

Article

Robust Fault Diagnosis of Mine Hoisting Rigid Guides Under Variable Operating Conditions Using Physics-Informed Features and Zero-Space Observers

Bo Wu ¹, Hengyu Cheng ², Qiliang Zang ¹ and Fan Jiang ^{2,*}

¹ School of Transportation Engineering, Jiangsu Vocational Institute of Architectural Technology, Xuzhou 221116, China; 10884@jsviate.edu.cn (B.W.); zangqiliang@jsviate.edu.cn (Q.Z.)

² School of Mechanical and Electrical Engineering, China University of Mining and Technology, Xuzhou 221116, China; tb18050003b0@cumt.edu.cn

* Correspondence: jfcme713@cumt.edu.cn

Abstract

In vertical mine hoisting systems, the rigid guide serves as a critical safety component whose failure may induce severe dynamic disturbances and potentially trigger cascading safety incidents. Existing data-driven diagnosis methods for rigid guides often lack robustness under variable operating conditions and require substantial labeled data. Yet in practical mine hoisting operations, variations in hoisting speed and lifting mass are inevitable, and acquiring sufficient fault samples is challenging due to safety constraints. To address these problems, this paper proposes a novel fault diagnosis framework that integrates a physics-informed feature-extraction pipeline with the zero-space observer theory. Vibration signals are processed to extract dimensionless and relative features, which are deliberately designed based on the dynamic mechanisms underlying different fault states. These features rely solely on the geometric characteristics of the waveform at the fault location, rendering them sensitive to fault types while remaining robust to variations in operating conditions. The feature set is subsequently optimized using the minimum redundancy maximum relevance (mRMR) algorithm to enhance computational efficiency, mitigate overfitting, and improve the generalization ability of the method. A set of zero-space observers is then constructed to perform efficient fault classification through geometric operations in the feature space, with each observer specifically sensitive to its corresponding health state while remaining insensitive to others. Experimental validation across multiple health states and operational variations demonstrates that the proposed method outperforms four widely used intelligent models in both classification accuracy and computational efficiency, showing strong suitability for real-world deployment in coal mining applications.

Keywords: rigid guide; fault diagnosis; physics-informed features; zero-space observers; variable operating conditions



Received: 25 January 2026

Revised: 18 February 2026

Accepted: 20 February 2026

Published: 23 February 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

1. Introduction

The rigid guide system, shown in Figure 1, plays a crucial role in vertical mine hoisting installations. Its primary function is to guide and stabilize the trajectory of the conveyance within the shaft, thereby preventing hazardous collisions and ensuring smooth operation [1,2]. Failures of the rigid guide can induce significant abnormal vibrations and impact forces on the conveyance. These dynamic interactions not only accelerate

component degradation but also pose severe safety risks, including conveyance jamming, rope breakage, and catastrophic conveyance fall [3,4]. Therefore, the development of reliable fault-diagnosis methodologies for rigid guides is paramount to ensuring the structural integrity and operational safety of mine hoisting systems [5].

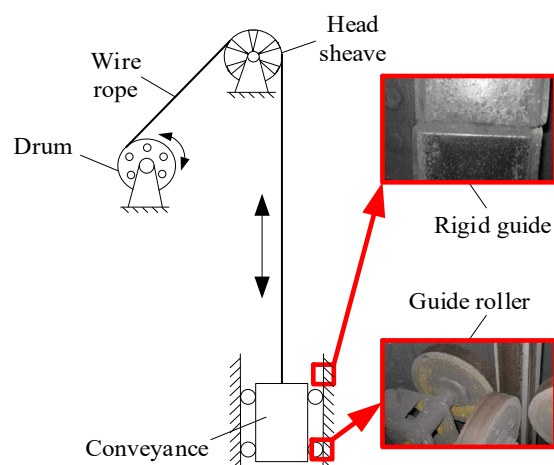


Figure 1. Schematic diagram of a rigid guide system in vertical mine hoisting installations.

Traditionally, rigid guide inspection has relied on manual visual checks or periodic geometric surveys, which are labor-intensive, time-consuming, and inherently subjective [6]. To overcome these limitations, significant research efforts have been directed toward non-destructive condition-monitoring techniques. These approaches can be broadly categorized into three streams. The first stream focuses on vision and laser-based inspection. Methods that utilize improved YOLO algorithms for image-based fault detection [7] or 3D reconstruction with line structured light [8] provide high precision in assessing the surface geometry of rigid guides. Nevertheless, their effectiveness is frequently undermined by challenging underground environmental conditions, such as inadequate lighting, dust, and moisture. The second stream utilizes vibration signal analysis from mobile conveyances [9,10]. By installing sensors on the moving conveyance, vibrations induced by rigid guide faults can be captured. Early work by Ma et al. [11,12] explored pattern recognition using features extracted from these signals with classifiers such as support vector machines (SVM) and boosting trees. More recently, the convolutional neural network (CNN) [13] has been applied to these signals, achieving high recognition rates for specific faults. While these methods exhibit satisfactory performance under constant operating conditions, their effectiveness under variable conditions remains to be further validated. The third stream investigates the fundamental dynamics and structural health employing numerical simulations and field measurements [14–17]. While providing deep physical insights, these methods are often complex and not directly suited for online, rapid fault identification.

Given that vibration signals from the conveyance contain abundant condition-related information and demonstrate practical applicability in coal mine environments, this study concentrates on vibration-based diagnosis. As previously mentioned, certain limitations persist within these approaches. The vibration signals of rigid guide faults exhibit considerable sensitivity to variations in operating conditions. Traditional global features derived from raw signals often encapsulate this extraneous variability, resulting in models that demonstrate effective performance solely under the specific conditions encountered during training. Moreover, many high-performing methods, especially deep-learning models, require substantial volumes of labeled data for training, which is difficult to obtain in practice.

To address these challenges, this paper proposes a novel fault-diagnosis framework by integrating a physics-informed feature-extraction pipeline with the zero-space observer theory. Physics-informed features, designed based on a system's underlying physical mechanisms, reflect intrinsic properties such as structural dynamics, energy flow, and fault response patterns. These features enhance model interpretability and generalization by remaining consistent and meaningful even as operating conditions vary, making them particularly suitable for addressing robustness issues [18–20]. Zero-space observers, which exploit the geometric properties of feature vectors in high-dimensional space [21,22], enable fault classification through simple algebraic operations such as dot products and comparisons. Their core advantages lie in model simplicity, extremely low computational overhead, and minimal data requirements, making them well-suited for situations with limited fault data [23,24].

The remainder of this paper is organized as follows. Section 2 details the fundamentals and procedures of the proposed fault diagnosis method. Section 3 describes the experimental setup and the comprehensive test matrix covering multiple fault types, severity levels, and varied operating conditions. Section 4 presents and discusses the experimental results, demonstrating the superiority of the proposed method through comparative analysis. Section 5 concludes the study by summarizing the key findings, highlighting advantages, and suggesting future research directions.

2. Description of the Proposed Approach

2.1. Physics-Informed Feature Extraction

This subsection details the physics-informed feature-extraction pipeline designed to generate discriminative and robust inputs for the subsequent zero-space observer.

2.1.1. Signal Preprocessing

Prior to feature calculation, raw vibration signals undergo a two-step preprocessing stage to isolate the fault-induced transient and remove low-frequency components that could confound feature values.

1. Impact Segment Truncation

The continuous vibration signal is examined to identify the distinctive transient resulting from a rigid guide fault. A sliding-window energy detection method, combined with an adaptive threshold, is employed as an efficient and robust approach for automatic impact signal segmentation [25]. The threshold is determined based on the classical 3σ statistical criterion, with the dual objectives of completely retaining the impact waveform while minimizing the inclusion of non-impact normal signal points. Its statistical foundation guarantees the ability to deal with various operating conditions. This step ensures that the subsequent analysis concentrates exclusively on the signal segment that contains the diagnostic information, thereby effectively isolating the fault signature from background vibrations produced during normal operation.

