International Journal for Housing Science and Its Applications
Publish August 4, 2025. Volume 46, Issue 3 Pages 1632-1641

https://doi.org/10.70517/ijhsa463126

Research on fault detection and compensation control method based on adaptive filtering algorithm in electromechanical system

Ji Feng1, Siyang Zhan[2,*] and Wei Xiong[3]
[1] Academic Affairs Office, Hubei Railway Transportation Vocational College, Wuhan, Hubei, 430064, China
[2] Locomotive and Rolling Stock Department, Hubei Railway Transport Vocational College, Wuhan, Hubei, 430064, China
[3] School of Mechanical and Electrical Engineering, Changjiang Institute of Technology, Wuhan, Hubei, 430212, China
Corresponding authors: (e-mail: zsyjhun2025@163.com).

Abstract Aiming at the problems of complex fault propagation paths, insufficient diagnostic robustness and low accuracy of fault-tolerant control in electromechanical systems, this paper proposes a fault detection and compensatory control method integrating ISM model and adaptive filtering algorithm. Based on the ISM, we analyze the fault hierarchy and identify the key propagation paths, and propose the DDAF-FD algorithm to realize the online identification of faults. The state feedback fault-tolerant controller is designed to utilize the real-time diagnosis results to dynamically compensate the performance degradation caused by faults. Experiments show that DDAF-FD achieves optimal results in the diagnosis of four different migration tasks with an average accuracy as high as 98.98% compared with six comparison algorithms. The average control accuracy of the fault-tolerant control system based on fault compensation reaches 95.2%, and the research results verify the effectiveness of the method in fault diagnosis and fault-tolerant control of complex electromechanical systems.

Index Terms electromechanical systems, fault detection, compensated control, ISM, DDAF-FD modeling

I. Introduction

The electromechanical system is an important part of the mechanized equipment system, which involves a number of typical electromechanical subsystems such as fuel, hydraulics, environmental control, fire prevention, etc. [1]. As the components work in harsh environments for a long time, they are very prone to failures, and serious failures may even threaten operational safety. Relying only on hardware to provide system redundancy, such as through the redundancy design of pumps and valves to improve safety, the volume, quality and cost of the system design, as well as the time for failure detection and maintenance will also increase [2]-[5]. Therefore, making the necessary analysis of the main links of the electromechanical system to locate the faults in time when they occur will greatly improve the task reliability and maintainability of the system [6], [7].

With the rapid development and popularization of information and communication technologies, sensors and other intelligent devices are embedded in electromechanical equipment to realize real-time and high-speed acquisition of massive, diversified, high-efficiency, and low-authenticity sensory data [8]-[10]. By analyzing these data through the establishment of an intelligent fault detection model, it is possible to predict in advance the abnormalities occurring in the operation of the equipment, find out the hidden dangers of the equipment, and realize the efficient fault diagnosis and monitoring of the electromechanical system, so as to ensure the safety of the electromechanical equipment [11]-[14]. In addition, in order to avoid falling into the local optimal solution, and at the same time to improve the accuracy of parameter identification of the myoelectric system control model, intelligent algorithms are used to construct the design of the control compensation method to compensate for the fault parameters effectively, and to improve the control accuracy of the system [15]-[17].

In order to ensure that the electromechanical equipment has good fault detection and fault isolation ability, improve the reliability and maintainability of electromechanical systems, a large number of scholars to carry out electromechanical system fault diagnosis method research. Literature [18] shows that advanced monitoring strategies are necessary for fault detection and maintenance of electromechanical systems in multi-fault complex scenarios, for which a data fusion scheme supported by deep learning is proposed to effectively improve the degree of data adaptivity in fault detection and condition detection of electromechanical systems. Literature [19] establishes a data analysis model based on genetic algorithms, which is integrated into the electromechanical system fault detection and isolation (FDI) method to predict early failures of electromechanical systems, which improves the safety of the system operation as well as reduces the cost of equipment maintenance. Literature [20] analyzed the characteristics and quality of the output of the filter when applied to the task of fault detection and diagnosis of electromechanical systems, and solved the problem of robustness when modeling uncertainty causes faults. Literature [21] used higher order spectral multiple correlation techniques to identify and process electrification data of electromechanical systems and mathematical modeling to detect faults in system components, thus containing faults at a very early stage of development. Literature [22] used a Long Short-Term Memory (LSTM) neural network to acquire sensor time-series data for modeling analysis, and introduced a sliding window to speed up the efficiency of the model in processing time-series data, thus improving the performance of the proposed method for detecting and identifying the types of faults in electromechanical systems. The above study shows that the intelligent algorithm is suitable for large-scale and highly coupled problem solving in similar scenarios, and plays a high effectiveness in the fault diagnosis problem of electromechanical systems.

