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Intelligent evolution method for obstacle-avoidance algorithm of unmanned surface vehicles in real sea trial based on machine learning

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Abstract: [**Objectives**] The performance of unmanned surface vehicles (USVs) is defined as the ability to complete specific tasks in specific environments within a given time scale as a result of the cooperation of multiple technical aspects. However, the traditional optimization method that focuses on a single part of the system provides a limited effect on improving the performance of USVs. [**Methods**] For the features of an autonomous system of USVs, two main forms of the intelligent evolution of USVs are proposed from the perspective of algorithms: the evolution of algorithm functions and the evolution of algorithm parameters. In this case, a machine learning-based intelligent evolution method is proposed. An automatic USV control system that satisfies the requirements of intelligent evolution is then designed and tested in a sea trial. [**Results**] The obstacle-avoidance task in the sea trial proves the capability and feasibility of the proposed method. [**Conclusions**] The machine learning-based intelligent evolution of USVs is an effective way to continuously improve the performance of USVs, making it a worthy research topic with high application value.

Key words: unmanned surface vehicles (USV); intelligent evolution; real sea trial; machine learning

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0 Introduction

With the penetration and application of artificial intelligence in marine equipment, intelligent marine equipment and systems represented by unmanned surface vehicles (USVs) have ushered in unprecedented development. They have been applied to waterway transportation, marine mapping, and military operations [1-3]. Unlike traditional equipment based on human-machine interaction, USVs are the equipment whose functions are essentially defined by software. The problems of critical technologies of the USV autonomous system in practice, such as information perception, planning, decision-making, and motion control, have been gradually recognized. Thus, the concept of "intelligent evolution of USVs" was proposed [1].

The performance of USVs is defined as the ability to complete specific tasks in specific environments within a given time scale, which is a measure of the USV value [4-5]. Therefore, the target of the intelligent evolution of USVs is to improve the equip-

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ment performance. The intelligent evolution of USVs is to achieve continuous iterative optimization of autonomous systems by learning the measurement data in the operation [6]. However, compared to unmanned equipment such as unmanned aerial vehicles and unmanned vehicles, the autonomous system of USVs faces greater challenges in learning and iteration.

The first challenge is that the USV system is complicated. Similar to systems of other complex equipment, the USV system inherits a large number of subsystems, which is a "system of systems". The performance of a single sub-function of the USV system is not improved linearly with the growth of the USV performance. Thus, the evaluation of USV performance is characterized by lack of information, multi-level, and strong coupling. For example, the output of the perception system significantly affects the performance of the planning algorithm, which in turn places higher requirements on the control system.

The second one is that the operating environment of USVs is complex. In the sea, the external random loads such as wind, waves, and currents faced by USVs are mostly in the same magnitude as the control force of hulls. Under severe conditions, there may even be situations where the external loads are much larger than the control force of hulls [7]. At present, after most of the USV control algorithms are put into application, their control parameters should be adjusted manually according to the characteristics of the operating environment. This has been widely discussed in the ship control field, and some methods have been developed. However, in the unpredictable marine environment, it does not work if we only rely on self-adjustment for control algorithm parameters of USVs. For example, the parameters of the filtering algorithm in the image recognition and pre-processing should be changed at any time according to the weather and light conditions. The step size of the path planning algorithm should be adjusted according to the operation range and obstacle distribution.

To address the above problems, this paper argues that the intelligent evolution of USVs should focus on the evolution of algorithm functions and algorithm parameters in the USV autonomous system, and proposes the process of the corresponding intelligent evolution method. On this basis, we try to give an evolvable control structure of the USV autonomous system. At last, with the obstacle-avoidance algorithm of USVs as an example, we will verify the feasibility and effectiveness of machine learning methods in the intelligent evolution of USVs in combination with a real sea trial.

1 Overview of intelligent evolution methods of USVs

After the preliminary design and construction, the hardware equipment and performance of an USV have been basically confirmed. Therefore, the intelligent evolution of USVs should focus on the evolution of algorithm functions and algorithm parameters in the autonomous system. Currently, many research methods have been developed in terms of algorithm functions of the autonomous system. For example, in terms of perception, there are image recognition algorithms such as the semantic segmentation algorithm and the supervised learning algorithm [8]. In terms of planning, there are path planning algorithms such as A^*, D^*, and rapidly-exploring random tree (RRT) algorithms [9]. In terms of control, there are navigation control algorithms such as the proportional integral derivative (PID) control and the active disturbance rejection control (ADRC) [7, 10]. The evolution of algorithm functions refers to expanding functions of the USV autonomous system through construction, invocation, or combination of functions, so as to provide the possibility for USVs to complete more complex tasks. In terms of algorithm parameters of the autonomous system, artificial intelligence methods have also been widely used for parameter adjustment in perception, planning, and control algorithms [11–12]. Most of the current adjustment methods of algorithm parameters are based on accurate quantitative objective functions. They have achieved some results at the simulation level or at the measurement stage, but there is no in-depth study on the problems considering the coupling effect between algorithms and the environmental influences. The evolution of algorithm parameters means making adaptive systems adapt to current marine environments and task requirements through collaborative adjustment of algorithm parameter sets, so as to continuously improve the USV equipment performance.

Then, the application process of the intelligent evolution method of USVs is shown in Fig.1.

