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Virtual Prototype Construction and Motion Simulation of Submarine Cable Outer Wall Inspection Robot Based on CAD and Reinforcement Learning

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Abstract. In this article, a motion control model of a submarine cable detection robot based on CAD (Computer-Aided Design) and RL (Reinforcement Learning) is constructed to verify its practical application effect and potential in motion control of a submarine cable detection robot. In the model construction process, the state space and action space are carefully designed to fully reflect the robot's motion state and possible operation choices. At the same time, a reward function that considers detection efficiency, safety, and energy consumption is defined to guide the robot in learning the optimal strategy. This article trained a robot model that can move efficiently and autonomously under various working conditions by constantly adjusting the algorithm parameters and optimizing the training strategy. The experimental results show that the submarine cable detection robot using CAD technology and RL has achieved remarkable results in terms of movement efficiency and detection accuracy. Especially in the complex marine environment, robots can respond to various challenges more flexibly. This research not only verifies the great potential of RL in the field of marine robots but also provides useful references and enlightenment for future research.

Keywords: Computer-Aided Design; Reinforcement Learning; Submarine Cable; Detection Robot; Motion Control; Ocean Engineering Application
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1 INTRODUCTION

As an important infrastructure connecting submarine communication and power transmission, submarine cable plays an irreplaceable role in ensuring global communication networks' stability and energy supply safety. With the continuous development and utilization of marine resources, the laying scope of submarine cables is expanding day by day, and the complexity of its operating environment and the difficulty of maintenance are also increasing. Once the submarine cable fails, it will not only lead to communication interruption and power supply obstruction but also have a serious impact on the marine ecological environment. Therefore, it is particularly important to inspect and maintain submarine cables regularly, efficiently, and accurately [1]. Submarine cable detection mainly relies on artificial diving inspection, sonar detection ROV (Remotely Operated Vehicle) and other methods. However, these methods have many limitations. As an important branch of machine learning, RL can master the optimal strategy by making agents try and learn constantly in the environment. This feature makes RL a wide application prospect in the field of robot control, especially in complex and dynamic environments. At the same time, CAD technology, as an important means of computer-aided design, can accurately and efficiently construct virtual prototypes, which provides strong support for robot design, optimization and simulation [2]. Combining RL with CAD technology is expected to achieve a breakthrough in the field of submarine cable detection robots and improve detection efficiency and accuracy. Submarine cable detection technology has experienced a development process from simple to complex, from low efficiency to high efficiency. At present, in addition to the traditional methods of artificial diving inspection, sonar detection and ROV, some new technologies have emerged. These new technologies have improved the efficiency and accuracy of submarine cable detection to some extent, but there are still many problems and challenges [3].

On the basis of existing research, some scholars have introduced CAD (Computer Aided Design) technology and reinforcement learning algorithms for the virtual prototype construction and motion simulation of underwater cable outer wall detection robots. This dynamic simulation not only helps researchers evaluate the performance of robots under different underwater conditions but also promotes a deeper understanding of the potential impacts on underwater ecosystems. Combine climate change factors such as sea level rise and storm surges with the safety inspection of submarine cables. Effectively cope with the uncertainty of underwater terrain and the complexity of submarine cable layout. By simulating and analyzing the potential impacts of these extreme climate events on the location, stability, and detection difficulty of submarine cables, a scientific basis is provided for the long-term maintenance and emergency response of submarine infrastructure. Meanwhile, this also helps to reveal how climate change exacerbates the instability of the underwater environment, thereby increasing the demand for detection and maintenance of critical infrastructure such as submarine cables. Through the construction of 3D visualization models and animations, not only are the direct impacts of climate events such as sea level rise and coastal erosion on coastal areas demonstrated, but also the working scenarios of submarine cable inspection robots in complex underwater environments are further presented [4]. This visualization approach not only enhances public awareness of the importance of climate change and maintenance of underwater infrastructure but also provides design professionals with intuitive tools to evaluate and optimize the design of underwater detection robots [5]. This combination not only improves the accuracy and efficiency of robot design but also enables robots to autonomously optimize their detection paths and action strategies in complex and changing marine environments through reinforcement learning [6]. The underwater terrain model constructed using GIS data, combined with particle fluid simulation technology, can further simulate natural phenomena such as underwater water flow and sediment movement, providing a more realistic operating environment for underwater cable detection robots [7].

