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Working Process Analysis of Submarine Cable Detection Robot Using Machine Vision and Reinforcement Learning

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Abstract. The purpose of this study is to explore the CAD modelling and working process of a submarine cable detection robot that integrates machine vision (MV) and reinforcement learning (RL). Aiming at the complexity and high efficiency of submarine cable inspection, this article proposes a method combining YOLO algorithm improvement and RL mechanism. By lightweight optimization of the YOLO-V3 algorithm, small target detection branches are removed to adapt to the linear characteristics and large proportion of submarine cables, and an efficient target detection network is constructed. At the same time, the RL mechanism is introduced to optimize the robot's autonomous navigation and defect identification strategy. The results show that compared with the traditional MV method, the accuracy of submarine cable defect identification is improved by 11.2%, reaching 92.5%. After long-term operation, the error is reduced by 27.46%. The introduction of the RL mechanism also significantly improves the robot's recognition accuracy in the case of unknown scenes and many interferences. To sum up, this article successfully applies MV and RL technology to submarine cable detection robots and realizes efficient and accurate defect detection.

Keywords: Machine Vision; Strengthen Learning; Submarine Cable Detection; CAD Modeling; Working Process
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1 INTRODUCTION

Under the background of global energy structure transformation and marine resources development, the submarine cable is the key link between offshore energy facilities and the land power grid. Its safe and stable operation is of inestimable value for ensuring energy supply and promoting the sustainable development of the marine economy [1]. The laying scope of submarine cables is gradually expanding, extending from offshore shallow water to deep ocean, which puts forward higher requirements for cable inspection and maintenance. Traditional patrol inspection methods, such as artificial diving inspection or simple shooting with AUV/UUV, are expensive and inefficient, and it is difficult to cope with the complex and changeable seabed environment, especially the high pressure, low temperature and strong corrosion conditions in the deep sea area, which brings great challenges to patrol inspection [2]. In this context, the research and development of intelligent inspection robots has become an important way to solve the problem of submarine cable inspection. This kind of robot integrates advanced sensor technology, MV, artificial intelligence algorithm and autonomous navigation and control system, and can independently perform inspection tasks in extreme environments, and realize comprehensive, efficient and accurate monitoring of submarine cables. As a key means to perceive the external environment, MV technology can capture the image information of submarine cables in real-time, and identify abnormal situations such as damage, corrosion and foreign body adhesion on the cable surface through image processing and analysis [3]. RL, as an advanced machine learning method, can make the robot optimize the decision-making strategy in the process of trial and error and learning, improve the inspection efficiency and intelligence level, especially in the face of complex and changeable seabed environment, and adjust the inspection path independently to avoid obstacles and ensure the smooth completion of the task. The submarine cable detection robot that combines MV and RL can represent the latest development of intelligent robot technology, and it is also a model of cross-integration of marine engineering technology and artificial intelligence. To achieve this goal, a series of technical problems need to be solved first, including how to design a robot structure adapted to the deep-sea environment, how to develop an efficient and accurate MV algorithm, and how to build an RL model suitable for submarine inspection.

Traditional FFC detection methods are often limited by fixed bounding box regression, making it difficult to accurately capture the complex morphology and non-axis alignment characteristics of FFC. Reinforcement learning algorithms can learn how to effectively identify the position, angle, and state of FFCs in complex underwater environments through continuous trial and error and optimization, thereby improving detection accuracy and efficiency [4]. Introducing reinforcement learning into FFC detection can dynamically adjust detection strategies to adapt to different environmental conditions and changes in FFC layout. This includes the design of the position, angle, and field of view of visual perception components such as cameras and sensors, as well as the development of corresponding image processing software and algorithms. Further refining the application of machine vision technology can not only accurately reflect the physical size and angle information of FFC through oriented bounding boxes, but also enhance the discrimination between FFC and background environment through advanced image processing techniques, especially in complex and cluttered work environments [5]. Through precise CAD modelling, it can be ensured that the machine vision system can fully utilize its efficiency in practical applications and accurately capture image information of submarine cables. In the CAD modelling process of submarine cable detection robots, the layout and integration of machine vision systems can be fully considered. Meanwhile, reinforcement learning can further optimize the parameters and detection logic of the detection model based on the actual operational feedback of the robot, achieving a more intelligent and adaptive detection system. The working process of submarine cable detection robots is complex and varied, involving multiple links such as positioning, recognition, and grasping. Reinforcement learning techniques can play an important role in this process. Meanwhile, reinforcement learning can gradually improve the adaptability and intelligence level of robots in complex environments through continuous trial and error and learning [6]. By setting reasonable reward functions and state spaces, reinforcement learning algorithms can guide robots on how to choose the optimal operation strategy in different underwater environments, such as path planning, detection angle adjustment, grasping force control, etc.