Currently, robust tuning of controller parameters in electromechanical systems is an important strategy to improve system control performance and maintain stable operation of electromechanical systems. Literature [23] emphasizes that the motion trajectory tracking task is an important part of precision electromechanical systems, and for this reason analyzes the advantages and shortcomings of various feed-forward compensation strategies in different industrial environments to provide a comprehensive and reliable guide to improve the system's control capability. Literature [24] addresses the lack of robustness of offline feedforward compensation strategies against uncertainty disturbances, and proposes an iterative compensation (RIC) control framework for electromechanical systems, which can effectively predict the tracking error at the sampling moment in order to improve the stability and convergence of the motion control system. Literature [25] designed a friction compensation algorithm based on the mathematical model of the motion system, and combined it with a multi-loop controller, which can fully understand the motion force generated by unbalanced mass in the electromechanical system, and then realize the accurate tracking of the motion system. Literature [26] outlines the robustness of loop shaping methods and fractional order controller tuning rules for controller parameter tuning of electromechanical systems to provide stable operation and control of electromechanical systems in uncertain environments. Although the compensating control methods proposed in the above studies play an important role in improving the motion tracking performance of electromechanical systems, the tracking error of the system commands is large, and the enhancement of the system control accuracy is similarly limited, which is urgently in need of further research.

In this paper, firstly, a brief overview of the electromechanical system is given, and the fault sources of the system are found based on the ISM theory. Secondly, under the framework of data-driven filtering and recursive least squares algorithm, the DDAF-FD algorithm is designed to realize the real-time accurate estimation of fault failure factors. Fault diagnosis experiments are conducted on the bearing failure dataset to explore the diagnostic accuracy of the DDAF-FD algorithm on different migration tasks. Comparison experiments are conducted between the DDAF-FD algorithm and six control algorithms to investigate its performance stability. Finally, a fault-tolerant control system based on fault compensation is constructed to realize fault-tolerant control of electromechanical systems.

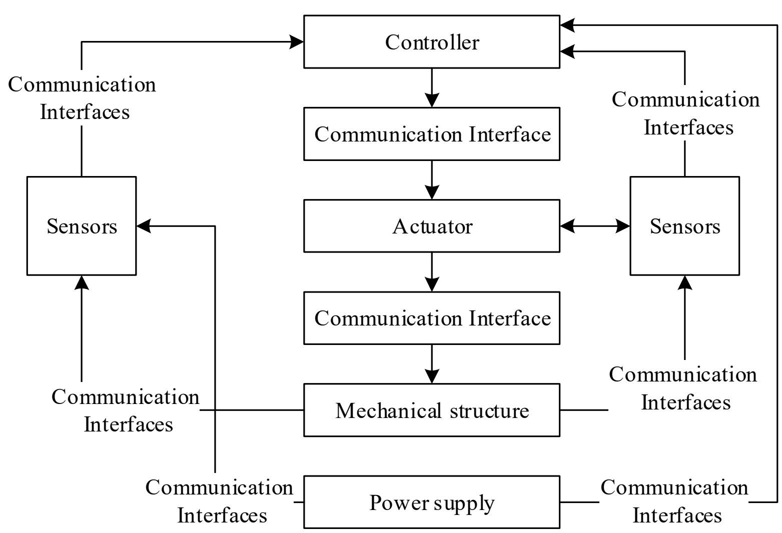


Figure 1: Electromechanical system structure

II. Fault detection in electromechanical systems based on adaptive filtering algorithms

As a typical representative of the deep integration of mechanical and electrical engineering, mechatronic systems are widely used in industrial automation, aerospace, energy and other fields. Its core function relies on the synergistic operation of mechanical structure, electrical components and control system, but the aging of components, external interference and coupling failure under complex working conditions can easily lead to systematic failures, resulting in performance degradation or even catastrophic consequences. Traditional fault detection methods rely on a single sensor signal or fixed threshold judgment, which is difficult to cope with dynamic nonlinear fault propagation and multi-source uncertainty. In this paper, a fault detection model based on adaptive filtering algorithm is proposed to address the problems of complex fault propagation paths, high diagnostic accuracy and real-time requirements of electromechanical systems.

II. A.ISM-based Fault Path Recognition for Electromechanical Systems

II. A. 1) Overview of electromechanical systems

A mechatronic system is a system that is a fusion of two fields, mechanical and electrical, designed to realize the synergy of mechanical motion and electrical control. Such systems often include multiple components such as mechanical structures, electrical components, sensors, actuators, control systems, etc., and their structure is shown in Figure 1.

The following is a general overview of the electromechanical system:

(1) Mechanical parts

Mechanical structure: includes a variety of mechanical parts, such as gears, bearings, transmissions, etc., which are used to support and transmit mechanical movements.

Actuators: Components responsible for performing mechanical actions, such as motors, cylinders, etc.

(2) Electrical parts

Electrical components: including switches, cables, power supplies, etc., constitute the basic components of the circuit system.

Sensors: devices used to sense the environment and mechanical movement status, such as temperature sensors, pressure sensors, etc.

Motor: device used to convert electrical energy into mechanical energy, one of the key components of the electromechanical system.

(3) Control Module

Controller: usually an electronic device used to monitor the feedback information from sensors and control the action of actuators to realize the automated control of the system.

Programming and algorithms: electromechanical systems usually require some programming and algorithms to realize complex control strategies, such as PD control, fuzzy logic control, etc.

