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Research on composite fault diagnosis technology of underwater vehicle actuator with positioning error constraint

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ABSTRACT

When diagnosing the composite fault of the actuator, the characteristics of the motion force of the underwater vehicle are not analyzed, and there are diagnostic errors, resulting in the low accuracy of the diagnosis technology. In order to solve this problem and improve the operation safety of underwater vehicle actuators, this paper proposes a compound fault diagnosis technology for underwater vehicle actuators under positioning error constraints. Analyze the motion force of the underwater robot actuator, control the motion of the underwater robot actuator according to the analysis results, and extract real-time data parameters according to the control results. Under the constraint of positioning error, the composite fault features of the underwater robot actuator are divided, and the diagnosis model is built according to the deep fusion of the features to complete the fault diagnosis. The experimental results show that the technology can diagnose the composite fault data of the actuator, and the positioning error of the horizontal axis and the horizontal axis can be significantly improved, which can improve the diagnosis effect of the composite fault of the actuator and to the improvement of underwater robot running safety of actuators provide certain reference.

1. Introduction

The pace of human exploration of the ocean has been expanding. In the fields of seabed energy mining, underwater cable laying, fishing and so on, underwater robots play an important role [1,2]. Marine work environment is complex and highly unpredictable, underwater vehicle in the business environment has the characteristics of strong coupling and slow movement, has strong nonlinear in the process of movement and large inertia [3,4]. The actuator is one of the most important power components for the underwater operation of the AUV, and the movement of the AUV is completed by the thrust generated by the actuator. It is for these reasons, the underwater robot fault are mostly caused by the actuator failures. Therefore, in order to improve the stability of the AUV operation process, it is very necessary to carry out compound fault diagnosis for AUV actuators.

Reference [5] proposes a fault diagnosis technology for multi-legged robot actuators, which introduces frequency domain information and fuses multi-sensor data to increase features and expand the difference between normal data and fault data. A framework based on generating countermeasures network is designed to calculate the probability that the enhancement data belongs to the normal category. Using the generator network as the feature extractor and the discriminator network as the fault probability evaluator, a new use of the generator antagonism network in the field of fault diagnosis is created. Reference [6] proposes a field fault diagnosis method for industrial robot harmonic reducer based on deep learning, which combines one-dimensional convolution neural network

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with matrix kernel adaptive model. By adjusting the size of the convolution kernel, this method can focus on the context feature extraction of continuous time domain data, while maintaining the ability to process multi-channel fusion data. Compared with the traditional two-dimensional cellular neural network, deep sparse automatic coding network, multi-layer perception network and support vector machine, its performance is superior. In Ref. [7], the authors first identify anomalies related to the use of conventional TWDP parameterization in moment estimation, and show that existing Δ-based estimators cannot provide meaningful estimates under certain channel conditions. Then we derive recently introduced physically proven moment-based estimators for TWDP parameters K and Γ. Its performance is analyzed by the asymptotic variance and Cramer-Rao bound metrics to improve the overall moment-based estimation accuracy. The method for the extraction of the real-time data parameters in this article provides a theoretical basis.

Based on the above background, this paper proposes the research on the composite fault diagnosis technology of the underwater robot actuator with positioning error constraints. Through this design, the underwater operation level of the robot will be improved. With the analysis of the underwater robot manipulator's motion dynamics, this study aims to achieve precise control over its motion process. Real-time acquisition and feedback of control results enable the extraction of performance parameters for further system optimization. Under the constraint of positioning errors, the compound fault characteristics of the underwater robot manipulator will be delineated, and corresponding diagnostic models will be established. Emphasizing the integration of multiple data parameters, particularly highlighting the incorporation of deep fusion techniques, efficient fault diagnosis can be achieved. Through the aforementioned research, a more comprehensive analysis of the motion dynamics of the underwater robot manipulator can be attained, serving as the foundation for precise control operations. Moreover, reliable diagnostic models will be established to extract valuable information from data through comprehensive deep fusion techniques, enabling timely diagnosis of compound faults. The implementation of these research endeavors will provide robust support for the optimization control and fault diagnosis of underwater robot manipulators, paving the way for the development and application of underwater robot technologies.

2. Motion analysis and control of underwater robot actuator

2.1. Analysis of motion force of underwater vehicle actuator

In the process of performing underwater tasks, the external force acting on the underwater robot actuator is expressed as F, and its calculation equation is shown in equation (1):

$$F=\sum_{i=1}^{n}L_i+(B_o+C_o+D_o) \tag{1}$$

in equation (1), $\sum_{i=1}^{n}L_i$ represents the resultant force of all thrusters; n represents the number of thrusters of the underwater vehicle; B_o, C_o and D_o all represent the hydrodynamic force acting on the underwater robot actuator, and the total robot torque generated by the external force on the AUV actuator F_H is calculated as equation (2):

$$F_H=(M_1+M_2+M_3+M_4)\times F \tag{2}$$

in equation (2), M_1 represents the moment of longitudinal freedom [7]; M_2 represents the moment of transverse freedom; M_3 represents the moment of freedom of diving; M_4 represents the moment of yaw freedom.

