Fault Diagnosis Method of Autonomous Underwater Vehicle Based on Deep Learning

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Abstract. In order to solve the questions that autonomous underwater vehicle(AUV) can’t accurately predict thrusters’ fault only depend on sensor’s information, which is caused by the effect of closed-loop control system, and shallow neural network can’t well fit the complex nonlinear system, this paper proposes a new method for the fault diagnosis of AUV’s thruster, based on Deep Neural Network(DNN) and Denoising Autoencoder(DAE). In this proposed method the difference between AUV’s theoretical state value and measured state value are used as input signal. Considering the disturbance of AUV’s working environment, when using DAE to pre-training the DNN, Gaussian noise was added in the input signal to simulate environment. The trained DNN network was finally used to detect the AUV’s fault propeller components. The results show that the proposed method is more effective, accurately and robust than other traditional methods.

1. Introduction
Nowadays, when developing offshore and deep-sea resources, the Autonomous Underwater Vehicle (AUV) is becoming an indispensable part of the exploration and development of marine resources, because it can complete the extreme tasks that divers cannot. AUV generally works in an unknown complex marine environment, working offline for a long time, frequent changes in the payload could change the shape and weight balance, which will cause changes in the motion characteristics of the robot and the dynamic performance of the system, and the ability to respond to system commands [1].

In the field of machine learning in recent years, deep learning with a deep hidden layer structure extracts the hidden features of data by mimicking the cognitive processes of the human brain, and has achieved remarkable results in the fields of image and speech recognition. The results show that when the human brain receives an external signal, the brain does not immediately process the signals directly but extracts the characteristics of the signal through a multi-layered neural network[2]. In this paper, deep learning is introduced into the field of underwater robot fault diagnosis, and a deep learning based underwater robot thruster fault diagnosis method is proposed.

2. Auv platform and fault modelling
2.1. AUV platform introduction
The tunnel AUV is equipped with a variety of acoustic detection sensors that can perform a variety of underwater detection tasks. Its actuator uses a propeller and is equipped with five propellers. There is a set of vertical pushes and side pushes on each of the rafts, and a horizontal main thruster is additionally arranged on the raft[3].
2.2. Fault modelling
As mentioned above, the underwater robot is a motion with a multi-degree of freedom for a strong nonlinear system. The existing AUV thruster fault diagnosis methods mostly judge the robot propulsion by comparing whether the difference between the theoretical state value of the robot and the measured state value is exceeded the threshold. However, this method ignores the influence of the compensation effect of the closed-loop control system on the control quantity on the fault detection system[4].

\[
\begin{align*}
x(k+1) &= F(k,u(k),x(k), f(k)) + w(k) \\
y(k+1) &= G(k+1,x(k+1)) + n'(k) \\
w(k) &= d(k) + Bn'(k) \\
v(k+1) &= | y(k+1) - x(k+1) |
\end{align*}
\]

where \(x(k)\) and \(y(k)\) are the theoretical state output of the AUV at time \(k\) and the actual measured output of the sensor, respectively, and the nonlinear function of the AUV system, \(u(k)\) is the propeller control amount, and \(f(k)\) is The fault vector of the thruster, and the self-noise of the thruster and the sensor, \(d(k)\) is the external disturbance of the system, \(B\) is the uncertainty coefficient, and \(v(k)\) is the difference between the theoretical state output of the AUV and the actual measured output of the sensor at time \(k\). It can be seen from Equation (1) that when the AUV is operating normally and the propeller is not faulty, when the propeller is faulty, by judging whether \(f(k)\) is zero or not, we can know if the AUV's thruster has failed[5]. However, in the actual operation and state detection process of AUV, we can't directly measure \(f(k)\) directly through the sensor. For the tunnel AUV, the variables that can be directly obtained through software and hardware mainly include AUV speed, target yaw angle, and propeller control. The voltage, the actual measured speed of the sensor and the actual measured turn angle. We will study the measurable data to determine whether \(f(k)\) is not equal to zero.[6]

3. Pre-training and tune

3.1. Denoising autoencoder
As shown in Figure 1, the automatic encoder (AE) is an unsupervised three-layer neural network model, which consisting of an input layer, a hidden layer and an output layer. The core idea of the model is to extract the signal characteristics in the input data. Reconstruct the original input signal, and then train the network weights by maximizing the restored input data through the network output[7].