The manual evolution stage of USVs means that at the early design stage of the USV autonomous system, designers should establish algorithm function libraries based on standardized inputs and out-

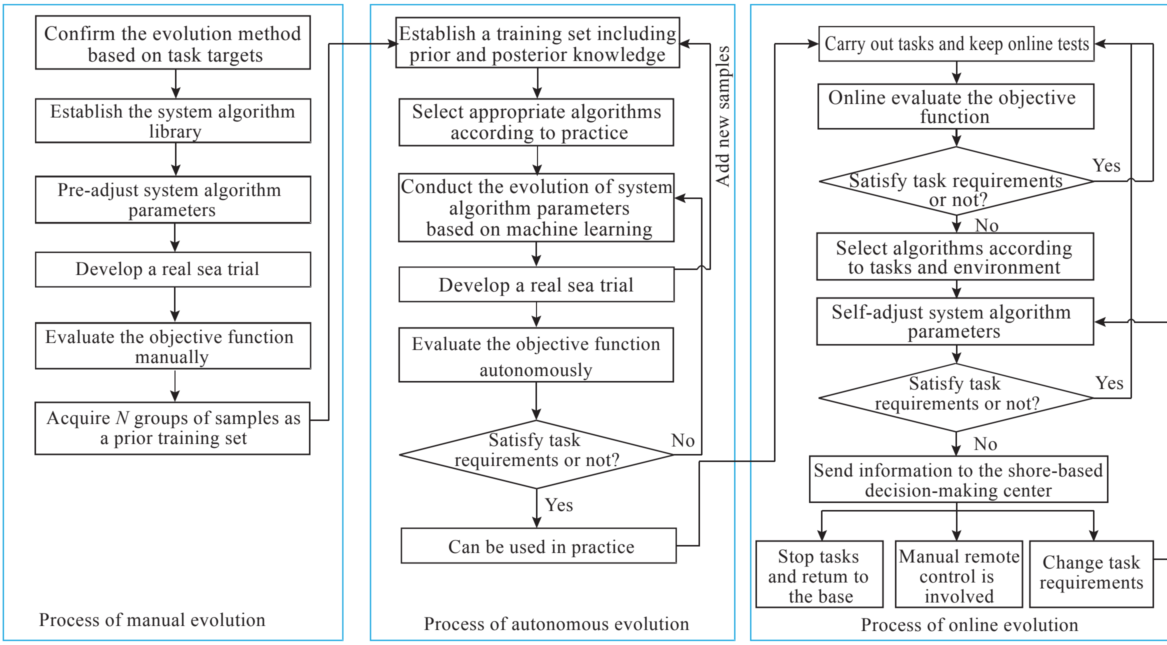


Fig. 1 Application process of USV intelligent evolution

puts to enrich the reserve of algorithm libraries of the USV autonomous system and make a preliminary adjustment for algorithm parameters based on real sea trials. The USV equipment performance can be evaluated manually. The evolution at this stage can help designers to know the performance and applicability range of algorithms, and provide a referenced classification of parameter sets, feasible parameter domains and objective functions of evolution for subsequent autonomous evolution and online evolution stages.

The autonomous evolution stage of USVs refers to that USVs carry out many standard tests in the real sea sites, and autonomously adjust algorithm parameters in different marine environments according to autonomous evaluation results of equipment performance by objective functions [13]. After the evolution at this stage, the USVs will form a group of algorithm functions and parameter sets that can cope with the characteristics of many kinds of loads in the marine environment and accomplish tasks.

The online evolution stage of USVs refers to conducting continuous dynamic tests and evaluation for the USV autonomous system in the process of practical tasks. If the system judges that the current algorithm function and parameters can meet the task requirements, it will accept the reduction of equipment performance to a certain degree, so as to decrease the impact of frequent replacement of algorithms or change of system parameters on the system stability. When the equipment performance decreases to a certain threshold and is judged to be unable to meet the task requirements, the system will adjust the algorithm parameters or select other algorithm functions according to accumulated online test data and previous training sets. Due to the limitation of USV hardware performance, the influence of external loads may exceed the adjustment range of USVs in some extreme weather. In this situation, the system can provide timely feedback and choose to return, manually remote control or change the task requirements according to shore-based decisions, so as to reduce the loss in severe situations.

2 Structure of evolvable USV control system

The evolvable USV autonomous system (see Fig.2) is an intelligent system that can select different algorithm functions and adjust parameters to improve the USV equipment performance for different overall task requirements. The data flow of the system is an object-oriented process, and the algorithms can be defined as processing methods for corresponding data objects. Thus, changes in algorithms do not influence the transfer of data objects, which ensures that the system operates effectively.

The evolvable USV autonomous system includes four subsystems, the evolver, the perceptron, the planner, and the actuator. It demonstrates different performances depending on overall tasks and the marine environment [7, 14]. The evolver parallelly acts on the perceptron, the planner, and the actuator. It uses the data generated by the subsystems for tests and evaluation of the USV equipment perfor-