Assume that X represents the gravity of the underwater robot actuator, and the gravity action point is $W(x_1,y_1,z_1)$. At this time, the expression of gravity B is shown in equation (3):

$$\begin{cases} X=\sum X_i \\ x_1=\left(\sum x_{Wi}X_i\right)\Big/X \\ y_1=\left(\sum y_{Wi}X_i\right)\Big/X \\ z_1=\left(\sum z_{Wi}X_i\right)\Big/X \end{cases} \tag{3}$$

Among them, x_{Wi}, y_{Wi}, z_{Wi} in the corresponding direction on the gravity weight value. Assume that Y represents the buoyancy of the underwater robot actuator during operation, and the center point of buoyancy is $V(x_2,y_2,z_2)$. At this time, its calculation process is shown in equation (4):

$$\begin{cases} Y=\sum Y_i \\ x_2=\left(\sum x_{Vi}Y_i\right)\Big/Y \\ y_2=\left(\sum y_{Vi}Y_i\right)\Big/Y \\ z_2=\left(\sum z_{Vi}Y_i\right)\Big/Y \end{cases} \tag{4}$$

Among them, x_{Vi}, y_{Vi}, z_{Vi} in the center of buoyancy corresponding direction of buoyancy weight value. Let Z represent the force acting on the actuator of the underwater vehicle during its movement, and its expression can be expressed as equation (5) [8,9]:

$$Z = \sum_{i=1}^{n} N_{T_i} + (N_A + N_B + N_C) \times X \times Y \tag{5}$$

In equation (5), $\sum_{i=1}^{n} N_{T_i}$ represents the torque generated by the total thrust in the motion of the underwater robot actuator; N_A represents the moment generated by hydrodynamic force in the motion of the underwater robot actuator; N_B represents the moment generated by gravity in the motion of the underwater robot actuator; N_C represents the moment generated by the motion buoyancy in the underwater robot actuator, thus completing the analysis of the motion force of the underwater robot actuator, and controlling the motion of the underwater robot actuator according to the results.

2.2. Motion control

Control the motion of the underwater robot actuator under the constraint of positioning error. The specific control algorithm η can be described by equation (6):

$$\eta = K_P \times T_D \times (X, Y, Z) \times T_m \tag{6}$$

in equation (6), K_P represents the proportion coefficient; T_D indicates the deviation signal of the actuator during the control process; T_m represents the integration time.

The control output of the actuator changes regularly. The sigmoid function can be used to fit the change curve, and the sigmoid function can be used to obtain the output change function of the horizontal axis position of the underwater robot actuator [10], the specific calculation process is shown in equation (7):

$$H_1 = \frac{1}{\exp(-k_1 \times X)} \tag{7}$$

in equation (7), k_1 represents the deviation control parameter.

The output change function of the vertical axis position is obtained based on the sigmoid curve function, the specific calculation process is shown in equation (8):

$$H_2 = \frac{1}{\exp(-k_2 \times Y)} \tag{8}$$

in equation (8), k_2 represents the deviation rate of change control parameter.

During the motion of the underwater robot actuator, the acquired incremental signal is used to complete the motion control of the actuator, the specific calculation process is shown in equation (9):

$$\Delta\varpi = (H_1 + H_2) \times \eta \times F(G) \tag{9}$$

in equation (9), $F(G)$ represents the deviation value. From the above analysis, it can be seen that the deviation control parameters and the deviation change rate control parameters directly affect the accuracy of the motion control of the underwater robot. Therefore, in order to improve the motion control accuracy of the underwater robot actuator, it is necessary to adjust the above parameters and extract real-time data.

2.3. Extract real-time data

Diagnose the complex fault of the underwater robot actuator, use the camera to track the underwater robot actuator in real time, extract the real-time data, and gather them in the coordinate system. There are four coordinate systems. Take the three-dimensional

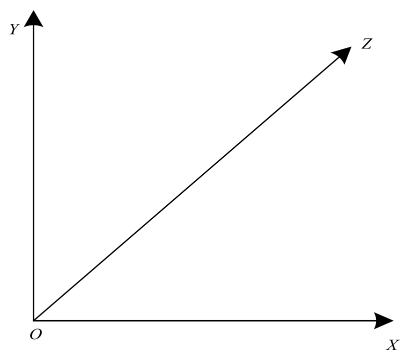


Fig. 1. Structure of three-dimensional spatial position coordinate system.

spatial position coordinate system as an example, and the structure is shown in Fig. 1.

