frac{y_e'}{w} \right\rfloor \bullet w + \left(\frac{w}{2} \right) \end{cases} \quad (12)$$

Therefore, in the case where the coordinates and direction angle (x_r, y_r, θ_r) of the AUV are known, combined with obstacles data (r, θ) from the ultrasonic sensor, the coordinates of the obstacles within the radiation of the AUV polar coordinate can be transformed into the inertial grid coordinates by Eqs. (11) and (12),

which is conducive to updating the corresponding grid distribution values.

2.4 The D-S Information Fusion and Its Application in Map Building

D-S evidence theory in the application of multi-sensor data fusion is common. The related information data obtained from sensors is the theory of evidence, and it can constitute belief function assignment for the target model to be identified. The credibility of each target model is described and treats each sensor as an evidence group. The multi-sensor data fusion is combined with a number of evidence groups using D-S rules to generate a new comprehensive evidence group.

According to D-S joint rules [17], m_1 and m_2 are belief function assignments, corresponding to the same identification framework Θ . The target models to be identified are $A_1, A_2 \dots A_k$ and $B_1, B_2 \dots B_k$. Assuming

$\sum_{\Phi=A_i \cap B_j} \{m_1(A_i)m_2(B_j)\} < 1$, the fusion rule can be expressed

by the following equation (13):

$$m(A) = \begin{cases} \frac{\sum_{A=A_i \cap B_j} \{m_1(A_i)m_2(B_j)\}}{1 - C}, & A \neq \Phi \\ 0, & A = \Phi \end{cases} \quad (13)$$

$$\text{and } C = \sum_{\Phi=A_i \cap B_j} m_1(A_i)m_2(B_j)$$

The sonar data fused by the D-S theory of evidence are collected and updated into a map using the same theory of evidence. In the approach, the probability assignment corresponding to a range readings r and θ is obtained directly using Eqs. (5)-(10). Finally, each cell in the map is updated using Dempster's rule of combination. This rule allows the independent evidence to be combined about a certain target model A , $m_1(A)$ and $m_2(A)$. In the paper, they will be the probability assignments for the old map belief $m_A^{t-1}(i, j)$ and the current sensor reading $S_A^t(i, j)$, and the current fusion map belief $m_A^t(i, j)$. For the target models E and O , the update rules are:

$$\begin{aligned} m_O^t(i, j) &= m_O^{t-1}(i, j) \oplus S_O^t(i, j) \\ &= \frac{m_O^{t-1}(i, j)S_O^t(i, j) + m_O^{t-1}(i, j)(1 - S_E^t(i, j) - S_O^t(i, j))}{1 - m_E^{t-1}(i, j)S_O^t(i, j) - m_O^{t-1}(i, j)S_E^t(i, j)} \\ &\quad + \frac{(1 - m_E^{t-1}(i, j) - m_O^{t-1}(i, j))S_O^t(i, j)}{1 - m_E^{t-1}(i, j)S_O^t(i, j) - m_O^{t-1}(i, j)S_E^t(i, j)} \end{aligned} \quad (14)$$

$$\begin{aligned}
m_E^t(i, j) &= m_E^{t-1}(i, j) \oplus S_E^t(i, j) \\
&= \frac{m_E^{t-1}(i, j) S_E^t(i, j) + m_E^{t-1}(i, j) (1 - S_E^t(i, j) - S_O^t(i, j))}{1 - m_E^{t-1}(i, j) S_O^t(i, j) - m_O^{t-1}(i, j) S_E^t(i, j)} \\
&\quad + \frac{(1 - m_E^{t-1}(i, j) - m_O^{t-1}(i, j)) S_E^t(i, j)}{1 - m_E^{t-1}(i, j) S_O^t(i, j) - m_O^{t-1}(i, j) S_E^t(i, j)}
\end{aligned} \tag{15}$$

Then, the corresponding grid obtains new belief probability, $m_O^t(i, j)$ and $m_E^t(i, j)$. With the AUV in the process of moving, continuous information is received and data conversion and fusion continues, thus updating the belief distribution of the overall grid map. Finally, based on pre-established identification rules for overall grids, dynamic maps are built until the AUV reaches the target point. Next, the state identification rules for every grid in the map are developed. The basic principles to decide the state model for each cell are described by:

- (1) The state model to be decided should have a maximum probability value larger than a certain threshold, 0.4 is set in this paper.
- (2) The difference of probability values between the decided state model and other models should be larger than a threshold of 0.15.
- (3) The uncertainty model's probability value must be less than a certain threshold, 0.2 is set in this paper.

Furthermore, based on the basic principles, the state pattern for any grid and building in the dynamic map can be decided. Of course, according to different situations, to be more realistic, these rules can be modified to improve the recognition accuracy.