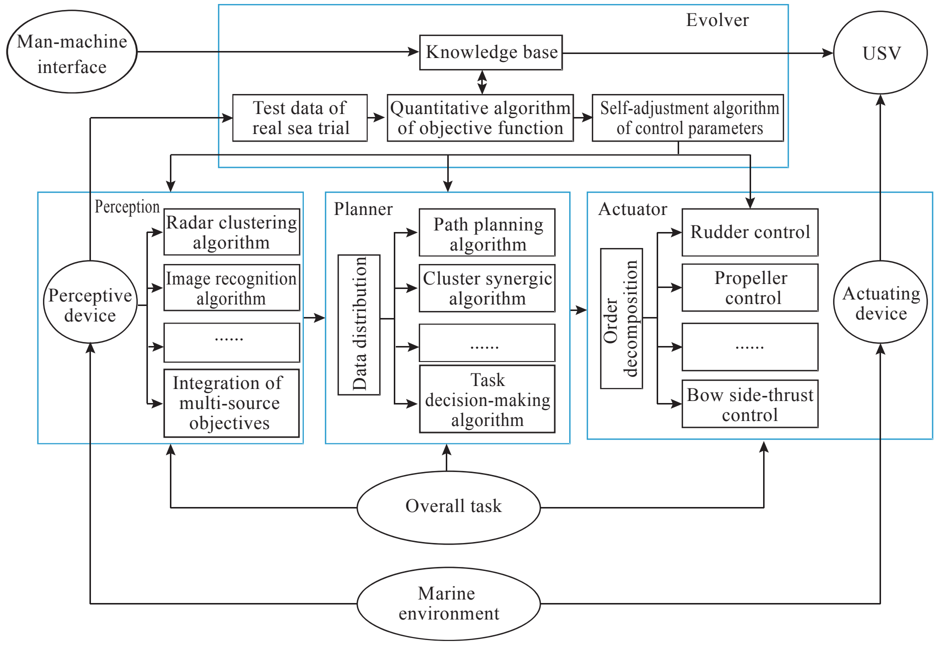


Fig.2 Control structure of evolvable USV autonomous system

mance and as a reference for the individual optimization of subsystem algorithms and uses the overall performance in tasks as the evolution direction of the system. Changes in algorithm functions and adjustment of parameters do not affect the architecture and operation mode of the system. The evolutionary objective of the USV autonomous system is to improve the USV equipment performance, namely to improve the ability of USVs to complete specific tasks in specific environments within a given time scale.

The ability of USVs to complete specific tasks is influenced by the coupling of multiple levels and multiple technical nodes. As shown in Table 1, the index level refers to the hardware base of USVs, such as the propulsion power, the fuel consumption, the configured calculation power, and the optical image resolution. The optimization at this level is mainly targeted at the preliminary design and construction level of USVs. The behavior level means the performance of USV hardware under a series of temporal orders, such as the technical radius of ships, the braking distance, and the heaving acceleration. The optimization at this level is mainly aimed at the frequency and manner in which orders are sent. The function level refers to the performance of different intelligent algorithms, such as the image recognition algorithm and the path planning algorithm. The optimization at this level mainly focuses on algorithm functions and algorithm parameters. The task level refers to the equipment performance of USVs when they are used in practice. This level is the coupling result of influences of multiple technical nodes in the first three levels based on the design architecture of the system. It can be seen that most traditional optimization methods for autonomous systems are aimed at single nodes, such as replacing the power equipment, changing the control mode, and optimizing the control algorithm. There is no comprehensive consideration of equipment performance in the optimization process.

Currently, many studies focus on independent optimization of subsystems but fail to pay enough attention to the interaction among subsystems. For example, the recognition results of the perceptron are necessary information for the planner. The planning results (such as planning path points) affect the parameters of the auto-steer in the controller, which in turn affects the recognition accuracy and the recognition time of the perceptron. Therefore, the intelligent evolution of a well-designed USV autonomous system should take full consideration of coupling among different parts based on independent optimization of algorithms in each part to conduct learning iteration for algorithms [6]. Thus, continuous improvement of the USV equipment performance is achieved.

The evolvable USV autonomous system can make full use of the measurement data in the sea area, and optimizes the subsystems and equipment performance based on the established quantitative algorithm of the objective function. Its advantage lies in that based on the independent optimization of algorithms in previous subsystems, the system

Table 1 Hierarchical division and corresponding features of technical nodes for USV autonomous system

Level	Example	Form	Test method	System attribute	Environment influence
Index level	Thrust power	Physical quantity	Objective calculation	Hardware level with single hardware working	No
Behavior level	Tactical radius	Physical quantity	Objective calculation	Hardware level with single hardware working	Little
Function level	Image recognition function	Physical quantity and score	Objective calculation and subjective description	Sub-system level with multiple algorithms working	Large
Task level	Patrol task	Score	Subjective description and objective calculation	Overall system level	Significant

can continuously improve the algorithm characteristics with the coupling relationship according to the complex influence of the marine environment and overall task requirements. Thus, better equipment performance can be obtained.

3 Example of intelligent evolution of obstacle-avoidance algorithm of USVs

The primary problem faced by the intelligent evolution of USVs, which are equipment defined by algorithmic software, is that there is no quantifiable mathematical representation of the relationship between algorithms and equipment performance. It is difficult to decompose the evolutionary objective function into sub-algorithms by analytical methods. This problem belongs to the performance evaluation field of intelligent unmanned equipment [13]. Therefore, in order to quickly verify the feasibility and effectiveness of the proposed method, our research team selected the local path planning algorithm, RRT, whose evolutionary objective function is clear, to carry out example research on the intelligent evolution of USVs in the sea area.

3.1 Performance evaluation function of the path planning algorithm

The computational performance of a local path planning algorithm, such as time complexity and space complexity, is determined by the structure of the algorithm itself. In the case of the RRT algorithm, for example, its impact on the equipment performance is reflected in the variation of the step size and the target deviation probability of the algorithm, so they can be selected as parameters to be evolved [8]. In the real sea trial, the final performance of the path planning algorithm is influenced by the characteristics of the USV control system and environmental loads. The transfer of motion state signal is shown in Fig.3.