With O as the origin of the pixel coordinate system, the number of columns and rows of the point in the image are α and β respectively. The basic idea of binocular depth estimation is introduced to match all pixel points in 3D space position, so as to extract real-time data. The relationship between X axis, Y axis and axis coordinate system can be expressed as equation (10):

$$\begin{cases} X = \dfrac{x}{r_x} + \alpha \times \beta \\ Y = \dfrac{y}{r_y} + \alpha \times \beta \\ Z = \dfrac{z}{r_z} + \alpha \times \beta \end{cases} \tag{10}$$

in equation (10), (r_x, r_y, r_z) represents pixel coordinates; r_x is the physical size of the unit pixel on the horizontal axis, the vertical axis is r_y, and the vertical axis is r_z. In the process of pixel point matching, diagnose whether there is a fault, and obtain the amount of information contained in the image. Since the rotation around the coordinate axis is related to the rotation axis and rotation angle, the attitude transformation obtained by different rotation angles is naturally different, but even if the rotation angle is the same, the rotation order according to different coordinate axes will also change the attitude of a rigid body, so the rotation order is particularly important and irreversible. The motion of the underwater robot actuator is formed by the joint motion of each joint [11]. Controlling the motion of the underwater robot actuator is actually controlling the rotation angle of each joint. The end position and posture of the robot are obtained by the successive changes of each rotation joint. This requires building a diagnosis model for the robot and deriving the transformation matrix between each joint.

3. Diagnosis model of underwater vehicle with localization error constraint

3.1. With positioning error constraint

The positioning error constraint is an important basis for the composite fault diagnosis of the underwater robot actuator. In order to improve the accuracy performance of the underwater robot diagnosis [12], it is necessary to first measure the positioning error of the underwater robot, and analyze the causes of each positioning error, so as to carry out the positioning error constraint. The measuring instrument selected in this paper is the laser interferometer, which generates the Doppler effect through moving the reflector to measure the displacement, Measure angle, linearity, straightness and other data according to different measurement combinations. After the displacement measurement, the measuring light and the reference light are reflected by the reflector to make the beam return to the laser generator after the measurement is completed, so as to obtain the measurement data of the positioning error of the measuring light on the underwater robot [13], so as to achieve the positioning constraint. After recording the optical path change, compare the readings, and obtain the constraint value. The calculation process of constraint distance is shown in equation (11):

$$L = \frac{\alpha}{2} \times M_J \times (X, Y, Z) \tag{11}$$

in equation (11), α represents the laser wavelength; M_J represents the cumulative number of pulses. Linear data are collected by laser interferometer and input into the computer for laser calibration to calculate various accuracy indexes and complete the positioning error constraint of underwater robot.

Forward error and reverse error are important factors that affect the positioning accuracy of the underwater vehicle. If effective positioning error constraints are not carried out, the operation time of the underwater vehicle will continue to increase. The positioning constraint is to adjust the control parameters of the underwater vehicle accordingly. According to the positioning error diagnosis result of the laser interferometer, the positioning error constraint is performed [14], and the membership degree F_G of the parameter is obtained. The calculation process is shown in equation (12):

$$F_G = \min(A_1, A_2) \times \beta \times L \tag{12}$$

in equation (12), A_1 represents the input deviation; A_2 is the rate of change of deviation; β represents membership degree of fuzzy subset. According to the deviation and deviation change rate obtained from the above equation, the membership parameters are obtained, and the membership parameters are corrected, that is, the calculation equation with positioning error constraint is obtained, and the calculation process can be described as equation (13):

$$Q_W = (a_1 + a_2 + a_3) \times \theta \times F_G \tag{13}$$

in equation (13), a_1, a_2 and a_3 are the corrected values of membership parameters; θ represents the initial value, thus realizing the constraint with positioning error.

3.2. Dividing the composite fault characteristics of underwater vehicle actuator

On the basis of the constraint of positioning error, the data information obtained by the underwater robot is supervised by the support vector machine. In the training process of the data subset, the maximum processing edge of the underwater robot execution image is defined to divide the complex fault feature of the underwater robot actuator.

It is assumed that the real-time training data only contains two types of samples, which are represented by a positive sign and a negative sign, and exist on both sides of the hyperplane respectively. The decision edge expression of the actuator is set as equation (14):

$$E_{RT} = (u \times p + i) \times Q_W \tag{14}$$

in equation (14), u represents the actuator edge axis; p and i both represent decision edge parameters. Mark different types of data and set them according to the two-classification method. The expression is as equation (15):

$$A_D = \begin{cases} 1(u \times p + i > 0) \\ -1(u \times p + i < 0) \end{cases} \tag{15}$$

Divide the area of the image in a plane. The two closest points to the plane are p_1 and p_2 respectively, then, equation (16) can be obtained:

$$J_H = A_D \times (p_1 - p_2) \tag{16}$$

After calculation, the result is that the corresponding J_H is the selected maximum boundary scale, that is, the division of composite

