Proceedings of the 2nd International Conference on Software Engineering and Machine Learning
DOI: 10.54254/2755-2721/76/20240593

Research on single target search and rescue in underwater environment based on machine learning

Nannan Ma[1,2], Lina Jin[1,3,*], Wenhui Shi[1,4]

[1]Department of Artificial Intelligence and Software, LiaoNing Petrochemical University, Fushun, 113001, China

[2]15716416525@163.com,
[3]275464494@qq.com,
[4]1449517283@qq.com
*corresponding author

Abstract. Machine learning has demonstrated its exceptional performance in addressing complex problems across various domains. This paper proposes an underwater search-rescue system based on the artificial immune algorithm, which effectively solve the problem of finding the optimal local search network in unknown underwater environments and shorten searching time. The system comprises multiple underwater search-rescue robots that form a global search network. Once target victims are identified, the global search network is broken down to form one or more local search networks to track and rescue them. To evaluate the robustness and effectiveness of the system, three indicators were designed: searching time, energy consumption, and tracking distance, and a simulation experiment with a single target is conducted. The results demonstrate that under the identical conditions, the artificial immune algorithm outperforms other methods in underwater target search-rescue tasks.

Keywords: AIA, local search network, searching time, energy consumption, tracking distance.

1. Introduction

China has vast sea areas and abundant inland navigation resources, with numerous rivers, dense waterways, and complex water conditions, resulting in frequent occurrence of water accidents. Due to the search and rescue capabilities of traditional manual method is poor, and factors such as weather, environment and infrastructure, the difficulty of search and rescue work increases [1,2]. With the characteristics of high precision, high efficiency and sustainable work, robots can replace human work without considering the working environment and psychological state. Although a single robot can take the place of humans to complete dangerous and challenging tasks, the working time of a single robot is much longer than that of multiple robots working together [3]. The collaborative control of multi-robots can carry out underwater search-rescue work preferably, reduce search time, shorten tracing distance, decrease energy consumption and complete the search-rescue tasks [4,5].

Artificial immune algorithm has good global search ability and strong adaptability, which can find the optimal solution in multi-dimensional complex problems, and can automatically adjust parameters according to specific problems without too much prior knowledge [6,7]. This paper presents an USRS (underwater search-rescue system) based on artificial immune algorithm. The system consists of multi-

USRRs(underwater search-rescue robots) to form a global search network,which is broken to form one or more local search networks when any USRR finds a victim. Artificial immune algorithm is used to select the optimal local search network and lock the target for rescue in this system. The performance of this system is evaluated by three indexes: salvage time, energy consumption and tracking distance.

These guidelines, written in the style of a submission, show the best layout for your paper using Microsoft Word. If you don't wish to use the Word template provided, please use the following page setup measurements.

2. System Model

2.1. Preparative Conditions

Multiple robots can navigate in an unknown three-dimensional boundaryless underwater environment, forming a search-rescue global network, detecting the target with vital signs actively, and each robot can report and share its position at any time throughout the entire system. In this section, the following assumptions are proposed for USRR, which are necessary to describe search, communication, tracking, and rescue processes.

Assumption 1: USRR has the same search range $R_S$and communication range R_C, and can navigate in unbounded underwater environments in non-polar regions E_{BU}.

Assumption 2: USRR can move on a two-dimensional horizontal plane steadily, can sink down at a uniform speed and have the ability to detect the distance between the robot and the target victim T, as well as the communication distance between the robot and the robot.

2.2. The Motion Model of USRR

The kinematic and dynamic equations of search-rescue robots in underwater navigation are described in two coordinate systems [8], namely the Earth coordinate system {E} and the object coordinate system {B}. The USRR motion model is represented by two coordinate systems, fuselage fixed frame and earth fixed frame.

To facilitate the study of the USRR coordination work, it is simplified as a quality point. The simplified model of standard named kinematic and dynamic equations is available for each USRR.

$$\begin{cases} \dot{\eta} = J(\eta)v \\ M\frac{dv}{dt} = \tau_w + \tau_c \end{cases} \tag{1}$$

2.3. Mapping Relationship

Artificial immune algorithm is a heuristic optimization algorithm based on the immune system, where multiple mechanisms work together such as generation, selection, evolution, memory, and synergism[9,10]. In the learning stage, the algorithm analyses the problem and generates a set of solution vectors based on antibodies, and evaluates and selects them. In the evolutionary stage, the algorithm uses evolutionary operators (mutation, recombination, selection, etc.) to generate the new solution vectors and update them, and then seeks the optimal solution gradually[11]. The collaborative working system of underwater search and rescue intelligent group is a distributed architecture with the ability of target recognition and self-adaptation. This system activates USRRs for rescue by identifying the victim target, which has clear similarity with artificial immune system.

