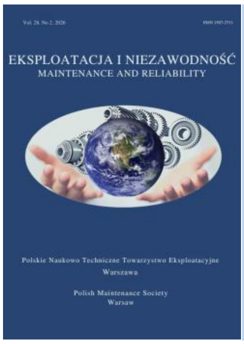

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A Physical Feature Residual Model for Actuator Fault Detection of Autonomous Underwater Vehicles

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Highlights

- We establish a model-fault-feature transmission path to support the identification.
- The PIEN framework integrates a hybrid prediction network.
- We develop a first-principles residual generator that quantifies causal relationships.

Abstract

Real-time fault diagnosis for autonomous underwater vehicles (AUVs) is crucial for ensuring overall system safety. As a critical component, the thruster operates is prone to failure under complex environments. This study proposes a Physics-Informed Estimation Network (PIEN) to address thruster fault diagnosis. First, sensor data from the thruster are collected to establish corresponding fault mechanism models. The estimation network then constructs a predictive model to generate online residual data by physical parameters. Finally, a residual fault detector determines thruster malfunction status. The experimental validation with the "Haizhe" AUV dataset demonstrates PIEN's ability to quickly detect different thruster faults in prototypes. It also achieves better diagnostic performance than manually designed models.

Keywords

autonomous underwater vehicles (AUVs), thruster faults, physics-informed, long short-term memory (LSTM)

1. Introduction

Thrusters are core components of autonomous underwater vehicles (AUVs), with their operational status being pivotal for fault diagnosis in AUV systems [1,2]. Given the environmental complexity [3], AUVs face unpredictable operational disruptions from external factors such as ocean currents, waves, and floating debris [4,5]. Thus, developing reliable, high-quality fault diagnosis methods is critical. In harsh environments, thrusters may experience reduced rotational speeds and sudden current surges due to entanglement with underwater vegetation or debris, often resulting in blockages [6]. Timely detection and mitigation of entanglement-induced malfunctions are essential to minimize operational risks. Thruster failures in AUVs can disrupt mission schedules and compromise vehicle integrity, potentially leading to total loss [7,8]. Therefore, accurate diagnosis of thruster operational status is critically important for improving both efficiency and safety-reliability of AUVs.

Qualitative diagnosis relies primarily on empirical knowledge, predefined rules, and logical reasoning to assess faults via expert systems or rule-based methods. This approach

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typically integrates techniques such as expert experience and fault tree analysis. However, due to its reliance on subjective judgments, qualitative diagnosis often lacks consistency and reproducibility. In contrast, quantitative diagnosis methods include both model-based approaches (e.g., dynamic system models) and data-driven techniques [9,10]. For instance, researchers have developed an observer-based fault detection filter designed for networked system models. This approach integrates a coordinated controller specifically optimized for AUV dynamics. [11]. Further advancements include an observation-based model-driven framework that explicitly incorporates network environmental factors [12].

Model-based methods depend on accurate mathematical models of vehicle dynamics, as demonstrated by Freeman et al. [13]. While theoretically effective, their diagnostic performance is constrained by complex underwater environmental dynamics and inherent modeling uncertainties. For instance, [14] introduced a model-based fault diagnosis framework for AUV rudder systems. Due to the construction of an accurate radar system model, this method has achieved good recognition results for radar faults. However, this approach faces generalization challenges when the underlying model inadequately represents system behavior across diverse fault scenarios.

Data-driven methods have shown increasing promise in addressing fault diagnosis challenges for AUVs, particularly in complex underwater environments characterized by dynamic AUV behaviors [15–17]. Machine learning techniques, for instance, leverage sensor data to achieve robust fault detection. Building on this paradigm, [18] proposed a multi-channel fully convolutional neural network to diagnose AUV faults under missing data conditions, directly utilizing raw state data as input. Similarly, [19] demonstrated that model-free approaches exhibit strong adaptability to environmental variations but face limitations in generalization when training data lacks diversity. Recent innovations include [20]'s self-attention-enhanced architecture for improved feature extraction and [21]'s multi-source data fusion framework, which significantly boosts diagnostic accuracy. Notably, deep learning excels in this domain by extracting high-level features through its inherent nonlinear modeling capabilities, offering a complementary advantage to conventional methods. This advantage is fully utilized in the above-mentioned application scenarios.