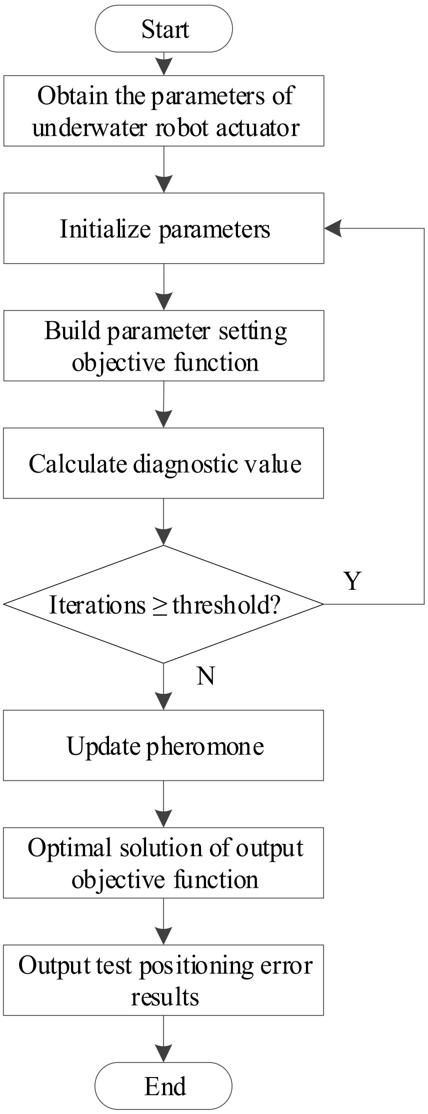


Fig. 2. Composite fault diagnosis flow chart of underwater robot actuator.

fault characteristics of the underwater robot actuator is completed. Through the feature fusion of the solution results, the diagnosis model of the underwater vehicle is constructed, and the composite fault diagnosis of the robot actuator is completed.

3.3. Feature deep fusion to build diagnosis model

The diagnosis data can not completely restore the site conditions, and the collected feature information will lose some specific semantics, which will affect the fault diagnosis accuracy. Based on the technical theory of deep feature fusion, the fault diagnosis model of underwater vehicle is constructed to locate the fault target.

In the selection of various diagnostic indicators, a multi-layer fault diagnosis model is established based on the accuracy and sensitivity of features as well as specificity and accuracy. Based on the V_B classification index, classify the divided sample data to calculate the correct classification probability of fault characteristics, the calculation process can be expressed as equation (17):

$$V_B = \frac{S_a + S_b}{S_a \times J_1 + S_b \times J_2} \tag{17}$$

in equation (17), S_a represents the number of correct fault characteristic samples, and the greater the value, the better; S_b refers to the number of samples of non-fault features. Similarly, the larger the value, the better; J_1 represents the number of fault feature samples for error classification, and the smaller the value, the better; J_2 represents the number of normal data samples misunderstood. The smaller the value, the better. The total number of correctly divided features is $S_a + S_b$; The total number of all features collected is $S_a \times J_1 + S_b \times J_2$. Calculate the accurate mean V_B of all the sample data $\overline{V}_B$ after diagnosis, and get equation (18):

$$\overline{V}_B = \frac{1}{N} \times Q_{kl} \tag{18}$$

in equation (18), N represents the number of feature classifications of the diagnostic model. After calculating the accurate mean value of the sample data, the characteristic sensitivity and specificity in the diagnostic model are obtained according to the sample data, equation (19) is obtained:

$$\begin{cases} T_{EN} = \dfrac{S_a}{S_a \times J_1} \times \overline{V}_B \\ T_{PE} = \dfrac{S_b}{S_b \times J_2} \times \overline{V}_B \end{cases} \tag{19}$$

in equation (19), T_{EN} represents the sensitivity of the composite fault characteristics of the actuator; T_{PE} represents specificity. Filter the fused fault diagnosis data, define the representative fault target, get the feature depth fusion result, and build the composite fault feature model of the underwater robot actuator according to the result, and the calculation equation can be described as equation (20):

$$K = R_C \times (E_L + E_K) \times (T_{EN} + E_{PE}) \tag{20}$$

in equation (20), R_C represents the underwater robot joint; E_L represents the deviation of connecting rod; E_K represents the joint angle. According to this model, the angle response control of the joint can be performed [15]. The specific process of composite fault diagnosis technology for underwater robot actuator is shown in Fig. 2.

