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Sensor Fault Diagnosis of Autonomous Underwater Vehicle Based on LSTM

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Abstract: Autonomous underwater vehicle (AUV) is a complex nonlinear system, and it is difficult to establish its accurate mathematical model and further deal with fault diagnosis problem. Therefore, a novel fault diagnosis method based on a predictive model with using the Long Short-Term Memory Network (LSTM) is proposed in this paper. First, the LSTM network is trained by AUV experimental data, such as acceleration navigation, changing the depth of navigation, changing the direction of navigation and changing the speed of navigation. Then, the trained network can be used to establish the motion model of AUV by fitting the sensor system. Furthermore, the residual generated by comparing the output of the predictive model of the sensors with the actual measured value of the sensors can be used to diagnose sensors fault of AUV, which contains a lot of fault information. Finally, sensor fault diagnosis simulation experiment of the AUV is carried out. The results of the simulation show that the method is effective.

Key Words: Autonomous underwater vehicle, Fault diagnosis, Sensor fault, LSTM

1 Introduction

Autonomous underwater vehicle (AUV) is an important tool to perform underwater tasks. Its working environment is complex and changeable, and there are many disturbing factors. Therefore, a reliable fault diagnosis system is very important for ensuring its accurate operation [1, 2, 3]. In fact, simple system failures can cause mission abort. While the adoption of fault diagnosis techniques, it allows to safely terminate the task. The realization of autonomous fault diagnosis of AUV is an important embodiment of its intelligent level [4]. Among fault diagnosis approaches developed in the past few years, model-based techniques are widely adopted. For the case of complex nonlinear systems like AUV, they can be roughly classified in three main groups: observer-based approaches, model-based parameters estimation and learning-based methodologies [5]. The fault diagnosis method based on analytical model is faced with the difficulty of establishing its accurate mathematical model. Therefore, the method of fault diagnosis based on knowledge has become a practical and feasible method [6].

Neural network has the characteristics of nonlinear mapping, information distribution and storage, parallel processing, self-organization and self-learning, making it an effective method in the field of fault diagnosis, and has been successfully applied in some systems [7, 8, 9, 10, 11]. Recurrent Neural Network (RNN) is a deep learning model for processing sequence data, which is based on the traditional neural network to add the "memory" component. Recurrent Neural Network is learning on a sequence data. It can remember the previous data and predict the data with previous data. Taking into account the sequence data generated by AUV, RNN can be applied to AUV fault diagnosis.

In order to realize the fault diagnosis of the AUV sensor, a sensor fault diagnosis method of AUV based on LSTM network is put forward based on the actual working environment of AUV and the sensor characteristics equipped with it [12]. It is easier to implement in engineering. Based on the fault-free experimental data of a AUV, the computer simulation experiment results verify the effectiveness and feasibility of the method.

2 Long Short-Term Memory Network

Unlike traditional neural networks, RNN's neurons have a recursive structure that can pass the information of the previous state to the current state. The output state $h(t+1)$ of the RNN model at the next moment depends not only on the input $x(t+1)$ at the next moment, but also on the output state $h(t)$ at current moment. Therefore, RNN can memorize the information in front of it, and it can persist information, and then predict the next information based on the previous information. Its structure is shown in Fig. 1. When the input is a time sequences, it can be expanded into a series of interconnected neurons.

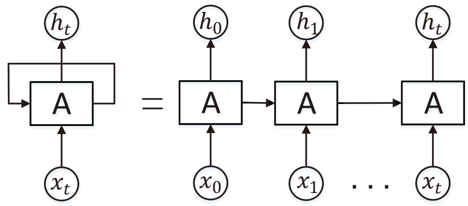

Fig. 1: The architecture of RNN

As the memory distance increases, the memory effect of the simple recurrent neural network will decline. Therefore, LSTM with long time memory ability effectively solves the

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problem of long-term dependence. LSTM clearly avoids the problem of long-term dependence in the design, and can remember long term information. The architecture of LSTM memory module can be described as Fig. 2.