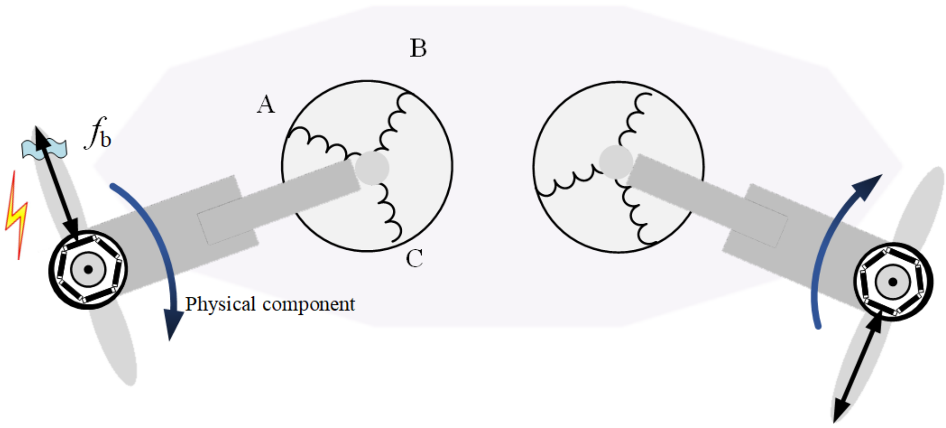

Figure 1. The concept of thruster fault cases.

Deep learning-based models have achieved notable success in thruster fault diagnosis. For example, [22] developed a specialized recurrent neural network for fault detection in magnetically coupled thrusters, while [23] proposed an LSTM-based predictive modeling framework for temporal fault pattern recognition. However, LSTMs require large-scale training datasets to effectively learn long-term temporal dependencies and complex dynamic behaviors. This poses significant challenges in real-world AUV applications, particularly in complex underwater environments where acquiring sufficient high-quality sensor data is often impractical.

Moreover, many machine learning-based diagnostic methods cannot be fully trusted in autonomous systems, particularly in safety-critical AUV operations where human oversight remains mandatory [24]. Recent progress in explainable artificial intelligence aims to bridge this trust gap—for example, Chen et al. [25] formalized explainability requirements for AI systems transitioning across diverse marine applications. This is crucial for AUVs, as operators depend on interpretable diagnostic outcomes to justify high-stakes decisions. Integrating physical knowledge further enables condition-based maintenance by quantifying asset remaining useful life and failure likelihood, thereby minimizing unnecessary maintenance interventions while enhancing operational safety and availability.

This study focuses on thruster faults, a predominant failure mode in AUVs. Despite their operational criticality, existing diagnostic methods struggle to handle time-varying dynamics and strong cross-system couplings. To address these limitations, we propose a physics-informed machine learning framework comprising three steps: A dynamic data selection mechanism weights monitoring variables in real-time based on their relevance to system behavior, mitigating coupling effects; LSTM networks automatically engineer discriminative features from time-series sensor data, capturing latent fault signatures; A fault detector leverages residual analysis to isolate optimal monitoring variables, enhancing sensitivity to incipient faults. Finally, experimental validation confirms that this integrated approach significantly improves diagnostic robustness in coupled, dynamic AUV systems.

This work advances thruster fault diagnosis through three key innovations:

1. The method proposed in this article extracts fault related feature information through a known AUV physical model, and establishes a model-fault-feature transmission path to support the identification and prediction network. This approach uniquely preserves fault-relevant interaction patterns while suppressing environmentally induced spurious correlations, transforming cross-variable dependencies from diagnostic liabilities into assets.

2. We develop a first-principles residual generator that quantifies causal relationships between thruster fault and system states. By embedding hydrodynamic thruster models into the residual calculation, this module isolates failure-specific physical deviations from ambient operational noise, achieving fault discriminability in validation trials.

3. The PIEN framework integrates a hybrid prediction network that synergizes data-driven temporal modeling with physics-based state estimation. This dual-channel architecture compensates for environmental variability and maintains perfect performance for degradation.