Machine vision technology can be integrated into underwater cable detection robots, capturing real-time images of the underwater environment through high-definition cameras and combining them with image processing algorithms to achieve precise cable positioning [7]. In the CAD modelling stage of submarine cable detection robots, the integration requirements of machine vision and reinforcement learning systems should be fully considered, including sensor layout, camera position, and design of data processing units. In the analysis of the work process, combining the actual operational data of machine vision and reinforcement learning can further optimize the detection strategy and algorithm parameters of the robot. This helps robots quickly locate and track cables in complex underwater terrain, reducing misjudgments and missed detections [8]. Through precise CAD modelling, it is possible to simulate the performance of robots in different underwater environments and evaluate their detection efficiency, accuracy, and fault response capabilities. By utilizing the image processing capabilities of machine vision, it is possible to analyze the morphological changes and color anomalies on the surface of cables in order to preliminarily determine whether there are potential issues such as wear, corrosion, or breakage in the cables. When the robot detects abnormal events on the cable (such as impact or breakage), reinforcement learning algorithms can quickly make decisions based on historical data and current environmental information, such as adjusting detection strategies, issuing alerts, or implementing emergency repair measures. Reinforcement learning algorithms can dynamically adjust the movement path of robots based on the environmental information and task objectives collected in order to avoid obstacles and optimize detection efficiency [9]. By combining the vibration signal of the fibre optic sensor, the health status of the cable can be further confirmed. In submarine cable exploration missions, this means that robots can plan routes more intelligently, ensuring comprehensive coverage of cable areas while reducing energy consumption and time costs. By continuously iterating and providing feedback, the robot can better adapt to the complex and ever-changing underwater environment, improving the intelligence and reliability of underwater cable detection. This intelligent decision-making capability can significantly improve the response speed and accuracy of submarine cable detection [10].

The purpose of this study is to explore the CAD modelling method of submarine cable detection robots integrating MV and RL and provide an intelligent solution for submarine cable inspection. In terms of the MV algorithm, an efficient and accurate image processing and analysis algorithm will be developed according to the characteristics of submarine images to realize accurate identification of submarine cables. In terms of the RL model, an RL framework suitable for submarine inspection will be constructed, and the robot's path-planning ability will be continuously optimized through simulation training and field tests. The significance of this study is to improve the intelligent level of submarine cable inspection by integrating MV and RL technology and provide a strong guarantee for the safe operation and maintenance of marine energy facilities. Through this study, it is expected to provide a set of practical and intelligent solutions for solving the problem of submarine cable inspection.

(1) In this article, an RL framework suitable for submarine cable inspection is constructed. By defining reasonable state space, action space and reward function, the autonomous decision-making of robots in a complex submarine environment is realized.

(2) Transfer learning technology is introduced in the study, which transfers the inspection experience of land or shallow water to deep sea environment, accelerates the training process of the RL model, and improves the convergence speed and generalization ability of the model.

(3) The RL strategy adjustment method based on visual feedback is proposed, which enables the robot to adjust the inspection strategy in real-time according to the cable state detected by MV.

(4) In this study, a method of robot parameter adjustment based on multi-objective optimization is proposed, and the overall improvement of robot performance is realized by comprehensively considering multiple performance indexes.

Organization:

This article expounds the research background, significance and research status at home and abroad, and defines the research content and methods. Then, the CAD modelling process of the robot is introduced, and the application of MV and RL in submarine cable detection is expounded. On this basis, the workflow of the robot is designed, and its performance is assessed through simulation experiments. Finally, the research results are summarized, the research significance is emphasized, and the future research direction is prospected.