2.5 Simulation Results of Map Building

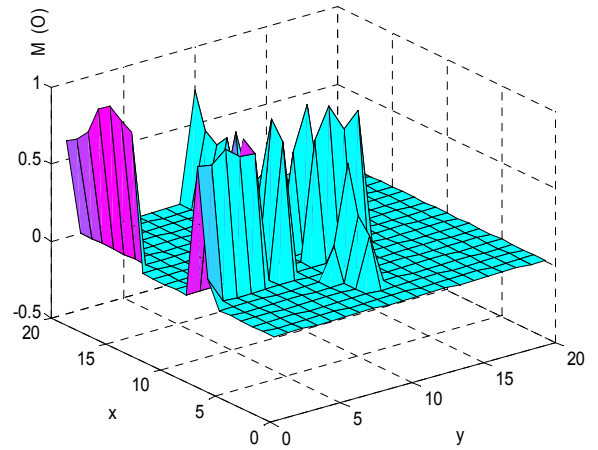
The proposed approach is applied to a unknown environment and the experimental simulation environment includes 20×20 grids representing the 2D workspace of the AUV. Initialization for every grid should meet Eq. (4). The AUV selects a travel path and uses ultrasonic sensor to collect external environment data. Combined with coordinate transformation and the ultrasonic sensor model, these data are converted into a probability assigned value. As the data from the external environment are continuous, the constructed map is constantly updated. In order to clearly show the effectiveness of the D-S evidence theory, in this paper proposed an approach to calculate the accuracy of the constructed map. Specifically, parameter η is the ratio of the total number $\sum A$ of obstacles in the constructed grid map and the total number $\sum B = 40$ (shown in Figure 8(b)) of obstacles in the original map,

and η is defined as the accuracy of map building, described by:

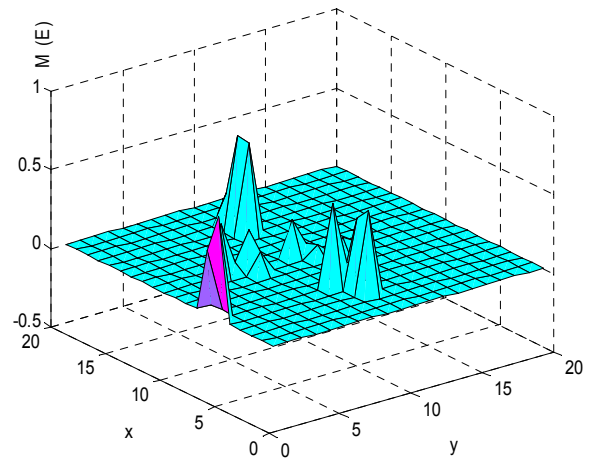
$$\eta = \frac{\sum A}{\sum B} \tag{16}$$

The next sector will give the constructed grid map at the moment of reaching the target point.

It is known that the probability values for every cell in the map are constantly updated. When the AUV reaches a target point (19, 3), the final belief distribution of the grid map is shown as in Figure 5.



(a) For occupied obstacle cells



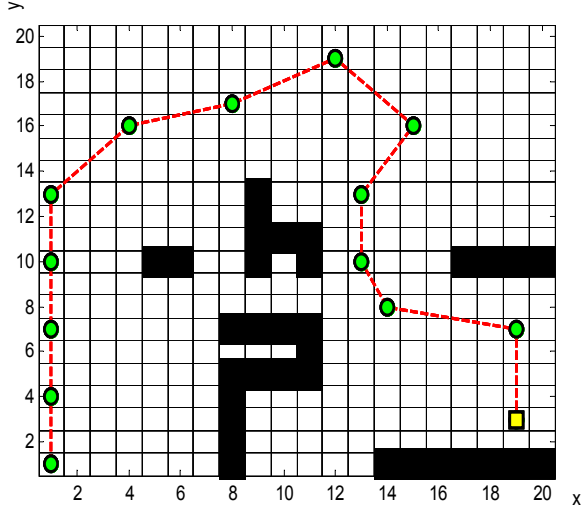
(b) For empty cells

Figure 5. The belief distribution of the map when AUV reaches a target

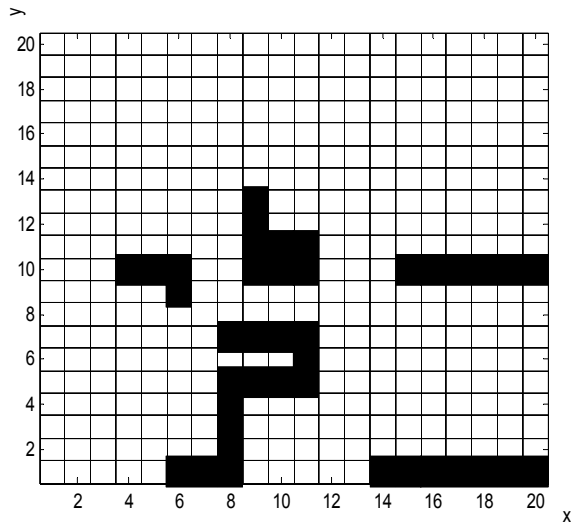
According to the identification rules, the final map can be built, as shown in Figure 6(a), while the original