2. Problem Description and Preliminaries

2.1. Preliminaries

The motion of an AUV can be described by the surge-sway-yaw model, commonly used as in [26]. The model considers the vehicle's physical variables along different directions. The equations of motion are given by

$$\begin{cases} M\dot{v}(t) + Nv(t) + G\varphi(t) = Eu^F(t) + \xi(t) \\ \dot{\eta}(t) = J(\psi(t))v(t) \end{cases} \tag{1}$$

where M represents the matrix of inertia; N denotes damping; G is mooring forces; E represents the thruster configuration matrix; and $J(\psi(t))$ is the kinematic transformation matrix,

$$J(\psi(t)) = \begin{bmatrix} \cos(\psi(t)) & -\sin(\psi(t)) & 0 \\ \sin(\psi(t)) & \cos(\psi(t)) & 0 \\ 0 & 0 & 1 \end{bmatrix} \tag{2}$$

where v(t)=[ζ(t) v(t) r(t)] ,ζ(t), v(t), and r(t) represents the surge velocity, sway velocity, and yaw velocity, respectively; η(t) and ψ(t) denote position and the yaw angle, respectively; u^F(t) represents the thruster input.

Assumption 1. A fault in the rotating thruster can be represented as the introduction of a virtual mass m (which may be positive or negative). The thruster rotates when fouled at velocity ω_f. Fig. 1 shows the conception of the thruster fault for the whole AUV. The fault in the physical system when the thruster is fouled can be expressed as follows [27]

$$\mathcal{P}^{\mathrm{f}}\colon J\frac{\mathrm{d}\omega_{\mathrm{f}}}{\mathrm{d}t} = T_{\mathrm{im}} + B\omega_{\mathrm{f}} + C_q\omega_{\mathrm{f}}^2 - T_e \tag{3}$$

where J denotes the shaft rotational inertia; B denotes the friction coefficient of thruster rotors; C_q denotes the aerodynamic torque coefficient; T_{im} is the imbalance torque; T_e denotes the total electric torque. The system P^{f} explains the physical relationship between the variables when thrusters are operating. Therefore, the fault transmission path can be derived from (3), which can extract the physical meaning of fault features. Because the propeller model is included, the resultant state-space model is nonlinear and is expressed as follows:

$$\dot{x} = Ax(t) + Bu(t) \tag{4}$$

and

$x = \{I \quad \omega_{\mathrm{f}} \quad \theta\}^{\top}$

$$A = \begin{bmatrix} -\frac{R}{L1} & 0 & 0 & -\frac{(K_e F_a(\theta))}{L1} & 0 \\ 0 & -\frac{R}{L1} & 0 & -\frac{(K_e(\theta))}{L1}(1) & 0 \\ 0 & 0 & -\frac{R}{L1} & -\frac{(K_e F_c(\theta))}{L1} & 0 \\ \frac{(K_e F_a(\theta))}{J} & \frac{(K_e F_b(\theta))}{J} & \frac{(K_e F_c(\theta))}{J} & -\frac{B}{J}\frac{L_q \omega_f}{J} & 0 \\ 0 & 0 & 0 & \frac{P}{2} & 0 \end{bmatrix} \tag{5}$$

$$B = \begin{bmatrix} \frac{1}{L1} & 0 & 0 & 0 \\ 0 & \frac{1}{L1} & 0 & 0 \\ 0 & 0 & \frac{1}{L1} & 0 \\ 0 & 0 & 0 & \frac{1}{J} \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

$u = \{V_x \quad T_{im} \quad \}^{\top}$

where I denotes the current of the thruster; θ denotes the electrical angle of the motor; K_{e} denotes the coefficient of the back electromotive force; F_{k} is the back electromotive force; R is the resistance; L_1 is the inductance; V_{x} is the thruster voltage. In AUVs, sensor-collected data typically reflects the system state. This data consistently corresponds to movement scenarios. Through analyzing AUV state data, operators can determine whether the vehicle is in a normal state, and this data serves as the basis for fault detection. Various sensor signals require screening, including angular signals (yaw, roll, and pitch angles), acceleration signals, and electrical signals. Effective information is considered when screened through the fault physics transmission mechanism.

2.2. Problem Description

AUVs often operate in diverse and unpredictable underwater environments, which can affect sensor readings and thruster performance. Fault characteristics are typically nonlinear and influenced by various external factors such as currents, waves, and floating objects. These factors increase system complexity and complicate fault diagnosis, particularly regarding real-time and accuracy requirements. In this study, AUVs' dynamics are inherently nonlinear. The surge-sway-yaw model in (1) captures these dynamics, but actuator faults further complicate system behavior. AUVs require real-time fault diagnosis to ensure timely responses to actuator malfunctions. The computational demands of advanced diagnostic algorithms, especially deep learning-based ones, can be high, potentially causing delays in fault detection and response.