According to the map information given by the USV sensing algorithm, after the path planning algorithm gives the desired route information $T(x, y)$, the USV motion state at each sampling period is related to the motion state at the last moment, the control order at the last moment, environmental loads and delay of USV software and hardware systems. The motion state $\boldsymbol{s}$ of USVs is directly measured by the inertial navigation system and expressed by the position, the velocity, and the acceleration, namely,

$$\boldsymbol{s} = [x, y, z, u, v, r, \alpha, \beta, \gamma, \cdots] \tag{1}$$

where x, y, and z indicate the position information; u, v, and r represent the velocity information; α, β and γ denote the acceleration information. Meanwhile, the motion state can also include high-order quantities such as acceleration and angular acceleration.

The control algorithm of USVs can be indicated as the mapping of the control quantity $\boldsymbol{e}$, which is generated based on the expected route and the motion state $\boldsymbol{s}$, namely,

$$\boldsymbol{e} = f_c(\boldsymbol{s}, T(x, y)) \tag{2}$$

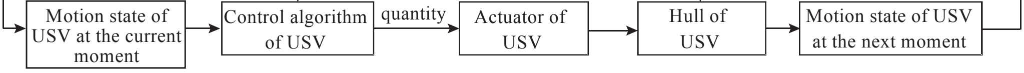


Fig. 3 Transfer model of motion state quantities of USV

where f_c is the mapping of the control algorithm from the motion state to the control quantity. The control quantity $\boldsymbol{e}$ varies with the USV power system.

In this case, in consideration of the precondition of virtual obstacles, the expected route is a fixed value in a single obstacle-avoidance task.

Moreover, the marine load is generally difficult to be measured. Fossen et al. [7] used the probability distribution method to describe it, and the environmental load is given by

$$f_{\mathrm{env}}(PDF(\omega_{\mathrm{w}}, A), \boldsymbol{s}) \tag{3}$$

where f_{env} is the predicted value of the external load at the current motion state; $PDF(\omega_{\mathrm{w}}, A)$ is the probability distribution of the wave frequency ω_{w} and the wave height A at the current marine situation. Under specific sea conditions, the probability distribution can be considered unchanged in a period, namely that this function is time-invariant.

Then, in the actual operation of the USV system, the communication and computational delays between algorithmic functional modules are determined by the system design and algorithms, which are generally constant. The delays of software and hardware systems in the marine enviroment are mainly reflected in the delay of the execution time of the actuator. For example, the steering time is related to the rotating size of the steering engine. Therefore, the impact of delay of the USV system on the motion state can be expressed as a function related to the control quantity $\boldsymbol{e}$, namely,

$$f_{\mathrm{d}}(\boldsymbol{s}) = g_{\mathrm{d}}(f_{\mathrm{c}}(\boldsymbol{s})) = g_{\mathrm{d}}(\boldsymbol{e}) \tag{4}$$

where f_{d} is the mapping from the motion state to the delay of the system; g_{d} is the mapping from the control quantity to the system delay. Therefore, the change in the motion state of the USV in a single obstacle-avoidance task in the specific marine enviroment can be represented as a convolution of multiple influencing factors' mapping functions, namely,

$$\boldsymbol{s}_{t(k+1)} = (f_{\mathrm{c}} * f_{\mathrm{env}} * f_{\mathrm{d}})\boldsymbol{s}_{tk} \tag{5}$$

where $\boldsymbol{s}_{t(k+1)}$ and $\boldsymbol{s}_{tk}$ denote the motion states of the USV at two consecutive measurement moments, respectively.

Thus, the overall performance of the USV motion state can be obtained, which includes many kinds of information such as the performance of the control algorithm, the environmental load, and the system delay. The obstacle-avoidance performance of USVs can be evaluated from the USV trajectory (position, velocity, and other information) and the motion stability (angular velocity and other information).

From the above analysis, the obstacle-avoidance performance of the USV in a single task in the specific marine enviroment can be measured by the USV motion state during the test. The unknown factors such as the USV's characteristics and the environmental load have been coupled in the changes of the motion state. In addition, as the motion state is the most easily monitored and recorded system information in practice, the performance evaluation based on the analysis of the motion state is extremely important.

In this case, limited by the measurement data, the research team selected two indexes based on the task requirements, the path length and the path smoothness, to generate the objective function for the algorithm evolution. The path length is used to examine the efficiency of the planned obstacle-avoidance path by the path planning algorithm in the case of a given starting point and end point. A smaller path length means that the USV can avoid obstacles in the map more effectively. The path smoothness affects the requirements of the planned path on the USV maneuverability. Smaller path smoothness means that the generated path requires less for the hydrodynamic performance of the USV and has higher stability in more complex environments. The two can be calculated as

$$\begin{cases} E_{\mathrm{length}} = \sum\limits_{i=1}^{n} \Delta L_i \\ E_{\mathrm{smooth}} = \sum\limits_{i=1}^{n-1} |\Delta\theta_i| \end{cases} \tag{6}$$

where n is the number of path segments; ΔL_i indicates the length of No. i path; $\Delta\theta_i$ is the change in the angle between No. i path and No. i+1 path. For the test results in one group, the test indexes are mapped to the range of [0, 100] by the normalization method.

The traditional optimization method for the path planning algorithm is to find the algorithm parameters that minimize the values of the two expressions based on the two objective functions in Equation (6). Although this method can improve the performance of the algorithm to a certain extent, it does not pay enough attention to the coupling effect between the generated path and the trajectory tracking algorithm as well as the perturbation of external loads in the marine enviroment.