However, when the input layer data is affected by noise, the obtained input data itself may not obey the original distribution. In this case, the results obtained by the encoder will also be incorrect. In order to solve the data deviation caused by noise, we adopt the network structure of Denoising Autoencoder (DAE) [1], as shown in Figure 2. Compared with the automatic encoder, the DAE adds a noise processing process between the input layer and the hidden layer, and the data of the original distribution is processed to obtain the noise data, and then the maximum output of the DAE is restored. Noise data to train network weights to improve network robustness.

![Figure 1 - Autoencoder](image1)

![Figure 2 - DAE structure](image2)
Where $x$ and $z$ are both $m$-dimensional input column vectors and $X$ is an $n$-dimensional output column vector.

$$\{x^{(n)}\}_{n=1}^N \rightarrow \{x^{(n)}\}_{n=1}^N$$

$$x^{(n)} = x^{(n)} + \varepsilon^{(n)}$$

$$\varepsilon^{(n)} \sim E(\theta)$$

(2)

Where $E(\theta)$ is the distribution type of noise, considering the characteristics of the working environment of the underwater robot, we use Gaussian noise in the method introduced:

$$\tilde{x}^{(n)} = x^{(n)} + \text{Normal}(0,1)$$

Then pre-training the weight by minimizing the energy loss function, constructing the optimization objective function based on the energy loss [2] which is shown as follows:

$$\min_{\theta} J(\theta) = \frac{1}{N} \sum_{n=1}^{N} \| x^{(n)} - x^{(n)} \|_2^2 + \lambda \cdot R(\theta)$$

(3)

In the above formula, the parameter is defined as a regular term as:

$$\theta = [W, b; W, b]$$

$$R(\theta) = \| W \|_2^2 + \| W \|_F$$

(4)

3.2. Fine-tuning using BP algorithm
After the DNN network pre-training is over, we use the BP algorithm to fine tune the network weights. We reversely update the weight parameters based on the output of the pre-trained DNN network. For a vectors of input $x^{m}$, $y^{m} = f_{h_{N+1}}(h_{N}^{m})$ is the corresponding DNN network output, the optimization function is:

$$\varnothing_{\text{opt}}(\Theta) = \frac{1}{M} \sum_{m=1}^{M} L(y^{m}, d^{m})$$

(5)

Where $\Theta$ is the parameter set of weight, $\Theta = \{\theta_1, \theta_2, \ldots, \theta_{N+1}\}$, the parameter of weight is iterated as follows:

$$\Theta = \Theta - \eta \frac{\partial \varnothing_{\text{opt}}(\Theta)}{\partial \Theta}$$

(6)

Where $\eta$ is the learning rate of Bp algorithm[8].

3.3. Dropout method
Since the fault samples in the AUV state samples are less than the normal samples, it is easy to cause over-fitting of the network structure during network training. In order to prevent the over-fitting phenomenon from affecting the accuracy of the fault diagnosis of the diagnostic system, we introduce the dropout algorithm. Dropout is a method to prevent overfitting during training with a small sample network. In essence, Dropout can be thought of as setting the output of some hidden layer neurons at a certain ratio to 0, so that these selected neurons will not participate in the forward propagation of the training[9].

3.4. Auv’s thruster fault diagnosis method based on deep learning
In this section, we apply deep learning to the propeller fault diagnosis of underwater robots. Firstly, the theoretical state value of the AUV yaw angle is obtained by the motion simulation model of the tunnel AUV, and then the residual of the measured state value is used as a fast Fourier transform to obtain 4000 sets of Fourier coefficients, due to the Fourier coefficient. Symmetry We take the first 2000 coefficients as input vectors for the DNN network. Secondly, a deep neural network consisting
of multi-layer DAEs is built, and the noise-processed input vectors are used for pre-training, and the weights between the layers of the DNN are trained layer by layer. After pre-training with DAE, the weight parameters of the DNN network are initialized, and then the bp algorithm is used to fine tune the network weights. The technique of dropout is used in the training process to prevent over-fitting caused by the network due to fewer fault samples [10].