Many machine learning-based fault diagnosis methods operate as black boxes, impeding operator comprehension of the diagnostic rationale. In safety-critical applications requiring human oversight, this lack of explainability undermines trust in automated systems. Operators require transparent insights into fault detection mechanisms to make informed decisions regarding vehicle operation and maintenance interventions.

3. Fault Detection Frameworks

The proposed PIEN provides interpretability for data inputs to LSTM networks. This physically meaningful interpretability enhances the network's memory efficiency, enabling acquisition of high thruster-fault-correlated residuals to complete the final fault detection model.

3.1. Designs of Physical-informed Feature Extraction

To effectively diagnose faults in the thrusters, a robust physical model must be constructed. It relates the input parameters (control signals) to the output performance (thrust generated). This model serves as the foundation for understanding how various factors, including actuator faults, influence the vehicle's behavior.

The physical model for AUV thrusters can be derived from fundamental principles of fluid dynamics and thruster mechanics. Laboratory experiments enable validation and optimization of the physical model by measuring thruster thrust under different input conditions. Experimental data aids in identifying model limitations and refining parameters, especially under failure conditions. By adjusting the LSTM structure, the model's predictive performance can be significantly improved. Based on the state-space equations of the AUV thruster in the background section, a simplified input-output correspondence can be obtained as follows:

$$\dot{x} = A x_F(t) + B u_F(t) \tag{6}$$

Due to the large number of variables in the output set x_F, variable filtering must be considered. Equation (3) shows that thruster failure induces changes in the overall rotational speed, subsequently altering a subset of electrical signals through electrical angle variation,

$$V_x = E_R + K_e * \omega_f \tag{7}$$

and therefore the electrical signals can be used as a part of the outputs of the discernment space. The thrust produced by a thruster can be expressed as a function of several key parameters, including voltage and its gate signal (P_x), which directly affects its performance. Then, since the scenario applied in this paper is a brushless DC motor, the battery voltage will not be able to be added directly to the motor terminal and needs to be converted to AC through an inverter, so the gate switching signals of the inverter need to be taken into account when considering again the creation of an interpretable physical model,

$$u_F(t) = \{V_x \;\; P_1 \;\; P_2 \;\; P_3 \;\; P_4\} \tag{8}$$

In practical applications, experimental data are often used to refine this model. For instance, thruster performance can be characterized through laboratory experiments measuring thrust under varying input conditions. Based on the physical state of AUVs, state variables can be predicted using the inputs as follows:

$$s_f = \{r_f \;\; p_f \;\; y_f\}^T \tag{9}$$

where r_f denotes the roll angle; p_f denotes the pitch angle; y_f denotes the yaw angle. In case of thruster failure, the attitude-characterizing angles of the AUV will change. Estimating these variables enables more accurate failure characterization. Therefore, a physical prediction model can be established between state and input variables, yielding

$$\check{s}_f = \aleph\{u_F\} + v_n \tag{10}$$

where v_n represents the process and measurement Gaussian noise.

Remark 1. The physical model outputs exhibit distinct fault frequency characteristics. Consequently, developing an accurate physical model that precisely represents input-output relationships is essential for reliable thruster fault diagnosis in AUVs. Such models serve dual purposes: (1) characterizing normal operational behavior, and (2) enabling effective fault detection and isolation, ultimately improving AUV operational reliability and safety.

3.2. Prediction Paradigms: LSTM

An LSTM network comprises multiple memory cells, each containing three key gating components [23]. These gates collectively regulate information flow, preserving long-term dependencies while filtering irrelevant data. This architecture is particularly effective for modeling thruster dynamics, where temporal relationships between inputs (voltage, current) and outputs (thrust) exhibit time-varying characteristics. The input gate's mathematical formulation is expressed as:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{11}$$

where: x_t represents the input at time t; For AUV thrusters, LSTM networks can be trained to predict thrust output using historical input signal data. This approach enables powerful performance analysis and fault diagnosis through input-output signal prediction. Within AUV fault detection frameworks, LSTMs serve as particularly valuable diagnostic tools.