In the real sea trial, the coupling effect between the path planning and the trajectory tracking algorithm is reflected as the actual trajectory of the USV in the marine enviroment based on the given planned path. Therefore, the performance of the path planning algorithm can be indicated by the trajectory length and the accumulated heading change of the USV accordingly, and it is given by

$$\begin{cases} E_{\text{length}}^{\text{real}} = \int \mathrm{d}l \\ E_{\text{smooth}}^{\text{real}} = \int |\mathrm{d}\theta| \end{cases} \tag{7}$$

where $E_{\text{length}}^{\text{real}}$ and $E_{\text{smooth}}^{\text{real}}$ respectively indicate the trajectory length and the accumulated heading change in the real sea trial; $\mathrm{d}l$ and $\mathrm{d}\theta$ are the differential forms of the path length and the angle change, respectively.

The randomness of the RRT algorithm, namely that there may be different solutions for each set of hyperparameters values, and the limited real sea trial resources are taken into consideration. In the process of path planning by the algorithm, we use Equations (6) and (7) to analyze the planning results and select the one with the best effect among several actually generated sets of paths as the planned path under this set of hyperparameters for the real sea trial.

After being processed by the normalization method, the objective function of the local path planning algorithm in the real sea trial is given by

$$E^{\text{real}} = <\boldsymbol{\omega}, \boldsymbol{E}_{\text{normal}}> \tag{8}$$

where $<\boldsymbol{\omega}, \boldsymbol{E}_{\text{normal}}>$ is the dot product of the vector $\boldsymbol{\omega}$ and $\boldsymbol{E}_{\text{normal}}$; $\boldsymbol{E}_{\text{normal}} = 100 \times \left(\dfrac{E_{\text{length}}^{\text{real}}}{\text{Max}(E_{\text{length}}^{\text{real}})}, \dfrac{E_{\text{smooth}}^{\text{real}}}{\text{Max}(E_{\text{smooth}}^{\text{real}})} \right)^{\text{T}}$; $\boldsymbol{\omega}$ is the weight coefficient vector. The value of $\boldsymbol{\omega}$ can be set manually, which is influenced by the design requirements of the tested USV and is a subjective quantity.

From the objective function of the path planning algorithm, it can be known that a smaller value of the objective function leads to a better performance of the path planning algorithm in the real sea trial.

3.2 Evolution of algorithm parameters based on the surrogate model

Due to the complexity of the actual environment, the relationship between the system parameters and the USV equipment performance can be generally considered as a multi-modal function. It is difficult to fit the relationship by traditional linear or nonlinear regression methods. Meanwhile, a single test is time-consuming and complex, and the acquired data samples are small in size. In view of this, by using the principle of experiment design, the research team selected scattered data points in the high-dimensional parameter space, so as to reduce the requirement for data in the marine enviroment [15]. Then, the machine learning method represented by the Gaussian regression process (GRP) is used to replace the relationship between the objective function and the optimal parameters in the optimization algorithm with a surrogate model [16-20]. Then, the parameter set which can achieve the optimal equipment performance is obtained by optimization algorithms such as the rapid traversing method or the genetic algorithm.

The evolution process of the algorithm parameters is shown in Fig.4. On the one hand, the fitting accuracy of the Gaussian surrogate model is influenced by the distribution of sample sets. On the other hand, the models of its kernel function, mean function, and likelihood function all affect its convergence accuracy. For different parameter sets, an appropriate mathematical model is selected by considering the characteristics of the physical process during the operation. This is beneficial to improving the reliability and accuracy of the evolution of algorithm parameters.

Moreover, for the parameter adjustment in practice, it is not difficult to determine the definition domain of an available parameter, but it is difficult to confirm that the parameter set which achieves the optimal performance must fall within the selected definition domain. Therefore, the evolution of algorithm parameters based on the surrogate model mainly addresses the problem of finding the optimal parameter set in the definition domains and their neighborhoods which are formed based on the data distribution of the sample set.

3.3 Design of real sea trial

The "Zhuimeng-3" USV was used to develop the

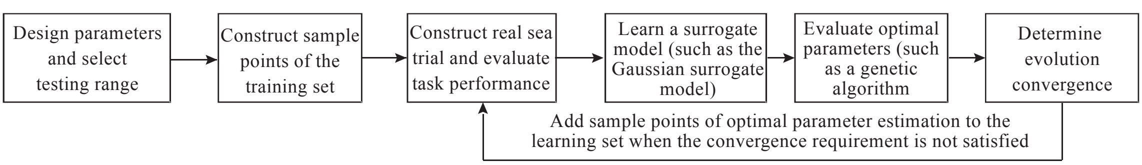


Fig. 4 Evolution process of algorithm parameters based on a surrogate model

test, which is about 7 m long and has a planned speed of 8-10 kn. Its photograph is shown in Fig.5.

Fig. 5 "Zhuimeng-3" USV

The "Zhuimeng-3" USV includes a power supply system, an actuator system, a monitoring system, a sensing system, a computing system, and a network system. The power supply system includes generators and storage batteries; the sensing system includes maritime radars, the camera cluster, and anemographs; and the actuator is the Mercury outboard engine. As the control algorithm of trajectory tracking is limited by the physical characteristics of the outboard engine, this USV has lower control accuracy and higher requirements on the results of the path planning algorithm than traditional screw-rudders or pumps. Moreover, the test sea area is often at sea state 3-4. This sea state means a large external load for the tested USV. Therefore, this has a high practical value for the parameter evolution of the path planning algorithm.

In the test, the navigational speed is about 8 kn. As a single test does not exceed 30 min, the size of the selected map is 2 400 m × 2 400 m. In the algorithm, the number of actually used grids is 600 × 600. Thus, the length of a single grid corresponds to 4 m length in the map. With the top left corner of the grid as the zero point, the positions and the radii of obstacles (the expansion safety radius is 15 m) are shown in Table 2.