(4) Communication module

Communication interface: Used for information transfer between different components, for example, the mechanical part transmits sensor data to the control system, or the control system sends control commands to the actuator.

Bus system: provides standardized interfaces for communication between different components.

(5) Maintenance and monitoring system

Monitoring system: used to monitor the performance, status and faults of the electromechanical system.

Maintenance system: Includes regular maintenance, fault diagnosis and repair to ensure stable operation of the system over a long period of time.

II. A. 2) ISM principles

Every system consists of two or more elements that are interconnected and interact with each other to form a complete system. The elements of a system form a special structure and sequence through their relationships with each other, under some kind of synergistic control, which enables the whole system to function properly. In the field of contemporary systems engineering, ISM is a fundamental and unique approach. This new research idea originated from the study of problems related to complex socio-economic systems, and it has been remarkably effective in dealing with the analysis of systems with multivariate, complex relationships and complex structures. After a long period of application and improvement, together with the development of modern computer technology, the method has become quite mature in the industrial field. Failures occurring in complex electromechanical systems usually originate from the failure of one system element, which in turn triggers the failure of a chain of system elements. The rapid propagation of such related faults eventually leads to the collapse of the whole system. In this paper, based on the analysis of fault mechanisms, we construct an adjacency matrix and use the interpreted structural modeling method to build a fault transmission model, which is used to find the fault sources of the system, clarify the root causes and main paths of fault transmission, and thus identify the critical fault transmission paths.

The workflow of ISM usually includes the following steps, and its specific process is shown in Fig. 2.

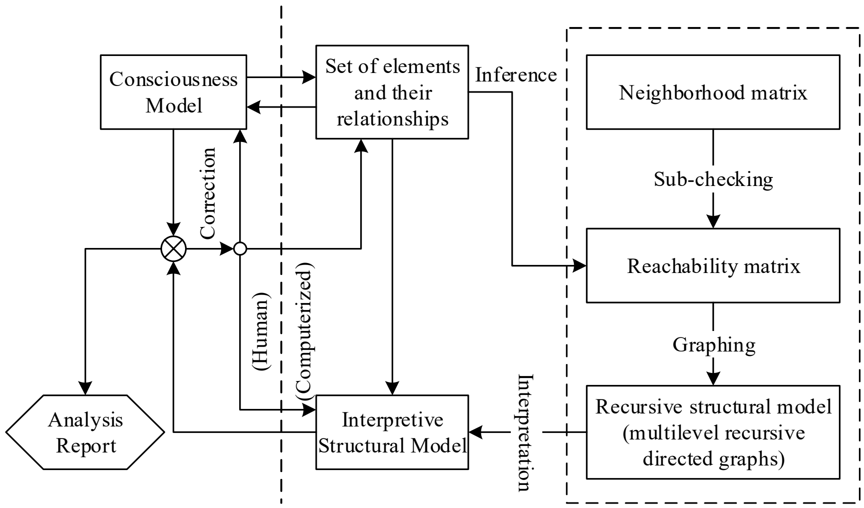


Figure 2: ISM workflow

(1) The team that performs ISM usually consists of three components: experts, coordinators, and participants;

(2) Identify the key problem and select the key elements affecting the problem; identify the binary relationships between the elements: imagine that a system contains $n(n \geq 2)$ elements, then there are two elements S_i as well as S_j in a relationship referred to as R_{ij} (shorthand for R), and there are three scenarios: S_i has some binary relation $R(S_i R S_j)$; There is no binary relation S_i to S_j $R(S_i \bar{R} S_j)$; Uncertainty about the relationship between S_i and S_j $R(S_i \tilde{R} S_j)$

(3) Determine the binary relationship between the factors;

(4) Constructing the adjacency matrix and reachability matrix from the binary relationship between the factors;

(5) By analyzing the reachable matrices, the structure of multiple recursive directed graphs is derived and the corresponding interpretations are given.

II. B. Data-Driven Adaptive Fault Diagnosis for Electromechanical Systems

II. B. 1) System identification

In order to adaptively recognize the electromechanical system matrix $A(k)$ and the input matrix $B(k)$, the DDAF-FD algorithm in this paper can be obtained as follows

$$y(k+1) = \Omega^T(k) X(k) + Fw(k) \tag{1}$$

where $X(k) \in \mathbb{R}^{2n+2}$ denotes the unknown parameter vector satisfying

$$X(k) = \left[-a_1(k), -a_2(k), \cdots, -a_{n+1}(k), b_1(k), b_2(k), \cdots, b_{n+1}(k)\right] \tag{2}$$

$\Omega(k) \in \mathbb{R}^{2n+2}$ represents the known I/O data vector that satisfies the

$$\Omega(k) = \left[y(k), y(k-1), \cdots, y(k-n), u(k), u(k-1), \cdots, u(k-n)\right] \tag{3}$$

For Eqs. (2)-(3), the parameter identification can be performed by the DDAF-FD algorithm, i.e.

$$K_I(k) = P_I(k-1)\Omega(k)\left(FSF^T + \Omega^T(k) P_I(k-1)\Omega(k)\right)^{-1} \tag{4}$$

$$P_I(k) = \left(I - K_I(k)\Omega^T(k)\right)P_I(k-1) \tag{5}$$

$$\hat{X}(k+1) = \hat{X}(k) + K_I(k)\left(y(k+1) - \Omega^T(k)\hat{X}(k)\right) \tag{6}$$

where I is the unit array.