3.3. Fault Detection Threshold

At the fault detection process, It first need to compute the residual, which represents the difference between the actual thrust signal and the predicted signal generated by LSTM models. The residual Rt at time t is mathematically defined as:

$$R_t = T_{actual,t} + T_{predicted,t} \tag{12}$$

where $T_{actual,t}$ is the actual output measured by the sensors at time t; $T_{predicted,t}$,t is the output predicted by the LSTM model at time t.

The residual R_t quantifies model prediction accuracy. Small residuals indicate close alignment between predictions and actual measurements, while large residuals suggest potential thruster faults. For effective fault detection, we introduce a threshold β defining the acceptable residual range during normal operation. When $|R_t| > \beta$, a fault condition is indicated. This threshold is derived from the training data distribution.

Residual analysis comparing predicted versus actual thrust signals offers an effective fault identification solution for AUV thrusters. Fig. 2 illustrates the proposed method's workflow. By implementing an optimized detection threshold, the system achieves reliable actuator fault identification, enhancing both mission safety and operational efficiency.

Algorithm 1 Explainable Fault Diagnosis Model.

1: **Input** Voltage and PWM signals, V(t), PWM(t)
2: **Output** Physical state variables, s(k)
3: Normalize and scale historical input and output data.
4: deliver raw data V(t), PWM(t) to denoising.
5: Initialize LSTM model with appropriate architecture.
6: Train the LSTM model using historical input data to predict output.
7: Determine threshold β.
8: prediction layer: Obtaining probability to determine the signal.
9: **Return** s(k)

3.4. The procedure of fault detection

The proposed AUV thruster fault monitoring methodology is depicted as shown in Fig. 2, which comprises three steps: 1) Signal Acquisition & Screening: Multiple sensor signals are acquired from the AUV, with inputs and outputs filtered through the thruster failure mechanism model; 2) Output Prediction: An LSTM network predicts the thruster's fault-related output variables; 3) Residual Analysis: Physical residuals between real-time and predicted data are computed to determine the thruster's fault state.

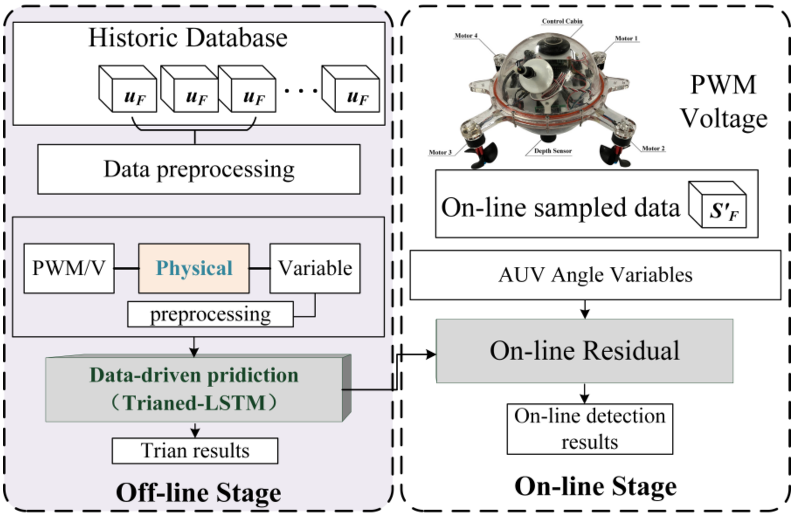

Figure 2. The procedure of proposed method.

4. Case Studies

The experimental platform for this study is the 'Haizhe' autonomous underwater vehicle (AUV), equipped with comprehensive instrumentation for operational control and fault diagnosis.

4.1. AUV Prototypes

The 'Haizhe' AUV was designed for underwater operation (Fig. 3), with its performance monitored through multiple sensors providing real-time operational data. The collected dataset included thrust commands, depth measurements, and IMU readings - all critical for fault diagnosis. Key specifications are detailed in [28]. Using the 'Haizhe' AUV as an experimental prototype enables verification of detection accuracy.

The experimental evaluation incorporated three representative fault scenarios in the 'Haizhe' AUV (Assumption 1). Normal operation: The AUV functioned without any faults. Propeller damage: Severe impairment to the propeller caused a notable decrease in thrust. Depth sensor malfunction: A bias was artificially introduced into the depth readings.