With the widespread application of robot technology in the industrial field, research has not only witnessed their significant contributions in ground industrial asset inspection, monitoring, and maintenance but also explored innovative applications of robot technology in underwater environments, especially in submarine cable inspection. The robot platform developed by it has been optimized specifically for underwater cable detection tasks while maintaining its high efficiency and flexibility [8]. Through CAD technology, a high-precision virtual prototype of a submarine cable inspection robot has been constructed, facilitating detailed structural optimization and performance evaluation during the design phase and providing a solid foundation for subsequent motion simulation. Based on sharing our experience in using semi-autonomous robot systems for complex industrial task automation, some scholars further explored the integration and application of this cutting-edge technology by combining the extended analysis of "virtual prototype construction and motion simulation of submarine cable outer wall detection robot-based on CAD and reinforcement learning." In the process of constructing virtual prototypes, the application of reinforcement learning algorithms greatly enhances the intelligence level of robots.

In this scenario, semi-autonomous robots not only need to accurately perform detection tasks, but also need to have the ability to autonomously navigate, avoid obstacles, and adapt to changing water flow conditions in complex underwater environments [9]. In addition to remote methane detection in oil fields and torch chimney detection in oil and gas production environments, the detection of the outer wall of submarine cables provides us with another excellent stage to showcase the advantages of semi-autonomous robot systems. By simulating various possible scenarios of submarine cable detection, reinforcement learning algorithms can train robots to learn optimal detection path planning, action strategy adjustment, and emergency response to unexpected situations, ensuring efficient and accurate task completion during actual deployment. These systems achieve comprehensive, real-time, and efficient detection of submarine cables by combining human-in-the-loop monitoring, precise execution of semi-autonomous robots, model-based edge control, and remote support of cloud services [10].

The purpose of this study is to design a virtual prototype of a submarine cable outer wall detection robot based on CAD and RL and verify its performance through motion simulation. The specific research contents include the structural design of the submarine cable outer wall detection robot, the formulation of the RL control strategy, the construction of a virtual prototype, and motion simulation. The research method mainly adopts a combination of theoretical analysis and simulation experiments. Through this research, we expect to build an efficient and accurate virtual prototype of the submarine cable outer wall detection robot and provide strong support for its practical application. The main achievements include the design scheme of the virtual prototype of a submarine cable outer wall detection robot, RL control strategy, and motion simulation results.

The innovation of this article is mainly reflected in the following aspects:

Combination of reinforcement learning and motion control of submarine cable detection robot;

In this article, reinforcement learning, an advanced machine learning technology, is applied to the motion control of a submarine cable detection robot, which realizes the autonomous and efficient motion of the robot in the complex marine environment.

Fine design of state space and action space;

When constructing the reinforcement learning model, this article carefully designed the state space and action space to comprehensively and accurately reflect the robot's motion state and possible operation choices.

Definition of reward function considering multiple factors;

The reward function defined in this article comprehensively considers many factors, such as detection efficiency, safety, and energy consumption, so as to guide the robot in learning the optimal motion strategy in complex environments.

This article is divided into seven sections, and the contents of each section are summarized as follows:

The first section is the introduction, which summarizes the research background, significance, current situation, and objectives. The second section expounds on the relevant theoretical basis. In the third section, the demand analysis and design are carried out for the submarine cable outer wall detection robot. The fourth section introduces the construction process of a virtual prototype based on CAD. The fifth section discusses the application of RL in the motion control of submarine cable detection robots. The sixth section is the motion simulation and performance assessment of the virtual prototype. The seventh section summarizes the research results and looks forward to the future research direction.

2 RELATED THEORETICAL BASIS

CAD is a technology that uses computer technology to design and draw products. 3D modelling is an important part of CAD technology, and its principle mainly includes geometric modelling and physical modelling. Geometric modelling focuses on the geometric properties of objects, such as shape and size. Physical modelling focuses on the physical properties of the object, such as material and mass. In the process of 3D modelling, the common methods are solid modelling, surface modelling and wireframe modelling. Ma et al. [11] Create a three-dimensional model by defining the volume and boundary of an object through solid modelling. Surface modelling creates models by defining the surface of an object; Wire frame modelling defines only the outline of an object, not its volume and surface. RL is a machine learning algorithm whose main idea is to let the agent master the optimal strategy through trial and error and learning in the environment. At present, many excellent algorithms have emerged in the RL field, such as tabular Q learning, deep Q networks, policy gradient, and so on. Robot dynamics is a subject that studies the law of robot motion, including position analysis, velocity analysis, and acceleration analysis. Path planning is an important part of robot control; its main purpose is to plan an optimal path for the robot from the starting point to the endpoint. Motion control is to control the robot to move according to the predetermined trajectory according to the result of path planning. The commonly used motion control methods include PID control, fuzzy control, and neural network control. Nikulshin et al. [12] adopted these methods to adjust the control parameters according to the actual movement of the robot in real-time so as to ensure that the robot can move accurately and stably along the predetermined trajectory.