For accurately describing the intelligent group collaborative control, underwater search-rescue robot system is linked to AIS (artificial immune system), and the mapping relationship of them was established as shown in Table 1.

2.4. Algorithm Flow of AIA

The artificial immune algorithm has seven elements: recognizing antibodies, generating initialized antibodies, calculating affinity, memory cell differentiation, stimulating and inhibiting antibodies, producing new antibodies, and ending conditions. In the collaborative work system of underwater

DOI: 10.54254/2755-2721/76/20240593

search-rescue intelligent groups, the artificial immune algorithm described below is used in the searching and communicating stages between USRRs and the victim target. The algorithm flowchart is presented below.

Step 1: Generate the initial population of antibodies. USRRs are distributed.

Step 2: Antigen recognition. Identify the target of interest and proceed to the next step if found; otherwise, continue searching.

Step 3: Generate initial antibodies. After locating the target, establish a local search and rescue network.

Step 4: Affinity calculation. Determine the distance between USRR and target T.

Step 5: Promotion and inhibition of antibodies. If behavioral events among USSRs promote each other, enhance their intensity; conversely, reduce their intensity.

Step 6: Group update. Update the local search and rescue network. If termination conditions are met, track and rescue using USRRs; otherwise, return to Step 4.

Table 1. The mapping relationship between AIS and USRS.

AIS	URSS
Antigen	The Victim Target
Antibody	USRR
Antigen Recognition	Search for the Victim Targets
Antibody Stimulation	Enhanced USRR Behavioral-Intensity
Antibody Inhibition	Reduced USRR Behavioral-Intensity
Eliminating Antigens	Rescue the Target Victim

3. Affinity Calculation

3.1. Behavior Modules

There is an intimate relationship between the self-behavior states of USRR during the work process. The self-states of every SURR are not only affected by the stimulation the victim target, but also by the stimulation of other robots in the local search-rescue network and the energy consumption of the SURR itself. The working states of search-rescue robots during the operation is defined have two states: power on and power off. The state of power on consists of four discrete behavioral events, including rescue, search, communication, and tracking; the state of power off only contains a discrete behavioral event. The self-states and discrete events description of USRR are shown in Table 2.

Table 2. The self-states and discrete events description of USRR.

State	Symbol	Event	Description	Priority
Power on	E_R	Rescue	In local search-rescue network N_{LSR},the robots which participates work begin to rescue victim after tracing the target.	1(Low)
	E_S	Search	In global search-rescue network N_{GSR}, robots execute search event; in local search-rescue network N_{LSR}, robots participating in rescue do not execute search event.	2
	E_C	Communication	In local search-rescue network N_{LSR}, the center broadcasts rescue signals to other robots.	3
	E_T	Tracing	In local search-rescue network N_{LSR}, robots participating in rescue trace the target T.	4
Power off	E_E	Exhaustion	Robots cannot participate in all rescue operations due to energy depletion.	5(High)

DOI: 10.54254/2755-2721/76/20240593

A behavioral event $e^l \in [E_E, E_S, E_C, E_T, E_R]$ is assigned a higher priority P^l according to its greater degree of demand than other events, where $l = 1,2,\cdots,Q,Q = 5$, The symbol l is consistent with the value of priority P^l, and the larger the number, the higher the priority.

3.2. Antibody Concentration Calculation

According to the flowchart shown in Figure 2 of the second section, the output of the optimal search-rescue network is inseparable from the calculation of affinity, in which the calculation of antibodies concentration is a crucial part. In the underwater search-rescue systems, a differential equation model is established for calculating the concentration of antibodies by the robots' behavioral state, target stimulus, the external environment and other factors, as follows:

$$\Omega\left(e_i^l(t)\right) = c[\Omega_1(t) - \lambda_1\Omega_2(t) + \Omega_3(t)] - \lambda_2\Omega_4(t) \tag{2}$$

Where, $\Omega_1(t)$ is the behavioral intensity of the i-type robots under the stimulation of the j-type robots; $\Omega_2(t)$ is the behavioral intensity of the i-type robots under the inhibitory effect of the j-type robots.