2 RELATED WORK

In the CAD modelling stage of the submarine cable detection robot, the integration requirements of machine vision and reinforcement learning systems should be fully considered to design a robot structure that meets the requirements of underwater operations and is easy to maintain and upgrade. Although traditional terahertz technology has shown high sensitivity in detecting humidity inside cables, Shao et al. [11] combined it with machine vision to further improve detection efficiency and accuracy. The machine vision system can capture and analyze image data generated by terahertz pulses in real-time, automatically identify moisture features in the image, and quickly locate water-stained areas inside the cable. In submarine cable detection, machine vision is not limited to two-dimensional image analysis, but can also be combined with depth cameras or laser scanning technology to construct a three-dimensional model of the cable and its surrounding environment. This helps the robot to navigate and locate more accurately while gaining a more comprehensive understanding of the geometric shape of the cable and potential water intrusion paths during the waterproof performance evaluation process. For example, when the robot detects that there may be a high humidity risk in a certain part of the cable, it can automatically increase the detection density of that area or change the detection angle to obtain more detailed internal humidity information. By combining historical data with current detection results, reinforcement learning algorithms can also predict potential fault points in future cables, providing a scientific basis for preventive maintenance. Reinforcement learning algorithms can train underwater cable detection robots to dynamically adjust their detection paths and strategies based on real-time environmental feedback. This can not only reduce the risk of power outages caused by cable failures but also significantly improve the reliability and economy of submarine cable systems. Wu et al. [12] conducted a detailed analysis of the robot's working process by simulating different underwater environmental conditions and cable states in order to evaluate its detection efficiency, accuracy, and adaptability in different situations.

Xu et al. [13] used machine vision technology, combined with specially designed magnetic field-sensitive cameras or sensor arrays, to convert the environmental magnetic field generated by alternating current around cables into visual images or data. Combined with deep learning algorithms, robots can autonomously identify and report potential problems, improving the timeliness and accuracy of maintenance. Reinforcement learning algorithms enable underwater cable detection robots to dynamically adjust their detection path and speed based on real-time environmental feedback in order to complete the current detection task in the best possible way. Machine vision can also be used to detect physical damage, signs of corrosion, or abnormal magnetic field changes on cable surfaces, which may be signs of leakage or imminent failure. Based on these predictions, robots can automatically plan preventive maintenance tasks such as fixed-point detection, cleaning up surrounding debris, or marking cable segments that need to be replaced, thereby further improving the reliability and economy of the power grid. This visualization not only helps to observe the magnetic field distribution directly but also extracts key features through image processing algorithms to accurately calculate the current intensity. Yu et al. [14] combined long-term accumulated current detection data with machine vision observations of cable status, and the reinforcement learning model can predict the future health status and possible fault types of cables. This adaptive capability helps to reduce energy consumption, improve detection efficiency, and minimize potential impacts on underwater ecology.

Machine vision technology can be integrated into underwater cable inspection robots, using high-definition cameras for real-time image monitoring of underwater cables. Reinforcement learning algorithms can train underwater cable detection robots to dynamically adjust their detection paths and strategies based on real-time environmental feedback, including earthquake monitoring data, underwater terrain, obstacle positions, etc. Zhu et al. [15] combined data collected from optical seismic sensors to transform the propagation process of seismic waves in optical cables into visual images or animations using machine vision. This helps researchers better understand the propagation mechanism of seismic waves and the interaction between seismic waves and seabed geological structures, thereby improving the accuracy of earthquake prediction and warning. By combining long-term earthquake monitoring data with real-time information collected by robots, reinforcement learning models can predict potential failure points of submarine cables, such as vulnerable areas susceptible to earthquakes. Based on this, robots can autonomously perform preventive maintenance tasks, such as reinforcing fibre optic cable support structures, cleaning up surrounding debris, or reporting fibre optic cable segments that need to be replaced, thereby ensuring the long-term stable operation of earthquake monitoring systems. Through image processing algorithms, robots can automatically recognize abnormal changes on the surface of optical cables. These anomalies may be precursors of seismic activity or seabed geological changes related to earthquakes. In earthquake monitoring tasks, this means that robots can plan detection routes more intelligently, cover potential seismic activity areas more effectively, and reduce unnecessary energy consumption and mechanical wear.

3 CAD MODELING OF SUBMARINE CABLE DETECTION ROBOT

The overall design of a submarine cable detection robot should comprehensively consider its functional requirements, working environment, and performance requirements. First of all, the robot should have efficient mobility so as to shuttle underwater and conduct a comprehensive inspection of cables freely. Secondly, the robot needs to be equipped with high-precision sensors and cameras to capture the subtle changes on the cable surface. In addition, robots need to have enough stability to cope with the extreme conditions of the deep-sea environment. In underwater photography, water acts as a special medium for light propagation, and this process is not as straightforward as in air because water has a significant absorption and scattering effect on light. The underwater image-forming mechanism is shown in Figure 1.

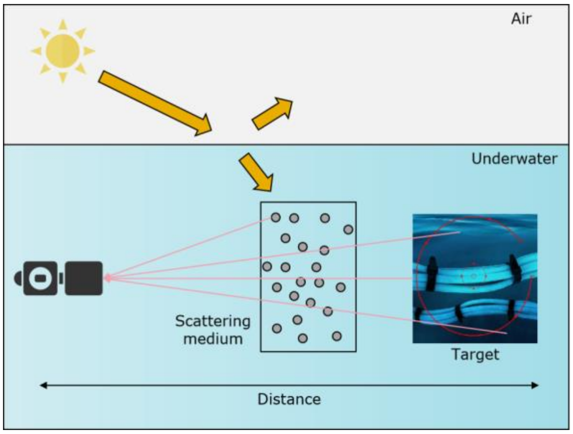

Figure 1: Imaging principle of underwater image.