experimental map of the environment is shown in Figure 6(b). By comparing the two constructed maps, the ultimate accuracy of the map building using the D-S information fusion algorithm can be calculated:

$$\eta_{end} = \frac{\sum A}{\sum B} = \frac{33}{40} = 82.5\%.$$



(a) The AUV reach the target point (19,3)



(b) The original map of the environment

Figure 6. The original map and the map building using D-S information fusion

It shows that the constructed map is closer to the original underwater environment by using an information fusion algorithm. It can be said that map building using the D-S information fusion algorithm in underwater dynamic environment is practical and effective. It is also conducive to path planning for an AUV.

3. Path Planning

In this paper, a biologically inspired neural network approach is proposed for path planning in an AUV with obstacle avoidance in an unknown environment. The experimental workspace is based on a constructed map. The constructed map can be seen as partially knowing environment. In this section, the originality of the proposed neural network approach is briefly introduced. Then, the model algorithm of the proposed approach is presented.

3.1 Originality of The Biologically Inspired Approach

A computation model for a uniform patch of membrane in a biological neural system using electrical circuit elements was first proposed by Hodgkin and Huxley [22]. In the model, the dynamics of the voltage across the membrane V_m is described using a state equation:

$$C_m \frac{dV_m}{dt} = -(V_r + V_m)g_r + (V_e - V_m)g_e - (V_s + V_m)g_s \quad (17)$$

where C_m is the membrane capacitance, V_s , V_e and V_r are the resting potentials (saturation potential) in the membrane and g_s , g_e and g_r represent the synaptic and resting conductance of potassium, sodium and passive channels, respectively. This model lays the foundation for the shunting model.

By setting $C_m = 1$ and substituting $x_i = V_r + V_m$, $A = g_r$, $B = V_e + V_r$, $D = V_s - V_r$, $S_i^e = g_e$ and $S_i^i = g_s$ in Eq. (17), a shunting equation is obtained as

$$\frac{dx_i}{dt} = -Ax_i + (B - x_i)S_i^e - (D + x_i)S_i^i \quad (18)$$

where x_i is the neural activity (membrane potential) of the i th neuron in the neural network, A, B, D are nonnegative constants describing the passive decay rate and the upper and lower bounds of the neural activity x_i , respectively and S_i^e and S_i^i are the excitatory and inhibitory inputs to the neuron, respectively. This shunting model was used to understand the real-time adaptive behaviour of individuals to complex and dynamic environmental contingencies and has many applications such as visual perception and sensory motor control, and many other areas [18-20].

The proposed topologically organized model is expressed in a 2D workspace of the AUV. The fundamental concept of the proposed model is to develop a neural network architecture, whose dynamic neural activity landscape represents the dynamically varying environment. The position of the i th neuron in the neural network, denoted by vector q_i , uniquely represents a position in the 2D workspace. In the proposed model [21-24], the excitatory input results from the target and the lateral neural connections, while the inhibitory input results from the obstacles only. Each neuron has local lateral connections to its neighbouring neurons that constitute a sub-area. The sub-area is called the receptive field of the i th neuron in neurophysiology. The neuron responds only to the stimulus within its receptive field. Thus, the dynamics of the i th neuron in the neural network is characterized by a shunting equation:

$$\frac{dx_i}{dt} = -Ax_i + (B - x_i)([I_i]^+ + \sum_{j=1}^k w_{ij}[x_j]^+) - (D + x_i)[I_i]^- \quad (19)$$