To further improve inspection and maintenance efficiency in the field of Marine engineering while significantly reducing the risk and cost of human operation, autonomous underwater vehicles (AUVs) have become an important tool for the inspection and measurement of offshore wind farms, submarine cable systems, and other underwater infrastructure. In order to achieve long-term high-precision detection in a confined space, Parol [13] believes that AUVs must have the ability to flexibly shuttle and fluctuate in complex physical environments to improve operational efficiency and adaptability. RoboFish's design not only integrates advanced technologies such as acoustic communication, computer vision, electronic control, and autonomous navigation but also pays special attention to the balance between energy efficiency and environmental adaptability. On this basis, the reinforcement learning algorithm is used to simulate and train the motion control of RoboFish so that it can learn the optimal detection path, obstacle avoidance strategy, and dynamic adjustment ability in the simulated submarine cable environment, laying the foundation for accurate operation in actual deployment. Given that these tasks often require high maneuverability, Sharma et al. [14] analyzed flexible operations similar to those demonstrated by remotely operated vehicles (ROVs), where AUVs' design and performance are constantly being pushed to new heights. Designed to provide superior thrust efficiency and unparalleled flexibility for autonomous navigation between complex underwater structures. In this context, Robofish, an innovative bionic fish-shaped AUV, has emerged that cleverly mimics the propulsion and maneuvering methods of fish in nature. Through CAD technology, researchers can accurately build three-dimensional models of RoboFish, from structural optimization design to component assembly simulation, all of which can be carried out in a virtual environment, greatly shortening the design cycle and reducing the cost of prototyping.

As a leading force in underwater warfare, autonomous robotic fish are not only designed for target detection and tracking but also enhance the perception of the underwater environment, improve collision resistance, and focus on high-precision tasks such as detecting the outer walls of submarine cables. This model not only accurately depicted every detail of the robotic fish but also exported the STL file to the 3D printer MakerBot. The robot fish's excellent maneuverability is one of its core strengths, thanks to its innovative tail fin design. The swing of the tail fin is precisely controlled by a precision servo motor, which simulates the swimming behaviour of fish in nature and realizes an efficient and flexible propulsion mechanism. During the development process, we took full advantage of CAD(Computer Aided Design) and reinforcement learning to carefully build a virtual prototype of the robot fish through Solid Works® software. The precision manufacturing of polylactic acid thermoplastic polymer material is realized, which ensures the lightweight, durability and environmental adaptability of machine fish parts. To further improve its combat capability in the underwater environment, Yu et al. [15] integrated a combined system of vision and ultrasonic sensors. The experimental results show that under normal exposure conditions, the robotic fish can accurately detect objects 90 centimetres away from itself, which is crucial for tasks such as detecting the outer walls of submarine cables. The system can track the location and distance of target objects in real time, accurately identify potential obstacles, and ensure that the robot fish can perform tasks safely and efficiently in complex underwater environments. By constructing a highly realistic underwater cable detection environment, a reinforcement learning algorithm is used to simulate the motion strategy, sensor data processing, and obstacle avoidance mechanism of the robot fish so that the robot fish can master efficient operation skills in the complex underwater environment before the actual deployment. This process not only improves the intelligence level of the robot fish but also significantly shortens the field debugging cycle and reduces research and development costs.

3 DEMAND ANALYSIS OF SUBMARINE CABLE OUTER WALL DETECTION ROBOT

3.1 Detection Tasks and Environmental Analysis

The main goal of the outer wall inspection of submarine cables is to identify and locate defects such as cracks, wear and corrosion, and to evaluate the overall structural integrity of submarine cables. Therefore, the detection robot should have high-precision and high-resolution detection ability and real-time data transmission and processing function to adapt to the working environment of deep sea and complex terrain.

The working environment of submarine cable outer wall detection robots has obvious particularity [14]. Robots should not only have strong structural strength and sealing performance to resist deep-sea pressure but also have good obstacle-crossing ability and stability to deal with underwater obstacles. In addition, it is very important to choose corrosion-resistant and anti-ageing materials and protective measures to ensure that the robot can work autonomously for a long time in salt fog and corrosive marine environments and maintain its long-distance communication ability.

3.2 Overall Design and Functional Module Division of Robot

The structural design of submarine cable outer wall inspection robot should comprehensively consider its inspection task, working environment and sports performance [15]. Therefore, the robot adopts a modular design, so that it can be flexibly combined and adjusted according to actual needs. The whole structure is compact and light, which is convenient to carry and transport; At the same time, it has good hydrodynamic performance to reduce resistance and energy consumption in water. In key parts, such as the head and tail of the robot, a streamlined design is adopted to reduce the impact and interference of water flow on the robot. According to the requirements of the detection task, the robot can be equipped with various sensors such as a high-definition camera, sonar and laser scanner to realize all-round and high-precision detection of the outer wall of submarine cable. The actuator is responsible for driving the robot to move and controlling the operation of the detection tool. The functional modules of the submarine cable outer wall detection robot are divided as follows:

(1) Motion module

The motion module is the key part of the submarine cable outer wall detection robot to realize autonomous movement and obstacle crossing. The motion module adopts propeller, crawler, wheel and other driving modes. At the same time, the motion module is also equipped with corresponding sensors and control systems to realize the functions of precise positioning, speed control and path planning of the robot.