The attenuation characteristics of light underwater are quite different from those in air, which is mainly due to the absorption ability of water molecules and the scattering effect of suspended particles. Light with different wavelengths will be weakened to varying degrees when penetrating water.

Figure 2 provides a comparison of attenuation rates of light waves with different wavelengths in water and shows the propagation performance of three basic colors of light in water: red, green, and blue. The wavelength of the red wave is about 700 nanometers. Because long-wavelength light is more easily absorbed by water, in deep waters, the red colour tends to be significantly weakened or even disappeared, which leads to the blue colour of underwater images. In contrast, green wave (wavelength is about 546 nm) and Ranbo (wavelength is about 436 nm) have strong propagation ability in water, especially in Ranbo, and their attenuation rate is relatively low.

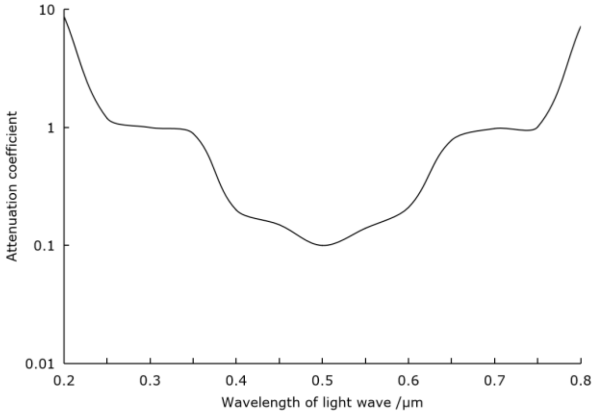

Figure 2: Attenuation rates of light waves of different wavelengths in water.

In CAD modeling, the basic configuration of the robot is first determined, including the main structure, driving system, sensor configuration, and energy supply. The main structure adopts a streamlined design to reduce underwater resistance and improve moving speed. The driving system is selected according to the robot's moving mode and inspection requirements, which may include propeller, propeller, or crawler. In the aspect of sensor configuration, the camera and lighting equipment required by MV, as well as other sensors used for positioning, navigation, and obstacle avoidance, are mainly considered. In the aspect of energy supply, the appropriate energy conversion device is selected according to the working time and power demand of the robot.

The design of the manipulator should consider its flexibility, load capacity, and operating accuracy. A multi-joint structure is adopted to realize the free movement of the manipulator in three-dimensional space. At the same time, by optimizing the joint layout and driving mode, the load capacity and operation accuracy of the manipulator are improved. Cor corrosion-resistant and high-strength alloy materials are selected to ensure the stability of the manipulator in a deep-sea environment.

The camera is the core component of the MV system, and its performance directly affects the quality of image acquisition and the accuracy of subsequent processing. A camera with high resolution, low noise, and wide dynamic range is selected, and suitable lighting equipment is equipped to deal with the problem of insufficient light in deep-sea environments. In addition, the installation position and angle of the camera are optimized to ensure that it can capture comprehensive information on the cable surface.

The design of the propeller needs to consider its thrust, efficiency and noise. The propeller with high efficiency, low noise and easy control is selected, and customized design is carried out according to the moving mode and inspection requirements of the robot. By optimizing the layout and parameter setting of the propeller, the precise control of the robot underwater is realized.

4 DETECTION OF SUBMARINE CABLE DEFECTS BY COMBINING MV AND RL

In the process of submarine cable inspection, accurately and quickly identifying the defects on the cable surface is the key to ensuring the safe operation of the cable. Traditional image processing methods often rely on the characteristics and rules of artificial design, and it is difficult to cope with the complex and changeable seabed environment. With the rapid development of deep learning technology, MV shows great potential in the field of defect detection. In particular, YOLO(You Only Look Once) series algorithms, with their high efficiency and accuracy, have achieved remarkable results in target detection tasks. YOLO algorithm is a kind of target detection algorithm based on a convolutional neural network. Its core idea is to transform the target detection task into a regression problem of single forward transmission, thus achieving extremely high detection speed. Based on YOLO-V1, YOLO-V2 has made many improvements, the most important of which is to adjust the prediction network from 7×7 to 13×13, which improves the detection ability of small targets. YOLO-V3 further divides the prediction network into three branches, which correspond to grids with different sizes (13×13, 26×26, and 52×52), respectively, so as to realize accurate detection of large, medium, and small targets.