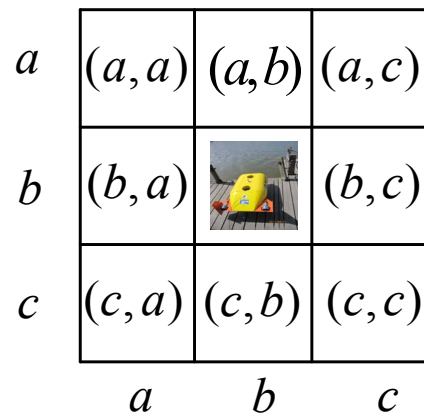
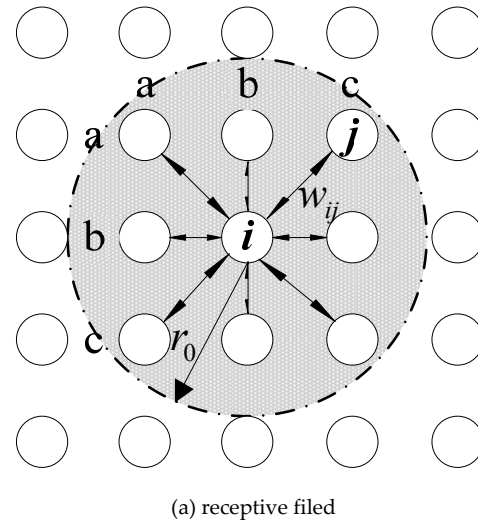
where k is the number of neural connections of the i th neuron to its neighbouring neurons within the receptive field. The external input I_i to the i th neuron is defined as:

$$I_i = \begin{cases} E, & \text{if it is target} \\ -E, & \text{if it is an obstacle} \\ 0, & \text{otherwise} \end{cases} \quad (20)$$

where $E \gg B$ is a very large position constant, which guarantees that the target can always be attained at the peak and the obstacles can always stay in the valley in the neural activity landscape of the neural network. The terms $[I_i]^+ + \sum_{j=1}^k w_{ij}[x_j]^+$ and $[I_i]^-$ are the excitatory and inhibitory inputs S_i^e and S_i^i in (18), respectively. Function $[a]^+$ is a linear-above-threshold function defined as $[a]^+ = \max\{a, 0\}$ and the nonlinear function $[a]^-$ is defined as $[a]^- = \max\{-a, 0\}$. The connection weight w_{ij} between the i th and j th neurons can be defined as $w_{ij} = f(|q_i - q_j|)$, where $|q_i - q_j|$ represents the Euclidean distance between vectors q_i and q_j in the neural network and $f(a)$ is a monotonically decreasing function, e.g., a function defined as:

$$f(a) = \begin{cases} \frac{\mu}{a}, & \text{if } 0 \leq a \leq r_0 \\ 0, & \text{if } a \geq r_0 \end{cases} \quad (21)$$

where μ and r_0 are position constants. Therefore, each neuron has only local lateral connections in a small region $[0, r_0]$. It is obvious that the weight w_{ij} is symmetric, $w_{ij} = w_{ji}$. Note that the neural connection weights that satisfy the fundamental concept of the proposed approach are predefined in (21) at the stage of the neural network design. Thus, they are needed to obtain a proper connection weights among neurons. A schematic diagram of the neural network is shown in Figure 7, where r_0 is chosen as $r_0 = 2$. The receptive field of the i th neuron is represented by a circle with a radius of r_0 . Thus, it has lateral connections to only its eight neighbouring neurons within its receptive field.



(b) 8 neighbouring neurons

Figure 7. Schematic diagram of the neural network for path planning

The proposed neural network is a stable system. The neural network activity x_i is bounded in the finite interval $[-D, B]$. In addition, the stability and

convergence of the proposed shunting neural network model can also be rigorously proved using a Lyapunov stability theory [22].

Because there are excitatory neural connections in (19), the proposed neural network characterized by (19) guarantees that the position neural activity can propagate to the entire neural network, but the negative activity stays locally only. Therefore, the target globally attracts the AUV, whereas the obstacle areas just locally push the AUV away to avoid collisions. The locations of targets and obstacles may vary with time, for example if there are moving obstacles or sudden obstacles in the front of the AUV. The activity landscape of the neural network dynamically changes due to the varying external inputs from the changing environment and the internal activity propagation among neurons. For a given current AUV location in a neural network, denoted by p_c , the next AUV location p_n is obtained by:

$$p_n \Leftarrow x_{p_n} = \max \{x_j, j = 1, 2, \dots, k\} \quad (22)$$

where k is the number of neighbouring neurons of the p_c th neuron, which also is all the possible next locations of the current location p_c . After the current location reaches its next location, the next location becomes a new current location (if the next location found is the same as the current location, the AUV stays there without any movement). The current AUV location adaptively changes according to the varying environment.

The dynamic activity landscape of the topologically organized neural network is used to determine the next AUV location. However, when the next location is not immediately available, for example, in a deadlock situation, the AUV has to wait until the next location toward the target is available from the neural activity landscape. Whenever the neural activity at the current AUV location is smaller than the largest neural activity of its neighbouring locations, the AUV starts to move to its next location. Thus, the AUV movement is determined by both the neural activity landscape and the previous location. The neural activity landscape will never reach a steady state as in a static environment or dynamic environment. In a fast changing environment, for example, where obstacles suddenly appear in front of the AUV, the neural activities at those locations will immediately reduce to a very large negative value due to their very large inhibitory input. Thus, the AUV should be able to avoid those suddenly appearing obstacles. In the proposed model, due to the very large external input constant E , the target and the obstacles stay at the peak and the valley of the activity landscape of the neural network. The AUV keeps moving toward the target with obstacle avoidance until the designated objective is reached.