2. Detrending

The truncated impact segment may contain low-frequency trends arising from sensor drift, conveyance oscillation, or slow system dynamics unrelated to the impact event. To mitigate the influence of these trends on the subsequent statistical and shape-based features, a polynomial trend is fitted to the segment and subsequently subtracted. This process produces a transient signal whose dominant components are directly related to the impact and its immediate decay.

2.1.2. Initial Feature Set

To comprehensively characterize the impact waveforms associated with rigid guide faults, eight distinct features are extracted. These features are chosen to capture complementary aspects of the signal morphology, statistical distribution, energy content, and complexity, providing a multi-dimensional signature for each fault type [26,27]. Their physical interpretations and computational formulas are presented in Table 1.

Table 1. Description and mathematical formulation of the eight extracted features.

Feature	Description	Mathematical Formulation
Skewness (<i>S</i>)	Measures the asymmetry of the probability distribution around its mean.	$\frac{1}{N} \sum_{i=1}^N \frac{(x_i - \mu)^3}{\sigma^3}$
Kurtosis (<i>K</i>)	Quantifies the sharpness of the probability distribution.	$\frac{1}{N} \sum_{i=1}^N \frac{(x_i - \mu)^4}{\sigma^4}$
Shape Factor (<i>SF</i>)	Describes the dispersion of the signal energy.	$\sqrt{\frac{1}{N} \sum_{i=1}^N x_i^2}$
Crest Factor (<i>CF</i>)	Evaluates the severity of peaks.	$\frac{\max(x_i)}{\sqrt{\frac{1}{N} \sum_{i=1}^N x_i^2}}$
Impulse Factor (<i>IF</i>)	Assesses the impulsive nature of the signal.	$\frac{\max(x_i)}{\frac{1}{N} \sum_{i=1}^N x_i }$
Permutation Entropy (<i>PE</i>)	Quantifies the complexity and randomness of the signal series.	$-\sum_{\pi \in \Pi} p(\pi) \log_2 p(\pi)$
Relative Half-life (<i>RHL</i>)	Characterizes the energy decay rate of the impact transient.	$\frac{t_{E(p \rightarrow 0.5p)}}{t_{E(p \rightarrow b)}}$
Mutation Symmetry Index (<i>MSI</i>)	Evaluates the temporal symmetry of the waveform around the impact peak.	$\frac{t_{b \rightarrow p}}{t_{p \rightarrow b}}$

x_i ($i = 1, 2, \dots, N$) is the signal series; μ and σ are the mean value and the variance of the series, respectively; Π is the set of all possible permutation patterns; $p(\pi)$ is the probability of the i -th permutation pattern; $t_{E(p \rightarrow 0.5p)}$ is the duration required for the signal envelope to decrease from its peak value to half of its peak value; $t_{E(p \rightarrow b)}$ is the time taken for the signal envelope to transition from its peak value to its baseline value; $t_{b \rightarrow p}$ is the time from the baseline value to the peak value, and $t_{p \rightarrow b}$ is the time from the peak value to the baseline value.

Notably, the selected eight features encompass three major categories: statistical features, entropic features, and time-domain dynamic features, all of which are dimensionless or relative measures. This inherent design ensures insensitivity to variations in operating conditions and signal segment lengths, thereby guaranteeing both discrimination and robustness in fault diagnosis.

2.1.3. Feature Postprocessing

Following the computation of the initial eight-dimensional feature vector $F_{init} = [S, K, SF, CF, IF, PE, RHL, MSI]^T$, a feature selection stage is implemented to optimize the feature set. The aim is to identify a compact subset of features that collectively provide maximal discriminative power for fault classification while minimizing information redundancy. Since these features serve as inputs to the zero-space observers, dimensionality reduction will enhance the method's generalization and improve diagnostic performance [28]. To accomplish this, the minimum-redundancy maximum relevance (mRMR) algorithm is employed [29].

The mRMR algorithm operates on the principle of mutual information, selecting features based on their relevance to the target fault types and redundancy with respect to already selected features. For a discrete target variable C (representing fault types) and a feature set F_{init} , the objective is to find the feature subset that maximizes the following criterion:

$$\max_{f_j \in F_{init}/F_{final}} [I(f_j; C) - \frac{1}{|F_{final}|} \sum_{f_i \in F_{final}} I(f_j; f_i)] \quad (1)$$

where $I(\cdot; \cdot)$ denotes mutual information, $I(f_j; C)$ quantifies the relevance of candidate feature f_j to the fault type C , and the average term $\frac{1}{|F_{final}|} \sum_{f_i \in F_{final}} I(f_j; f_i)$ quantifies the redundancy between f_j and the features already in the selected subset F_{final} .

By eliminating redundant features, the mRMR algorithm reduces the dimensionality of the input space, thereby mitigating the risk of overfitting and improving the efficiency of zero-space computations. Crucially, the mRMR method operates on the original features, thus preserving their physical meaning, which is a significant advantage over dimensionality reduction transforms such as principal component analysis (PCA) [30]. The resulting optimized feature vector F_{final} provides a robust and efficient input to the zero-space observers, ensuring its performance is driven by the most informative and non-redundant signal characteristics.

2.2. Zero-Space Observer Theory

This subsection presents the mathematical foundation of the zero-space observer [31]. The core principle exploits geometric relationships in feature space to construct a set of dedicated observers, each designed to be sensitive to one target health state while remaining insensitive to all others. This approach transforms the fault diagnosis problem into a series of efficient algebraic operations.

2.2.1. Geometric Foundation in Feature Space

As mentioned in Section 2.1.3, $F_{final} \in R^M$ denotes the final feature vector obtained from the postprocessing stage, where M ($M < 8$) is the number of features selected by the mRMR algorithm. For a given system with K predefined health states, each state is characterized by a unique cluster of points in this M -dimensional feature space.

The centroid for the k -th state, estimated from a representative training set, is defined as:

$$F_k = \frac{1}{N_k} \sum_{i=1}^{N_k} F_{final}^k(i) \quad (2)$$

where N_k is the number of training samples for state k , and $F_{final}^k(i)$ is the feature vector of the i -th sample from that state. According to the law of large numbers, the sample mean F_k serves as a consistent estimator of the population centroid for state k when N_k is sufficiently large. It should be noted that, due to the statistical independence of vibration signals corresponding to different health states, the resulting feature centroid vectors are linearly independent. This property ensures the existence of a dedicated zero-space observer for each health state.

2.2.2. Construction of the Zero-Space Observer

The fundamental design objective is to create a linear observer for each state k . This observer, denoted as $Z_k \in R^{1 \times M}$, should satisfy two key properties:

- It yields a zero output when applied to the feature centroids of all other states.

- It yields a non-zero output when applied to the feature centroid of its own target state k .

To achieve this, the complement space matrix U_k is defined for state k :

$$U_k = [F_1, F_2, \dots, F_{k-1}, F_{k+1}, \dots, F_K] \in R^{M \times (K-1)} \quad (3)$$

This matrix aggregates the centroids of all states except the k -th state.

The zero-space of U_k is the set of all row vectors Z that satisfy:

$$ZU_k = 0 \quad (4)$$

Geometrically, any vector Z in this space is orthogonal to the column space of U_k , meaning it is orthogonal to the centroid vectors of all non- k states.

A vector Z_k is then selected from this zero-space such that:

$$Z_k F_k \neq 0 \quad (5)$$

This ensures that Z_k maintains sensitivity to its designated target state k . Consequently, the observer Z_k can effectively separate samples of state k from samples of all other states.

2.2.3. Residual Generation and Fault Decision Logic

For an incoming, unknown test sample with feature vector F_{test} , its interaction with the k -th observer generates a residual r_k :

$$r_k = |Z_k F_{test}| \quad (6)$$

In practice, residuals are rarely zero even for samples not belonging to state k , due to measurement noise and system variations. However, these noise-induced residuals are significantly smaller in magnitude than those produced when the sample belongs to state k . Leveraging this disparity, the diagnostic decision follows a simple logic:

$$Diagnosis = \arg \max_k (r_k) \quad (7)$$

For a given test sample, the residuals from all K observers are computed in parallel. The final diagnosis is made by identifying the state corresponding to the observer with the maximum residual.