With the DDAF-FD algorithm of Eqs. (4) to (6), $\hat{A}(k)$ and $\hat{B}(k)$ can be easily obtained from the unknown parameter estimation vectors to identify the parameters in the system.

II. B. 2) Joint state-parameter estimation

Rewrite the system as

$$\begin{cases} x(k+1)=\hat{A}(k)x(k)+\hat{B}(k)u(k)+\Phi_a(k)\rho(k)+Fw(k) \\ y(k)=Cx(k)+\Phi_b(k)\sigma(k)+v(k) \end{cases} \tag{7}$$

where $x(k)\in\mathbb{R}^{n+1}$, $u(k)\in\mathbb{R}^{n+1}$, $\Phi_a(k)\in\mathbb{R}^{n+1}$, $\hat{A}(k)$, $\hat{B}(k)\in\mathbb{R}^{(n+1)\times(n+1)}$, $\Phi_b(k)\in\mathbb{R}$, $w(k)\in\mathbb{R}^{n+1}$, $v(k)\in\mathbb{R}$. When both actuator and sensor failures occur in the system, the system input $u(k)$ will deviate from the desired value, while the measured value $y(k)$ will also deviate from the desired value. $\Phi_a(k)\rho(k)$ denotes the actuator fault term and $\Phi_b(k)\sigma(k)$ denotes the sensor fault term, where $0\le\rho(k)<1$, $0\le\sigma(k)<1$, ρ is the actuator failure factor, σ is the sensor failure factor, which is 0-1 in the case of actuator and sensor failures (e.g., loss of gain), and $y(k)$ is the value of the output of the system with measurement noise. $\Phi_a(k)=-\hat{B}(k)u(k)$, $\Phi_b(k)=-Cx(k)$, so that $f(k)=\begin{bmatrix}\rho(k)\\ \sigma(k)\end{bmatrix}$, $\Sigma_1(k)=[\Phi_a(k),0_{(n+1)\times 1}]$, $\Sigma_2(k)=[0_{1\times 1},\Phi_b(k)]$, then equation (7) can be written as

$$\begin{cases} x(k+1)=\hat{A}(k)x(k)+\hat{B}(k)u(k)+\Sigma_1(k)f(k)+Fw(k) \\ y(k+1)=Cx(k+1)+\Sigma_2(k+1)f(k+1)+v(k+1) \end{cases} \tag{8}$$

The proposed DDAF-FD algorithm is divided into 3 parts according to the recursive sequence listed below.

$$P^-(k+1)=\hat{A}(k)P(k)\hat{A}^T(k)+Q(k) \tag{9}$$

$$\hat{x}^-(k+1)=\hat{A}(k)\hat{x}(k)+\hat{B}(k)u(k)+\Sigma_1(k)\hat{f}(k) \tag{10}$$

$$K_E(k+1)=P^-(k+1)C^T\left(CP^-(k+1)C^T+R(k)\right)^{-1} \tag{11}$$

$$P(k+1)=\left(I_{n+1}-K_E(k+1)C\right)P^-(k+1) \tag{12}$$

Eqs. (9) to (12) are part of the Kalman filtering for the covariance matrix $P(k+1)$ and the state estimation gain matrix $K_E(k+1)$, which can be used to calculate the auxiliary variables $G(k+1)$, $O(k+1)$, $H(k+1)$, $S(k+1)$ and the parameter estimation gain matrix $\Lambda(k+1)$.

$$\begin{aligned} G(k+1)&=\left(I_{n+1}-K_E(k+1)C\right)\hat{A}(k)G(k) \\ &\quad+\left(I_{n+1}-K_E(k+1)C\right)\Sigma_1(k)-K_E(k+1)\Sigma_2(k+1) \end{aligned} \tag{13}$$

$$O(k+1)=C\hat{A}(k)G(k)+C\Sigma_1(k)+\Sigma_2(k+1) \tag{14}$$

$$H(k+1)=\left[\lambda\left(CP^-(k+1)C^T+R(k)\right)+O(k+1)S(k)O^T(k+1)\right]^{-1} \tag{15}$$

$$S(k+1)=S(k)O^T(k+1)H(k+1) \tag{16}$$

$$S(k+1)=\lambda^{-1}S(k)-\lambda^{-1}S(k)O^T(k+1)H(k+1)O(k+1)S(k) \tag{17}$$

Recursions (13)-(17) are inspired by recursive least squares estimation with exponential forgetting factors to compute the parameter estimation gain matrix $\Lambda(k+1)$ and auxiliary variables $G(k+1)$, where $\lambda\in(0,1)$.