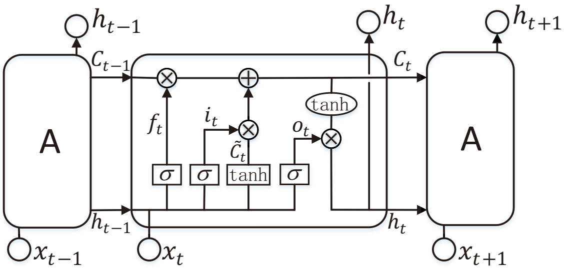

Fig. 2: The architecture of LSTM memory module

The key to LSTM is the Cell State (symbol C). LSTM has the ability to add or remove the Cell State information, and the ability to control the structure of a gate. The gate is a way to selectively allow information to pass. They are composed of a sigmoid neural network layer and an element level multiplication operation. Sigmoid layer outputs the value between the 0~1 and each value indicates whether the corresponding part of the information should be passed. The 0 value indicates that the information is not allowed to pass through, and the 1 value indicates that all the information is passed.

A LSTM memory module has 3 gates to protect and control Cell State, and the gates are forgetting gate, input gate, output gate.

Its formulas are as follows:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \tag{1}$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{2}$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \tag{3}$$

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \tag{4}$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{5}$$

$$h_t = o_t * \tanh(C_t) \tag{6}$$

The formulas (1), (2) and (5) are forgetting gate, input gate and output gate respectively. The Forgetting gate decides which historical information will be discarded from the Cell State. The input gate decides which information will be updated and the output gate decides which part of the Cell States will be outputted. x_t is current time input and h_{t-1} is hidden layer output of the previous moment. (W_f, W_i, W_o) are each gate's weights respectively, and (b_f, b_i, b_o) are each gate's bias respectively. σ is nonlinear function (σ here usually is Sigmoid function) and "·" means matrix multiplication. Then, formula (3) is used to produce a new candidate values that will be added to the new state (time *t*) described by formula (4), together with the values of old state (time *t*-1) which are regulated by forget gate. Eventually, the formula (6) represents the final outputs of LSTM unit. When the Cell State is transformed through a tan*h* function (the output value is between -1 and +1), the output is multiplied with the output gate, and the output h_t will be obtained. In addition, the point-wise multiplication of two vectors is denoted with "*".

3 Modeling of AUV

3.1 Motion Equation

In this paper, the origin of the fixed coordinate system (FCS) is fixed on a point on the earth. And, the origin of the moving coordinate system (MCS) is attached to the AUV.

In MCS, the AUV's movement speed is represented by a 6-dimensional vector $\vec{v} = [u \quad v \quad w \quad p \quad q \quad r]^T$.

In FCS, the position and attitude of AUV is described by the 6-dimensional vector $\vec{\eta} = [x \quad y \quad z \quad \phi \quad \theta \quad \psi]^T$.

The components of speed and force are the same as the direction of the axis. Variable symbols see Table 1.

Table 1: Variable Symbols

Form of Motion	Speed(Angular Velocity)	Position Posture
Surge	u	x
Sway	v	y
Heave	w	z
Roll	p	ϕ
Trim	q	θ
Heading	r	ψ

The motion equation of AUV in FCS is:

$$\dot{\vec{\eta}} = J(\vec{\eta})\vec{v} \tag{7}$$

$$J(\vec{\eta}) = \begin{bmatrix} R_m^f & 0_{3\times3} \\ 0_{3\times3} & T_m^f \end{bmatrix} \tag{8}$$

R_m^f and T_m^f are respectively:

$$R_m^f = \begin{cases} \cos\psi\cos\theta & \begin{matrix}\cos\psi\sin\theta\sin\phi - \\ \sin\psi\cos\phi\end{matrix} & \begin{matrix}\sin\psi\sin\phi + \\ \cos\psi\cos\phi\sin\theta\end{matrix} \\ \sin\psi\cos\theta & \begin{matrix}\cos\psi\cos\phi + \\ \sin\phi\sin\theta\sin\psi\end{matrix} & \begin{matrix}\sin\theta\sin\psi\cos\phi - \\ \cos\psi\sin\phi\end{matrix} \\ -\sin\theta & \cos\theta\sin\phi & \cos\theta\cos\phi \end{cases}$$

$$T_m^f = \begin{cases} 1 & \sin\phi\tan\theta & \cos\phi\tan\theta \\ 0 & \cos\phi & -\sin\phi \\ 0 & \sin\phi/\cos\theta & \cos\phi/\cos\theta \end{cases}$$

3.2 Hydrodynamic Equation

Establishing the hydrodynamic equation of AUV in MCS:

$$M\dot{\vec{v}} + C(\vec{v})\vec{v} + D(\vec{v})\vec{v} - g(\vec{\eta}) = \tau + g_0 \tag{9}$$

In this equation:

M : System inertia coefficient matrix.