The composite fault diagnosis of the underwater robot actuator is to process the sensor signal to extract the features, and input the feature signal into the classifier for calculation, so as to determine the current status of the equipment, that is, whether the equipment is faulty, what kind of fault it belongs to, and the severity of the fault. Generally, there are two cases: (1) when the composite fault diagnosis model of the actuator is only used as a classifier, the input of the model should be the features extracted by other methods, such as the mean value, peak value, skewness of the signal extracted by time, frequency and time-frequency methods, and the eigenvalues describing the frequency distribution; (2) when the training target of the fault diagnosis model is an end-to-end model, That is, the model not only acts as a classifier, but also acts as the function of feature extraction and feature dimensionality reduction. At this time, the input of the model should be the original signal or the signal that has been simply processed, and there is no need to use another method to extract features. In essence, the second case is to store each original signal data as a feature in the corresponding neuron node, and gradually fuse the information contained in each neuron node into new features and reduce the number of features through multi-layer network nonlinear processing.

The goal of fault diagnosis is to output the status of the current equipment, which belongs to the classification problem. Therefore, the output of the fault diagnosis technology in this paper is the classification information. For example, if the model needs to solve an N classification problem, the output can be set as an integer node, and the output range is 1~N. In order to facilitate the calculation of loss function, etc., on this basis, the output is processed by one-hop coding, and the current state is represented by 0 and 1. Take a 3-class problem as an example, the output is in the form of [1,0,0], [0,1,0], [0,0,0,1], respectively corresponding to the first, second and third states of the device. That is, the number of output neuron nodes in this paper is the same as the number of possible states of the device. Each time there is only one neuron node whose output value is 1, and the others are all 0, which means that the current device is in the corresponding state of the neuron node, thus completing the research on the composite fault diagnosis technology of the underwater robot actuator with positioning error constraints.

4. Experimental analysis

Through the advantages of positioning error constraints, the research on composite fault diagnosis technology of underwater vehicle actuator is completed. In order to verify the application effect of the new technology, comparative test is adopted for demonstration. reference [5] technology and reference [6] technology are used as a comparison to compare the composite fault diagnosis effect of different technologies. The experimental environment is Intel (R) Core (TM) i5-3470 CPU, 3.20 GHz, 8 GB memory PC-based, realized by MATLAB 7.6 programming, and LIBSVM is support vector machine software. Taking the LBF-300A underwater robot as the test object, it has the characteristics of intelligence, unmanned and modular generalization. It is equipped with a position sensor and a laser detection radar inside. The maximum scanning angle is 180°, the maximum angular resolution is 0.6°, and the scanning period is set to 25 ms. The manipulation and control system mostly uses a large-capacity computer, and the manipulator uses a multi-function feedback monitoring system, which can increase the number and power of actuators, Improve the ability and handling performance of top flow operation. The diagram of the underwater vehicle is shown in Fig. 3.

The experiment was carried out in a narrow underwater space, and multiple monitoring machines were placed outside the underwater space. Set the diagnosis path of the underwater vehicle and randomly place 8 fault points. The specific fault conditions of these eight fault points are shown in Table 1.

(1) Number of fault points: make statistics on the data of fault points diagnosed by three groups of methods, and compare the number of fault points diagnosed by different technologies to see whether it can meet the set path of the underwater vehicle.
(2) Fault point location: the fault point corresponding to the spatial location of the diagnosis is used to calculate the diagnosis error of different technologies.

According to the set two groups of test contents, they are imported into the MATLAB test platform, and three diagnostic methods are applied in the main control system of the underwater vehicle to verify the effect of fault diagnosis of different technologies. The relevant parameters of the diagnostic method experimental platform are shown in Table 2.

Use the technology in this paper to guide the telemetry data signal with fault fed back by the underwater vehicle into the experimental platform, as shown in Fig. 4.

The fault diagnosis curve is generated according to Fig. 4, as shown in Fig. 5, and the debugging summary is made according to the curve distribution results.

According to Fig. 5, the application technology of fault diagnosis, this paper can be continuous and smooth curve, this paper technology can continue to identify the fault data, and find a wave in the fault zone and the area of the positive wave data value, has the high accuracy. The technology in this paper can accurately diagnose the composite fault data of the actuator, which proves that the diagnosis effect of the technology studied on the composite fault of the underwater robot actuator meets the technical standards. The reason is that the technology in this paper uses the acquired incremental signals to complete the motion control of the actuator during the motion of the underwater robot actuator; The composite fault diagnosis of the underwater robot actuator is to process the sensor signal to extract the feature, input the feature signal into the classifier for calculation, and determine the current equipment status, which is beneficial to enhance the diagnosis effect to a certain extent.

In order to further verify the accuracy of the three groups of methods, the error statistics of the above diagnosis results are carried out, and the missing points cannot be included in the statistics, as shown in Fig. 6. Among them, Fig. 6(a) shows the horizontal axis position error, and Fig. 6(b) represents the vertical axis position error.

