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ARTIFICIAL IMMUNE INTELLIGENT MODELING FOR UUV UNDERWATER NAVIGATION SYSTEM BASED ON IMMUNE MULTI-AGENTS NETWORK

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Abstract. *In order to improve the intelligence and autonomy capability for unmanned underwater vehicle (UUV) underwater navigation system under underwater environment, drawing inspiration from the artificial immune system (AIS), and combining multi-agent system (MAS), a novel immune multi-agents network (IMASN) modeling and learning approach is creatively proposed, which mainly merges the modeling advantages of two different methodologies. In this paper, by investigating fundamentals of biological immune system (BIS) and immune principles, IMASN is designed from comparability of structure and function between BIS and MAS. Then, Immune-UUV is exploited based on IMASN by information procession and control, and corresponding learning algorithm is put forward and embedded in IMASN to achieve successful artificial intelligent modeling. Finally, typical experiments are designed to verify the proposed model and algorithm. Simulation results show the proposed model and algorithm have good performance, which has important theoretical innovation and application prospects.*
Keywords: Immune multi-agents network, Artificial immune system, Multi-agent system, UUV underwater navigation system

1. **Introduction.** With the rapid development of marine resource exploitation, unmanned underwater vehicle (UUV) as an underwater vehicle robot has been widely applied in many marine fields [1-3]. However, UUV underwater navigation system (UUNS) contains many complex subsystems and each subsystem is consisted of several modules that have complex internal and logic structure, which have a mutual dependency and coordination relationship between each others. Meanwhile, autonomous planning and control ability of UUNS are more complex compared with the ground and space vehicle robot in unknown and complex underwater environment, especially meeting the requirements for higher intelligent capability in UUV formation system in recent years [2,4].

Multi-agent system (MAS) as a new modeling tool can unify microscopic behavior and macroscopic emerged phenomenon organically, through the interaction of independent agents to implement communication, which has been widely applied in many fields. Many researchers have introduced MAS into vehicle robot modeling field in recent years [5-8]. For example, the vehicle robot was abstracted as Agent, and then constructing individual robot by MAS [5,6], the MAS-based robot was just a static formal model, which had no reasoning and learning ability. Mental mode was presented to describe mental state and process mental action for underwater vehicle, and defining mental mode language to express mixed logic system, the proposed mental mode can only enhance the formal reasoning [7,8]. Most early research focused on structure abstraction and semantic expression, which were all in a pure theoretical stage.

Biological immune system (BIS) as a highly intelligent coordinated adaptive system, by specific immune characteristics, eliminates foreign antigens invasion and maintains system stable [9]. Artificial immune system (AIS) as a novel approach extracts immune principles and mechanisms from BIS, and appropriate models and algorithms have developed for information processing in robot fields [10-15], which has drawn attention of many researchers. The concept of immune-robot was proposed on the international conference [10,11]. The essence of mobile immune robot was evolution robot based on AIS [12], which imitated biological immune system by establishing the immune computing algorithm and control structure [13]. However, immune computing algorithm and immune control structure have not got better research, which is a new research area [13-15].

In light of these problems, the novel immune multi-agents network (IMASN) modeling and learning approach is proposed and inspired by AIS and MAS methodology that integrate the advantages in [5,8,9,13,16], to design intelligence modeling for UUNS in this paper. The rest of this paper is organized as follows. Section 2 presents some preliminary knowledge. In Section 3, IMASN is established and logical structure is analyzed. In Section 4, the detailed mapping from BIS to UUNS is summarized, Immune-UUV is exploited by IMASN, and formal description is expressed. In Section 5, learning algorithm for Immune-UUV is designed. In Section 6, experimental results are demonstrated. Finally, Section 7 discusses the conclusion and future work.

2. Preliminaries Knowledge.

In order to better understand the IMASN modeling and learning approach, some preliminaries knowledge is introduced as follows in this section.

2.1. Biological immune system.

BIS is a highly intelligent coordinated system, which can adopt a proper response to invade antigen. Basic components of BIS are phagocytes and lymphocytes. These are two major types of B-Cell (B lymphocyte) and T-Cell (T lymphocyte). B-Cell takes part in immunity that secretes antibody, and T-Cell takes part in cell mediated immunity. Each B-Cell has distinct molecular structure and produces "Y" shaped antibodies from its surfaces. The antibody recognizes specific antigen. This antigen-antibody relation is often likened to a key and keyhole relationship, which is shown as Figure 1.

The key portion on the antigen recognized by the antibody is called an epitope (antigen determinant), and the keyhole portion on the corresponding antibody that recognizes the antigen determinant (idiotope) is called a paratope. The affinity between antibody and antigen is decided by the relationship between paratope and epitope, and the affinity between antibody is decided by idiotope and paratope.

Because of the better information processing mechanisms and properties, especially immune recognition memory and learning is drawn inspiration from the BIS, which has been applied in many fields [17-19].