$C(\vec{v})$: Centripetal force coefficient matrix.

$D(\vec{v})$: Viscous hydrodynamic coefficient matrix.

τ : Control input vector.

g_0 : Static pressure vector, usually 0.

$g(\vec{\eta})$: Restoring force / moment vector.

3.3 State Equation

In general, the rolling motion of an AUV is not considered. The state equations of the AUV motion system can be obtained by simplifying that combined motion equations and hydrodynamic equations.

$$\begin{cases} \dot{x} = \vec{f}(x) + d + B\tau \\ y = h(x) \end{cases} \tag{10}$$

In this equation:

$\vec{f}$: Matrix function, roll angle is 0,

$$\vec{f}(x) = \left[M^{-1} * \left[-C(\vec{v})\vec{v} - D(\vec{v})\vec{v} + g(\vec{\eta})\right]; J(\vec{\eta})\right].$$

x : A vector consisting of a motion state variable,

$$\left[u, v, w, q, r, x, y, z, \theta, \psi\right]^T.$$

B : Input matrix.

d : Interference term.

y : The measured value of the sensor.

This state equation is the mathematical model of AUV motion and fault diagnosis.

4 Establishment of AUV Fault Diagnosis Model Based on LSTM

The model of AUV consists of 4 parts. They are controllers, actuators, AUV models and sensors. The 4 parts form a complete feedback control system. In the whole control system, the sensor provides the real-time motion information of the AUV. If the sensor fails in operation, its output will no longer react to the true value of the motion of the AUV, which may lead to the failure of the whole system. when an AUV sensor fault occurs in the system in the work process, we hope to be able to timely find the fault location, and promptly issued a corresponding warning, to help maintenance personnel to quickly find the fault position and be convenient for maintenance. This paper mainly deals with the failure of the sensor and assumes that the AUV has no fault in other parts.

This paper takes a certain AUV as the research object. It mainly considers the sensors that affect the position and attitude of AUV, namely fiber optic gyroscope and Doppler velocity log [13]. The state parameters measured by the fiber optic gyroscope and the Doppler velocity log are shown in Table 2 as follows.

Table 2: The State Parameters of Sensor Measurement

Sensor	State parameters of measurement
Fiber Optic Gyroscope	Heading Angle
	Trim Angle
	Roll Angle
Doppler Velocity Log	Forward (surge) Velocity
	Sway Velocity
	Heave Velocity

The fault forms of the AUV sensors are varied, and there is a main type of faults in the fiber optic gyroscope and the Doppler velocity log. The output information of the sensor remains unchanged (no detection signal or sensor stops working, the main performance is that the output value of the sensor is 0 and remains unchanged for a period of time).

There are 6 output values of fiber optic gyroscope and Doppler velocity log of AUV. The experimental data are real-time discrete measurements of sensors obtained with time increasing, and the sampling period is 0.5s.

This paper adopts LSTM network model on the discrete measurement value of the sensor. The test data processing method for modeling strategy: at the time of k, the predictive value of sensor output signal is predicted by the sensor model from the k-1 moment to the k-m moment [14].

In order to obtain the predictive value of the sensor model at k time, the input of each moment of the sensor model is $x(k\text{-}m)$, $x(k\text{-}m+1), \cdots, x(k\text{-}i), \cdots, x(k\text{-}1)$ respectively. $x(k\text{-}i)$ is the input value of the sensor model at the time of k-i. The output value of each time is the input value of the next time, therefore, the output values corresponding to the above input are $x(k-m+1), x(k-m+2), \cdots, x(k-i+1), \cdots, x^*(k)$ respectively. In this way, the predictive value $x^*(k)$ of the sensor at the time of k are produced based on the time of k-m to the time of k-1. The sensor model is shown in Fig. 3.