2.3. Fault Diagnosis Framework

This subsection presents the proposed fault diagnosis framework, which integrates the feature extraction pipeline with the zero-space observer. The framework operates in two distinct phases: (1) an Offline Modeling Phase, where diagnostic observers are designed using historical data, and (2) an Online Diagnosis Phase, where real-time vibration signals are processed to identify the health state of the rigid guide. The overall architecture is illustrated in Figure 2.

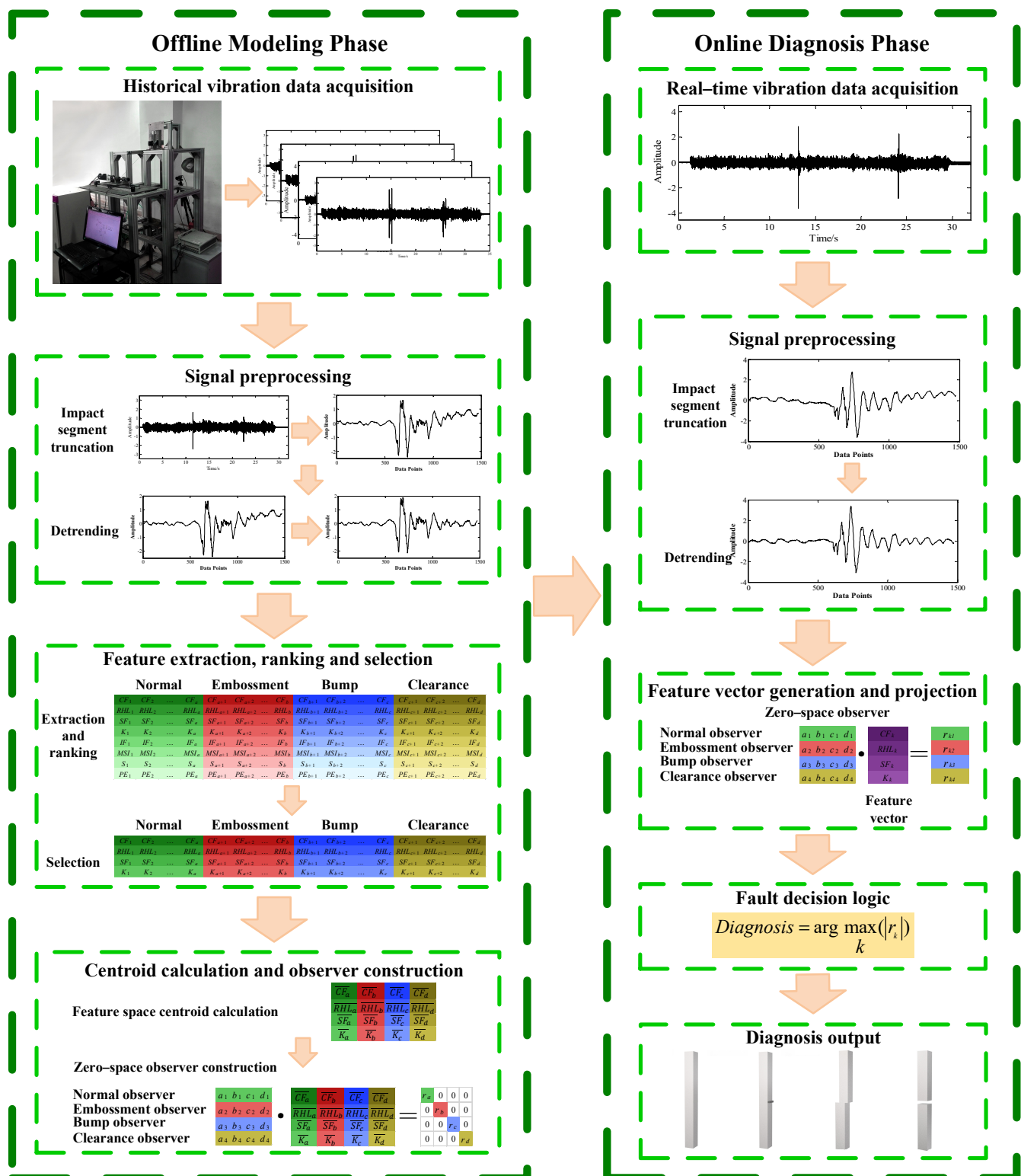


Figure 2. Schematic flowchart of the proposed fault diagnosis framework for rigid guides.

3. Experimental Setup

To validate the effectiveness and robustness of the proposed fault diagnosis method, a series of controlled experiments was conducted using a custom-designed fault simulator. This section details the experimental apparatus, data-acquisition system, and designed test scenarios employed in this study.

3.1. Fault Simulation Test Rig

A dedicated rigid-guide fault simulator was constructed to replicate the essential dynamics of a mine hoisting installation while enabling precise introduction and control of faults. The main components of the test rig, as illustrated in Figure 3, included:

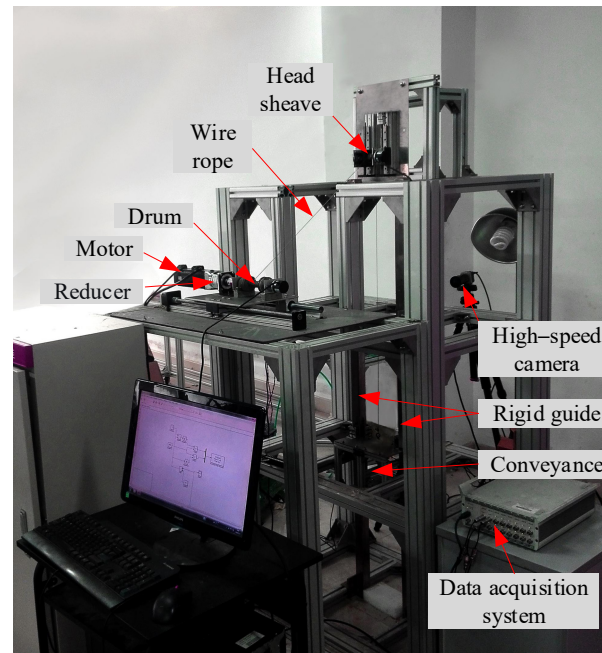


Figure 3. Photographic overview of the rigid guide fault simulation test rig.

Drive System: An AC motor coupled with a planetary gear reducer was employed to deliver controlled traction.

Hoisting Mechanism: A winding drum and a head sheave guided the hoisting rope, which was attached to a scaled conveyance.

Rigid Guide Assembly: Two parallel steel guides were mounted on a rigid frame, serving as the path for the conveyance. The rails were sectioned and mounted with adjustable fixtures to facilitate the simulation of local faults.

Conveyance and Guide Rollers: A conveyance was equipped with four sets of guide rollers (two per side).

Control and Data Acquisition System: An xPC target-based real-time controller governed the start-stop, direction, and speed of the motor. A National Instruments data acquisition system recorded sensor outputs. A high-speed camera captured the instantaneous interaction between the guide roller and the rigid guide fault.

3.2. Data Acquisition

Vibration signals, which served as the primary data source for rigid guide fault diagnosis, were captured using an IEPE triaxial accelerometer. As shown in Figure 4, the sensor was mounted on the top plate of the conveyance to measure vibrations in the longitudinal (Z-axis, parallel to rigid guides), transverse (X-axis, perpendicular to the rigid guide face), and lateral (Y-axis) directions. Preliminary investigations in both the time and time-frequency domains confirmed that the longitudinal component carried the most discriminative information for local faults, aligning with prior studies [32,33]. Therefore, all subsequent analyses focused on the longitudinal acceleration signal.

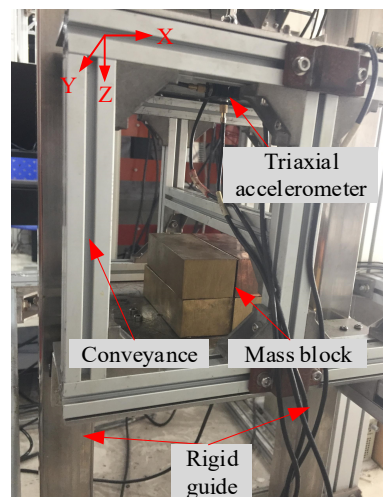


Figure 4. Location of the triaxial accelerometer on the conveyance.