2.2. Immune recognition.

Immune recognition is the main function of BIS, whose essence function is to distinguish between self and non-self, and to eliminate foreign pathogen through immune function execution units. On the surface of each lymphocyte cell are receptors that enable them to recognize only specific foreign antigens, and the binding between antigen and antibody can trigger by specific receptor. Immune recognition realizes the combination of antigen and antibody through the feature matching.

2.3. Immune memory.

When immune system encounters an antigen first time, lymphocytes require more time to better recognize antigen, and keep memory for antigen information. And when the immune system once faces with the same or similar existing antigen, the response speed is greatly improved under associative memory. Immune

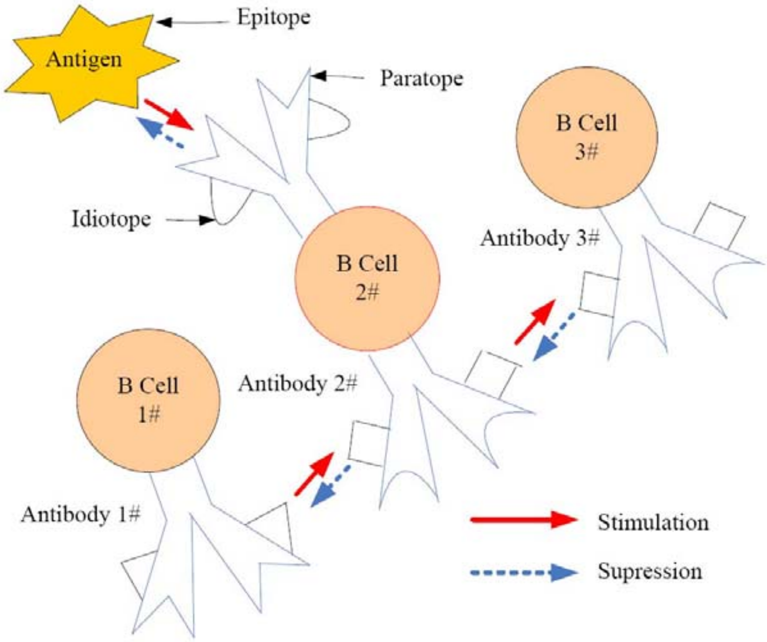

FIGURE 1. Relationship of the antigen and antibody

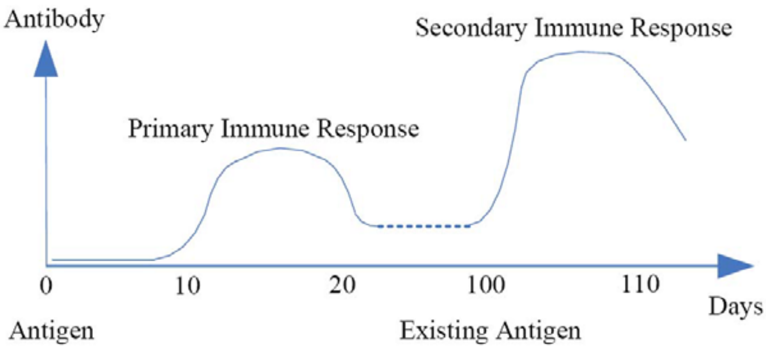

FIGURE 2. Immune memory

memory mainly corresponds secondary immune response, and this process is depicted as Figure 2.

2.4. **Immune learning.** Immune learning can improve the affinity degree of immune cell, which can be divided into two categories. Primary immune response responds when lymphocyte encounters an antigen first time, and there needs more time to learn the structure of antigen. And secondary immune response responds with a high speed when lymphocyte encounters an existing antigen, which is a reinforcement learning process.

So far, we have reviewed the fundamentals method of BIS and AIS, which will help us to establish and design the IMASN model and learning algorithm.

3. **Immune Multi-Agent System Network Model (IMASN).** AIS and MAS from the viewpoint of structure present a high degree of similarity, which are composed of many agent units to keep the system stability, where many properties have been summarized in experimentally or theoretically [2,5,8,9,13,16,20], which is shown as Table 1.

Table 1 shows some comparisons between AIS and MAS. The AIS is also inherited properties from BIS, such as recognition, learning, memory, self-tolerance, self-organizing,

TABLE 1. Comparison between MAS and AIS

Property	AIS	MAS
Recognition	YES (experimentally)	NO
Learning	YES (experimentally)	NO
Memory	YES (experimentally)	NO
Self-Tolerance	YES (theoretically)	NO
Self-Organizing	YES (theoretically)	NO
Coordination	YES (theoretically)	YES (experimentally)
Communication	YES (theoretically)	YES (experimentally)
Robust	YES (theoretically)	YES (theoretically)