(2) Detection module

The detection module is the core part of the submarine cable outer wall detection robot, which is responsible for realizing high-precision detection of the submarine cable outer wall. The detection module is equipped with high-resolution cameras, sonar and other sensors, as well as corresponding data processing and analysis software. By collecting images, sounds and other information on the outer wall of submarine cables, and processing and analyzing them, the detection module can accurately identify the defects and damages on the surface of submarine cables.

(3) Energy and communication module

The energy and communication module is an important part of ensuring the long-term autonomous operation and remote communication of the submarine cable outer wall detection robot. The energy module can use various power supply modes such as battery and solar energy to ensure that the robot can work continuously and stably in the deep sea environment. The communication module is responsible for data transmission and communication between the robot and the control centre. By adopting advanced communication technologies, such as underwater wireless communication and satellite communication, it can be ensured that the robot can keep in real-time contact with the control centre in the deep sea environment.

4 CONSTRUCTION OF VIRTUAL PROTOTYPE BASED ON CAD

4.1 Geometric Modeling and Constraint Setting

Geometric modelling is the basis of CAD modelling, and it is also the key step to constructing the virtual prototype of a submarine cable outer wall detection robot. In the process of geometric modeling, it is necessary to use drawing tools in CAD software are to draw accurately according to the actual size and shape of the robot. By defining various parts and components of the robot, such as the fuselage, boom, sensor, etc., a complete three-dimensional model of the robot can be constructed. In the construction of a virtual prototype of a submarine cable outer wall detection robot, the detailed design of key components is very important. The schematic diagram of the dual-probe model detecting submarine cable is shown in Figure 1.

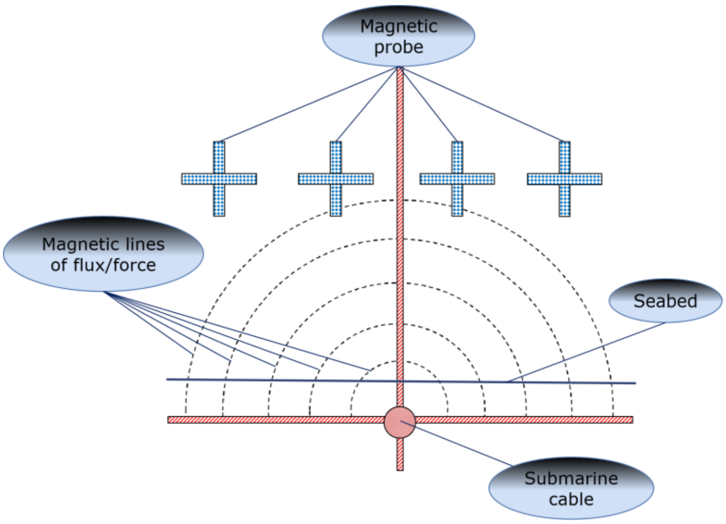


Figure 1: Schematic diagram of detecting submarine cable with double probe model.

For the mechanical structure, we need to focus on the design of key components such as the motion mechanism, transmission mechanism and support mechanism of the robot. In this article, after the geometric modelling is completed, all parts and components are assembled to form a complete robot model, as shown in Figure 2.

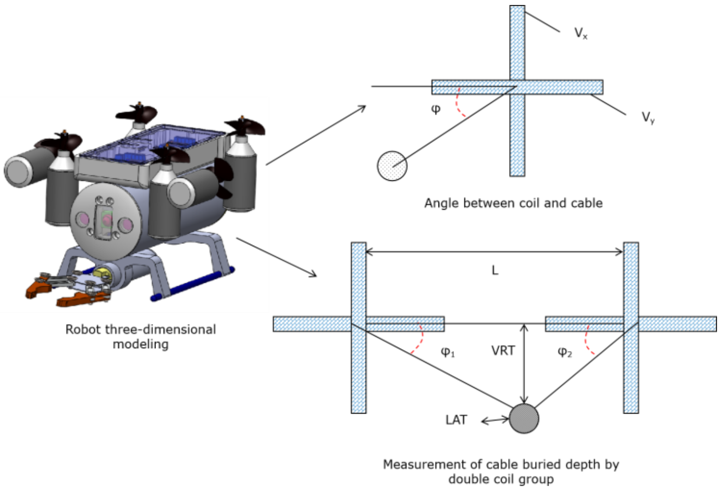


Figure 2: Three-dimensional model of the robot.