$$\tilde{y}(k+1)=y(k+1)-C\hat{x}^-(k+1)-\Sigma_2(k)\hat{f}(k) \tag{18}$$

$$\hat{f}(k+1)=\hat{f}(k)+\Lambda(k+1)\tilde{y}(k+1) \tag{19}$$

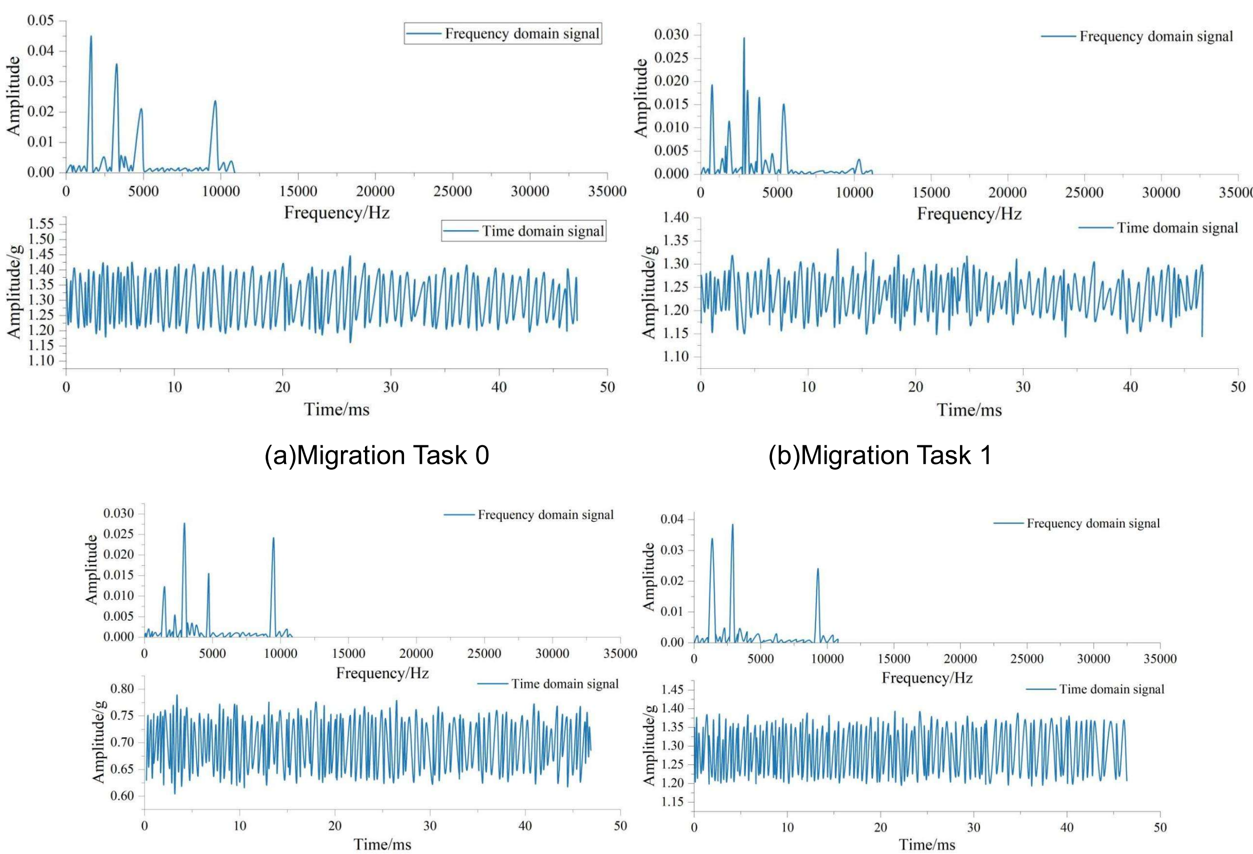
$$\begin{aligned}\hat{x}(k+1) &= \hat{x}^{-}(k+1) + K_E(k+1)\tilde{y}(k+1) \\ &+ G(k+1)\left[\hat{f}(k+1) - \hat{f}(k)\right]\end{aligned} \tag{20}$$

The recursive update equations (18)-(20) are adaptive Kalman filters, $\hat{x}(k)$, $\hat{f}(k)$ updated at each moment k, are used to compute the residuals $\tilde{y}(k+1)$, to estimate the fault parameters (update equation (19)) and the state (Update Eq. (20)).

III. Experimental analysis of fault diagnosis and compensatory control of complex electromechanical systems

III. A. Introduction to the data set

In this section, fault diagnosis experiments of complex electromechanical systems are conducted to evaluate the performance level of the DDAF-FD fault diagnosis model. The experimental data is obtained from the public bearing experimental dataset (Bearing Failure Dataset), which is collected from the bearing test equipment and includes both artificially simulated and real damage failure data. The equipment from which the data were collected consisted of an electric motor, torque measuring shaft, rolling bearing, flywheel and load motor. The raw vibration signals are collected by accelerometers mounted on the bearing box with a sampling frequency of 64 kHz. Bearing failures are categorized according to the bearing damage components, degree, combination and characteristics. In this experiment, using the real damage fault data in this dataset, which contains 13 types of fault information, the raw vibration signal waveforms and frequency domain waveforms of the No. 1 bearing fault under four different migration tasks are shown in Fig. 3. Fig. 3 (a~d) shows the frequency domain and time domain signal waveforms of fault No. 1 at migration tasks 0, 1, 2 and 3, respectively.