Set the seawater depth as h, seawater scattering parameter as s, submarine cable area to be monitored as S, cable medium parameter as j, and infrared spectrum parameters as f. The following formula can be used to calculate the dielectric damage parameters of submarine cables:3

$$\lambda = \frac{s^2 - 1}{\sqrt{j + f + S}} \tag{1}$$

Calculate the possible damage degree of the medium through the feedback medium damage parameters and judge the damage of the submarine cable by using the change of the feedback medium parameters:

$$\begin{cases} \lambda > v, \text{The cable is damaged} \\ \lambda \leq v, \text{The cable is undamaged} \end{cases} \tag{2}$$

N_{new} v is the threshold for judging the damage of submarine cables. By setting a reasonable threshold, the damage situation is judged.

In the specific scene of submarine cable defect detection, cables usually appear as lines in the image, and the proportion is relatively large. This means that the prediction of network branches for small target detection may not be applicable and may even lead to network redundancy and waste of computing resources. Xu et al. proposed a probabilistic abnormal trend detection method based on confidence interval estimation for the abnormal situation of cable-supported bridges. Egorov et al.'s research topic is to determine the functionality of nonwoven polymer materials by spectral modelling and computer-aided prediction of viscoelasticity. This method can also be applied to the quality monitoring of submarine cable materials, providing more accurate data support for cable detection. In this article, based on YOLO-V3, targeted optimization is carried out, and 52×52 grid branches for detecting small targets are removed, as shown in Figure 3, which is the original YOLO-V3 prediction network module, while Figure 4 shows the lightweight prediction network.

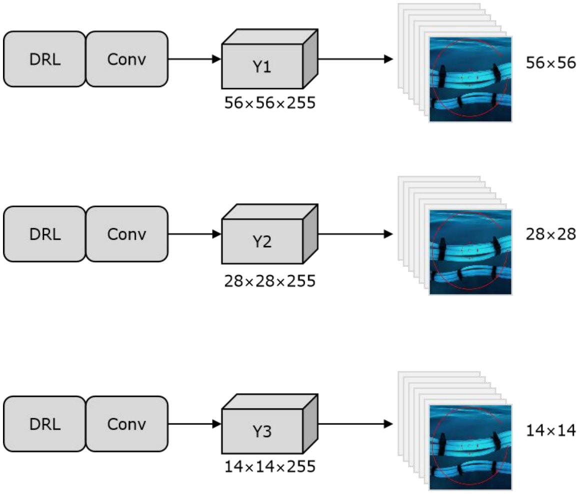

Figure 3: YOLO-V3 prediction network module.

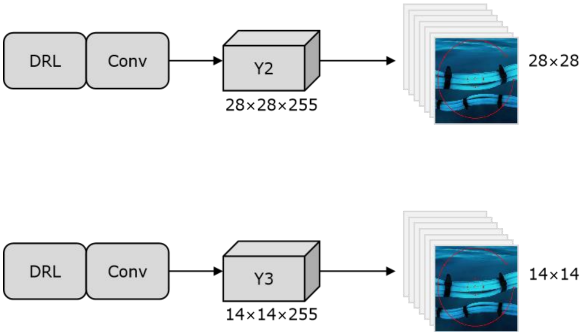

Figure 4: Lightweight prediction network.

By removing the small target detection branch in YOLO-V3, a more lightweight prediction network is obtained. This operation reduces unnecessary network calculation and the complexity of the model, thus speeding up the prediction speed of the network. For submarine cable defect detection, this lightweight design is particularly important because the complexity of the deep-sea environment requires that the detection algorithm must have high real-time and robustness.

Identify the faulty section of the submarine cable using the visual recognition module, subsequently mapping its positional data $\left[x,y,z\right]$ into 3D space utilizing the 2D-pixel coordinate $\left[u,v\right]$ of the detected defect:

$$\begin{bmatrix} x \\ y \\ z \end{bmatrix} = H \begin{bmatrix} \frac{1}{f_x} & 0 & 0 \\ 0 & \frac{1}{f_y} & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} u - C_x \\ v - C_y \\ 1 \end{bmatrix} \tag{3}$$

H represents the depth data captured by the depth camera while $\left[C_x, C_y\right]$ denoting the central coordinate of the image. Subsequently, the 3D data from the camera's coordinate system is transformed into the corresponding 3D data $\left[X,Y,Z\right]$ within the world coordinate system:

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} R_1 & t_1 \end{bmatrix} \begin{bmatrix} R_2 & t_2 \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \end{bmatrix} \tag{4}$$

R_1 and t_1 represent the rotation and translation matrices of the robot's base coordinate system with respect to the manipulator's end, while R_2 t_2 denote the corresponding matrices for the manipulator's end relative to the camera.