The accelerometer's analog signals were conditioned and digitized by a dynamic signal analyzer at 20 kHz, ensuring adequate resolution of the high-frequency impact components. Concurrently, a high-speed camera sampled the motion of the guide roller at 1 kHz, synchronizing the visual data with the vibration signals and the hoisting cycle.

3.3. Experimental Scenarios and Test Matrix

Based on fault-dynamics characterization, rigid guide faults can be broadly categorized into two types: slow-progressive faults and impact faults. Slow-progressive faults, such as gradual inclination or distributed deformation, influence conveyance in a sustained yet moderate manner, primarily because of their extended spatial distribution, which dilutes instantaneous dynamic interactions.

In contrast, impact faults are distinguished by a highly localized geometric discontinuity. This concentrated defect generates intense transient vibrations during conveyance passage, posing immediate risks of rope overload, operational interference, or conveyance jamming. Consequently, the timely diagnosis of impact faults is essential for root-cause analysis and the development of preventive maintenance protocols. This investigation, therefore, focuses on three representative impact modes: embossment, bump, and clearance (see Figure 5b–d), which encompass the majority of impulse-generating defect scenarios, such as those caused by attached debris or fastening failure. These three impact fault states, together with the normal state, are predefined as the four health states of the rigid guide considered in this study.

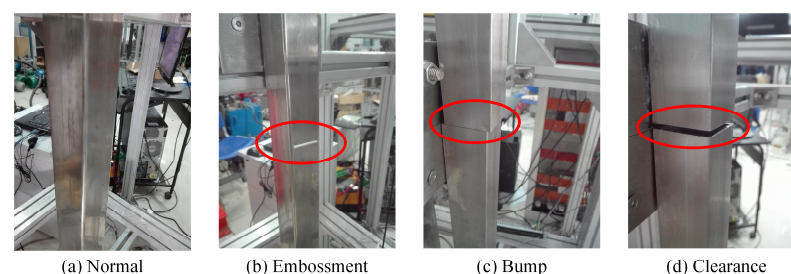


Figure 5. Four health states of rigid guide: (a) normal; (b) embossment; (c) bump; (d) clearance.

To evaluate the proposed fault diagnosis framework, experiments were conducted on the fault simulation test rig. Faults were introduced on one rigid guide while the opposite guide remained intact.

Embossment Fault: Simulated by attaching a rectangular shim of specified thickness onto the rail surface (marked by a red circle in Figure 5b).

Bump Fault: Simulated by introducing a controlled height difference at the junction between two rail segments (marked by a red circle in Figure 5c).

Clearance Fault: Simulated by creating a vertical gap at the junction between two rail segments (marked by a red circle in Figure 5d).

For each health state, key operational parameters were systematically varied to assess the robustness of the method. Hoisting speed was adjusted by controlling motor speed, while lifting mass was varied by adding mass blocks (see Figure 4) in increments of 1.1 kg. A full-factorial test matrix was implemented, as summarized in Table 2.

Table 2. Experimental parameter matrix for fault simulation tests.

Parameter	Symbol	Values/Levels
Health state	S	Normal, Embossment, Bump, Clearance
Fault severity (mm)	d	1.0, 2.0, 3.0
Hoisting speed (m/s)	v	0.02, 0.04, 0.06, 0.08, 0.10
Lifting mass (kg)	m	3.45, 4.55, 5.65, 6.75, 7.85

For each parameter combination $\{d, v, m\}$ under the fault states, five independent runs were conducted to mitigate random errors and ensure reproducibility. For the normal baseline, where fault severity is inapplicable, fifteen runs were performed per speed-load combination $\{v, m\}$. This design ensured that all four health states contributed an equal number of samples (375 each), providing a balanced dataset for fair classifier training and evaluation. From these replicates, 3/5 were randomly selected per combination for training and the remaining 2/5 for testing, preserving proportional representation of all operating conditions.

Consequently, the final dataset composition was as follows:

Total dataset: 1500 samples (375×4).

Training Set: 900 samples ($1500 \times 3/5$).

Testing Set: 600 samples ($1500 \times 2/5$).

4. Results and Discussion

This section presents and discusses the experimental results to comprehensively evaluate the proposed fault diagnosis framework. The analysis proceeds in three stages. First, the rationale and effectiveness of the physics-informed feature-extraction pipeline are examined to establish a foundation for robust diagnosis. Subsequently, the diagnostic accuracy of the zero-space observer is evaluated under variable operating conditions. Finally, a comparative study comprising two cases is conducted against established benchmark methods, which serves to validate the overall superiority of the integrated framework and to isolate the specific contribution of the zero-space observer, respectively.

4.1. Signal Analysis and Feature Selection Results

Figure 6 shows the original vibration signals and magnified views under four rigid guide health states. Analysis of these waveforms reveals distinct morphological patterns unique to each state. This direct correspondence between waveform signature and health state validates the use of physics-informed features, enabling the extracted parameters to capture the essential diagnostic information of rigid guide fault dynamics.

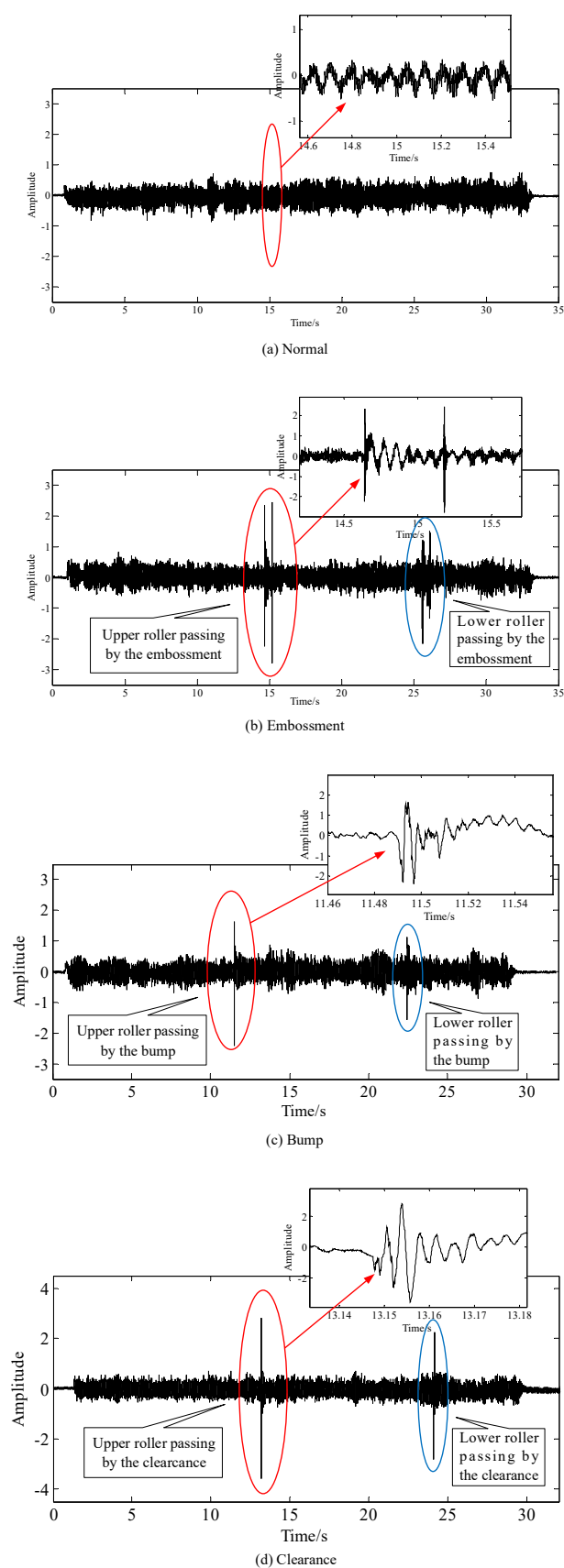


Figure 6. Original signals under four rigid guide health states and corresponding enlarged views: (a) normal; (b) embossment; (c) bump; (d) clearance.