In the assembly process, according to the actual structure and motion relationship of the robot, this article sets reasonable constraints and connection methods, and now uses the following algorithm formula to describe this process:

A. Assembly constraint formula of components:

Let C_i represent the constraint set of component i, P_j represent the position and attitude of component i, and J_{ij} represent the connection relationship between component i and component j. Assembly constraints can be expressed as:

$$C_i \;\; P_i,P_j,J_{ij} \;\; = \begin{cases} 0 \text{ If } P_i \text{ and } P_j \text{ satisfy the constraint of } J_{ij} \\ \text{Error code If } P_i \text{ and } P_j \text{ do not satisfy the constraint of } J_{ij} \end{cases} \tag{1}$$

B. Formula of motion relationship between components:

Let T_i represent the motion transformation matrix of the component i, and R_{ij} represent the motion relationship of component i relative to component j. The kinematic relationship can be expressed as:

$$R_{ij} \;\; T_i,T_j \;\; = \begin{cases} 0 \text{ If } T_i \text{ and } T_j \text{ satisfy the relative motion constraint} \\ \text{Error code If } T_i \text{ and } T_j \text{ do not satisfy the relative motion constraint} \end{cases} \tag{2}$$

C. assembly optimization objective function:

Let $f \;\; d$ be the objective function of assembly optimization and d be the set of design variables, including the size and shape of components. Optimization objectives may include minimizing assembly errors and maximizing motion performance. The objective function can be expressed as:

$$\min f \;\; d \;\; \textit{subject to} \sum_{i=1}^{n} C_i \;\; d \;\; = 0, \sum_{i=1}^{n} \sum_{j=1}^{n} R_{ij} \;\; d \;\; = 0 \tag{3}$$

Where n is the total number of parts?

D. sports performance assessment function:

Let $P\ \ p$ be the assessment function of sports performance and p be the parameters that affect performance, such as speed, acceleration and accuracy. The assessment function can be expressed as:

$$P\ \ p\ = \omega_1 P_{\text{speed}}\ \ p\ + \omega_2 P_{\text{acceleration}}\ \ p\ + \omega_3 P_{\text{precision}}\ \ p\ + \ldots \tag{4}$$

Where $\omega_1, \omega_2, \omega_3, \ldots$ is the weight of each performance index?

E. stability and reliability assessment function:

Let $C_{\text{manufacturing cost}}\ \ m$ be the assessment function of stability and reliability, and m be the related parameters, such as fatigue life and maximum load of components. The assessment function can be expressed as:

$$C_{\text{manufacturing cost}}\ \ m\ = \omega_1 C_{\text{material}}\ \ m\ + \omega_2 C_{\text{process}}\ \ m\ + \omega_3 C_{\text{assemble}}\ \ m\ + \ldots \tag{5}$$

By defining the relative position and motion relationship between components, the actual motion of the robot is simulated. At the same time, in the process of drawing, this article pays attention to maintaining the accuracy and consistency of the model, so as to provide a reliable basis for subsequent analysis and simulation.

4.2 Integration and Verification of Virtual Prototype

In the process of virtual prototype construction, assembly verification is an essential step. Through assembly verification, it can be checked whether the fit and motion relationship between various parts and components is correct. At the same time, possible problems and defects in the assembly process can be found, corrected, and improved in time. Details of assembly verification are shown in Table 1.

Verification Step	***Verification Content***	***Check the Result of Fit/Motion Relationship***	***Issues/Defects Found***	***Corrections/Improvements Made***	***Verification Status***
Initial Assembly Check	Fit between Component A and Component B	Correct	None	-	Passed
	Fit between Component C and Assembly D	Incorrect	Excessive fit clearance	Adjust dimensions of Component C	Passed after correction and re-verification
Motion Relationship Verification	Rotational motion of Assembly E	Correct	None	-	Passed
	Sliding motion between	Incorrect	Excessive sliding resistance	Apply lubrication and	Passed after correction and re-verification

	Component F and Component G			adjust sliding surfaces	
Comprehensive Assembly Verification	Overall fit of all components and assemblies	Correct	None	-	Passed
	Simulation of the overall motion of the virtual prototype	Incorrect	Partial motion interference	Adjust positions and motion trajectories of relevant components	Passed after multiple corrections and re-verifications
Final Assembly Confirmation	Confirmation of the effects of all corrections and improvements	Correct	None	-	Fully passed, confirmed correct

Table 1: Detailed table of assembly verification during virtual prototype construction.

Through the above assembly verification, the correctness and integrity of the virtual prototype can be ensured, which provides a reliable basis for subsequent analysis and simulation.