According to Fig. 6, under the application of this technology, the horizontal and vertical axis position errors are less than 1 mm. Among the fault points diagnosed by reference [5] technology and reference [6] technology, the position errors are more than 10 mm, which indicates that the technical diagnosis effect of this technology is better. The reason is that this technology uses sigmoid function to fit the change curve, and uses sigmoid curve function to obtain the horizontal axis position of the underwater robot actuator Vertical

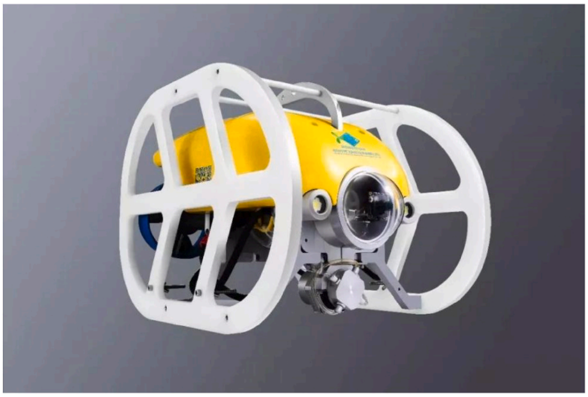


Fig. 3. Illustration of the underwater vehicle.

Table 1
The specific fault conditions of the eight fault points.

Failure point number	The fault types	The specific fault condition
1	Power failure of underwater vehicle	A depleted battery or broken power cord causes the underwater vehicle to stop working.
2	Navigation failure	The navigation sensor fails, causing the underwater vehicle to become disoriented or unable to locate accurately.
3	The thrusters failed	The thrusters failed, causing the underwater vehicle to be unable to advance or change direction.
4	Pressure sensor fault	The failure of the pressure sensor makes the underwater vehicle unable to detect the pressure situation of the underwater environment correctly.
5	Temperature sensor failure	Underwater vehicle can't correct temperature sensor failure detection of underwater environment temperature.
6	Communication failure	The communication link between the underwater vehicle and the monitoring machine fails, which makes the underwater vehicle unable to exchange data and control with the monitoring machine.
7	Camera malfunction	Camera failure unable to get clear images of the underwater vehicle or to visual monitoring task.
8	Trapezoidal tank liquid level sensor fault	A faulty liquid level sensor causes the underwater vehicle to fail to correctly detect the liquid level change in the trapezoidal tank.

The test contents include.

Table 2
Relevant parameters of diagnostic method experimental platform.

Number	Project	Parameters/Configuration
1	Simulation/modeling software	Matlab
2	Database	MySQLServer
3	Temperature	20°C–27 °C
4	Development language	Python + C++
5	Transmitter	Star instrument CWDZ11A
6	PC	DELLOptiPlex990

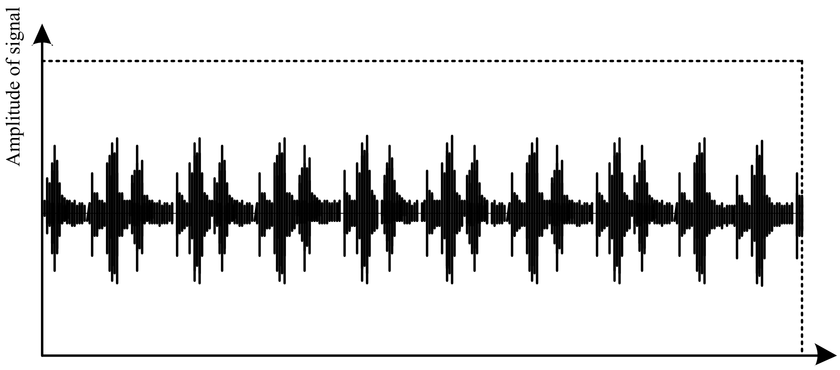


Fig. 4. Signal wave of underwater vehicle telemetry data.

axis position output change function.

Diagnose the positioning error of the underwater vehicle on the horizontal and vertical axes, and compare the data before and after the positioning error diagnosis. The specific results are shown in Table 3.

It can be seen from Table 3 that the positioning error of the horizontal axis decreases from [−0.36, −1.02] to [0.03, −0.18] before and after diagnosis, and the positioning error of the horizontal axis decreases from [−0.46, −1.79] to [0.04, −0.25] before and after diagnosis. It can be seen that the positioning error of the horizontal axis and the horizontal axis has significantly improved after the error diagnosis by the technology in this paper, which proves that the technology in this paper has good positioning error diagnosis effect and good feasibility.

Select the joints of the underwater vehicle to conduct the angle response test, and the results are shown in Fig. 7.

It can be seen from the analysis of Fig. 7 that the joint angle of the underwater robot completes the joint position command tracking within 0.2s, and the obtained route is consistent with the expected route, which indicates that the response speed of the position and attitude change of the underwater robot is fast, which can verify that the diagnosis technology in this paper has good position and attitude servo control effect of the underwater robot, and can improve the composite fault diagnosis effect of the actuator.