Therefore, the biologically inspired approach is suitable for static environments and fast changing environments. Any change in the environment directly results in changes in the external inputs at those locations. The activity landscape of the neural network is automatically changing due to neural activity propagation. It can therefore deal with arbitrarily changing environments.

3.2 Simulation Results

In the simulation, the neural network has 20×20 topologically organized neurons, where all the neural activity is initialized to zero. The model parameters are set as $A = 2$, $B = 1$ and $D = 1$ for the shunting equation, $\mu = 0.7$ and $r_0 = 2$ for the lateral connections and $E = 100$ for the external inputs.

(1) Path planning in a static environment

In the proposed model, because of the neural activity propagation among neurons, the target is able to attract the AUV in the complete search process. The AUV starts to search from the left side in Figure 8(a).

It shows that the target point (19, 3) has the largest neural activity due to the very large external excitatory input; the obstacles areas have the smallest neural activity due to their very large inhibitory inputs. Meanwhile, due to the lateral excitatory connections among neurons, the positive neural activity from the target in the neural network will propagate toward the current AUV location through neural activity propagation and the neural activity is constantly changed.

From Figure 8 we can easily see the process of the search by the AUV and the neural activity of neighbouring neurons at some moments are shown in Table 1. In Table 1 the first column represents current locations, the last column represents next locations and the other columns represent the neural activity of neighbouring neurons at current locations for Figure 7(b). For example, for current location (2, 2), it can be found that the neural activity of neighbouring neuron (3, 3) is the largest among eight neighbouring neurons, so the next location of the AUV is (a, c).

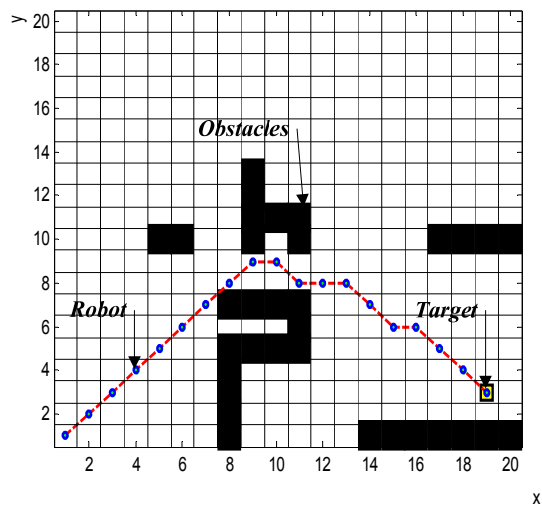
The activity landscape for when the AUV arrives at point (9, 9) is shown in Figure 8(b). At this time, the activities of all neighbouring neurons around the current point are compared with the activity of the current AUV location, searching for the largest neural activity and recording the location of the neuron with the largest neural activity. According to the algorithm of the proposed model, the recorded location with the largest neural activity is regarded as the next location of the AUV. From the result of Figure 8(a) and (b), the next location is point (10, 9). The target point (19, 3) has a very large external input and keeps the largest neural activity. Therefore, its neural activity keeps propagating toward the all over neural network. When the

AUV arrives at point (15, 6), the activity landscape is shown in Figure 8(c). The next location of the AUV is point (16, 6) (see Figure 8(c) and Table 1). The final neural activity landscape for when the AUV arrives at target (19, 3) is

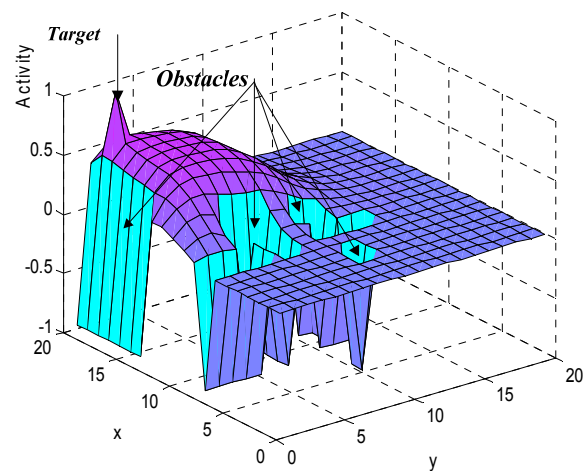
shown in Figure 8(d). The AUV path is shown in Figure 8(a), it shows that the AUV is able to move without any collisions, pass through the workspace and reach the target from start point (1, 1) in the shortest distance possible.