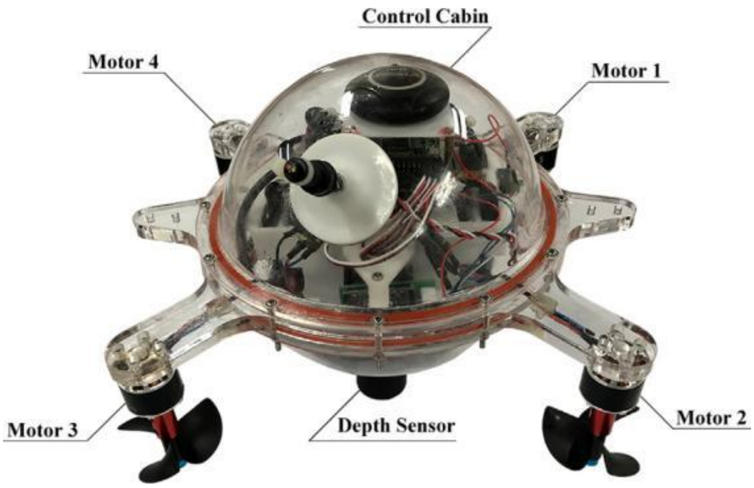

Figure 3. The AUV prototype underwater.

Figure 4. The thruster blade fault type.

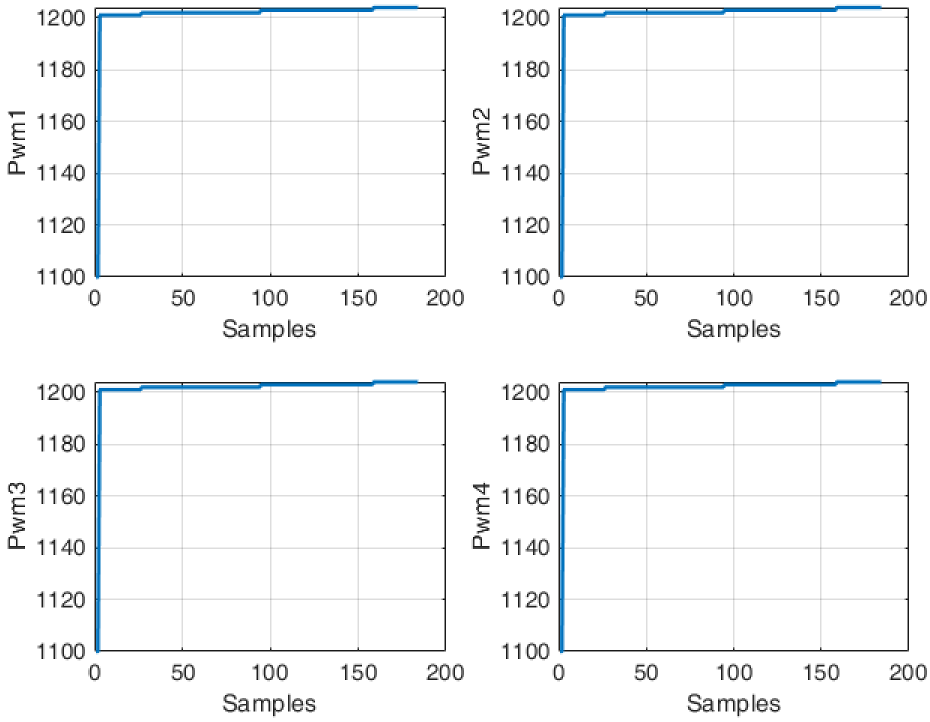

Figure 5. The thruster controller signal.

For example, when the actual depth measured 0.5 m, the faulty sensor reported 0.6 m. Each fault condition underwent multiple 10-20 second trials to ensure sufficient state data collection. The acquired data were systematically labeled according to fault type. The data collection process involved the following steps. 1) The specific fault type was configured for the 'Haizhe' AUV; 2) The initialization was executed to verify that all components were functioning correctly; 3) The dataset generated from these experiments included 1225 samples across the five fault types, where the 20% dataset are employed to test the model.

4.2. Comparisons with State-of-the-Art Methods

All experimental data are collected from operational AUVs and professionally labeled by domain experts. As illustrated in Fig. 5, each thruster utilizes dedicated gate signals for control input. Fig. 6 presents the voltage signals under various fault conditions, which combined with gate signals form the prediction network inputs. While voltage signals alone exhibit no discernible fault characteristics in the time domain, our physical model (Section III) enables thruster fault prediction by processing both voltage and control signals as inputs to generate dynamic thruster outputs. Comparative results of different prediction methods are shown in Figures 7-9.