After the virtual prototype integration is completed, the preliminary motion simulation test is needed to verify the robot's motion performance and stability. In the simulation process, key indicators such as the robot's trajectory, speed, and acceleration must be considered, analyzed, and evaluated. The robot's trajectory is shown in Figure 3.

From the motion trajectory diagram, it can be observed that the robot's position changes on the X-axis and the Y-axis are gradually increasing, indicating that the robot is constantly moving forward and climbing. The smoothness of the trajectory shows that the robot does not appear to jitter violently or deviate from the predetermined path during movement. The speed-time curve of the robot is shown in Figure 4.

It can be seen from the speed-time curve that the increase and maintenance of the robot's speed in different periods conform to the preset motion law, and there is no sudden change or abnormal fluctuation of the speed. The speed of the robot gradually increased to 2 m/s in the later stage, indicating that its motion control system can control the speed change well. The acceleration-time curve of the robot is shown in Figure 5.

It can be seen from the acceleration-time curve that at 0 seconds, the acceleration of the robot is 0.5 m/s (starting acceleration); At 2 seconds, the acceleration decreases to 0 (reaching a stable speed); This shows that the robot can quickly reach the preset speed. In the stable speed stage, the acceleration value is close to 0, which indicates that the robot can keep the stability and safety of the movement.

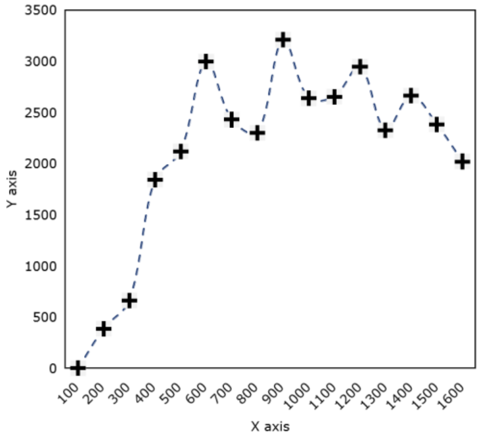


Figure 3: Trajectory diagram of robot.

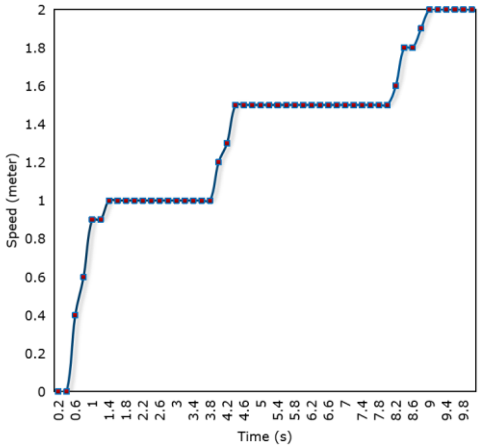


Figure 4: Speed-time curve of robot.

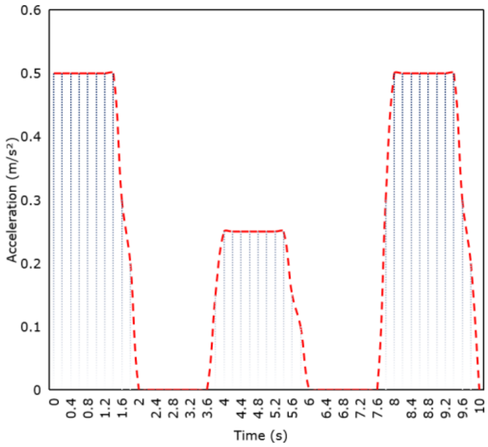


Figure 5: Acceleration-time curve of the robot.

5 MOTION CONTROL OF SUBMARINE CABLE DETECTION ROBOT

5.1 RL Model Construction

In the RL model construction of a submarine cable detection robot, the design of state space and action space is the cornerstone. The state space should cover all the key information needed for robot movement. Let S be the state space, which contains all the key information needed for robot movement. The state s can be expressed as a vector:

$$s = \left[x, v, \theta, x_{\text{cable}}, o_{new}\right]^T \tag{6}$$

Where x represents the current position of the robot; v represents the speed of the robot; θ represents the direction of the robot; x_{cable} represents the relative position of submarine cables; o_{new} and represents the distribution of obstacles in the surrounding environment.