4. Experiment test
In order to verify the effectiveness of the deep DAE-based DNN method in the AUV thruster fault diagnosis system, and taking into account that the AUV is vulnerable to personnel and property losses when testing in the external field with fault conditions, the AUV fault motion is adopted. Simulation platform failure data. The data is collected by the semi-physical simulation platform of the laboratory tunnel robot project. The simulation program runs under the VC6.0 environment of 64-bit win10, and the motion control program runs in the PC104 board. The signal acquisition frequency is 2Hz.

The task of this test is to determine the fault degree of the AUV thruster by the residual signal of the theoretical steering angle data predicted by the sensor's measured heading angle and motion simulation during the AUV operation. In this study, we collected 600 sets of samples for each fault level. In each set of samples, the signal was subjected to fast Fourier transform to obtain 2000 Fourier coefficients (sample feature points). 4 Fourier map under fault level.

4.1. Influence of DNN hyperparameter
In the noise reduction automatic encoder, the noise pollution coefficient has a great influence on the final diagnosis result. Therefore, it is listed as one of the network hyperparameters in this paper. The influence of this coefficient on the diagnostic accuracy of DNN network is studied. It has great meaning. As shown in Figure 3, the pollution coefficient changes from 0 to 0.5, and the change of each step is 0.1. It can be seen from the figure that the diagnostic accuracy of DNN increases from the coefficient of 0 - 0.4 with the increase of the pollution coefficient. Out: Before the coefficient reaches 0.4, the pollution resistance of the input signal can increase the anti-interference ability and robustness of the DNN structure. At the same time, when the pollution coefficient is greater than 0.4, the diagnostic accuracy of the DNN network is also obviously degraded. It can be explained that when the pollution coefficient is too large, the quality of the signal is affected, resulting in a decrease in diagnostic accuracy. This confirms that the SAE trained with appropriate noise data can extract more powerful features than the traditional ones.

Figure 3 – denoising rate influence

Figure 4 – dropout rate influence

In addition, over-fitting problems due to insufficient samples for deep networks have long been a major problem faced by researchers. This paper also studies the impact of the dropout rate on the diagnostic accuracy of the network structure. Here, the same interval and step size as when studying the noise rate are used. It can be seen from Figure 4 that the DNN network achieves the best performance when the dropout rate is close to 0.3. When the dropout rate exceeds 0.3, the diagnostic accuracy decreases. It can be concluded that the dropout rate of about 0.3 can better compensate the network.
4.2. Analysis of results
In order to prove the processed method can effectively learn the characteristics of each fault level signal of AUV propeller through DAE pre-training and fine-tuning, we show the classification result of DNN network through an effective data visualization technology "t-SNE"[11]. As shown in Figure 5, the same fault types are effectively gathered together, and different fault levels are effectively distinguished.

![Figure 5 – feature map of four typical faults](image)

Because the motion state of the AUV has great delay, it is difficult to accurately separate the normal state to the fault when extracting the fault data sample. The samples at the time of transition between states, so that in Fig. 5, there will be a case where a small number of data points of each fault state are gathered with normal state data points.

Finally, in order to prove that the selected DNN network structure and the traditional fault diagnosis method SVM, bp network have obvious advantages in diagnostic accuracy, we randomly conducted 50 sets of comparative experiments. The experimental results are shown in Table 1. From Table 1, we can see that the proposed method not only can identify different fault levels of the propeller, but also has obvious advantages in diagnostic accuracy compared with the traditional fault diagnosis method.

| Method     | Classification accuracy |
|------------|-------------------------|
| Proposed method | 98.21                  |
| SVM based   | 93.45                   |
| BP based    | 73.58                   |

5. Conclusion
In this paper, a fault diagnosis method for intelligent underwater robot propeller based on DNN deep neural network is proposed. The method can intelligently extract the characteristics of the thrust level of the thruster from the residual signal of the theoretical state and the measured state of the AUV, and perform a higher precision distinction. It has been found through experiments that the diagnostic accuracy is higher when the noising rate is around 0.4. Then, according to the characteristics of fewer fault samples in the normal condition of AUV operation, the dropout strategy is introduced to prevent over-fitting during network training. It is found through experiments that when the dropout rate is around 0.3, the DNN network is for AUV.

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