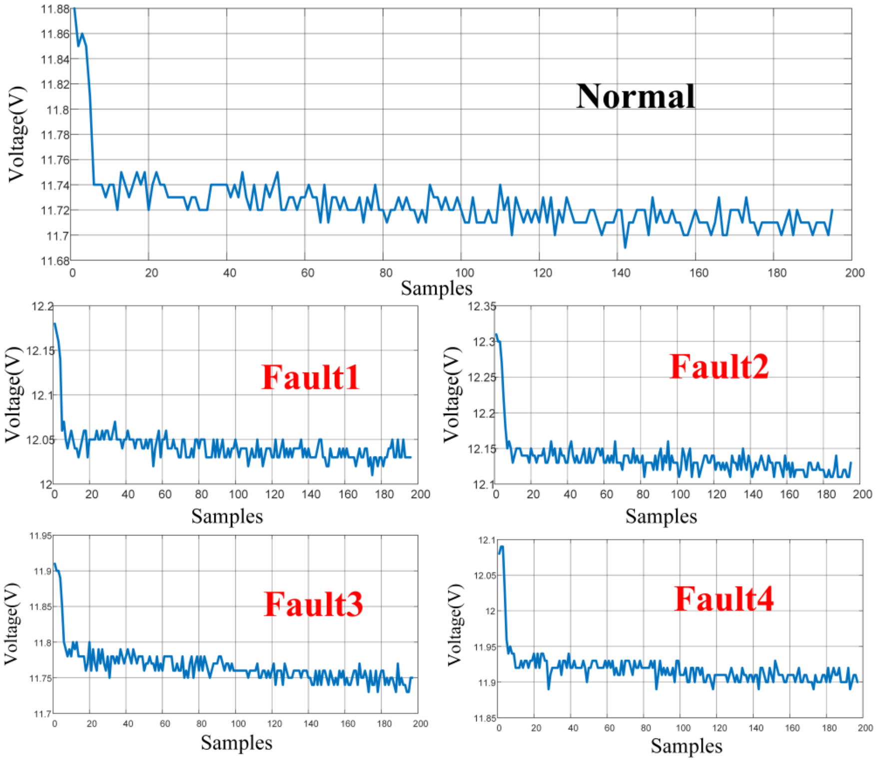

Figure 6. The state variable of AUVs.

Table 1. The accuracy of thruster fault detection (%).

Fault type	Slight	Sensor fault	Abnormal load	Propeller Damage
LSTM	81.5	92.5	89.5	90
TCN	76.5	91.7	81.6	85.6
WT+LSTM	88	92	91	90.5
WT+CNN	90.5	96	92	93.7
Proposed PIEN	95	98	94.5	96

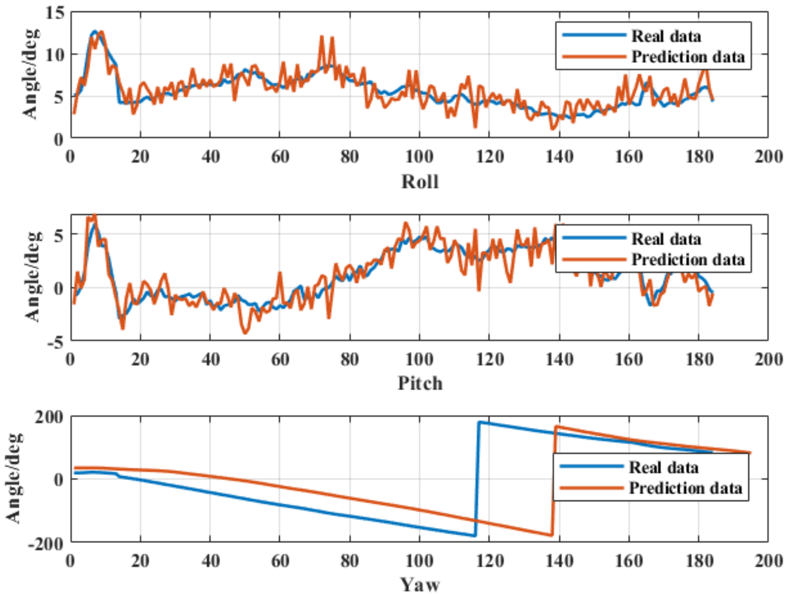

Figure 7. The prediction result of LSTM.