As illustrated in Figure 6a, the vibration signal under normal state exhibits low-frequency fluctuations throughout the time domain, with no prominent impulsive components observed. This pattern reflects the inherent properties of the system and environmental background noise.

Regardless of fault type, the raw vibration signals consistently exhibit two impulse groups (marked by red and blue circles in Figure 6b–d), which are produced by the sequential interactions of the upper and lower guide rollers with the rigid guide fault. The amplitude disparity between these groups arises from two combined factors. Firstly, the lower guide roller is located farther from the accelerometer (see Figure 4), and the vibration signal thus undergoes greater attenuation over the longer propagation path through the conveyance structure. Secondly, differences in the stiffness and damping of the upper and lower roller buffer assemblies also contribute to the observed amplitude variation. For rigid guide fault diagnosis in this study, the first impulse group was selected for analysis.

On an extended time scale, the embossment fault exhibits a characteristic dual-impulse signature, distinguishing it from bump and clearance faults. Physically, the first impulse corresponds to the initial impact as the guide roller strikes the leading edge of the embossment. The second impulse arises when the guide roller disengages from the trailing edge and re-engages with the nominal rail surface.

In contrast, bump and clearance faults each typically present a single dominant impulse. However, their localized waveform morphologies differ fundamentally. High-speed camera observations and prior literature [17,34–36] indicate that this difference stems from distinct generation mechanisms: the bump fault waveform is governed by direct collision dynamics, whereas the clearance fault waveform results from a sequence of stress release and re-application as the guide roller traverses the gap.

Thus, the geometric waveform, resulting from the interaction between the guide roller and the rigid guide fault, is determined solely by the fault type. This conclusion is supported by the consistent waveform characteristics observed across all experimental fault signals. Consequently, the waveform morphology provides an effective basis for diagnosing rigid guide faults.

Based on the preprocessed waveforms, an initial eight-dimensional feature vector F_{init} is obtained. The mRMR algorithm is subsequently applied to rank the eight features and select an optimal subset. The ranking and selection results are presented in Figure 7.

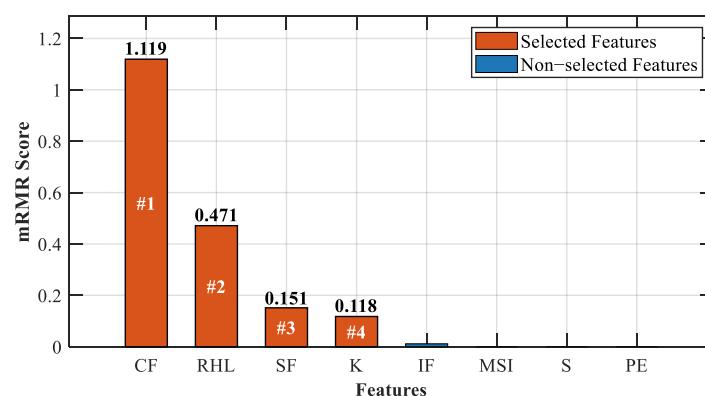


Figure 7. Feature ranking and selection results from the mRMR algorithm.

The mRMR scores of the first four features are significantly higher than those of the remaining four, indicating their superior discriminative power. Accordingly, the subset {CF, RHL, SF, K} is selected to form the four-dimensional feature vector for the zero-space observer. This result confirms that these four shape and energy-based parameters most effectively characterize the distinctive waveform signatures of rigid guide faults.

4.2. Diagnostic Performance of the Zero-Space Observer

Following the methodology in Section 2.2, the zero-space observer is applied to the training set and evaluated on the test set. The resulting health-state classifications, obtained via Equation (7), are shown in Figure 8. The figure segments the sample sequence into four blocks: samples 1–150 represent the normal state, 151–300 the embossment fault, 301–450 the bump fault, and 451–600 the clearance fault.

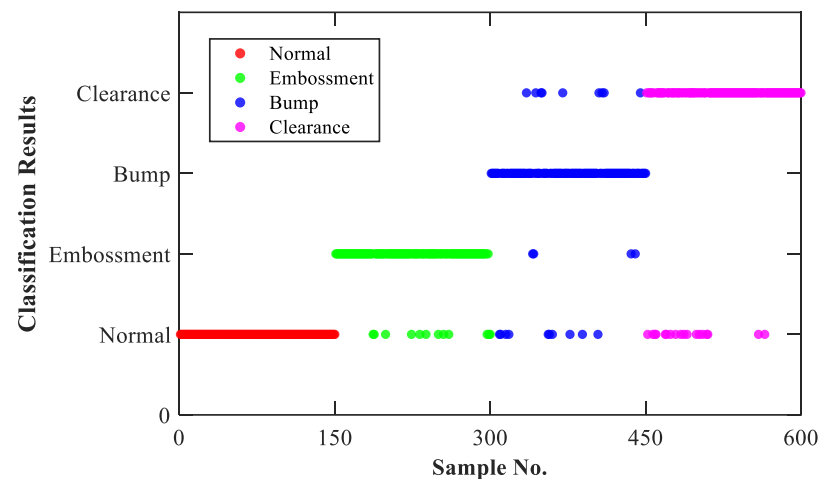


Figure 8. The health state identification results for the test set.

The results indicate that all samples in the normal state block (1–150) are correctly identified, yielding a classification accuracy of 100%. For the embossment fault block (151–300), 12 samples are misclassified, resulting in an accuracy of 92.0%. The bump fault block (301–450) shows 23 misclassifications, corresponding to an accuracy of 84.7%. For the clearance fault block (451–600), 18 samples are misclassified, achieving an accuracy of 88.0%. The method achieves an overall diagnostic accuracy of 91.2% across all test samples, demonstrating its effectiveness in identifying rigid guide health states under varied operating conditions.

The perfect classification of the normal state is readily understood. As shown in Figure 6a, its vibration signal exhibits a low-amplitude, random profile without significant impulses, making its feature vector fundamentally distinct from those of the impact faults.

Notably, all misclassifications of the embossment fault are assigned to the normal state. In theory, a statistical boundary exists between the sample clusters of the normal and embossment states. While the majority of embossment samples lie far from the normal cluster, a small subset may lie close to this boundary. This occurs when intense oscillation in the extracted impact segment reduces the relative prominence of the primary peak. As indicated by the formulas of CF and K , such samples may yield feature values that fall within the periphery of the normal cluster. However, this type of misclassification can be easily eliminated by incorporating additional criteria, such as the overall vibration severity of the raw signal or the number of local peaks within the impact region.

Similarly, all misclassifications of the clearance fault are assigned to the normal state, albeit for a different reason. Specifically, this phenomenon arises from the low severity level of the clearance fault, where the corresponding impact energy is closely comparable to the background noise or the inherent vibration amplitude during normal operation. In practical terms, such misclassification does not pose significant consequences, as a small clearance has a negligible effect on the hoisting conveyance.

The few remaining misclassifications occur primarily between bump and clearance faults. These can be attributed to the occasional similarity in their single-impact waveforms under specific conditions of low fault severity and high hoisting speed.

4.3. Comparative Analysis with Widely Used Methods

To comprehensively benchmark the performance of the proposed method, a comparative study is conducted against several widely used intelligent fault diagnosis approaches, including the radial basis function (RBF) neural network [37,38], SVM [39–41], long short-term memory (LSTM) network [42–44], and one-dimensional convolutional neural network (1DCNN) [45,46]. The comparison is structured into two cases. In Case 1, the complete proposed framework is compared against the four models to assess its overall superiority. In Case 2, the classification capability of the zero-space observer is specifically evaluated by isolating its performance from that of the feature extraction pipeline.