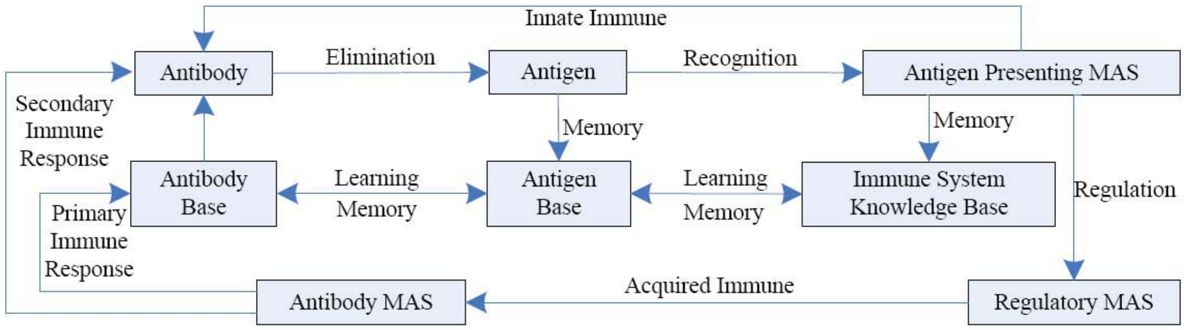

FIGURE 3. Immune multi-agents network model

coordination, communication and robust. Meanwhile, there are several properties that MAS might realize in experimentally. Accordingly, the goal of the IMASN is to combine advantages from AIS and MAS. For those properties marked "YES" to both MAS and AIS such as coordination and communication, agent mechanism can be applied to AIS. On the other hand, for those properties marked "NO" to MAS but "YES" to AIS, related theory of the latter can be contributed to MAS. Therefore, IMASN is proposed and shown in Figure 3, and multiple Agents (B-Cell, T-Cell and Antigen Presenting Cell) with immune function constitute interaction immune network.

In Figure 3, Antigen Presenting MAS (APMAS) composed by multiple Antigen Presenting Agent (APCA), can achieve antigen recognition and feature extraction through interaction with antigen, which is corresponding antigen presenting cell in BIS. The Regulatory MAS (RMAS) composed by multiple Regulate Agents (TA) is to adjust activation and inhibition level of the Antibody MAS (ABMAS), and implement status monitoring and information collecting according to antigen presenting information, which is corresponding regulatory T-Cell in BIS; Antibody MAS (ABMAS) composed by multiple Antibody Agents (ABA), can eliminate foreign antigen invasion, which is corresponding B-Cell in BIS. The IMASN model realizes the control and coordination between APMAS, RMAS and ABMAS based on Knowledge-Base, Antigen-Base and Antibody-Base, which can imitate the immune response by immune characteristics, especially immune recognition, learning and memory.

4. **Designing of Immune-UUNS.** In this section, intelligent modeling for Immune-UUNS is developed by IMASN. To make it clear, we introduce UUV system structure, establish mapping relationship, and design immune logic and Antibody/Antigen-Base, as follows.

4.1. **UUV system structure.** UUV as an underwater vehicle robot can carry different sensors to complete underwater mission through high precision and high efficiency motion control under unknown and complex underwater environment. UUV structure is briefly illustrated in Figure 4, which includes five subsystems: sensor system, communication system, control decision-making system, actuator system and knowledge system [20].

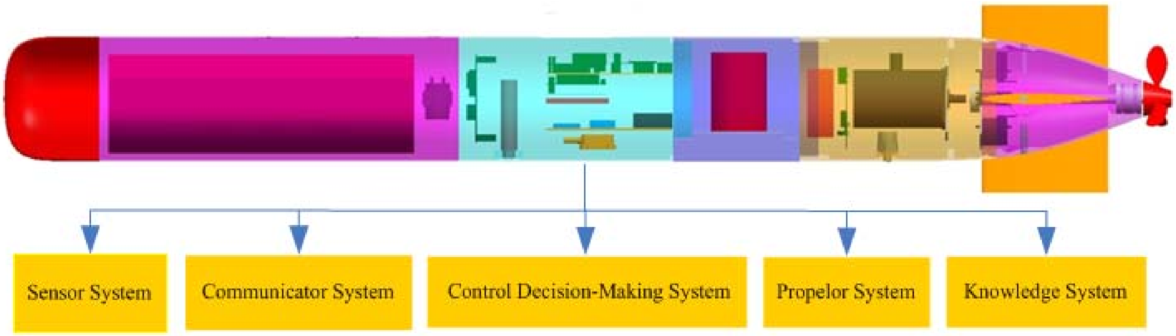

FIGURE 4. UUV system structure

(1) Sensor system mainly contains two categories: detecting underwater environment and perception of UUV own state.

(2) Communication system is mainly responsible for information communicating.

(3) Control decision-making system is the core of UUV, including decision control calculation module and motion control calculation module subsystems. Decision control calculation module is responsible for the upper planning, including path planning and mission assignment. Motion control calculation module is responsible for the real-time controlling plan of speed, depth, height and heading.

(4) Propulsion system is to achieve movement for UUV in underwater environment.