(a)Migration Task 0 (b)Migration Task 1

(c)Migration Task 2 (d)Migration Task 3

Figure 3: Waveform of 1 kind of fault under different tasks

III. B. Troubleshooting results

III. B. 1) Accuracy

The diagnostic results of DDAF-FD and the six comparison algorithms on the bearing failure dataset are shown in Figure 4 and Table 1. Compared with the other algorithms, DDAF-FD achieves optimal results on the diagnosis of four different migration tasks, with an average accuracy of 98.98%, which is 3.35% higher than DSAN, which is the best performer among the comparison algorithms.

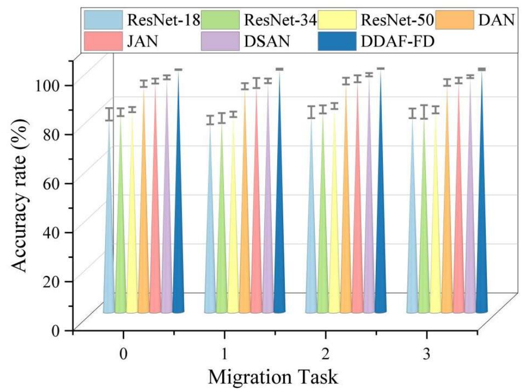


Figure 4: Comparison of diagnostic accuracy results of different methods

Table 1: Description of bearing health status (%)

Algorithm	Migration Task 0	Migration Task 1	Migration Task 2	Migration Task 3	Average
ResNet-18	80.57±2.53	78.23±1.76	81.44±2.44	80.97±1.96	80.30
ResNet-34	81.43±1.59	79.04±2.04	82.58±1.64	81.53±2.77	81.15
ResNet-50	82.49±1.05	80.56±1.11	83.95±1.22	82.41±1.45	82.35
DAN	93.05±1.32	92.01±1.26	94.11±1.37	93.55±1.35	93.18
JAN	94.13±1.01	93.33±2.05	95.07±1.42	94.37±1.15	94.23
DSAN	95.66±0.82	94.22±0.94	96.72±0.68	95.93±0.59	95.63
DDAF-FD	98.79±0.12	98.97±0.23	99.23±0.11	98.92±0.34	98.98

III. B. 2) Stability

Accuracy and stability is the ultimate goal of fault diagnosis, good stability and accuracy is an important evaluation of fault diagnosis methods. Accurate and timely judgment of electrical instrumentation faults in order to maintain and repair in the shortest possible time. The stability of different algorithms in fault diagnosis is shown in Figure 5.

From Fig. 5, it can be seen that the fault diagnosis using the DDAF-FD algorithm is the most stable, which can maintain more than 95% stability at different times, while the DSAN algorithm, which has the best performance among the control algorithms, shows large fluctuations in 15s, 20s and 30s. The experiment proves that using adaptive filtering algorithm combined with recursive analysis theory to comprehensively judge the feature filtering can obtain better fault diagnosis performance and strong robustness.

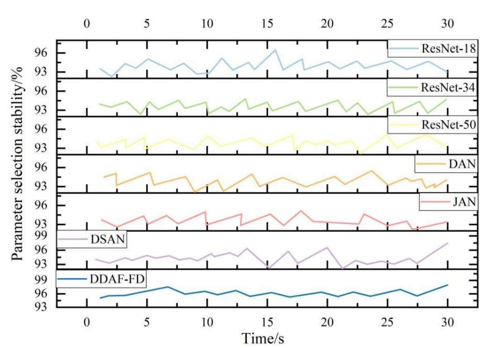


Figure 5: Stability of fault diagnosis with different algorithms

IV. Fault-tolerant control based on fault compensation

IV. A. System design

Existing fault-tolerant control strategies are often designed based on exact mathematical models, which are not robust enough to parameter uptake and structural changes. In order to improve the problem, this paper proposes a fault-tolerant control system design based on fault compensation.

Under the premise that the controller structure remains unchanged, the fault detection and diagnosis results make the faulty system operating state close to the normal system operating state.

Let the dynamic equation in the normal system operation state be:

$$\begin{aligned} Z(x) &= A\alpha(x) + B\beta(x) \\ W(x) &= C\alpha(x) \end{aligned} \tag{21}$$

where $\alpha(x)$ denotes the state vector; $W(x)$ denotes the measurement vector; $\beta(x)$ denotes the control vector; and A, B, C are the system parameters.

The state feedback fault compensation process is shown in Fig. 6, which is utilized to improve the system fault compensation capability.