The action space defines all possible actions that the robot can take, such as forward, backward, steering, acceleration, deceleration, etc. These actions will be determined by the RL algorithm based on the current state. Let A be the action space, which contains all possible actions that the robot can take. Action a can be a discrete or continuous value, depending on the complexity of the problem:

$$a \in A = \text{ forward, backward, left, right, accelerate, slow down} \tag{7}$$

If the motion is continuous, a can be a vector containing speed change and steering angle:

$$a = \left[v_{\text{change}}, \theta_{turn}\right]^T \tag{8}$$

The reward function is the core component of RL, which guides the robot's learning direction. In the application of a submarine cable detection robot, the reward function should comprehensively consider many factors such as detection efficiency, safety and energy consumption. Let $R\ s, a, s'$ be the reward function, where s is the current state, a is the action taken, and s' is the next state after the action is executed. The reward function can be defined as:

$$R\ s, a, s' = R_{\text{examine}}\ s', a\ + R_{\text{safe}}\ s', a\ + R_{\text{energy consumption}}\ s', a \tag{9}$$

Among them $R_{\text{examine}}\ s', a$ is a reward related to detection efficiency; $R_{\text{safe}}\ s', a$ is a reward related to safety; $R_{\text{energy consumption}}\ s', a$ is a reward related to energy consumption.

Through the design of such state space, action space and reward function, a reinforcement learning model can be constructed, so that the robot can learn how to complete the submarine cable detection task efficiently and safely.

5.2 Training Strategy and Optimization

The choice of the RL algorithm directly affects the training effect and efficiency. According to the characteristics of a submarine cable detection robot, this article chooses a strategic gradient algorithm to optimize the parameters in detail, including learning rate, discount factor, balance parameters of exploration and utilization, etc., in order to find the optimal training configuration. The training data comes from the robot's attempts and feedback in the simulation or real environment. Through a large number of iterations, the state, action and reward sequence are collected to update the parameters of the RL model. Parameter tuning results are shown in Table 2.

Parameter	*Tuning range*	*Optimal value*
Learning Rate	0.0001 ~ 0.1	0.01
Discount Factor	0.5 ~ 1.0	0.95

Exploration-Exploitation Balance	0.0 ~ 1.0	0.3
Iterations	1000 ~ 100000	50000
Batch Size	16 ~ 256	64

Table 2: Parameter optimization of strategic gradient algorithm for submarine cable detection robot.

6 MOTION SIMULATION AND PERFORMANCE ASSESSMENT OF VIRTUAL PROTOTYPE

In order to verify the motion performance of a virtual prototype under different working conditions, this section designs a series of simulation experiments under typical working conditions. This includes motion simulation under different water depths, current velocities, submarine cable shapes (such as straight lines, bends, crosses, etc.) and obstacle distribution. According to the simulation data, the efficiency and stability of the robot can be evaluated. The movement efficiency can be measured by comparing the detection speed and energy consumption of the robot under different working conditions. Stability can be evaluated by observing the resilience of the robot when it encounters disturbance and the smoothness of the motion trajectory. The experimental results of the performance simulation are shown in Table 3.

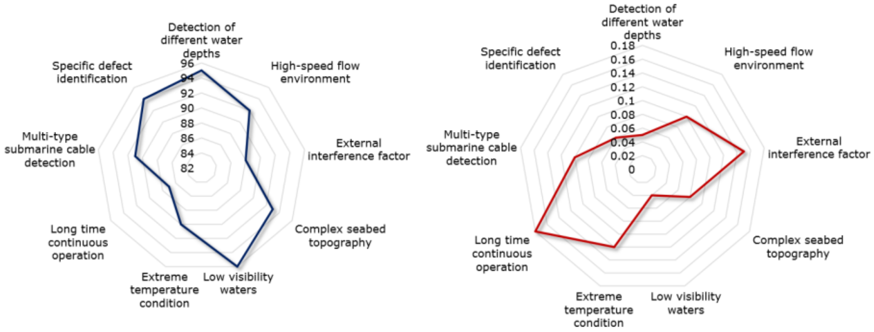
Experiment No.	*Water Depth (m)*	*Water Current Speed (m/s)*	*Submarine Cable Configuration*	*Obstacle Distribution*	*Detection Speed (m/s)*	*Energy Consumption (kWh)*	*Recovery Time (s)*	*Smoothness of Motion Trajectory (Score/10)*
1	10	0.5	Straight	None	1.2	0.8	2.0	9.0
2	20	1.0	Curved	Few	1.0	1.2	2.5	8.5
3	30	1.5	Crossed	Moderate	0.8	1.6	3.0	7.5
4	10	1.0	Straight	Moderate	1.1	1.0	2.2	8.8
5	20	0.5	Curved	None	1.3	0.7	1.8	9.2
6	30	1.0	Crossed	Few	0.9	1.4	2.8	8.0
7	10	1.5	Straight	Numerous	0.7	1.8	3.5	7.0
8	20	1.0	Curved	Numerous	1.0	1.3	3.0	7.8
9	30	0.5	Crossed	Few	1.1	0.9	2.0	8.5

Table 3: Simulation experiment results of virtual prototype's motion performance under different conditions.