In the design process of a lightweight prediction network, the image characteristics of submarine cables are fully considered. Because cables are usually long strips, and surface defects may take many forms, such as cracks, corrosion, foreign body adhesion, etc., this study optimizes the network structure according to these characteristics. In this study, the convolution layer for cable feature extraction is added, and the network parameters are adjusted to improve the ability to identify cable defects.

Although the lightweight YOLO network has been able to achieve efficient defect detection, relying solely on MV is not enough to meet all challenges in the complex seabed environment. For example, the MV algorithm may be seriously affected when there are a lot of interferences around the cable or the image quality is degraded due to the turbidity of water. In order to solve this problem, RL is introduced into the defect detection process.

RL is a machine learning method to optimize decision-making strategy through trial and error and reward mechanisms. In submarine cable defect detection, RL is used to optimize the inspection path and defect identification strategy of the robot. A reward function is designed, which gives a positive reward when the robot successfully identifies the cable defect, and a negative reward when the robot misreports or misses the report. Through continuous training and learning, robots can gradually learn to identify cable defects efficiently and accurately in complex environments.

An enhanced neural network is developed, selecting various feature vectors pertinent to submarine optical cable inspection as inputs: image characteristics, grey values of damaged points, computed pixel variance of damaged features, colour component ratios of damaged pixels, and energy. Initially, a neural network model is formulated, with its construction expressed as:

$$y_j = \sigma\left[\sum_{k=1}^{K} w_{kj} \sum_{i=1}^{l} x_i \psi_{a,b}\left(\frac{i-b_k}{a_k}\right)\right] \tag{5}$$

$$\psi_{a,b}\ x\ = \cos\ 1.75x\ \exp\left(\frac{-x^2}{2}\right) \tag{6}$$

$$\sigma\ x\ = \frac{1}{1+\exp\ x} \tag{7}$$

Here I , K , and J denote the node counts for the input, hidden, and output layers of the neural network, respectively. w_{kj} signifies the connection weight between node j in the output layer and node k in the hidden layer. Subsequently, the neural network undergoes iterative searching governed by the formula:

$$v_{id}\ t+1\ = w\ t\ v_{id}\ t\ + c_1 r_1\ p_{id}\ t\ - x_{id}\ t \tag{8}$$

$$x_{id}\ t+1\ = x_{id}\ t\ + v_{id}\ t+1 \tag{9}$$

In the formula, $c_1 = c_2 = 1.4944$ is the search acceleration constant, and $r_1\ r_2$ are random numbers with arbitrary values in the range of 0 to 1. To avoid iterating into local minima, a directional mutation operation is required, and its specific mutation algorithm is:

$$v_{id} = rand \times v_{\max}\ d \tag{10}$$

$$P_{id} = x_{id} \tag{11}$$

In the formula, $rand$ is a random number in the range of 0 to 1, and the maximum speed of each iteration is represented by $v_{\max}$, so as to obtain the accurate characteristics of damaged pixels.

In the deep-sea environment, robots need to be able to plan their own paths, avoid obstacles, and ensure a comprehensive inspection of cables. Through RL, the robot can dynamically adjust the inspection path according to the real-time perceived environmental information, thus improving inspection efficiency and accuracy.

5 EXPERIMENTAL RESULTS AND ANALYSIS

After the theoretical discussion of the submarine cable defect detection method based on MV and RL is completed, a series of experiments are carried out in this section to verify the effectiveness of the proposed method. This section will show the experimental results in detail and analyze the performance of the method.

5.1 Experimental Setup and Data Preparation

The core of the experiment is to compare and test the performance of two kinds of cable detection robots: one is a robot that only relies on traditional machine vision (MV-Only), and the other is a robot that combines deep learning and MV with this method (DL-MV). The experimental data covers 500 cable images collected from the seabed, which contain various defects such as cracks, corrosion, foreign body adhesion, etc., and the distribution of various defects in the images is uniform to avoid experimental deviation caused by uneven types of defects. Figure 5 shows an example of a partial cable image. In order to ensure the objectivity of the assessment, all experimental images were marked by experts. The labelling process is completed by experienced cable inspection experts, who accurately label the location and type of defects according to the characteristics of defects in the image.