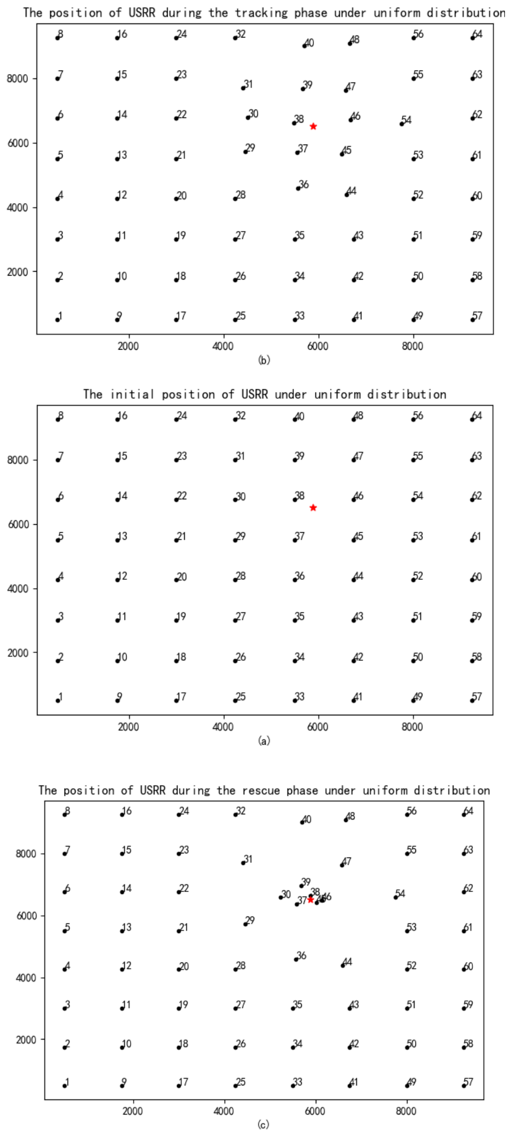

Figure 1. Search and rescue process under uniform distribution

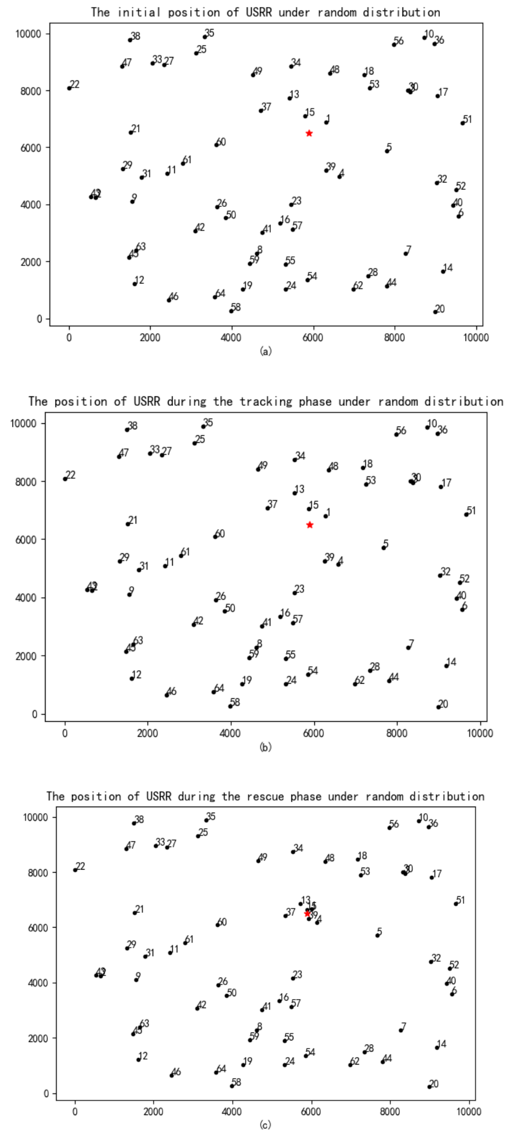

Figure 2. Search and rescue process under random distribution.

DOI: 10.54254/2755-2721/76/20240593

This paper focuses on single target search-rescue work, without considering the stimulation and inhibition effects between different types of antibodies. Therefore, only considering the factors of the antibodies themselves, the differential equation model for calculating the concentration of antibodies is:

$$\Omega\left(e_i^l(t)\right) = \lambda_1[\Omega_1(t) + \Omega_2(t)] - \lambda_2\Omega_3(t) \tag{3}$$

Where, $\Omega_1(t)$ is the behavioral intensity of mutual stimulation and inhibition behavior between robots; $\Omega_2(t)$ is the behavioral intensity of robots under the stimulation of external environment (the victim target); $\Omega_3(t)$ is the generated by the natural attenuation caused by the lack of behavioral interaction of the robot over time.