(5) Knowledge system mainly packages expert prior knowledge and a variety of target detection, recognition, tracking and threat assessment algorithms.

4.2. **Mapping relationship between BIS and UUNS.** From the analysis of structure and function, we draw the concept and mechanisms from BIS, to establish mapping relationship between BIS and UUNS, which is shown in Table 2.

Antigen induces the immune system to produce the immune response, which can be expressed as Underwater Environment and Task.

Self is the biological cells in body or harmless cells in vitro, which can be expressed as Normal-UUV or Safe Environment Element.

TABLE 2. Mapping relationship between BIS and UUNS

BIS	UUNS
Antigen	Underwater Environment/Task
Self	Normal-UUV/Safe Environment Element
Non-Self	Failure-UUV/Dangerous Environment Element
Antigen Presenting Cell	Sensor System
Regulatory T-Cell	Decision Control Calculation
B-Cell	Motion Control Calculation
Cytokine Network	Communication System
Memory Cell	Knowledge System
Antibody	Propulsion System Behavior Strategy

Non-Self is a harmful pathogen cell outside living body, which can be expressed as Failure-UUV or Dangerous Environment Elements.

Antigen Presenting Cell is a kind of phagocyte cell that presents Antigen for B-Cell and Regulatory T-Cell, which can be expressed as Sensor System.

Regulatory T-Cell produced in the thymus is mainly to regulate the activity of the B-Cell, which can be expressed as Decision Control Calculation to realize the upper planning.

B-Cell is mainly to secrete Antibody, which can be expressed as Motion Control Calculation.

Cytokine Network is an information transmission channel of immune system, which can be expressed as Communication System to realize interconnection.

Memory Cell can retain a certain number of pathogen information by B-Cell in the first encounter pathogen, and rapidly responses once confronted with the same pathogen again. It can be expressed as Knowledge System that can preserve successful solution (Antibody) in order to become the candidate solution at the last time.

Antibody is secreted by B-Cell which can realize specific binding with Antigen, which can be expressed as Propulsion System Behavior Strategy.

4.3. **Logic analysis.** According to mapping relationship, Immune-UUNS based on IMASN is designed, which mainly contains three patterns: perception recognition, decision-making controlling and response execution, whose logic structure is shown in Figure 5.

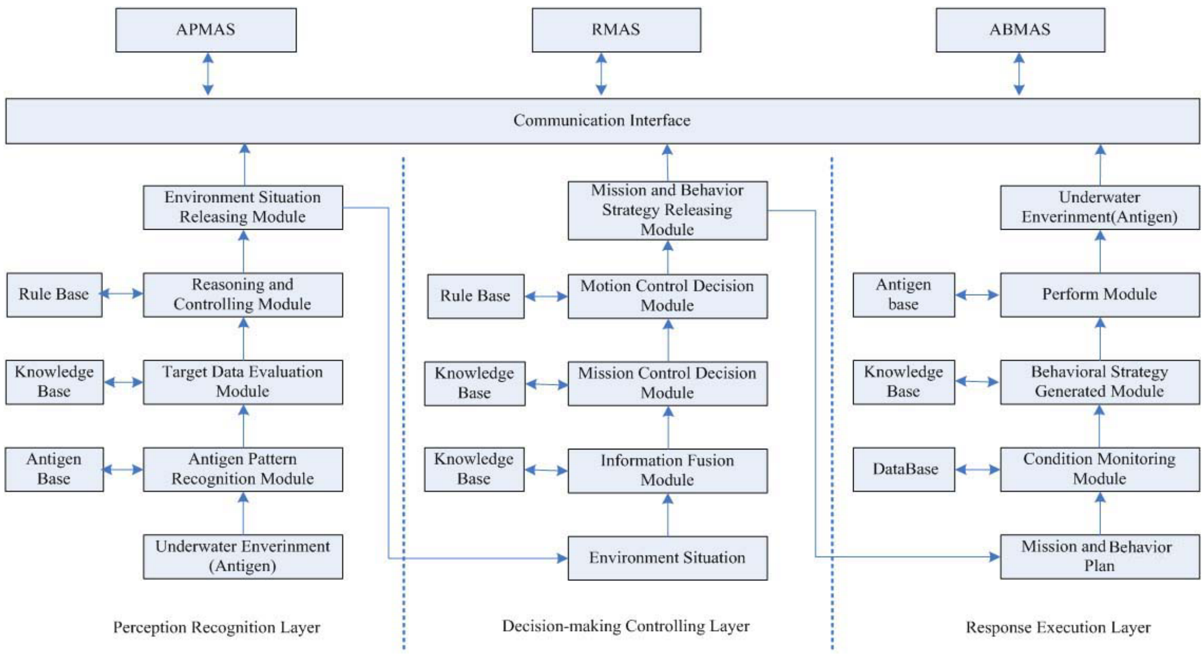

FIGURE 5. Logic structure of Immune-UUNS

Perception Recognition Layer: APMAS is corresponding sensor system, whose task is mainly to perceive and process underwater environment information. Antigen Pattern Recognition Module is to detect and judge motion parameters of target, and match with existing Antibody-Base; Target Data Evaluation Module is to identify environment type and determine the threaten-degree according to the feedback information from Antigen-Base and query the knowledge-base; Reasoning and Controlling Module that is the core of the APMAS, is mainly to process information fusion from local and global perception; Environment Situation Releasing Module is mainly to publish and update environment data.