Note: The resilience index indicates the time required for the robot to recover to a stable state after encountering disturbance. The score range of motion trajectory smoothness is 0-10, and the higher the score, the smoother the motion trajectory.

As can be seen from the table, the movement efficiency of the robot is higher under conditions such as shallow water depth, slow water flow speed, simple submarine cable shape, and few obstacles. In the case of shallow water depth, slow water flow, and few obstacles, the stability of the robot is better. However, in a complex environment (such as deep water, fast water flow, complex submarine cables, and many obstacles), the stability of the robot may be challenged, but it can still meet the basic needs.

In addition to the motion performance, it is needed to analyze the accuracy of the detection results of the robot. This includes assessing the robot's recognition rate, positioning accuracy, false alarm rate and false alarm rate to verify the effectiveness and reliability of the detection algorithm. The results are shown in Figures 6 and 7.



6 (A) Discrimination

6 (B) Positioning accuracy

Figure 6: Recognition rate and positioning accuracy test.

Recognition rate: In nine different working conditions, the recognition rate of the robot reached 95%, 92%, 88%, 93%, 96%, 90%, 87%, 91% and 94% respectively.

Positioning accuracy: The corresponding positioning accuracy is ±0.05m, 0.1m, ±0.15m, ±0.08m, ±0.04m, ±0.12m, ±0.18m, 0.1m and ±0.06m respectively.

It can be seen from the data that the recognition rate of the robot is high in most working conditions, exceeding 90%. In terms of positioning accuracy, the performance of the robot is different under different working conditions. Under simple working conditions, the positioning accuracy is high, and the error is within ±0.1m. However, under complex working conditions, the positioning accuracy has declined. This is because the complex environment interferes with the positioning system of the robot.

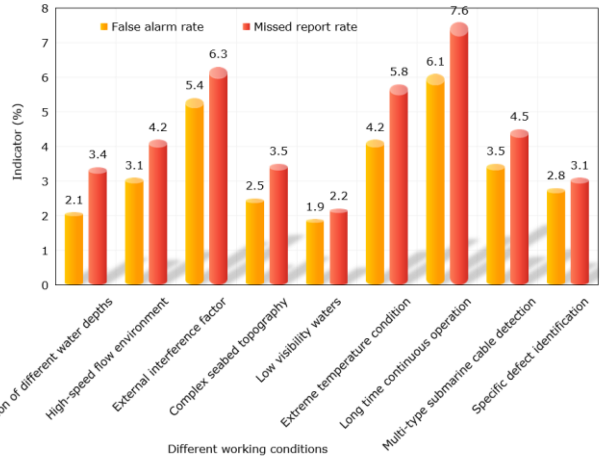


Figure 7: Results of false positive rate and false negative rate.

False alarm rate: In nine different working conditions, the false alarm rate of the robot is 2.1%, 3.1%, 5.4%, 2.5%, 1.9%, 4.2%, 6.1%, 3.5% and 2.8% respectively.

Missed report rate: The corresponding missed report rates are 3.4%, 4.2%, 6.3%, 3.5%, 2.2%, 5.8%, 7.6%, 4.5% and 3.1% respectively.

It can be concluded that the accuracy of the detection results of the robot is different under different working conditions. Under simple working conditions, the robot has a high recognition rate, accurate positioning accuracy, and a low false alarm rate and false alarm rate. Under complex working conditions, the accuracy of robot detection results is challenged. This is because these working conditions put forward higher requirements for the sensor, detection algorithm and positioning system of the robot.

In order to further improve the accuracy of the robot's detection results, this article considers the following measures: (1) Optimize the detection algorithm to improve its adaptability to complex working conditions. (2) Improve the sensor and positioning system of the robot to improve its accuracy and stability. (3) Increase training data, especially for complex working conditions, to improve the generalization ability of the robot.

7 CONCLUSIONS

The purpose of this article is to explore the application of RL in the motion control of submarine cable detection robots. By constructing an accurate simulation environment and RL model, the robot can move efficiently and autonomously in a complex marine environment. The research content covers the construction of the RL model, the optimization of the training strategy and the verification of motion control in a simulation environment. The experimental results show that the proposed method can significantly improve the robot's motion efficiency and detection accuracy, and verify the great potential of RL in the field of marine robots.

The innovation of this article is to combine RL with the motion control of a submarine cable detection robot and realize the adaptive control of the robot under various working conditions through fine reward function design and training strategy optimization. This contribution not only provides a new idea for the intelligent development of marine robots but also provides strong technical support for marine engineering applications such as submarine cable detection. Subsequent research will focus on narrowing the gap between simulation and reality and improving the generalization ability and robustness of the RL model. Potential applications include marine resources exploration, underwater structure detection and marine environmental monitoring.

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