4. Simulation

4.1. Experimental Simulation

To verify the rationality, feasibility, and effectiveness of the underwater search-rescue system, a single target experiment was conducted based on the system architecture. The obtained results were compared with alternative deep learning algorithms. During the experiment, we disregarded the drift speed of the victim target in water and the optimal number of robots in the search and rescue network was set to 6. Additionally, we increased the movement speed of USRR by 50%. The experimental setting consisted of a two-dimensional underwater environment measuring 10000×10000 units. The total number of USRR $N = 64$, the search radius for USRR was set at $R_D = 1800$, while its communication radius was defined as $R_C = 2400$. We assigned $\lambda_1 = 0.85$ and $\lambda_2 = 0.15$.

According to the setting of the initial position of the robot, the initial global search network is divided into two types: uniform distribution and random distribution. Search and rescue targets are carried out in a uniform and random distribution manner. The initial position of the search and rescue robots is the same as shown in Figure. 1(a) and Figure. 2(a), and the heading angle is set randomly.

From Figure. 1(a)~(c), we can see that all search and rescue robots can correctly track and rescue the only target victim through the search and rescue system proposed in this paper. Even in the case of the energy exhaustion or failure of the search and rescue robots, such as USRR 28 caused by malfunction, and other search and rescue robots excluded from the local search and rescue network, they can also independently search for other victim targets in the global search and rescue network, which is driven by the behavior intensity of all relevant search and rescue robots.

From Figure. 1 to Figure. 2, we can see that even if the initial positions of all search and rescue robots change, the system can complete target search, tracking, and rescue tasks in unknown environments. From the example of Figure. 2(a)~(c), even if the initial position of the search and rescue robots is not uniform, under the behavior-driven coordination control, the local search and rescue network formed with the victim target as the center can effectively and satisfactorily complete the search and rescue work.

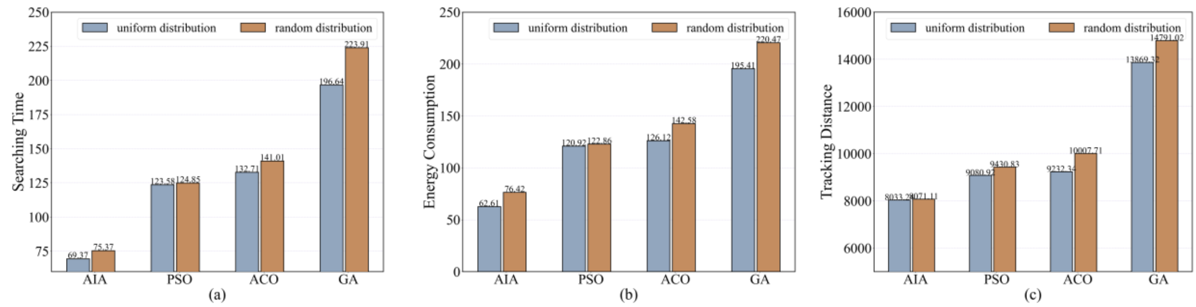

Figure 3. Comparison three indicators. (a)ST, (b)EC, (c)TD.

4.2. Performance Evaluation

In order to more effectively evaluate the effectiveness and efficiency of artificial immune algorithms on the system, three quantitative indicators were designed: ST(searching time), EC(energy consumption), and TD(tracking distance). ST: the time spent in the process of the global search and rescue network iterating to find the optimal local search and rescue network. EC: The total amount of energy required all four discrete events of search, communication, tracking and rescue for each search and rescue robot in the state of starting up. TD: the sum of the tracking distance of all robots in the local search and rescue network in the system.

From Figure. 3(a)~(b), we can see that the three quantitative indicators of randomly distributed data are higher than those of uniformly distributed data, indicating that random distribution has a greater impact on the formation of local search and rescue networks, especially in the search and communication stages. In addition, the application of artificial immune algorithms has significantly improved the performance of the system, especially in terms of search and rescue time. Compared with genetic algorithms, the search time has been reduced by nearly two-thirds.

Table 3. 100 comparative experiments for target on average value of three indicators.

Distribution Case	Uniform Distribution			Random Distribution		
	ST	EC	TD	ST	EC	TD
AIA	**69.37**	**62.61**	**8033.24**	**75.37**	**76.42**	**8071.11**
PSO	123.58	120.92	9080.92	124.85	122.86	9430.83
ACO	132.71	126.12	9232.34	141.01	142.58	10007.71
GA	196.64	195.41	13869.32	223.91	220.47	14791.02

In this paper, 100 repeated experiments are conducted on search and rescue robots with different initial position distributions. Table 3 shows the average searching time, energy consumption and tracking distance in the repeated experiments using the artificial immune algorithm, particle swarm optimization algorithm[12], ant colony optimization algorithm[13] and genetic algorithm[14] respectively. The results indicate that the use of artificial immune algorithms achieves the lowest search time, energy consumption, and tracking distance performance in different situations. Table 4 shows the standard deviations of search time, capacity consumption and tracking distance. The standard deviations of particle swarm optimization algorithm, ant colony optimization algorithm and genetic algorithm are much larger than that of artificial immune algorithm. The results show that the system using artificial immune algorithm is adaptable and robust to the external dynamic environment.