Decision-making Controlling Layer: RMAS is corresponding control decision-making system, being the centre of the Immune-UUNS, which is mainly to achieve mission control in upper plan and conduct detailed behavior strategy. Information Fusion Module coordinates conflict between APMAS, RMAS and ABMAS, and fuses information from underwater environment and UUV status attribute; Mission Control Decision Module generates the top mission planning, and monitors task executing; Motion Control Decision Module forms behavior strategy plan; Mission and Behavior Strategy Releasing Module is mainly to publish and update decision-making data.

Response Execution Layer: ABMAS is the corresponding propulsion system behavior strategy, which is mainly to implement specific behavior strategy. Condition Monitoring Module is mainly to provide physical properties and complete the UUV itself and target condition monitoring; Behavioral Strategy Generated Module processes calculating and reasoning according to status information monitored, expert knowledge provided and existing plan; Perform Module completes real-time control of position, attitude and velocity for UUV.

Communication interface realizes mutual collaboration APMAS, RMAS and ABMAS based on Antibody-Base, Antigen-Base, Knowledge-Base and Data-Base.

4.4. **Formal description.** In order to more clearly express the components and parameters, formal description of Immune-UUNS is described as follows [20].

Definition 4.1. *Immune-UUNS* ::=< *Environment, Mission, Target-State, UUV-State, Agent, Base* >.

In it, *Environment* denotes underwater environment information, *Mission* denotes task set of UUV; *Target-State* denotes state information of Target; *Agent* denotes covering all the Agents in the IMASN; *UUV-State* denotes UUV own state information; *Base* as the auxiliary repositories is used to recognize, learn and memory.

Definition 4.2. *Mission* ::=< *Search Forward, Avoid Obstacle, Attack Target* >.

Definition 4.3. *Target-State* ::=< *Quantity, Location-Information, Attitude-Information, Velocity-Information, Threaten-Degree* >.

In it, *Quantity* denotes the number of static or dynamic Target; *Location-Information*, *Attitude-Information* and *Velocity-Information* denote target's movement information; *Threaten-Degree* denotes underwater survival threaten for UUV.

Definition 4.4. *UUV-State* ::=< *Location-Information, Attitude-Information, Velocity-Information, Life, Capacity-Constraint* >.

In it, *Location-Information*, *Attitude-Information* and *Velocity-Information* denote own movement information; *Life* denotes UUV physical life state; *Capacity-Constraint* denotes energy constraint information of UUV.

Definition 4.5. *Agent* ::=< *APCMAS, TMMAS, ABMAS* >.

In it, $APCMAS = \{APCA_1, APCA_2, \ldots, APCA_n\}$ is composed of $APCA$; $TMMAS = \{TMA_1, TMA_2, \ldots, TMA_n\}$ is composed of TMA; $ABMAS = \{ABA_1, ABA_2, \ldots, ABA_n\}$ is composed of ABA.

Definition 4.6. *Life* ::=< *Well, Mechanical Failure, Electronical Failure, Destroyed* >.

In it, *Well*, *Mechanical Failure*, *Electronical Failure* and *Destroyed* respectively denote life state: normal, failure and destroyed, which can be changed state by Markov chain [21].

Definition 4.7. *Base* ::=< *Antibody-Base, Antigen-Base, Data-Base, Knowledge-Base* >.

4.5. **Antigen-Base and Antibody-Base.** We consider the environment, mission and target information that come from APCA$_i$ as the antigen. So according to antigen structure in Figure 1, Antigen-Base is designed as Table 3.

TABLE 3. Antigen-Base

<table>
<tr><td>AG</td><td colspan="4">Epitope</td></tr>
<tr><td>No.</td><td colspan="2">Environment</td><td>Mission</td><td>Target-State</td></tr>
<tr><td>1</td><td rowspan="3">Surface Environment</td><td rowspan="3">Sea Breeze
Sea Waves</td><td rowspan="6">Avoid Obstacle,
Search Forward,
...</td><td rowspan="6">Quantity,
Location-Information,
Threaten-Degree</td></tr>
<tr><td>2</td></tr>
<tr><td rowspan="3">...</td></tr>
<tr><td>Underwater Space</td><td>Light Field
Acoustic Field
Sea “Cliff”</td></tr>
<tr><td rowspan="2">Submarine Topography</td><td rowspan="2">Sea Trench
Sea Canyon
...</td></tr>
<tr><td>N</td></tr>
</table>

According to description of Antibody in Figure 1, there are two parts: paratope and idiotope. Since UUV behavior has highly complex and uncertain characteristics, production rule type namely *if-then* form [22], is proposed and used to construct the Antibody-Base that is designed as shown in Table 4.

