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Automatic Underwater Vehicle Fault Diagnosis Framework Based On Multi-Scale Attention Mechanism

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Intelligent autonomous systems (IASs) are increasingly utilized across diverse domains of human activities, including unmanned aerial vehicles, autonomous vehicles, and autonomous underwater vehicles (AUVs), owing to their remarkable autonomy and adaptability. AUVs, in particular, are highly regarded for their autonomous operation in deep-sea environments, exhibiting long-range capabilities and exceptional precision, contributing to their widespread adoption in marine applications. They are pivotal in offshore oil and gas exploration, marine rescue operations, and marine environmental surveys. However, operating AUVs within complex and unpredictable environments poses a significant challenge, as equipment faults or component failures can result in mission failure or even the loss of the AUV. Consequently, developing effective methods for condition monitoring and fault diagnosis is of utmost importance to ensure the safety and reliability of autonomous systems.

In this study, we propose an automatic underwater vehicle fault diagnosis framework that combines Discrete Wavelet Transform (DWT) and multi-scale attention mechanism. DWT, as an advanced signal processing technique, has been widely applied in recent years for the extraction of features from multi-sensor signals. The advantages of DWT in multi-sensor signal feature extraction lie in its multi-scale analysis capability, adaptability to non-stationary signals, and sensitivity to local details of complex signals. By applying DWT, critical features from multi-sensor systems can be extracted more accurately and comprehensively, providing reliable data support for real-time monitoring, intelligent diagnosis, and other applications.

The proposed multi-scale attention mechanism demonstrates significant advantages in multi-sensor signal feature extraction, particularly in the field of autonomous underwater vehicle fault diagnosis. Its core strength lies in its ability to adaptively focus on signal information at different scales, thereby more precisely capturing features and details across multiple scales. Traditional fault diagnosis methods often struggle to effectively handle the complex and multi-scale signal information generated by multi-sensor systems. The multi-scale attention mechanism addresses this challenge by dynamically adjusting the focus on different scales, enhancing the detection capability for concealed faults and anomalies within the system. Moreover, by assigning different weights to signals at each scale, the multi-scale attention mechanism makes the system more adaptive, capable of flexibly adjusting to different working conditions and environmental changes. This contributes to improving the autonomous decision-making and fault response capabilities of underwater vehicles in complex underwater environments, providing crucial support for achieving efficient and safe underwater missions.

The dataset is derived from a quad-rotor AUV, which is mainly composed of four motors and propellers, a depth sensor, a satellite positioning device, an IMU, and a control cabin (Ji et al., 2021). The structure of the AUV is shown in Figure 1. Various data of the AUV can be obtained from sensors and multiple components. In this study, we used 16 different sensor data, such as motor control signals, battery voltage, depth, angular velocity, acceleration, and vehicle attitude information. The collected data information is shown in Table 1. During the data collection process, five health states were set for the AUV, including normal state (F1), abnormal load (F2), depth sensor fault (F3), serious propeller fault (F4), and minor propeller fault (F5). For each health condition, the AUV is run multiple times, and the data is collected, with each run lasting approximately 10 to 20 seconds to obtain sufficient signal length. Ultimately, approximately 250 data samples were acquired for each health state, and 1220 data samples were acquired in total.

The proposed method has undergone extensive validation on the dataset of the autonomous underwater vehicle. The confusion matrix is illustrated in Figure 2. Experimental results indicate that the proposed method exhibits outstanding fault diagnosis performance, establishing itself as an efficient solution for autonomous underwater vehicle state monitoring.

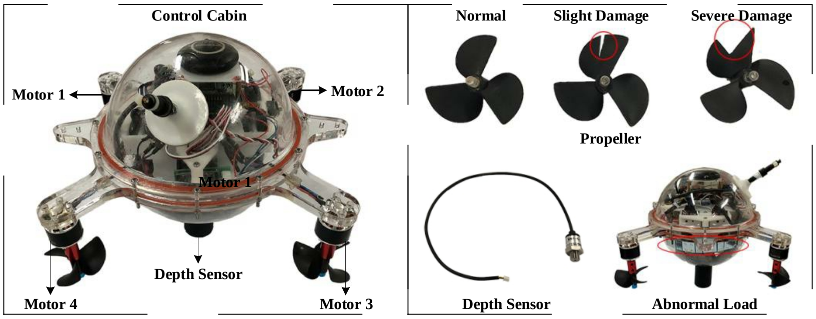

Fig. 1. Structure and fault categories of the autonomous underwater vehicle.

Table 1. The Collected Sensor Information of the Autonomous Underwater Vehicle

Term	Description	Term	Description
Pwm1	Control signal for motor 1	Pitch	Pitch angles measured by IMU
Pwm2	Control signal for motor 2	Yaw	Yaw angles measured by IMU
Pwm3	Control signal for motor 3	Acc_X	Acceleration (x-axis)
Pwm4	Control signal for motor 4	Acc_Y	Acceleration (y-axis)
Depth	Depth value of AUV	Acc_Z	Acceleration (z-axis)
Press	External pressure value of AUV	W_Row	Angular velocity of rotation around the x-axis
Voltage	Voltage value of battery	W_Pitch	Angular velocity of rotation around the y-axis
Roll	Roll angles measured by IMU	W_Yaw	Angular velocity of rotation around the z-axis

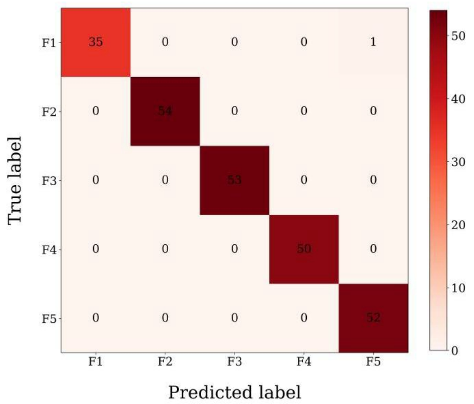

Fig.2. The confusion matrix of the proposed method.

References

Ji, D.X., Yao, X., Li, S., Tang, Y.G., Tian, Y. 2021. Autonomous underwater vehicle fault diagnosis dataset. Data Brief 39, 107477.