Table 2 Location of virtual obstacles and corresponding avoidance radii

Center point of an obstacle/m	Avoidance radius/m	Center point of an obstacle/m	Avoidance radius/m
(−180,180)	80	(−370,400)	50
(−310,250)	35	(−200,475)	95
(−150,330)	30	(−450,220)	95

The starting and end points of the path planning are set as (100 m, 100 m) and (480 m, 500 m), respectively. The map of the virtual obstacles is shown in Fig.6.

3.4 Results of real sea trial and analysis

In the simulation test of the preliminary algorithm, the ranges of the target deviation probability and the step size are set as [0.1, 0.3] and [150 m, 180 m], respectively.

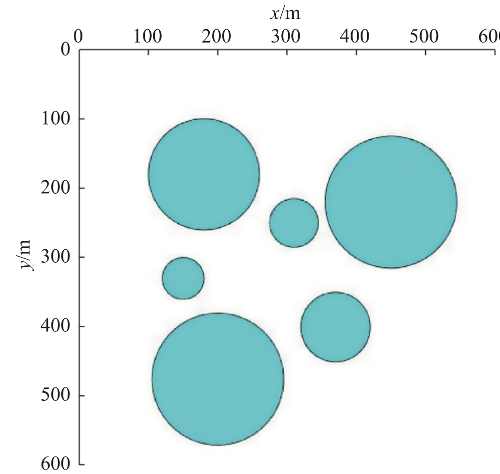


Fig. 6 Setting of virtual obstacles

According to the design principle of the test, nine sets of parameters are used as the sample points in the real sea trial. Let the weight vector $\omega=(0.5,0.5)^{\mathrm{T}}$. The parameters and the test results of the real sea trial are shown in Table 3 and Fig.7.

Table 3 Path results in a real sea trial

Step size D/m	Target deviation probability P	Path length/m	Path angle/(°)	Value of objective function
150	0.1	739.274	3.687	79.001
150	0.2	703.877	3.723	77.329
150	0.3	748.569	3.656	79.226
160	0.1	753.047	5.035	93.177
160	0.25	654.352	3.719	74.450
170	0.05	648.220	3.406	70.990
170	0.15	636.477	3.118	67.457
170	0.25	643.532	3.430	70.960
180	0.25	872.046	3.976	89.484

According to the above data, the Gaussian model is used to establish the surrogate model of the relationship between parameters and scores [16], and the kernel function is set as

$$k(\boldsymbol{x},\boldsymbol{x}')=\sigma^2\exp\left(-\frac{1}{2\xi^2}(\boldsymbol{x}-\boldsymbol{x}')^2\right) \tag{9}$$

where σ and ξ are respectively the predicted variance and the scale factor; $\boldsymbol{x}$ and $\boldsymbol{x}'$ are the input parameter sets. This kernel function suits the physical process in which output results vary with parameters smoothly [17]. Due to the randomness of the RRT algorithm, it can be assumed that the scores of the real sea trial will vary smoothly with the two parameters. Meanwhile, the convergence condition of the corresponding surrogate model is to adjust the