TABLE 4. Antibody-Base

<table>
<tr><td rowspan="2">AB</td><td colspan="6">Paratope</td></tr>
<tr><td colspan="5">if</td><td>then</td></tr>
<tr><td>No.</td><td colspan="2">Environment</td><td>Mission</td><td>Target</td><td>UUV</td><td>Action</td></tr>
<tr><td>1</td><td rowspan="3">Surface Environment</td><td rowspan="3">Sea Breeze,
Sea Wave</td><td rowspan="6">Search Forward,
Avoid Obstacle,
Salvage Rescue</td><td rowspan="6">Quantity,
Location-Information,
Attitude-Information,
Threaten-Degree</td><td rowspan="6">Location-Information,
Attitude-Information,
Velocity-Information,
Life,
Capacity-Constraint</td><td>$f_1(x, y, v_x, v_y)$</td></tr>
<tr><td>2</td><td>$f_2(x, y, v_x, v_y)$</td></tr>
<tr><td rowspan="3">i</td><td rowspan="3">$f_i(x, y, v_x, v_y)$</td></tr>
<tr><td>Underwater Space</td><td>Light Field,
Acoustic Field,
Sea “Cliff”</td></tr>
<tr><td rowspan="2">Submarine Topography</td><td rowspan="2">Sea Trench,
Sea Canyon</td></tr>
<tr><td>N</td><td>$f_N(x, y, v_x, v_y)$</td></tr>
<tr><td>...</td><td>...</td><td>...</td><td>...</td><td>...</td><td>...</td><td>...</td></tr>
</table>

In Table 4, the *if* portion can express task, environment, target and UUV information in Paratope, and *then* portion can express action strategy in Paratope. And the $f_i(x, y, v_x, v_y)$ denotes the i-th action strategy, which includes the position and velocity information.

5. Learning Algorithm.

Corresponding learning algorithm is put forward and embedded in IMASN in order to achieve bionic immune modeling for Immune-UUNS, which makes full use of immune recognization, memory and learning characteristics. The mechanism is proposed and shown as follows.

Step 1. Antigen-Base initialization: Loading the environment information as Antigen with random initialization, the Antigen-Base is established and defined as:

$$\text{Antigen-Base} = \{g_1, g_2, \cdots, g_i, \cdots, g_M\} \tag{1}$$

where, g_i denotes the i-th Antigen, and M is the number of Antigen in Antigen-Base.

Step 2. Antibody-Base initialization: According to the expert knowledge and previous case, the open Antibody-Base is established and defined as:

$$\text{Antibody-Base} = \{R_1, R_2, \cdots, R_i, \cdots, R_N\} \tag{2}$$

$$A_i(0) = a_i(0) = 0, \quad t = 0 \tag{3}$$

where, N is the number of Antibody in Antibody-Base, A_i denotes the stimulus value of Antibody R_i, a_i denotes concentration of Antibody R_i.

Step 3. Information perception and extraction: At time $t = k$, APCMAS accepts data information within perceptive range, obtaining Antigen information element set $\mathrm{X}(t)$, which is defined as:

$$\mathrm{X}(t) = \{x_1(t), x_2(t), \cdots, x_i(t), \cdots, x_a(t), t = k\} \tag{4}$$

where, a is the number of information element, which is like the epitope in Antigen-Base.

Step 4. Information fusion and make-decision: Immune-UUV adopts the different make-decision response processes according to information fusion from $\mathrm{X}(t)$.

Step 4.1. When $x_i(t) \in \mathrm{X}(t)$, $\exists x_i(t) \notin$ Antibody-Base, and Environment Elements is safe, then keeping immune tolerance, go to Step 6;

Step 4.2. When $x_i(t) \in \mathrm{X}(t)$, $\exists x_i(t) \in$ Antibody-Base, then suggesting that Immune-UUV has existing and corresponding Antibody to execute immune response from Antibody-Base;

Step 4.3. When $x_i(t) \in \mathrm{X}(t)$, $\exists x_i(t) \notin$ Antibody-Base, and Environment Elements is not safe, then keep waiting and adjusting in order to better recognize and learn antigen, and meanwhile the optimal Antibody r_{N+1} as the memory information of antigen is saved in Antibody-Base for the Secondary Immune Response. The optimal Antibody r_{N+1} is calculated by [23]

$$A_I(t+1) = A_I(t)\left(\alpha\frac{\sum\limits_{j=1}^{N}(m_{ij}a_j(t))}{N} + \beta m_i - k_i\right)a_i(t) \tag{5}$$

$$a_i(t+1) = \frac{1}{1+\exp(0.5 - A_I(t+1))} \tag{6}$$

Then, the new Antibody-Base is defined as:

$$\text{Antibody-Base'} = \{r_1, r_2, \cdots, r_i, \cdots, r_N, r_{N+1}, \cdots, r_{N+M}\} \tag{7}$$

Step 5. Behavior strategy performing: Decision command sends behavior strategy to propulsion system, and propulsion system executes the corresponding Antibody behavior strategy.