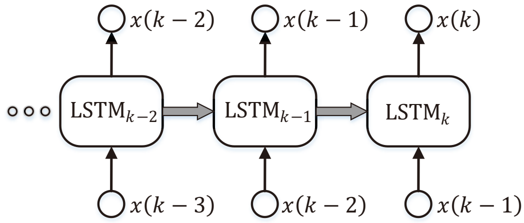

Fig. 3: Sensor model based on LSTM

Three layer networks structure is adopted in the sensor mode. The first layer is the input layer, and the number of the input layer units is 1. The second layer is a hidden layer composed of LSTM units, and the number of hidden layer units must be determined according to the specific data structure. The third layer is the output layer, and the number of the output layer unit number is 1.

According to the sensor model mentioned above, the predictive value of the sensor can be obtained by multistep recursion with time goes up. Abstract as a mathematical representation is:

$$x^*(k) = f_{LSTM}[x(k-m), x(k-m+1), \cdots, x(k-1)] \quad (11)$$

f_{LSTM} is the function of the sensor model from the input to the output. Then the output value of the model prediction after k+t time is as follows:

$$x^*(k+t) = f_{LSTM}[x(k-m+t), x(k-m+1+t), \cdots, x(k-1+t)] \quad (12)$$

At the time of k, after getting the predictive value of the sensor model, the predicted value of the sensor model is compared with the true output value of the sensor, and the corresponding residual is generated. Threshold d is set by analyzing residual. To judge whether a fault occurs by comparing the relationship between the threshold and the maximum of the absolute value of the residual [15]. The flowchart of the diagnosis is shown in Fig. 4 [16].

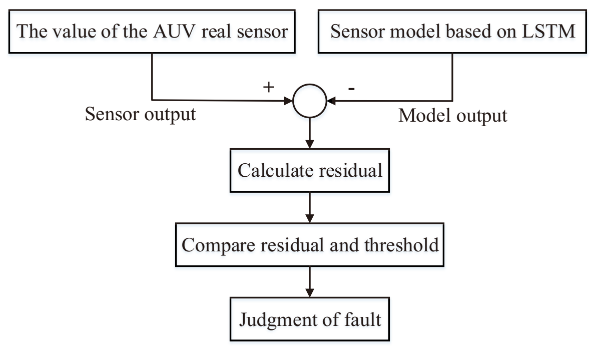

Fig. 4: Flowchart of AUV sensor based on LSTM

In a period of time, if the value of the absolute value of the residual is greater than that of the threshold, the sensor fault is judged. On the contrary, the sensor works well.

After the sensor model is learned, given $x(k\text{-}m)$, $x(k\text{-}m+1), \cdots, x(k\text{-}i), \cdots, x(k\text{-}1)$ to the sensor model, it can obtain the predictive value of $x^*(k)$. The actual output of the sensor at k time is $x(k)$. Seeing in Fig. 5. System residuals is:

$$e(k) = \left\| x(k) - x^*(k) \right\| \tag{13}$$

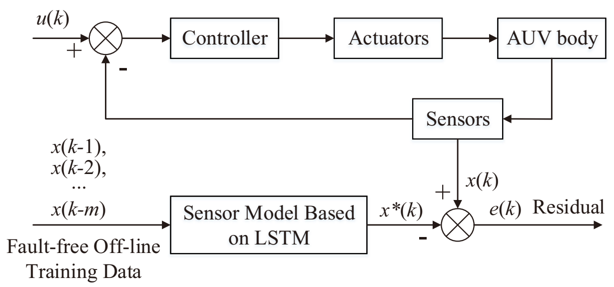

Fig. 5: AUV Fault Diagnosis Model

A large amount of fault information is included in the residual error, and the fault can be judged by the analysis of the residual. The following rules can determine whether the sensor is in fault.

$$\begin{cases} e(k) < d & NoFault \\ e(k) \geq d & Fault \end{cases} \tag{14}$$

In a period of time, if the value of the residual is greater than the threshold, the fault of the sensor can be judged.