Table 4. 100 comparative experiments for target on standard deviation of three indicators.

Distribution Case	Uniform Distribution			Random Distribution		
	ST	EC	TD	ST	EC	TD
AIA	**0.8611**	**0.8047**	**9.5068**	**1.0222**	**1.0682**	**12.7839**
PSO	1.3542	1.3158	28.4365	2.9423	2.7333	29.4051
ACO	2.3737	2.5076	33.3155	3.3355	3.2859	31.8137
GA	5.1341	5.1114	59.3909	5.8903	5.5721	57.3057

5. Conclusion

Target search is a challenging problem faced by underwater search and rescue work. This paper proposes a behavior-driven underwater search and rescue system between multiple agents to achieve search, tracking and rescue in location and uncertain underwater environments. Using artificial immune algorithm mechanism to solve behavioral conflicts under constraint conditions, evaluating the robustness and effectiveness of the system through single target simulation experiments. Finally, the results indicate that compared to the four machine learning algorithms, it has good performance under the same conditions. The results indicate that this method has better performance in underwater target search and rescue. Our future work will focus on improving the performance of multi-target

DOI: 10.54254/2755-2721/76/20240593

simultaneous search and rescue methods, improving the artificial immune algorithm process to adapt to multi-target search and rescue work.

References

[1] Yang Qin, Hu Peng, Wang Jianhua, et al. Analysis of spatial evolution patterns of water bodies in China over the past 40 years and suggestions for protection strategies [J]. China Water Resources, 2022 (07): 48-52

[2] Improving the level of ecological and environmental protection in China's water bodies in response to the implementation of the Convention on Ballast Water Management. China Maritime, 2018 (09): 18-20. DOI: 10.16831/j.cnki.issn1673-2278.2018.09.10

[3] Wang J, Jiao N, Tung S, et al. Target clamping and cooperative motion control of ant robots[J]. Bioinspiration & Biomimetics, 2019, 14(6): 066015.

[4] Shayok M ,Hassan U ,Koshish K .Multi-robot Map Exploration Based on Multiple Rapidly-Exploring Randomized Trees[J].SN Computer Science,2023,5(1):

[5] Jiansheng P ,Jinsong G ,Fengbo B , et al.Multi-Robot Privacy-Preserving Algorithms Based on Federated Learning: A Review[J].1 College of Automation, Guangxi University of Science and Technology ,Liuzhou, 545000 ,China;2 Department of Artificial Intelligence and Manufacturing, Hechi University ,Hechi, 547000 ,China,2023,77(3):2971-2994.

[6] Zheng J, Chen Y, Zhang W. A survey of artificial immune applications[J]. Artificial Intelligence Review, 2010, 34(1): 19-34.

[7] Li L, Lin Q, Ming Z. A survey of artificial immune algorithms for multi-objective optimization[J]. Neurocomputing, 2022, 489: 211-229.

[8] Fossen T I. Handbook of marine craft hydrodynamics and motion control[M]. John Wiley & Sons, 2011.Flew, Antony, Darwinian evolution. Transaction Publ. (1997)

[9] Yongbin Z ,Wenshan L ,Tao L .A hybrid Artificial Immune optimization for high-dimensional feature selection[J].Knowledge-Based Systems,2023,260

[10] Lingjie L ,Qiuzhen L ,Zhong M .A survey of artificial immune algorithms for multi-objective optimization[J].Neurocomputing,2022,489211-229.

[11] Liu L ,Niu Z .Artificial Immune Algorithm-based Airplane Path Planning under Complicated Environment[J].International Journal of Circuits, Systems and Signal Processing,2021,15792-799.

[12] Canglong Z .Step-by-Step Multi-Ship Collision Avoidance Navigation Path Planning Based on Particle Swarm Optimization[J].Journal of Control Science and Engineering,2022,2022.

[13] V A R ,V O Z ,P R K , et al.Algorithm of ant colony optimization (ACO) for 3D variation traveling salesman problem[J].Journal of Physics: Conference Series,2022,2288(1):

[14] Hong W .Collaborative Task Offloading Strategy of UAV Cluster Using Improved Genetic Algorithm in Mobile Edge Computing[J].Journal of Robotics,2021,2021