Current location	(a a)	(a b)	(a c)	(b a)	(b c)	(c a)	(c b)	(c c)	Next location
(2, 2)	0.0000	0.0001	0.0003	0.0000	0.0002	0.0000	0.0000	0.0001	(3, 3)
(4, 4)	0.0004	0.0005	0.0008	0.0003	0.0004	0.0002	0.0001	0.0001	(5, 5)
(6, 6)	0.0013	0.0017	0.0023	0.0016	0.0014	0.0011	0.0009	0.0008	(7, 7)
(8, 8)	0.0034	0.0053	0.0065	0.0035	0.0060	0.0030	-0.9803	-0.9801	(9, 9)
(10, 9)	-0.9772	0.0619	-0.9657	0.0587	0.2416	0.0511	0.1169	0.2523	(11, 8)
(12, 8)	0.3851	0.4844	0.5452	0.3789	0.5522	-0.9580	0.4585	0.5521	(13, 8)
(14, 7)	0.5652	0.5767	0.5770	0.5615	0.5797	0.5596	0.5774	0.5804	(15, 6)
(16, 6)	0.5802	0.5796	0.5777	0.5807	0.5804	0.5804	0.5809	0.5815	(17, 5)
(18, 4)	0.5815	0.5799	0.5604	0.5801	0.5887	0.5607	0.5888	0.9812	(19, 3)

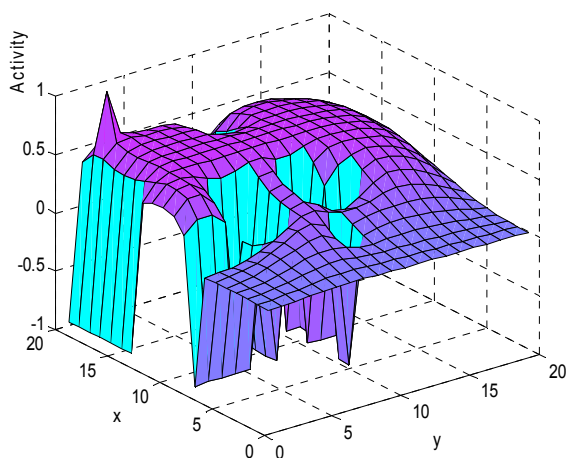
Table 1. The neural activity of neighbouring neurons at some moments in a static environment



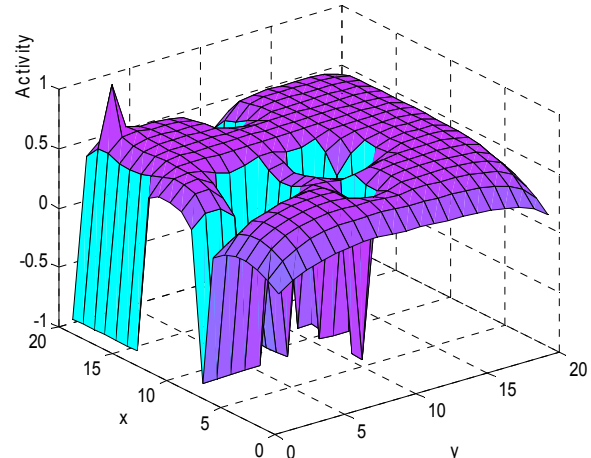
(a) AUV path



(b) Activity landscape when the AUV at location (9, 9)



(c) Activity landscape when the AUV at location (15, 6)



(d) Activity landscape when the AUV target

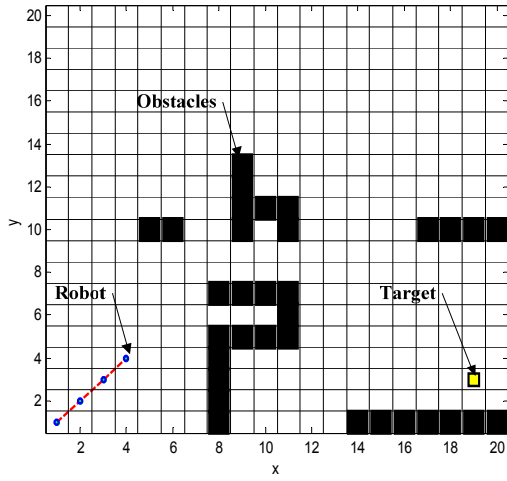
Figure 8. Path planning in the constructed map environment