1. Case 1

In this case, the proposed framework employs physics-informed feature extraction combined with the zero-space observer as the classifier. For the RBF, SVM, and LSTM models, four conventional features from the literature [12] are used: the maximum value, the mean value, the maximum value of the wavelet transform modulus maximum, and the area between the curve of the wavelet transform modulus maximum and its envelope. The wavelet scale is set to 64 to balance resolution and efficiency. For the 1DCNN model, which can process raw sequential data, the original vibration signals are used directly as input. Given the variable signal lengths under different operating conditions, a fixed-length segment of 20,000 points containing the impact transient is extracted from each signal. All computations are performed on a computer equipped with an Intel(R) Core(TM) i7-14650HX processor and 16 GB RAM. The performance comparison results are summarized in Table 3, and several key observations are discussed next.

Table 3. Performance comparison of different fault diagnosis methods.

Method	Accuracy (%)	Feature Preparation Time (s)	Training Time (s)	Test Time (s)
The proposed method	91.2	345.8608	0.0054	0.0023
RBF	74.2	769.4761	1.8582	0.0092
SVM	71.7	769.4761	0.0552	0.0127
LSTM	69.8	769.4761	10.3481	0.2765
1DCNN	81.8	243.8246	286.3264	7.1885

Firstly, the proposed method achieves a diagnostic accuracy of 91.2%, substantially outperforming the RBF (74.2%), SVM (71.7%), LSTM (69.8%), and 1DCNN (81.8%) models. This gap stems primarily from the fundamental difference in feature design. The proposed framework employs a physics-informed feature-extraction pipeline to capture the discriminative characteristics of fault-induced transient vibrations while explicitly decoupling operational variability. In contrast, the RBF, SVM, and LSTM models rely on four conventional time-domain and wavelet-based features. The calculation of the mean value and the area between the curve of wavelet transform modulus maximum and its envelope incorporates the entire signal, thereby introducing substantial non-fault-related components that dilute the salience of fault-related signatures. Meanwhile, parameters such as the maximum value and the maximum value of wavelet transform modulus maximums are highly susceptible to variations in operating conditions, which can lead to feature aliasing across different fault types and reduce overall discriminability. The LSTM yields the lowest accuracy among all compared methods, indicating its limited suitability for

processing the non-sequential features extracted from rigid-guide fault vibrations under variable operational conditions. Although the 1DCNN attains a relatively higher accuracy than the RBF, SVM, and LSTM models, its performance remains lower than that of the proposed method. To further examine the classification performance of the 1DCNN, the corresponding confusion matrix is provided in Figure 9. The matrix shows that the normal and embossment faults are identified with 100% accuracy, whereas the bump and clearance faults exhibit lower recognition rates. This can be attributed to the distinct impulse characteristics of each health state: the normal signal contains no significant impulses, and the embossment fault produces a double-impulse signature, whereas both the bump and clearance faults generate only a single impulse. When a fixed 20,000-point segment is used as the network input, the transient signature of a single impulse is diluted within the lengthy signal window, thereby reducing the discriminability of these two fault types and resulting in their mutual misclassification.

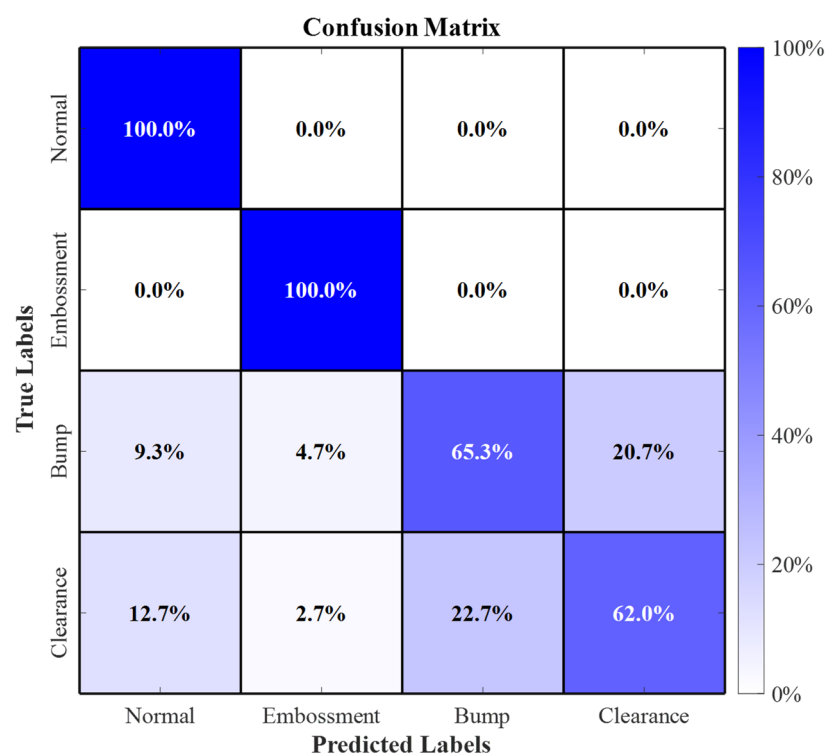


Figure 9. Confusion matrix of the 1DCNN method.

Secondly, the computational efficiency of the proposed method is also notable. The feature preparation time for the proposed method (345.8608 s) is shorter than that of the RBF, SVM, and LSTM models (769.4761 s), but longer than that of the 1DCNN (243.8246 s). This difference stems from where the computational effort is allocated. For both the proposed method and the 1DCNN model, the primary computational cost is due to the sliding-window energy detection algorithm used to truncate the impact signal segment automatically. The longer feature preparation time of the proposed method compared to the 1DCNN is due to its adaptive length truncation, which is more computationally intensive than the fixed-length segmentation used in the 1DCNN. For the RBF, SVM, and LSTM models, computation time is dominated by the continuous wavelet transform applied to the entire signal, a computationally intensive process. The most significant computational advantage is observed during model training and testing. The proposed method requires only 0.0054 s for training, orders of magnitude faster than those of RBF (1.8582 s), SVM (0.0552 s), LSTM (10.3481 s), and especially 1DCNN (286.3264 s). This efficiency stems from

the non-iterative, algebraic nature of observer construction, which eliminates the need for complex optimization or parameter tuning. Similarly, the test time is the lowest among all methods, underscoring the suitability of the proposed approach for real-time or online monitoring applications where rapid decision-making is critical.

2. Case 2

In this case, the three classifiers, namely RBF, SVM, and zero-space observer, are benchmarked directly using the same physics-informed features. This comparison highlights the intrinsic classification capabilities of each model, as shown in Figure 10.

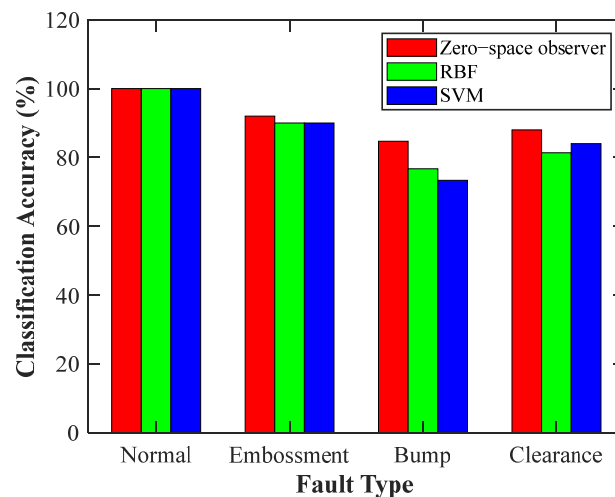


Figure 10. Performance comparison of different fault diagnosis classifiers.

As shown in Figure 10, the RBF and SVM classifiers achieve acceptable classification accuracy, while the zero-space observer consistently attains the highest recognition rate for each health state. The ability of RBF and SVM to generalize across varied operating conditions, avoiding significant mode confusion, can be attributable to the robustness of the proposed physics-informed features on which they were trained.

Furthermore, a key advantage of the zero-space observer is that it eliminates the need for parameter tuning. This step, involving critical choices such as kernel parameters for SVMs, expansion constants for RBFs, and network architectures and hyperparameters for LSTM and 1DCNN, often significantly influences the final performance of the intelligent models. In contrast, the zero-space observer constructs the decision model directly from the feature centroids via algebraic operations, ensuring both simplicity and reproducibility.