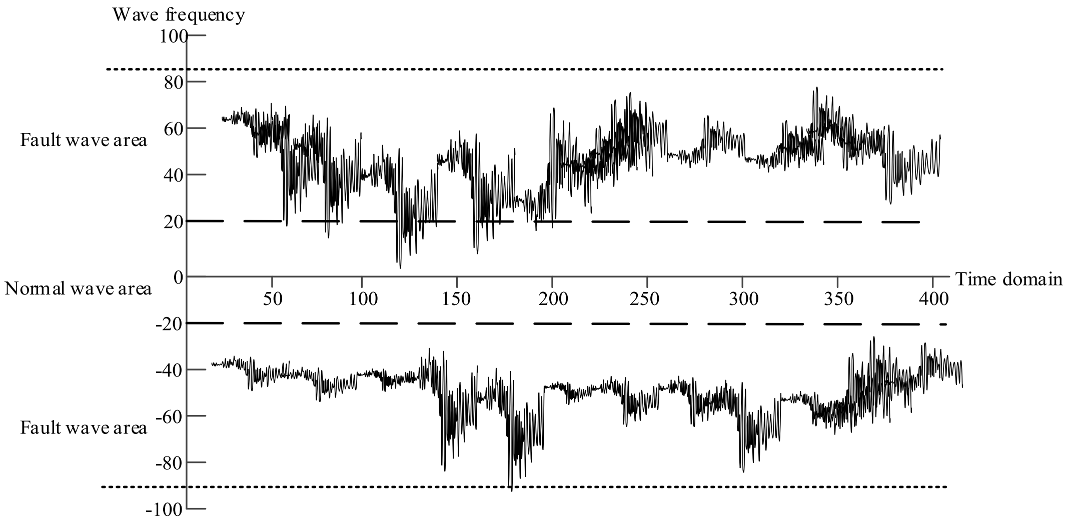


Fig. 5. Fault diagnosis curve.

5. Conclusion and prospect

5.1. Conclusion

In this paper, the research on composite fault diagnosis technology of underwater vehicle actuator with positioning error constraint is proposed, and the following conclusions are obtained through experiments.

(1) The technology in this paper can be used to accurately diagnose the composite fault data of the actuator and meet the technical standards;
(2) Under the application of this technology, the horizontal and vertical axis position errors are less than 1 mm, and the diagnosis effect is better; After the error diagnosis of this technology, the positioning error of its horizontal axis and horizontal axis has been significantly improved;
(3) The diagnosis technology in this paper has a good effect on the position and attitude servo control of the underwater vehicle, and can improve the diagnosis effect of the composite fault of the actuator.

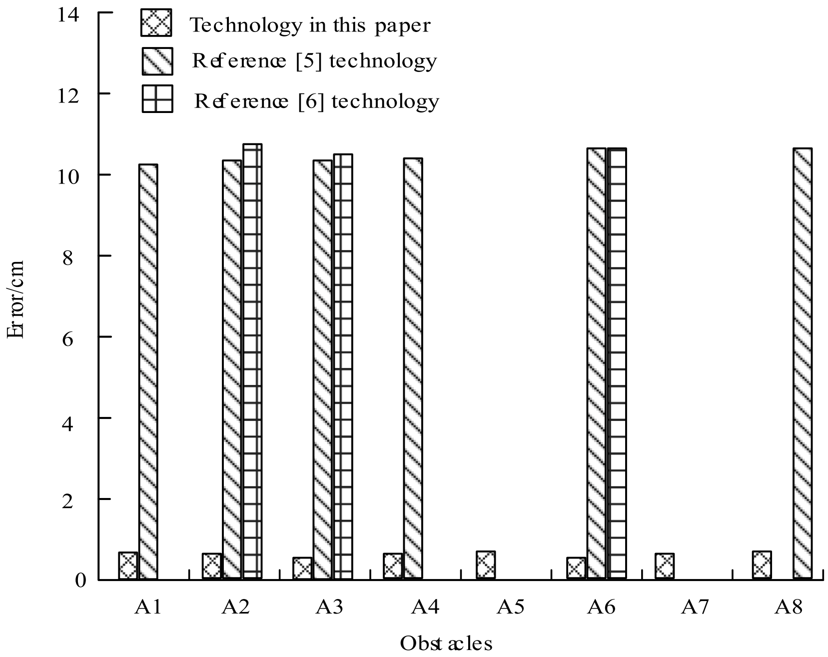
5.2. Prospect

Follow-up research can be further explored in the following directions.