(2) Path planning in dynamic environment with sudden changes

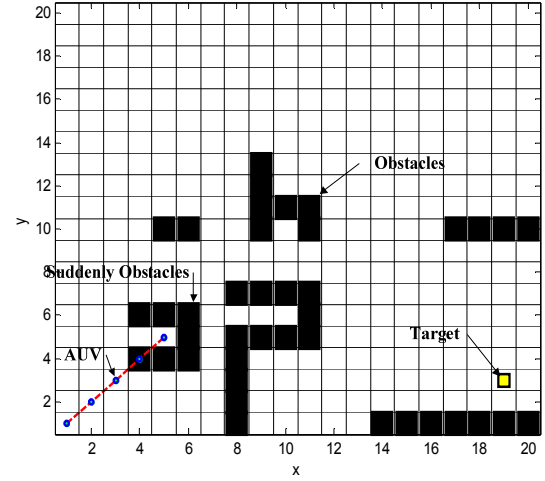
The proposed neural network approach is capable of generating a point to point path for an AUV in a dynamic environment, even with obstacles suddenly placed in front of the AUV. The network has 20×20 neurons, with initial neural activities of zero. The model parameters are chosen as the same as in the previous case. In the same environment, the AUV starts from point (1, 1) and when it arrives the point (4, 4), the front of AUV has not hit any obstacles (see Figure 9(a)), and continues to move forward. The activity landscape of the neural network is shown in Figure 9(c). When the AUV arrives the point (5, 5), a set of U-shaped obstacles suddenly appears in front of the AUV (see Figure 9(b)). The activity landscape

of the neural network right after the obstacles are placed is shown in Figure 9(d).

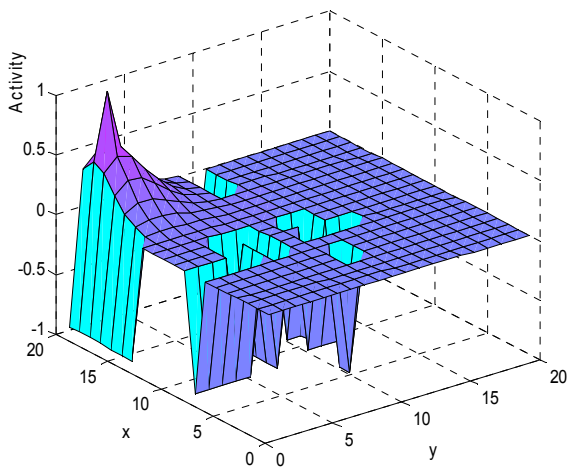
From Figure 9(d), it can be seen that the neural activities in the areas with the suddenly placed obstacles immediately become very large negative values. The AUV cannot move forward due to the suddenly added obstacles. The AUV has to move through several areas without obstacles to point (4, 5), as shown in Figure 9(d), then pass around the obstacles, to reach the target with obstacle avoidance. Thus, the proposed model is a suitable applied plan path for the AUV, where there are unstructured obstacles with arbitrary shapes in the workspace, as shown in Figure 10(a).



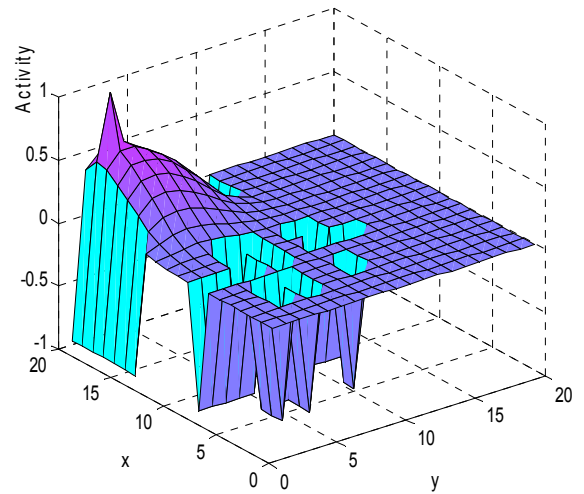
(a) AUV arrives the location (4, 4) without obstacles



(b) AUV arrives the location (5, 5) with U-shaped obstacles

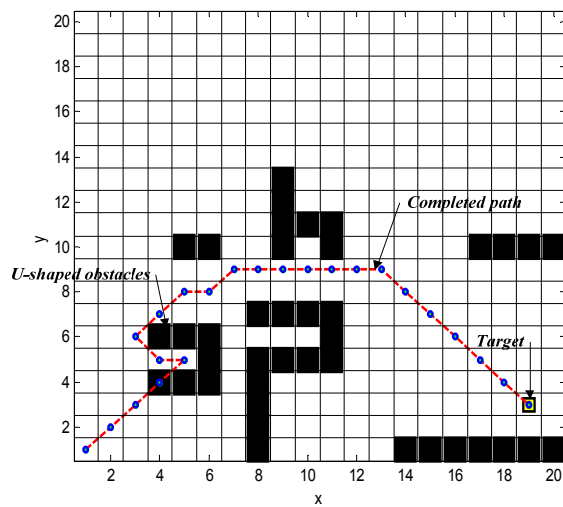


(c) Activity landscape AUV arrives at (4, 4)