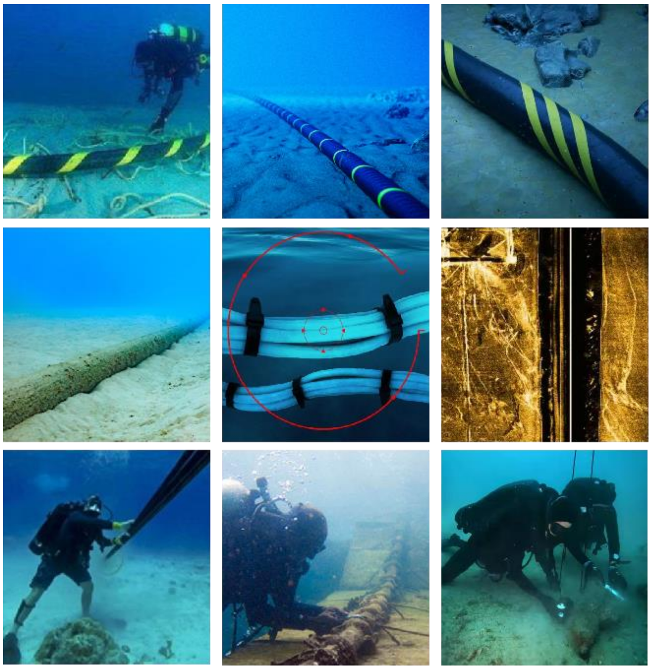

Figure 5: Cable image example.

Before the image data is used in the experiment, the necessary data preprocessing is also carried out. This includes image clipping, scaling, normalization and other operations to ensure that the image data has a consistent format and scale before being input into the robot model. In addition, the image has been enhanced, such as rotating and flipping, to increase the diversity of data. In order to obtain more reliable and stable experimental results, the experimental data were divided into several groups, and repeated experiments were carried out for each group. The advantage of this is that it can reduce the influence of accidental factors on the experimental results so that we can evaluate the performance difference between the two robots more accurately.

5.2 Display and Analysis of Experimental Results

Firstly, the performance of the traditional MV method (MV-Only) and this method (DL-MV) in the defect identification task is compared. Figure 6 shows the predicted value and actual value of the cable inspection robot using the traditional MV method for defect identification. It can be seen that the traditional method has a large prediction deviation in some cases.

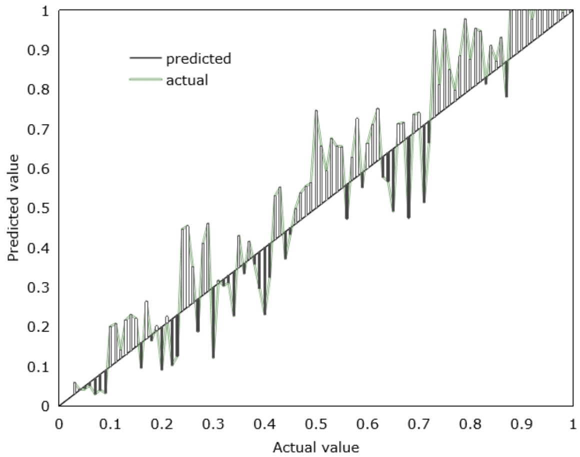

Figure 6: Traditional MV.

Figure 7 shows the predicted value and actual value of defect identification using DL-MV. By comparison, it can be seen that the predicted value of DL-MV is closer to the actual value, indicating that it is more accurate in defect identification. Thanks to the improvement of the YOLO-V3 algorithm and the introduction of the RL mechanism, the robot can better adapt to the complex and changeable seabed environment.

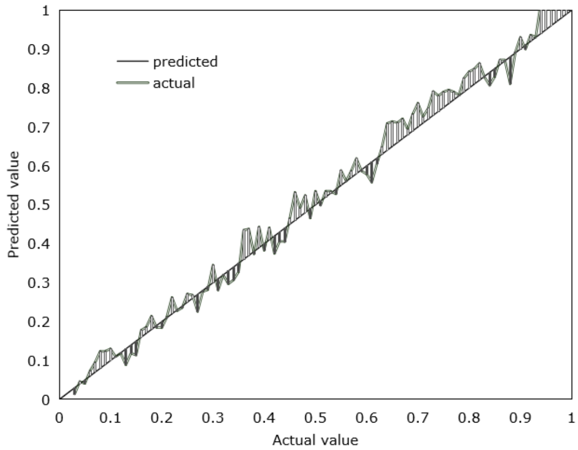

Figure 7: DL-MV.

In order to compare the performance of the two methods more intuitively, their detection accuracy on the test set is calculated, as shown in Figure 8. The accuracy of DL-MV is significantly higher than that of the traditional MV method. The accuracy of DL-MV is 92.5%, while the accuracy of traditional methods is only 81.3%.