5. Conclusions

Accurate fault diagnosis of rigid guides is essential for preventing unexpected failures and reducing maintenance costs in mine hoisting systems. However, this task is challenged by two inherent limitations of conventional methods: traditional global features often fail to generalize across different operating conditions, and most approaches require large amounts of labeled fault data, which are difficult to obtain in practice. To address these problems, this paper proposes a novel fault-diagnosis framework for rigid guides that integrates a physics-informed feature-extraction pipeline with geometric zero-space observers. The methodology systematically transforms raw vibration signals into reliable diagnostic decisions through three core stages: physics-informed feature selection, zero-space observer construction, and health state identification.

Experimental validation under variable operating conditions demonstrates the effectiveness of the proposed approach. The method achieves an overall diagnostic accuracy of

91.2% across four health states (normal, embossment, bump, and clearance), with per-class accuracies of 100% for the normal state, 92.0% for embossment faults, 84.7% for bump faults, and 88.0% for clearance faults. Comparative analysis reveals that the proposed framework substantially outperforms four widely used intelligent methods: RBF (74.2%), SVM (71.7%), LSTM (69.8%), and 1DCNN (81.8%). Furthermore, when benchmarked using identical physics-informed features, the zero-space classifier consistently achieves the highest recognition rates for each health state compared to RBF and SVM, confirming its superior intrinsic classification capability.

The framework presents several key advantages beyond accuracy. Firstly, it exhibits remarkable computational efficiency, as the Online Diagnosis Phase relies solely on straightforward matrix-vector operations, rendering it particularly suitable for real-time or embedded monitoring systems. Secondly, it demonstrates strong robustness under variable operating conditions, accomplished by decoupling diagnostic signatures from operating parameters through explicit feature design. Finally, it provides enhanced interpretability in comparison to black-box models, with a transparent decision logic based on residual analysis and geometric observers.

Despite its strengths, two limitations are noted, pointing to essential directions for future work. Firstly, as a supervised method, the framework is currently limited to classifying predefined health states. Identifying novel or unknown faults represents a critical next step. Secondly, the model assumes single-fault scenarios in the rigid guide system. Its performance when concurrent faults occur in both the rigid guide and the guide rollers warrants further investigation.

Author Contributions: Conceptualization, B.W. and H.C.; methodology, B.W. and F.J.; software, F.J.; validation, B.W. and F.J.; formal analysis, Q.Z.; investigation, B.W. and F.J.; data curation, F.J.; writing—original draft preparation, B.W. and H.C.; writing—review and editing, H.C.; visualization, H.C. and Q.Z. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Natural Science Foundation of the Jiangsu Higher Education Institutions (22KJD510003), the Scientific Research Project of Jiangsu Vocational Institute of Architectural Technology (JYA325-05), and the National Natural Science Foundation of China (52374163).

Data Availability Statement: The original contributions presented in the study are included in the article. Further inquiries can be directed to the corresponding author.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Chen, X.; Zhang, C.; Chang, J.C.; Zhao, G.M.; Zang, W.S.; Zhu, Z.C.; Shen, G. Longitudinal vibration estimation of a mine hoist using a hybrid signal fusion method combining UKF, ND and improved DE. *Meas. Sci. Technol.* **2024**, *35*, 045108. [\[CrossRef\]](#)
2. Yao, J.N.; Ma, Y.S.; Ma, C.; Xiao, X.M.; Xu, T. Effect of misalignment failures of steel guides on impact responses in friction mine hoisting systems. *Eng. Fail. Anal.* **2020**, *118*, 104841. [\[CrossRef\]](#)
3. Su, S.Z.; Xu, Z.L.; Ma, T.B.; Zhu, Y.M.; Li, C.P. Two-dimensional elastic space learning for fault diagnosis of rigid cage guides. *IEEE Sens. J.* **2025**, *25*, 43126–43137. [\[CrossRef\]](#)
4. Drzewoszewski, A.; Wolny, S. The problem of stability in mechanical systems using the example of mine hoist installations. *Appl. Sci.* **2024**, *14*, 6472. [\[CrossRef\]](#)
5. Wang, Y.Z.; He, J.C.; Zhang, X.G. A novel one-dimensional convolutional neural network with parallel attention for fault diagnosis of rigid guides. *J. Braz. Soc. Mech. Sci.* **2024**, *46*, 477. [\[CrossRef\]](#)
6. Zhao, J.L. Research on Operation Characteristics of Hoisting Conveyance Under Shaft Deformation and Its Identification. Ph.D. Dissertation, School of Mechatronic Engineering, China University Mining & Technology, Xuzhou, China, 2023.
7. Du, F.; Mo, D.D.; Ma, T.B.; Fang, J.X.; Shu, J.X.; Long, J.T. Rigid tank guide fault detection algorithm based on improved YOLOv7. *J. Real-Time Image Process.* **2025**, *22*, 2. [\[CrossRef\]](#)