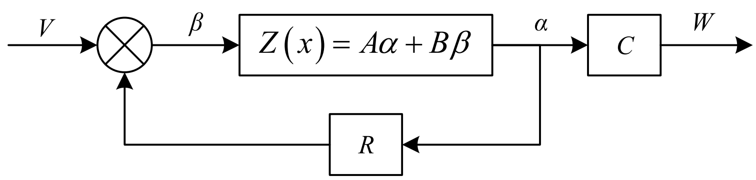


Figure 6: State feedback fault compensation

The dynamic equation of the closed-loop feedback system is:

$$\begin{aligned} Z(x) &= (A - BR)\alpha(x) + \beta v(x) \\ W(x) &= C\alpha(x) \end{aligned} \tag{22}$$

Where: $v(x) = \beta(x) - R\alpha(x)$.

The dynamic equations for the faulty system operating state are:

$$\begin{aligned} Z_i(x) &= (A_i - B_i R_i)\alpha_i(x) + B_i v_i(x) \\ W_i(x) &= C_i \alpha_i(x) \end{aligned} \tag{23}$$

In order to make the system performance close to the normal system performance, Equation (24) needs to be followed:

$$A - BR = A_i - B_i R_i \tag{24}$$

The feedback array of the faulty system that needs to modify the state based on the above equation can be:

$$R_i = B_i^{-1}\left(A_i - A\right) + B_i^{-1} BR \tag{25}$$

Full fault compensation can be achieved by continuously adjusting Eq. (25), and fault-tolerant control can be realized in this respect.

IV. B. Level of performance

The fault tolerant control system based on time series analysis is tested against the fault compensated based fault tolerant control system and the results of the comparison between the fault tolerant control system based on time series analysis and the control accuracy of the proposed system are shown in Table 2. Analyzing the data in Table 2, it can be seen that the highest control accuracy of the time series analysis based system is 57% and the highest control accuracy of the proposed system is 98% when targeting inner loop faults; For the outer ring fault, the highest control accuracy of the time series analysis-based system is 62%, and the highest control accuracy of the proposed system is 97%; for the roller fault, the highest control accuracy of the time series analysis-based system is 44%, and the highest control accuracy of the proposed system is 95%.

The above data show that no matter which kind of fault appears, the control accuracy of fault compensation-based fault-tolerant control system is higher, and the average control accuracy reaches 95.2%, which confirms the reasonableness of the fault compensation-based fault-tolerant control system design for rolling bearing faults.

Table 2: Comparative analysis of control accuracy of the two systems

Time/s	Time series based analysis system			The proposed system		
	Inner ring	Outer ring	Roller	Inner ring	Outer ring	Roller
3	0.51	0.58	0.44	0.96	0.97	0.93
6	0.54	0.56	0.42	0.94	0.96	0.91
9	0.57	0.62	0.39	0.97	0.96	0.94
12	0.52	0.59	0.38	0.96	0.95	0.95
15	0.53	0.57	0.36	0.98	0.96	0.93
18	0.49	0.61	0.35	0.95	0.97	0.94

V. Conclusion

In this paper, we design a fault detection and compensation control method for electromechanical systems based on adaptive filtering algorithm, and select the bearing fault dataset to carry out fault diagnosis experiments for complex electromechanical systems to explore the effectiveness of the proposed method.

DDAF-FD achieves optimal results on the diagnosis of four different migration tasks compared with six comparison algorithms, with an average accuracy of 98.98%, which is 3.35% higher than DSAN, the best performing control algorithm. Fault diagnosis using the DDAF-FD algorithm is the most stable, able to maintain more than 95% stability at different times, while the DSAN algorithm, which performs optimally among the control algorithms, shows large fluctuations at 15s, 20s and 30s. The experiment proves that using adaptive filtering algorithm combined with recursive analysis theory to comprehensively judge the feature filtering can obtain better fault diagnosis performance and strong robustness.

The fault tolerant control system based on time series analysis is compared and tested with the fault tolerant control system based on fault compensation, no matter which kind of fault appears, the control accuracy of the fault tolerant control system based on fault compensation is higher, and the average control accuracy reaches 95.2%, which confirms the reasonableness of the design of fault tolerant control system based on fault compensation of the fault tolerant control system of the rolling bearings.

Funding

This work was supported by Hubei Provincial Natural Science Foundation of China (2024AFB897).