Next, the detection errors of the two methods are compared and analyzed, and the results are shown in Figure 9. At the initial stage of operation, the error between the two methods is not much different. However, with the increase in running time, the error of DL-MV gradually decreases, and it shows obvious advantages in the later period of running. In the later stage of operation, the error of DL-MV is reduced by 27.46% compared with the traditional method. DL-MV has better stability in dealing with complex scenes and long-term operation and is more suitable for practical submarine cable inspection tasks.

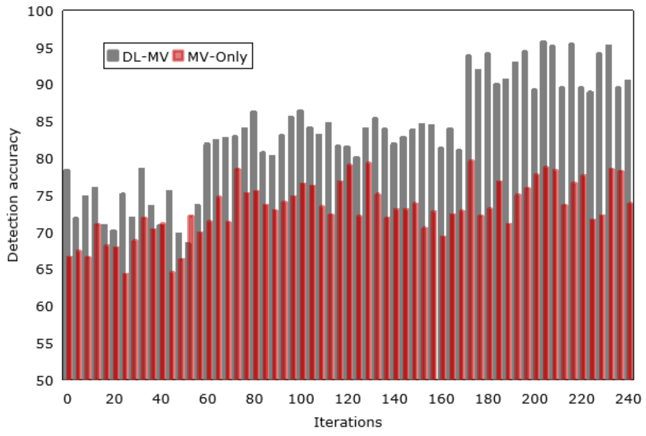

Figure 8: Accuracy comparison.

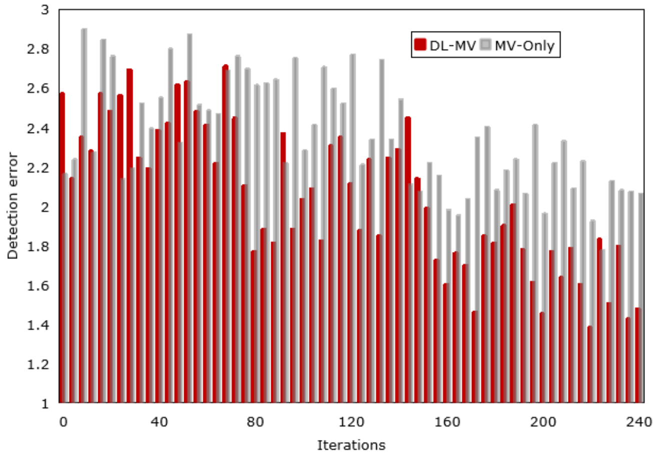

Figure 9: Comparison of detection errors.

In order to further analyze the advantages of DL-MV, all kinds of defect images in the test set are counted and analyzed in detail. It is found that DL-MV is particularly good at identifying cracks and corrosion defects. For crack defects, the recognition accuracy of DL-MV reaches 95.2%, while the traditional method is only 83.7%. For corrosion defects, the recognition accuracy of DL-MV is 93.8%, while that of traditional methods is 79.6%. This result shows that DL-MV is more sensitive to tiny and imperceptible defects and can identify potential safety hazards more accurately.

To sum up, this article realizes the efficient and accurate detection of submarine cable defects by combining MV and RL. The results show that DL-MV is superior to the traditional MV method in accuracy, error reduction and generalization ability. In the future, we will continue to deepen the research in this field, explore more efficient and accurate defect detection algorithms, and try to apply the proposed method to other marine engineering fields, such as submarine pipeline detection and marine biological identification.

6 CONCLUSIONS

MV technology captures submarine cable images in real-time and identifies abnormalities such as damage. RL enables the robot to optimize decision-making, improve inspection efficiency, adjust the path to avoid obstacles independently and ensure the completion of the task. By combining MV and RL technology, an efficient and intelligent submarine cable detection robot system is constructed in this study. In the aspect of CAD modelling, the powerful function of modern design software is used to accurately model and simulate the robot. In the aspect of working process analysis, the application of MV and RL in submarine cable defect detection is emphatically studied. By improving the YOLO algorithm and removing small target detection branches, a lightweight prediction network is obtained, which realizes efficient and accurate identification of submarine cable defects. The introduction of the RL mechanism further improves the robot's defect recognition ability in complex environments.

The results show that the method proposed in this article has obvious advantages over the traditional MV method, which improves the accuracy of defect identification, and also performs well in error reduction and generalization ability. This achievement provides strong support for the intelligent development of submarine cable inspection.

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Development of Lightweight Submarine Cable Inspection Equipment (GDKJXM20222438).

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