The AUV working environment are complex, the presence of noise and disturbance, sensor parameters fluctuation and other factors. They will influence the measurement of the value of the sensor, so the dynamic characteristics of sensor cannot accurately simulate by sensor prediction model. The predict output value of sensor prediction model and the actual output value of the sensor have a very small difference value. Therefore, there is a small error between the predicted output value of the sensor model and the actual output value of the sensor. The selection of the threshold size is critical. If the threshold is too small, it makes the system too sensitive to the fault. However, if the threshold is too large, the response of the system to the fault will be too slow, which leads to a larger delay in diagnosis or a direct omission of the fault report. Therefore, the selection of threshold size needs to be determined based on a large number of experiments and experiences, and to consider the noise and disturbance in the working environment. It is necessary to choose a threshold and corresponding residual error according to each measurement value of the sensor to conduct the sensor's fault diagnosis. The premise is to ensure that the threshold value is larger than the system's modeling error when there is no fault.

In order to better determine the faults of sensors, this paper establishes a sensor model for the forward velocity, sway velocity, heave velocity, rolling angle, trim angle and heading angle of the AUV sensor respectively. The correlation between the sensor output values of the m (always is 30) times before the k moment can product the predictive value of sensor at the k+1 time through the sensor model network.

5 Numerical Simulations

5.1 Software and Hardware Environment

- Experiments are run on a personal computer with Intel(R) Core(TM) i7-6700(3.4GHz) CPU, 12.0GB RAM and Ubuntu 16.04 (Linux) operation system.
- All codes are written by Python 2.7 with tensorflow-1.4.0.

5.2 Network Configuration

- Input x is organized as a one dimensional array, whose dimension represents experimental data representing a moment. Before, we need to preprocess the data x. All values of a quantity measured by a sensor need to get the mean and standard deviation. Then we subtract the mean from each value and then divide it by the standard deviation.
- The required training data structure is [-1, time_step, input_size], Where -1 represents the number of data related to the total amount of data. time_step is a time step for LSTM network training. That is, the m in the data $x(k\text{-}m)$. input_size is the number of nodes in the input layer. The specific training data structure is shown in Fig. 6. Each of the small squares represents a data point of one moment.
- The definition of the LSTM network is the tensorflow.nn.rnn_cell.BasicLSTMCell() function that is already defined by TensorFlow.
- The training function of LSTM network is tensorflow.train.AdamOptimizer().

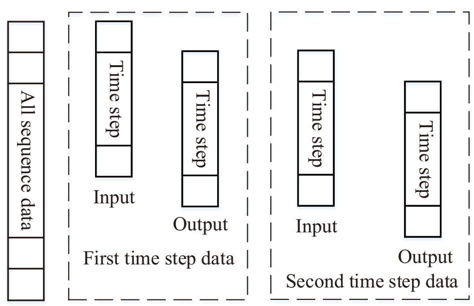

Fig. 6: Training data structure

5.3 Simulation Analysis

I: Simulation results of LSTM network training

Before the sensor model is put into use, each network needs to be trained off-line respectively. The data of the training network are mainly derived from the acceleration of navigation, changing the depth of navigation, changing the direction of navigation and changing the speed of navigation. The motion characteristics of the AUV can be simulated well by the trained sensor model. We use a lot of data to train the sensor networks. Fig. 7 displays an experiment process, and the result shows that 4 times to change the depth of the voyage. Fig. 8 displays an experiment process, and the result shows that 2 times to change the speed of navigation. As we can see in the Fig. 7 and Fig. 8, the Real state representing the true state of AUV is tracked well by the Estimated state representing the predictive value of sensor model.