Step 6. Time updating: $k = k + 1$, go to Step 3.

6. **Experimental Analysis.**

In this section, we design the experiments to verify the validity and effectiveness of the proposed modeling method and algorithm by avoiding obstacle for UUNS. The detailed experiments are designed as follows.

6.1. **Validity experiment.**

This experiment is mainly to prove validity of proposed model for the UUV modeling. The simulation environment conditions are set as follows.

Assuming that the simulation environment is a 10000×10000 underwater space, there are seven random obstacles described as the circular area $(1\#, 2\#, 3\#, 4\#, 5\#, 6\#, 7\#)$. The starting point is located at $(0, 0)$. The ending point is located at $(10000, 10000)$. The UUV movement velocity is set as k m/s, sensor ranger is set as circular area radius R, and energy capacity is set as 120000W.

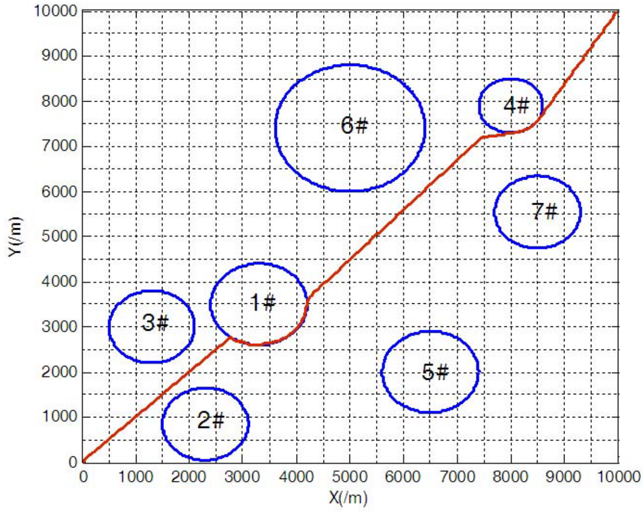

Figure 6. Primary Immune

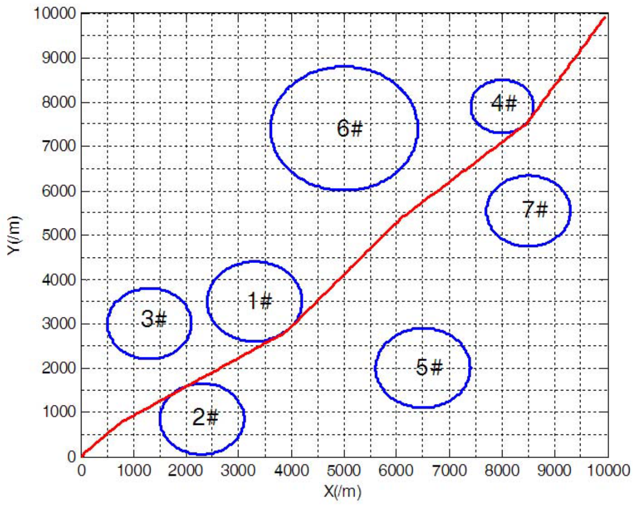

Figure 7. Secondary Immune

Under the same experimental conditions, performance of Immune-UUNS is evaluated by learning algorithm at different processes: Primary Immune and Secondary Immune. The results are shown in Figures 6 and 7.

Figure 6 is a simulation result in case of proposed Immune-UUV finishing tasks to implement the Primary Immune when it encounters the antigen (environment) first time. The UUV navigates information only from the APCA in Knowledge-Base. Here, Immune-UUV needs to recognize, memorize and learn relative information, and the optical strategy sequences (Antibody) can store and update to form the high-resolution Antibody-Base.

Figure 7 is a simulation result in case of proposed Immune-UUV finishing tasks to implement Secondary Immune when it encounters the same antigen second time. The UUV navigates information mainly from optical strategy sequences in the updated Antibody-Base. In this case, the Immune-UUV can rapidly respond and complete the task strategy sequence.

In order to quantitatively analyze effectiveness, three indexes energy consumption (W), run time (s) and run distance (m) are chosen in case of Primary Immune and Second Immune. Figure 8 shows a comparison of different cases.