References

[1] Ait-Alla, A., Lütjen, M., Lewandowski, M., Freitag, M., & Thoben, K. D. (2016). Real-time fault detection for advanced maintenance of sustainable technical systems. Procedia CIRP, 41, 295-300.
[2] Kudelina, K., Asad, B., Vaimann, T., Rassõlkin, A., Kallaste, A., & Khang, H. V. (2021). Methods of condition monitoring and fault detection for electrical machines. Energies, 14(22), 7459.
[3] Divya, D., Marath, B., & Santosh Kumar, M. B. (2023). Review of fault detection techniques for predictive maintenance. Journal of Quality in Maintenance Engineering, 29(2), 420-441.
[4] Salomon, C. P., Ferreira, C., Sant'Ana, W. C., Lambert-Torres, G., Borges da Silva, L. E., Bonaldi, E. L., ... & Torres, B. S. (2019). A study of fault diagnosis based on electrical signature analysis for synchronous generators predictive maintenance in bulk electric systems. Energies, 12(8), 1506.
[5] Gangsar, P., & Tiwari, R. (2020). Signal based condition monitoring techniques for fault detection and diagnosis of induction motors: A state-of-the-art review. Mechanical systems and signal processing, 144, 106908.
[6] Nithin, S. K., Hemanth, K., Shamanth, V., Mahale, R. S., Sharath, P. C., & Patil, A. (2022). Importance of condition monitoring in mechanical domain. Materials Today: Proceedings, 54, 234-239.
[7] Alsumaidaee, Y. A. M., Yaw, C. T., Koh, S. P., Tiong, S. K., Chen, C. P., & Ali, K. (2022). Review of medium-voltage switchgear fault detection in a condition-based monitoring system by using deep learning. Energies, 15(18), 6762.
[8] Nie, Q. (2024, March). Operation Fault Detection of Electrical and Mechanical Equipment Based on Kalman Filter. In Journal of Physics: Conference Series (Vol. 2717, No. 1, p. 012036). IOP Publishing.
[9] Wang, Y., & Wang, X. (2020). THE ON-LINE MONITORING ANALYSIS OF ELECTROMECHANICAL EQUIPMENT UNDER EMBEDDED SENSOR. International Journal of Mechatronics and Applied Mechanics, (8), 64-71.
[10] Moon, J., & Leeb, S. B. (2018). Wire less sensors for electromechanical systems diagnostics. IEEE Transactions on Instrumentation and Measurement, 67(9), 2235-2246.
[11] Yu, M., Li, H., Jiang, W., Wang, H., & Jiang, C. (2019). Fault diagnosis and RUL prediction of nonlinear mechatronic system via adaptive genetic algorithm-particle filter. IEEE Access, 7, 11140-11151.

[12] Villarreal-López, E. (2019). A new scheme for multiple fault detection and isolation for rotational mechatronic systems, by means of analytical redundancy and adaptive filtering. Dyna, 86(209), 40-48.
[13] Yu, M., Lan, D., Jiang, C., Xu, B., Wang, D., & Zhu, R. (2022). Hybrid condition monitoring of nonlinear mechatronic system using biogeography-based optimization particle filter and optimized extreme learning machine. ISA transactions, 120, 342-359.
[14] Cordoneanu, D., & Niţu, C. (2018, July). A review of fault Diagnosis in mechatronics systems. In International Conference of Mechatronics and Cyber-Mixmechatronics (pp. 173-184). Cham: Springer International Publishing.
[15] Oomen, T. (2018). Advanced motion control for precision mechatronics: Control, identification, and learning of complex systems. IEEJ Journal of Industry Applications, 7(2), 127-140.
[16] Yang, X., Deng, W., Yao, J., & Liang, X. (2021). Asymptotic adaptive tracking control and application to mechatronic systems. Journal of the Franklin Institute, 358(12), 6057-6073.
[17] Feng, Y., Zhou, M., Han, Q. L., Han, F., Cao, Z., & Ding, S. (2019). Integral-type sliding-mode control for a class of mechatronic systems with gain adaptation. IEEE Transactions on Industrial Informatics, 16(8), 5357-5368.
[18] Arellano-Espitia, F., Delgado-Prieto, M., Martinez-Viol, V., Saucedo-Dorantes, J. J., & Osornio-Rios, R. A. (2020). Deep-learning-based methodology for fault diagnosis in electromechanical systems. Sensors, 20(14), 3949.
[19] Dalla Vedova, M. D., Germanà, A., Berri, P. C., & Maggiore, P. (2019). Model-based fault detection and identification for prognostics of electromechanical actuators using genetic algorithms. Aerospace, 6(9), 94.
[20] AlShabi, M. A., Gadsden, S. A., Assad, M. E. H., & Khuwaileh, B. (2021, April). Application of the sliding innovation filter for fault detection and diagnosis of an electromechanical system. In Signal Processing, Sensor/Information Fusion, and Target Recognition XXX (Vol. 11756, pp. 47-53). SPIE.
[21] Ciszewski, T., Gelman, L., & Ball, A. (2020). Novel fault identification for electromechanical systems via spectral technique and electrical data processing. Electronics, 9(10), 1560.
[22] Yang, J., Guo, Y., & Zhao, W. (2019). Long short-term memory neural network based fault detection and isolation for electro-mechanical actuators. Neurocomputing, 360, 85-96.
[23] Zhou, R., Hu, C., Hou, B., & Zhu, Y. (2022). Comparative study of performance-oriented feedforward compensation strategies for precision mechatronic motion systems. IEEE Access, 10, 100812-100823.
[24] Hu, C., Zhou, R., Wang, Z., Zhu, Y., & Tomizuka, M. (2022). Real-time iterative compensation framework for precision mechatronic motion control systems. IEEE/CAA Journal of Automatica Sinica, 9(7), 1218-1232.
[25] Ristevski, S., & Cakmakci, M. (2019). Planar motion controller design for a modular mechatronic device with heading compensation. Mechatronics, 62, 102257.
[26] Ionescu, C. M., Dulf, E. H., Ghita, M., & Muresan, C. I. (2020). Robust controller design: Recent emerging concepts for control of mechatronic systems. Journal of the Franklin Institute, 357(12), 7818-7844.