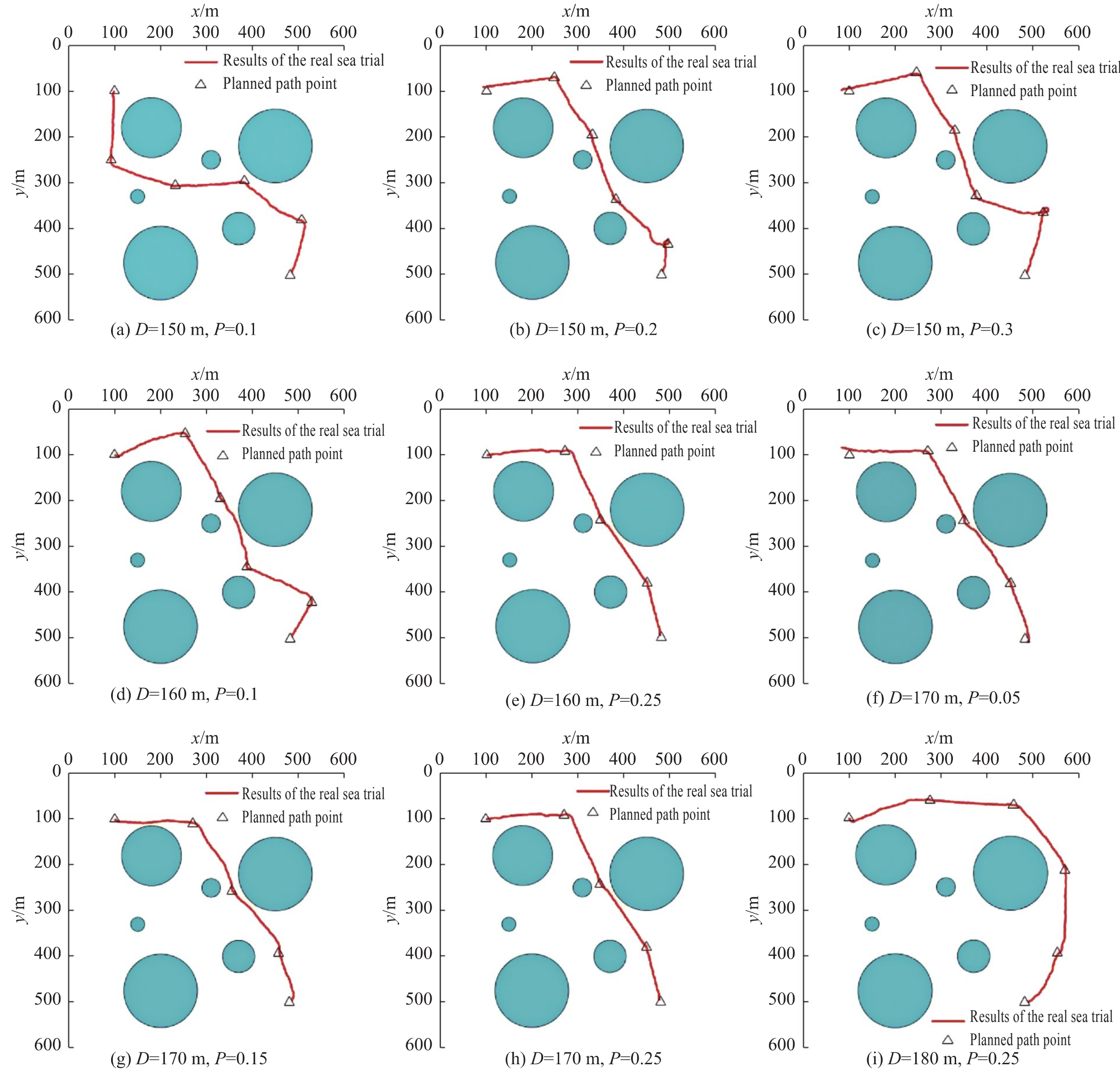


Fig. 7 Comparison between planned paths and paths in a real sea trial

values of σ and ξ to minimize the loss function. In other words, the corresponding predicted values should satisfy

$$y_{\text{optimal}}|\boldsymbol{x}_* = \arg\min_{y_{\text{guess}}} \tilde{R}_{\text{L}}(y_{\text{guess}}|\boldsymbol{x}_*) \tag{10}$$

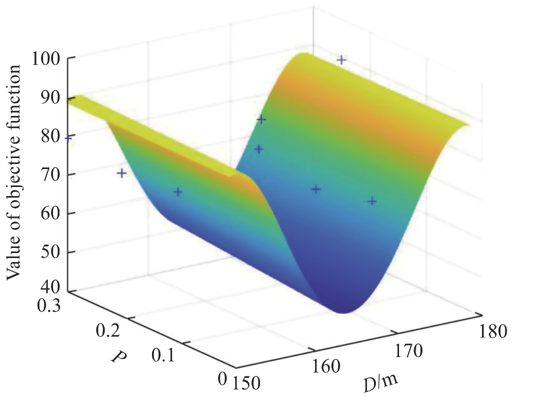
where $\boldsymbol{x}_*$ is the parameter pair that waits to be predicted; y_{guess} indicates the corresponding predicted value; $\tilde{R}_{\text{L}}$ is the expected loss function; arg min denotes calculating the predicted value with the minimum value of the loss function. The loss function used in this test is given by

$$\tilde{R}_{\text{L}} = \sum (y_{\text{guess}} - y*)^2 \tag{11}$$

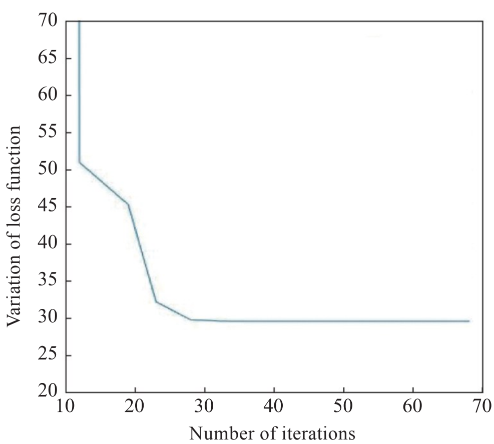
where y^* is the true value. $\tilde{R}_{\text{L}}$ is the quadratic sum of the difference between the predicted value y_{guess} and the true value y^*. The predicted model which makes this value minimum is the required parameter-score mapping model.

For the Gaussian model in which the test data of the real sea trial vary with the algorithm parameters, its regression results are shown in Fig. 8(a), where "+" denotes the measurement data and the curved surface is composed of fitting data. The trend of the loss function varying with the number of iterations is shown in Fig. 8(b). For the optimal RRT algorithm in the map and marine enviroment, which is obtained by fitting the Gaussian model, the parameters are the step size D = 164 m and the target deviation probability P = 0.05.

The obstacle-avoidance path generated by this parameter set is shown in Fig.9. According to the actual test results, the sample parameter sets for the test can meet the requirement in practice and are able to complete the obstacle-avoidance task. The results obtained by the surrogate model are the parameter set that performs better in the corresponding definition domains of parameter sets in the sample space.



(a) Comparison between fitting results by the Gaussian surrogate model and practical



(b) Variation of loss function value with the number of iterations

Fig.8 Fitting data of Gaussian surrogate model

Thus, the parameter-evaluation mapping generated based on the surrogate model already contains the comparison results between the USV performance of the optimal parameter set and that of an available parameter set that is randomly selected. By expanding the number of samples and adding the circulation test, we can more accurately generate the optimal obstacle-avoidance parameters of the "Zhuimeng-3" USV in the test sea area.