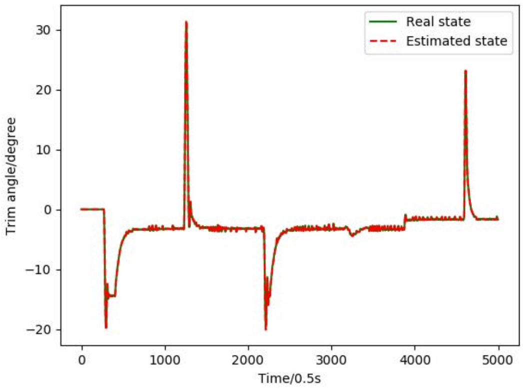

Fig. 7: Trim angle simulated motion results

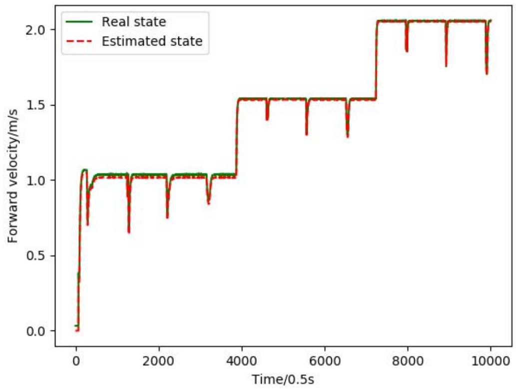

Fig. 8: Forward velocity simulated motion results

II: Simulation results of sensor fault diagnosis for AUV

Next, we can apply the above LSTM network for system fault diagnosis. In this paper, we assume that only one part of the system will fail at the same time. Fig. 9 is the part simulation of the output information of the fiber optic gyroscope of an AUV. The simulation conditions are as follows: Setting up an AUV to speed up the water at a depth of 0 meters. The target course is 90 degrees. The speed is 2 knots. Last some seconds. And then change the depth of the voyage. The target depth is 15 meters. The target course is 90 degrees. The speed is 2 knots. At the 210th time point in the Fig. 9. The output signals (Real state) of the fiber optic gyro change to zero and no longer change for a long time. A constant fault occurred. The residuals between the Real state and Estimated state obviously more than the predetermined threshold. However, the predefined state is the Source state. Therefore, the fault of the fiber optic gyroscope sensor is judged.

Fig. 10 shows the residuals of the Real state and the Estimated state. Its calculation process is formula (15). k represents the value of every moment. *error(k)* is the error value for k time. *R(k)* is the Real state value for k time. *E(k)* is the Estimated state value for k time. In Fig. 10, the solid line represents the residual value at each moment, and the dotted line is the threshold of selection. From the 210th time point, there is an obvious difference between Residuals and Thresholds. So, we can judge the failure.

$$error(k) = \|R(k) - E(k)\| \tag{15}$$

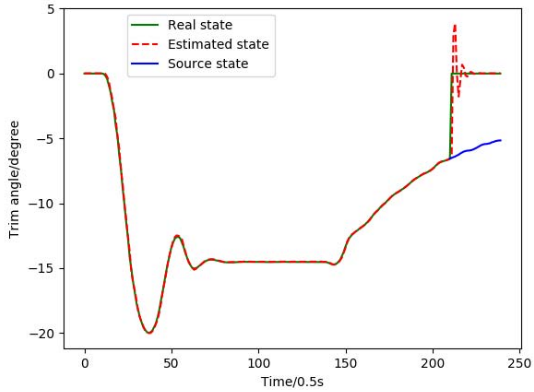

Fig. 9: Simulation experiment analysis

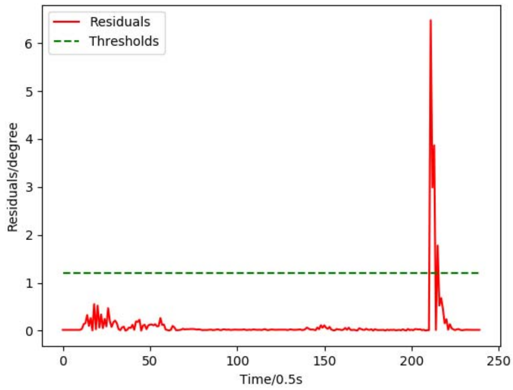

Fig. 10: The residuals between the Real state and Estimated state

6 Conclusions

The fault diagnosis technology of AUV is the key technology to ensure the reliability and safety of the AUV. In this paper, based on the characteristics of the experimental data of the AUV, a fault diagnosis model of the AUV sensor based on LSTM is established. Entering the experimental data of normal work into the fault diagnosis model, which is used to train the model, and the normal work of the sensor is obtained. When the sensor fails, the output data of the output of the AUV sensor at the next moment will fluctuate. By comparing the next time output of the sensor and the output of the sensor fault diagnosis model of AUV, if the residual error is greater than the threshold which set according to experience, we can predict the sensor failure. Through simulation analysis, it is verified that the diagnosis results of this method are consistent with those of AUV sensors, and the diagnosis accuracy is high, which shows the effectiveness of the method.

In recent years, with the continuous promotion of science and technology and underwater research and the increasing application requirements, the intelligent level of AUV is put forward higher request. Because of the poor working conditions of the AUV and the complex and changeable surrounding environment, it is very important to ensure the safe work of the AUV. This method provides a good reference for the intelligent fault diagnosis of the AUV sensor.

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