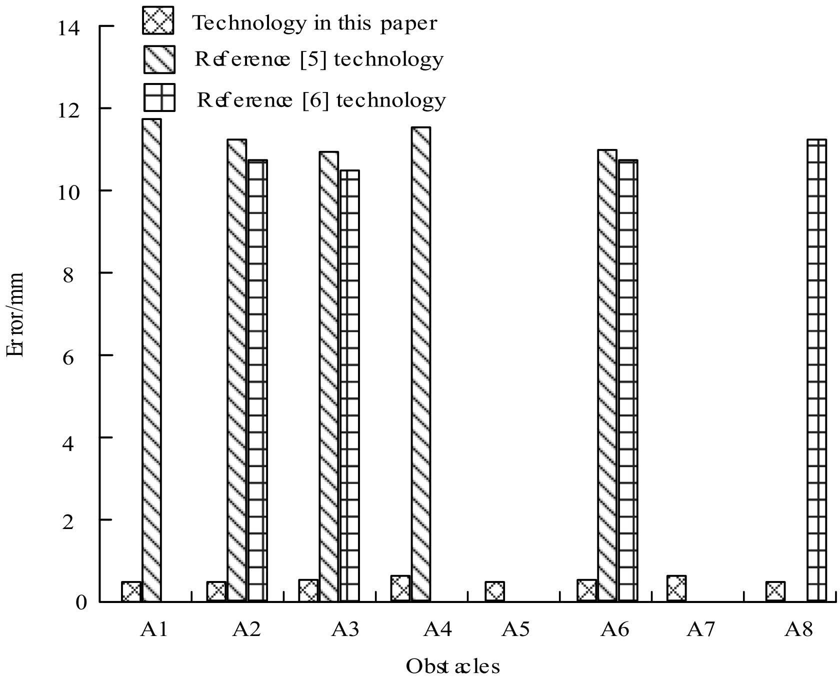
(1) In order to achieve higher diagnostic accuracy, multiple signals can be used for diagnosis first and then weighted based on information fusion diagnosis results. However, this method requires high data acquisition and is easy to introduce new diagnostic interference factors, so it is worth further exploration and research. Set more diversified faults and conduct joint fault experiments to obtain a large number of comprehensive sample sets, giving full play to the advantages of location error constraints.
(2) Next, we should realize the integration of fault diagnosis, fault location and fault identification in terms of composite fault location and joint fault diagnosis of underwater robot actuators, graphically display the hidden layer feature data, explore the multi-model fusion technology, explore the reasonable application of unsupervised learning, integrated learning and migration learning in the field of fault diagnosis of marine electromechanical systems, improve the classification accuracy of fault diagnosis models, and ensure the generalization ability of models.
(3) The fault diagnosis technology mostly adopts fixed input and output formats such as fully connected neural network, convolutional neural network, self-encoder, etc., but the sensor data is time series data, unlike image data, which is fixed in scale, and simply intercepts a segment of sensor data as model input. Because of the different forms and periods of different faults, the scale of data segmentation is not easy to grasp, Therefore, it is possible to study the application of time series models such as cyclic neural network in the field of composite fault diagnosis of underwater vehicle actuators and improve the fault diagnosis ability.

Data availability

No data was used for the research described in the article.



(a) Horizontal axis position error



(b) Vertical axis position error

Fig. 6. Error comparison results.

Table 3
Comparison of horizontal and vertical axis positioning errors before and after diagnosis/mm.

Target location	Before transverse axis diagnosis	After transverse axis diagnosis	Before transverse axis diagnosis	After transverse axis diagnosis
0	−0.36	0.03	−0.57	0.04
30	−0.39	0.11	−0.91	0.10
60	−0.57	0.23	−1.25	0.15
90	−0.75	0.28	−1.47	0.20
120	−0.81	−0.17	−1.51	−0.16
150	−0.98	−0.14	−1.59	−0.21
180	−1.02	−0.18	−1.66	−0.25

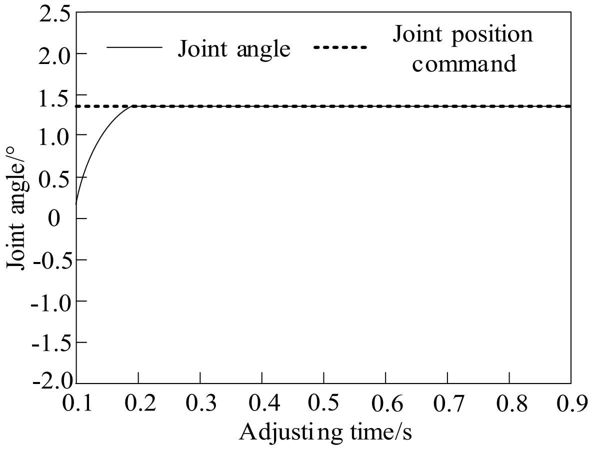


Fig. 7. Joint angle response test of underwater vehicle.

CRediT authorship contribution statement

Dewen Zhu: Project administration, Writing – original draft, Investigation. **Zhiyu Zhu:** Funding acquisition, Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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