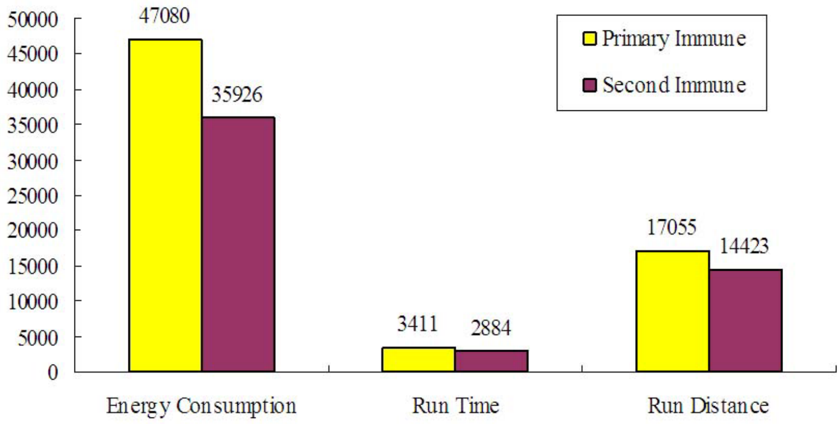

Figure 8. Quantitative analysis results

Compared with Primary Immune, the quantitative analysis results of Second Immune are better in Figure 8. From the above analysis, experimental results are consistent with the theoretical analysis, which can prove the validity and effectiveness of the proposed model and algorithm for the UUV modeling.

6.2. **Visualization system.** This experiment is mainly to more intuitively display movement of Immune-UUV, visualization system of UUNS based on IMASN is established by OSG (Open Scene Graph) rendering engine [24] and GPU (Graphic Processing Unit) acceleration [25], and trajectory of avoiding obstacle is shown in Figures 9-11.

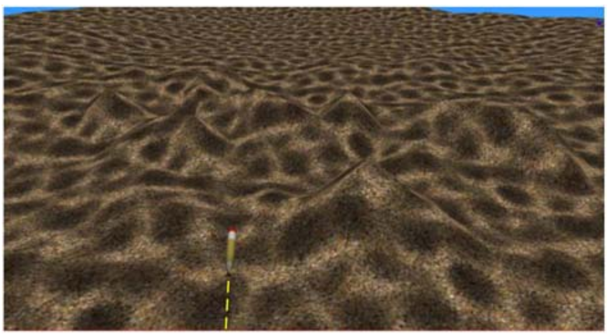

Figure 9. Trajectory of avoiding obstacle I

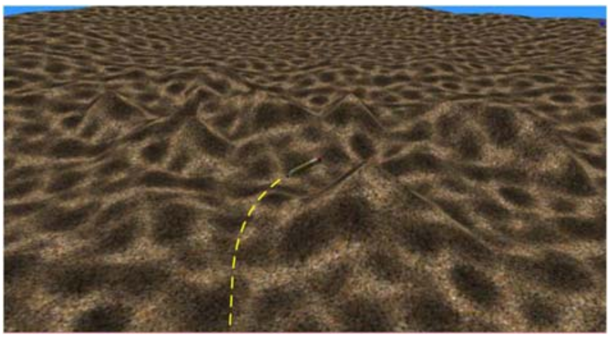

Figure 10. Trajectory of avoiding obstacle II

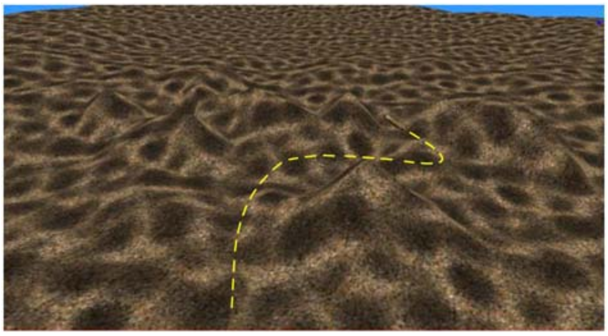

FIGURE 11. Trajectory of avoiding obstacle III

7. **Conclusions.** Theoretical research and application research of UUV are of great significance in marine science. In order to meet modeling requirements of high intelligent capability for the UUNS in this paper, based on the analysis of the mechanism of biological immune system and multi-agent system modeling theory, IMASN model and algorithm are proposed for the UUNS. There are several contributions as follows. (1) From the viewpoint of structure modeling, BIS and MAS theories are compared by advantages of each other, and many properties have been summarized in experimentally or theoretically, which can help to design IMASN. (2) From viewpoint of artificial immune intelligent modeling, mapping relationship between BIS and UUNS is established, and intelligent modeling for Immune-UUV is developed by IMASN, which focus on logic process and formal description. And (3) corresponding learning algorithm is put forward and embedded in IMASN to achieve artificial modeling for UUV. The theoretical and experimental results have shown that the proposed modeling approach has better performance for improving the intelligent and autonomous capability. In this paper, we have no consideration for macrophage and distinguishing the suppressor T-Cell and help T-Cell in designing procession of IMASN model in order to simplify modeling. However, these components play an important role in the real immune system. Therefore, artificial immune intelligent modeling with high fidelity is the focus of my future research, which can be used in UUV formation collaborative system.

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