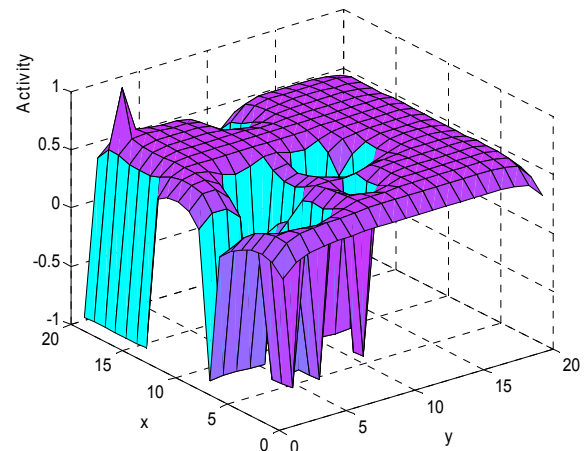


(d) Activity landscape when AUV arrives at (5, 5) with obstacles

Figure 9. Path planning in a dynamic environment with sudden obstacles in front of the AUV



(a) Completed path of the AUV.



(b) The activity landscape when AUV arrives at the target

Figure 10. Completed path planning in a dynamic environment with suddenly obstacles

Current location	(a a)	(a b)	(a c)	(b a)	(b c)	(c a)	(c b)	(c c)	Next location
(2, 2)	0.0000	0.0001	0.0003	0.0000	0.0002	0.0000	0.0000	0.0001	(3, 3)
(4, 4)	0.0004	0.0005	0.0008	0.0003	0.0004	0.0002	0.0001	0.0001	(5, 5)
(4, 5)	0.0012	-0.9791	-0.9791	0.0010	0.0009	0.0008	-0.9791	-0.9791	(3, 6)
(4, 7)	0.0020	0.0022	0.0025	0.0018	0.0023	0.0016	-0.9797	-0.9797	(5, 8)
(6, 8)	0.0035	0.0108	0.0268	0.0045	0.0232	0.0029	0.0067	0.0117	(7, 9)
(8, 9)	0.0943	0.1174	-0.9678	0.1220	0.2458	0.1088	0.1542	0.2150	(9, 9)
(10, 9)	-0.9605	0.2353	-0.9515	0.3581	0.4577	0.3143	0.3589	0.4418	(11, 9)
(12, 9)	-0.9505	0.4863	0.5660	0.4712	0.5687	0.4535	0.5248	0.5684	(13, 9)
(14, 8)	0.5691	0.5782	0.5749	0.5688	0.5782	0.5641	0.5784	0.5803	(15, 9)
(16, 6)	0.5803	0.5797	0.5778	0.5808	0.5804	0.5805	0.5809	0.5815	(17, 5)
(18, 4)	0.5815	0.5799	0.5604	0.5801	0.5887	0.5607	0.5888	0.9805	(19, 3)

Table 2. The neural activity of neighbouring neurons at some moments in a dynamic environment

From Figure 10, we can easily see the process of the search for the AUV and the neural activity of neighbouring neurons at some moments as shown in Table 2. In Table 2, the first column represents current locations, the last column represents the next locations and the other columns represent the neural activity of neighbouring neurons at current locations. For example, for current location (4, 5), it can be found that the neural activity of neighbouring neuron (3, 6) is the largest among eight neighbouring neurons from Table 1, so the next location of the AUV is (a, a).

This model will not be trapped in deadlock situations, since the rest of the target points can globally attract the AUV in the whole workspace through neural activity propagating. In Figure 10(a) the AUV can deal with the situation of changes in the environment with suddenly

appearing obstacles and avoid these sudden obstacles in front of the AUV. Meanwhile, the neural activity in these locations is changed. Thus, the AUV is able to escape from the complicated environment.

4. Conclusion

A biologically inspired neural dynamics and map planning based approach are proposed for obstacle avoidance of an AUV (Autonomous Underwater Vehicle) in a non-stationary environment. A novel application of the theory of evidence is presented for the map building of the AUV. The work considers the uncertainties of the ultrasonic sensor measurements and makes use of the D-S inference rule to fuse sensor information and build the map. The constructed map is compared with the original

map, the map-building accuracy is calculated, and the fusion algorithm is proved to be effective and feasible in map building for an AUV.

In this paper, a biologically inspired neural network approach to point-to-point path planning in an AUV is proposed. The developed approach is capable of autonomously planning a collision-free path for an AUV in a static and non-stationary environment. The model algorithm is computationally simple. The AUV path is generated through a dynamic neural activity landscape and the previous AUV location without any prior knowledge of the dynamic environment. This model can deal with changing environments and even with sudden environmental changes.

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