8. Lu, X.; Hao, H.F.; Li, X.; Shen, Y.C.; Guo, Y.J.; Bai, X.Z. Research on rigid guide deformation detection based on line structured light 3-D reconstruction algorithm. *IEEE Trans. Instrum. Meas.* **2025**, *74*, 3547112. [[CrossRef](#)]
9. Zhu, Y.; Yan, R.; Liu, D.; Deng, X.J.; Yao, J.N. Investigation of a new vibration-absorbing roller cage shoe with a magnetorheological damper in mine hoisting systems. *Appl. Sci.* **2023**, *13*, 12506. [[CrossRef](#)]
10. Zhao, J.L.; Han, J.N.; Ma, C.; Xiao, X.M.; Jiang, Y.Q.; Zhang, Y.C. Research on operation characteristics of hoisting conveyance under mining deformation action in mine vertical shaft. *Nonlinear Dyn.* **2024**, *112*, 2629–2659. [[CrossRef](#)]
11. Ma, Y.S.; Yao, J.N.; Ma, C.; Xiao, X.M. Pattern recognition of rigid hoist guides based on support vector machine. *Adv. Mech. Eng.* **2018**, *10*, 1687814018812307. [[CrossRef](#)]
12. Ma, C.; Wang, T.B.; Xiao, X.M.; Jiang, Y.Q. Pattern recognition of rigid hoisting guides based on vibration characteristics. *J. Vibroeng.* **2017**, *19*, 237–245. [[CrossRef](#)]
13. Lu, X.; Liu, Z.H.; Shen, Y.C.; Zhang, F.; Ma, N.; Hao, H.F.; Liang, Z. Research on fault diagnosis of rigid guide in hoist system based on vibration signal classification. *Meas. Sci. Technol.* **2024**, *35*, 116102. [[CrossRef](#)]
14. Jakubowski, J.; Fiolek, P. Data-driven approach to structural analysis of shaft steelwork under corrosion. *Eng. Struct.* **2023**, *281*, 115741. [[CrossRef](#)]
15. Fiolek, P.; Jakubowski, J.; Tomczak, K. Failure modes of shaft steelwork in the state of advanced corrosion. *Eng. Fail. Anal.* **2023**, *146*, 107059. [[CrossRef](#)]
16. Fiolek, P.; Jakubowski, J. Assessment of hoisting conveyance guiding forces based on field acceleration measurements and numerical simulation. *Appl. Sci.* **2024**, *14*, 10758. [[CrossRef](#)]
17. Fiolek, P.; Jakubowski, J. Structural safety assessment of shaft steelwork—A review. *Arch. Min. Sci.* **2023**, *68*, 655–670.
18. Mohamad, T.H.; Abbasi, A.; Kappaganthu, K.; Nataraj, C. On extraction, ranking and selection of data-driven and physics-informed features for bearing fault diagnostics. *Knowl-Based. Syst.* **2023**, *276*, 110744. [[CrossRef](#)]
19. Ding, L.; Xu, P.; Li, Z.Y.; Zhou, R.Y.; Gao, H.B.; Deng, Z.Q.; Liu, G.J. Pressing and rubbing: Physics-informed features facilitate haptic terrain classification for legged robots. *IEEE Robot. Autom. Lett.* **2022**, *7*, 5990–5997. [[CrossRef](#)]
20. Ma, Z.Y.; Pan, Z.L. Efficient machine learning of solute segregation energy based on physics-informed features. *Sci. Rep.* **2023**, *13*, 11449. [[CrossRef](#)]
21. Jiang, F.; Zhu, Z.C.; Li, W.; Chen, G.A.; Zhou, G.B. Identification and diagnosis of concurrent faults in rotor-bearing system with WPT and zero space classifiers. *J. Vibroeng.* **2014**, *16*, 901–912.
22. Jiang, F.; Zhu, Z.C.; Li, W.; Zhou, G.B.; Chen, G.A. Fault identification of rotor-bearing system based on ensemble empirical mode decomposition and self-zero space projection analysis. *J. Sound Vib.* **2014**, *333*, 3321–3331. [[CrossRef](#)]
23. Jiang, F.; Zhu, Z.C.; Li, W.; Chen, G.A.; Zhou, G.B. Robust condition monitoring and fault diagnosis of rolling element bearings using improved EEMD and statistical features. *Meas. Sci. Technol.* **2014**, *25*, 025003. [[CrossRef](#)]
24. Jiang, F.; Li, W.; Wang, Z.Q.; Zhu, Z.C. Fault severity estimation of rotating machinery based on residual signals. *Adv. Mech. Eng.* **2012**, *4*, 518468. [[CrossRef](#)]
25. Wang, L.L.; Wu, M.H. Research on bearing fault diagnosis based on machine learning and SHAP interpretability analysis. *Sci. Rep.* **2025**, *15*, 41242. [[CrossRef](#)]
26. Patil, S.S.; Salunkhe, V.G.; Jadhav, P.S.; Desavale, S.R.; Shinde, V.V.; Desavale, R.G. Intelligent fault diagnosis based on the EAO-VMD in dual-rotor cylindrical roller bearings. *J. Tribol.* **2026**, *148*, 014302. [[CrossRef](#)]
27. Antoni, J.; Kestel, K.; Peeters, C.; Leclerc, Q.; Girardin, F.; Ooijselaar, T.; Helsens, J. On the design of optimal health indicators for early fault detection and their statistical thresholds. *Mech. Syst. Signal Process.* **2024**, *218*, 111518. [[CrossRef](#)]
28. Salunkhe, V.G.; Khot, S.M.; Desavale, R.G.; Yelve, N.P.; Jadhav, P.S. An integrated dimension theory and modulation signal bispectrum technique for analyzing bearing fault in industrial fibrizer. *J. Nondestruct. Eval. Diagn. Progn. Eng. Syst.* **2024**, *7*, 031006. [[CrossRef](#)]
29. Bouali, F.; Fedala, S.; Andre, H.; Felkaoui, A. Intelligent bearing faults diagnosis in non-stationary conditions based on angular resampling and support vector machine. *Comptes Rendus Méc.* **2025**, *353*, 499–518. [[CrossRef](#)]
30. Mali, A.R.; Shinde, P.V.; Patil, A.P.; Salunkhe, V.G.; Desavale, R.G.; Jadhav, P.S. A novel method for bearing fault diagnosis based on novel feature sets with machine learning technique. *J. Tribol.* **2025**, *147*, 024301. [[CrossRef](#)]
31. Chen, J.; Yin, Y.Z. Zero space orthogonal projection method for array pattern synthesis. *IEICE Electron. Expr.* **2025**, *22*, 1–5. [[CrossRef](#)]
32. Zhu, Y.; Xu, T.; Ma, C.; Yao, J.N. Experimental study on longitudinal vibration of mine hosting rope subjected to disturbance excitations by ADAMS. *Adv. Mech. Eng.* **2022**, *14*, 16878132221076818. [[CrossRef](#)]
33. Molodova, M.; Li, Z.L.; Nunez, A.; Dollevoet, R. Automatic detection of squats in railway infrastructure. *IEEE Trans. Intell. Transp.* **2014**, *15*, 1980–1990. [[CrossRef](#)]
34. Zhang, H.C.; Borghesani, P.; Smith, W.A.; Randall, R.B.; Shahriar, M.R.; Peng, Z.X. Tracking the natural evolution of bearing spall size using cyclic natural frequency perturbations in vibration signals. *Mech. Syst. Signal Process.* **2021**, *151*, 107376. [[CrossRef](#)]

35. Luo, M.L.; Guo, Y.; Su, Z.Q.; Tang, Z.; Wang, X.; Andre, H.; Peng, Y.H. Defect element segmentation-based vibration analysis of ball bearings: Dynamic modelling and experiments. *Nonlinear Dyn.* **2025**, *113*, 25555–25587. [[CrossRef](#)]
36. Luo, M.L.; Guo, Y.; Su, Z.Q.; Andre, H.; Tang, Z.; Zhou, C.; Li, C. Defect quantification evaluation of a rolling element bearing based on physical modelling and instantaneous vibration energy investigation. *J. Sound Vib.* **2025**, *600*, 118875. [[CrossRef](#)]
37. Sowmya, S.; Saimurugan, M.; Kannan, N.; Edinbarough, I. Potential effects of statistical complexity measure in improving the fault diagnosis performance under speed fluctuations. *Meas. Sci. Technol.* **2025**, *36*, 036106. [[CrossRef](#)]
38. He, D.Q.; Zhang, Z.H.; Jin, Z.Z.; Zhang, F.; Yi, C.; Liao, S.X. RTSMFFDE-HKRR: A fault diagnosis method for train bearing in noise environment. *Measurement* **2025**, *239*, 115417. [[CrossRef](#)]
39. Mali, A.R.; Salunkhe, V.G.; Khot, S.M.; Shinde, P.V.; Yelve, N.P.; Desavale, R.G. Optimized multiclass support vector machines using empirical features for compound fault diagnosis in roller element bearings. *J. Tribol.* **2026**, *148*, 081103. [[CrossRef](#)]
40. Yu, P.B.; Zhang, J.J.; Zhang, B.B.; Cao, J.H.; Peng, Y.H. Research on small sample rolling bearing fault diagnosis method based on mixed signal processing technology. *Symmetry* **2024**, *16*, 1178. [[CrossRef](#)]
41. Salunkhe, V.G.; Desavale, R.G. An intelligent prediction for detecting bearing vibration characteristics using a machine learning model. *J. Nondestruct. Eval. Diagn. Progn. Eng. Syst.* **2021**, *4*, 031004. [[CrossRef](#)]
42. Meng, W.F.; Zhao, P.P.; Shi, Y.J.; Li, L.T.; Meng, Z.Y. Intelligent fault diagnosis of mechanical engineering using NLF-LSTM optimized deep learning model. *Optim. Eng.* **2025**, *26*, 891–912. [[CrossRef](#)]
43. Kollu, G.S.; Kittur, J. Integrating deep learning into mechanical engineering: A systematic review of applications and educational implications. *Comput. Appl. Eng. Educ.* **2025**, *33*, e70048. [[CrossRef](#)]
44. Salunkhe, V.G.; Khot, S.M.; Yelve, N.P.; Jagadeesha, T.; Desavale, R.G. Rolling element bearing fault diagnosis by the implementation of Elman neural networks with long short-term memory strategy. *J. Tribol.* **2025**, *147*, 084301. [[CrossRef](#)]
45. Gao, S.Z.; Li, T.C.; Zhang, Y.M.; Pei, Z.M. Fault diagnosis method of rolling bearings based on adaptive modified CEEMD and 1DCNN model. *ISA Trans.* **2023**, *140*, 309–330. [[CrossRef](#)]
46. Khowaja, A.; Daudpoto, J.; Kumar, D.; Shaikh, A. Bearing fault diagnosis using domain adaptation approach for acoustic data. *Trans. Can. Soc. Mech. Eng.* **2025**, *49*, 608–617. [[CrossRef](#)]

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.