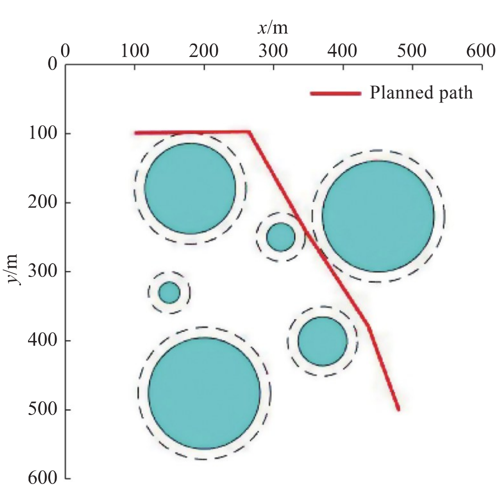


Fig.9 Obstacle-avoidance path generated by the RRT algorithm based on the optimal parameter set

In addition, considering the influence of the parameters of the RRT algorithm on its calculation results, the selection trend of the optimal step size is reflected in the search of boundaries of obstacle-avoidance areas as much as possible in the limited space. The path in Fig.9 is close to being tangent to the circle areas whose radii are the avoidance radii of obstacles after expansion. This indicates that the space is searched as much as possible. The selection trend of the target deviation probability is reflected in the divergence of the path search in the space. In the above obstacle map, there are many obstacles between the starting point and the end point, and the space between obstacles is small. The reasonable reduction of the target deviation probability helps the planning algorithm to search the space and thus search for high-quality paths in a narrow area. It can be seen that the Gaussian surrogate model can effectively fit the changing trend of the corresponding algorithm performance in the marine enviroment on the premise of limited data sets. The optimal parameter values generated by it are interpretable and in accordance with practice.

4 Conclusion and prospects

The marine environment is a huge complex and stochastic system, and USVs are composed of multiple complex subsystems. This leads to the fact that the USV equipment performance is the coupling result among multiple complex systems. Aiming at the above difficulties, this paper combined the algorithm characteristics of the USV autonomous system and proposed two main forms of the intelligent evolution of USVs from the perspective of intelligent algorithms: One is the evolution of algorithm functions and the other is the evolution of algorithm parameters. On this basis, with the obstacle-avoidance algorithm as the example, this paper preliminarily verified the feasibility and effectiveness of the proposed method in improving the equipment performance of USVs based on the test results in the real marine enviroment.

Limited by the insufficient understanding of the generation mechanism of intelligent combat effectiveness of unmanned equipment and the imperfection of testing technology in the real marine environment, this study is still in the experimental exploration stage. In the future, we will develop more extensive and in-depth research aiming at the intelligent evolution mechanism of unmanned marine equipment and testing technology in the real marine enviroment. The following research suggestions are proposed for the intelligent evolution of USVs.

The first one is the study on quantitative models of objective functions for USVs' intelligent evolution. As the USV equipment performance is the result of a complex environment coupled with multiple algorithms, it is difficult to describe objective functions of the intelligent evolution by analytical methods. Therefore, it is the premise for realizing intelligent evolution to propose quantitative models of objective functions of the intelligent evolution based on the generation mechanism of intelligent combat effectiveness of unmanned equipment.

The second one is the study on the construction method of machine learning models for USV's intelligent evolution. The underlying layer of machine learning is composed of various linear or nonlinear mathematical regression models, which are also called hyperparameters in machine learning. Many studies have proved that different hyperparameters show completely different results when facing different learning objects. Therefore, exploring the interaction mechanism between these hyperparameters and the USV equipment performance and further proposing the construction method of machine learning models is the path to realize intelligent evolution.

The third one is the study on efficient acquisition methods for learning data of USVs' intelligent evolution. The test of large and medium-sized USV in the real marine enviroment is costly and time-consuming, and a single test has a complicated process. Researchers should reasonably conduct representative tests according to the characteristics of USV systems. A large number of high-quality learning data sets are the raw material for USVs' intelligent evolution. Thus, it is the guarantee for the realization of intelligent evolution to study the formulation of standard testing subjects as well as the collection and processing of test data based on the construction of test sites for marine unmanned equipment in the real marine enviroment.

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多约束条件下无人艇和无人机集群协同航迹规划

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摘　要:［目的］为实现海上无人集群在执行任务过程中的安全航行和通信保持,开展无人艇(USV)和无人机(UAV)集群协同航迹规划问题的研究。［方法］采用禁入和禁出地理围栏进行场景建模,将规避威胁和障碍问题转化为地理围栏约束。针对平台之间的碰撞冲突和通信连接问题,提出基于时序检测的碰撞冲突和通信保持约束判断准则。以集群平均航行时间为航迹优化函数,将多约束条件转化为惩罚函数,采用自适应差分进化算法进行优化求解。［结果］仿真结果表明,所提方法能够在威胁和障碍环境中保持无人艇和无人机集群的安全航行和通信连接,并在满足多约束的条件下实现集群平均航行时间最短。［结论］该方法可用于海上无人集群面对威胁和障碍环境时的离线航迹规划,具有一定的应用价值。

关键词: 无人艇; 无人机; 海上无人集群; 协同航迹规划

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基于机器学习的实海域无人艇避碰算法智能演进方法

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摘　要:［目的］无人艇(USV)效能是指在给定时间内的特定海域完成指定任务的能力,是多层次多技术节点耦合作用的结果,而针对单一技术节点的传统优化方法,对无人艇效能的提升效果有限。［方法］针对无人艇自主系统的特点,从智能算法的角度,提出无人艇智能演进的2种主要形式:一是算法函数;二是算法参数。在此基础上,给出基于机器学习的无人艇智能演进方法,设计一种可演进的无人艇自主系统控制体系架构,并在实海域测试。［结果］以无人艇避碰算法为例,基于实海域测试结果,初步验证了所提方法在提升无人艇效能方面的可行性与有效性。［结论］基于机器学习的无人艇智能演进方法是持续提升无人艇效能的有效途径,具有较高研究价值和应用意义。

关键词: 无人艇; 智能演进; 实海域测试; 机器学习