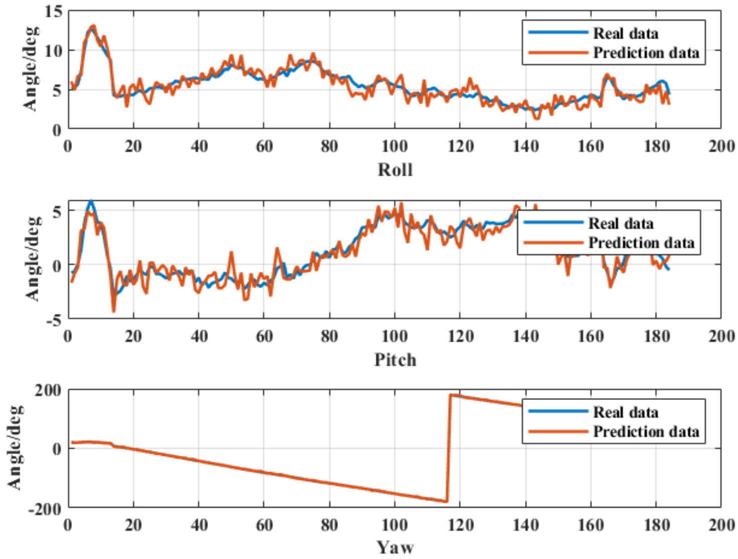

Figure 8. The prediction result of TCN.

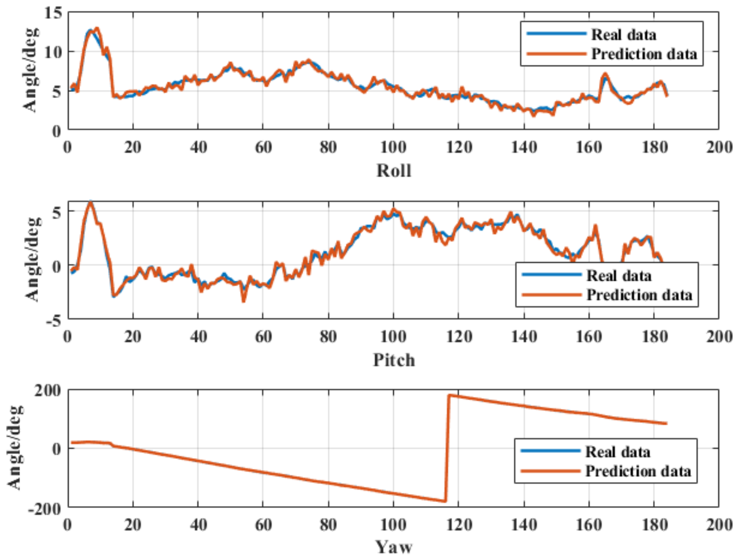

Figure 9. The prediction result of the proposed method.

Table 1 gives evidence of the superiority of the method proposed in this paper over other methods. The proposed method achieved the highest accuracy across all fault types. These results highlight PIEN's particular effectiveness in actuator fault diagnosis. While the LSTM baseline showed competent performance (81.5% for slight damage, 92.5% for sensor faults, 89.5% abnormal load, 90% propeller damage), it was consistently outperformed by PIEN. The Temporal Convolutional Network (TCN) exhibited competitive results, especially for sensor faults, yet failed to match PIEN's accuracy. The consistently high accuracy rates confirm PIEN's robustness in detecting diverse fault types, including cases where traditional methods struggle. This performance advantage stems from PIEN's integrated architecture, which combines LSTM-based prediction with physics-guided residual analysis for comprehensive fault condition assessment.

The experimental results demonstrate that the proposed method achieves high diagnostic accuracy in discriminating between normal and faulty operational states. By enabling real-time fault alerts through residual analysis, the system facilitates prompt corrective actions, significantly improving AUV operational safety.

5. Conclusions

This study presents an innovative fault diagnosis framework for AUVs that integrates long short-term memory networks with physics-guided residual analysis. The proposed method enables effective thruster fault detection by: predicting thrust output from control signals, and analyzing residuals between predicted and measured thrust values. Experimental validation using the instrumented 'Haizhe' AUV platform demonstrates the method's capability to reliably detect actuator faults. This approach establishes a robust diagnostic framework for maintaining vehicle control integrity across diverse marine operating conditions.

Acknowledgements

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