

Article

A Novel Approach for Denoising Magnetic Flux Leakage Signals of Steel Wire Ropes via Synchrosqueezing Wavelet Transform and Dynamic Time–Frequency Masking

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Abstract

Magnetic flux leakage (MFL) signals in steel wire rope defect detection are often corrupted by structural noise and environmental interference, leading to reduced defect recognition accuracy. This study proposes a denoising approach combining synchrosqueezing wavelet transform (SST) with dynamic time–frequency masking to enhance signal quality. The method first employs SST to redistribute time–frequency coefficients, improving resolution and highlighting defect-related energy concentrations. A dynamic masking strategy is then introduced to adaptively suppress noise by leveraging local energy statistics. Experimental results on a constructed dataset show that the proposed method achieves a signal-to-noise ratio (SNR) improvement compared to traditional wavelet denoising. This approach provides an effective solution for real-time monitoring of wire rope defects in industrial applications.

Keywords: magnetic flux leakage; synchrosqueezing transform; wire rope; signal denoising

1. Introduction

As an important mobile lifting equipment in modern industry, truck cranes play a crucial role in industrial and construction fields due to their high mobility and excellent lifting capacity [1,2]. Their application scenarios widely cover cargo loading and unloading, equipment installation in industrial production, and material hoisting and demolition operations in construction projects. Their flexible and efficient operation capability makes them indispensable equipment support in these fields [3,4].

As the core load-bearing component of truck cranes, steel wire ropes are directly related to the safety performance in engineering operations [5]. Steel wire ropes have the advantages of light weight, good elasticity, high tensile strength, and strong load-bearing capacity, and are key components for lifting machinery to realize the traction and load-bearing functions. During the actual operation of truck cranes, with the increase in service time, steel wire ropes are in long-term high-load, complex and harsh working environments during operation, which will inevitably generate defects such as wire breakage, wear, corrosion, and deformation [6,7]. These defects seriously affect the safety and stability of truck crane operations, leading to serious consequences, including threats to life and safety and property losses. Damages of different degrees will bring many serious consequences to the operation of truck cranes. Therefore, online monitoring of the status of steel wire



Academic Editor: Jie Zhang

Received: 9 October 2025

Revised: 3 December 2025

Accepted: 15 December 2025

Published: 19 December 2025

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ropes and timely maintenance have become important links to ensure the safe operation of lifting equipment [8].

MFL testing is a non-destructive testing (NDT) technique that has been extensively applied for detecting defects in ferromagnetic materials [9,10]. By magnetizing the wire rope to near-saturation, local changes in magnetic permeability at defect sites cause flux to leak from the material. This leakage field, which can be captured by magnetic sensors, carries rich information about the presence, type, and severity of defects [11]. Liu et al. [12] proposed a weak signal processing method for steel wire ropes, based on the improved Hilbert–Huang Transform (HHT) and filtering technology. They adopted an experimental scheme that combines the MFL detection method with multi-step filtering technology and conducted signal collection and analysis on steel wire rope samples with three different diameters. By comparing them with traditional methods such as low-pass filtering, wavelet denoising, and median filtering, the proposed improved method significantly improves the SNR and can effectively identify and distinguish the surface defect signals of steel wire ropes. The experimental results show that the method combining the improved HHT and low-pass filtering has great application potential in complex environments, especially in the accurate detection of micro-defects. Li et al. [13] proposed an innovative adaptive multi-scale Bayesian framework for the analysis of the MFL signals of steel wire ropes. By integrating discrete wavelet transform (DWT), adaptive thresholding, and multi-scale feature fusion, this framework can detect both micro-defects and large-area corrosion simultaneously. Extensive experiments on both simulated and real datasets have verified the superiority of this method. Compared with existing methods such as long short-term memory (LSTM), attention mechanism, and Isolation Forest, the proposed method exhibits significant improvements in metrics, including precision, recall, and F1 score. Especially in high-noise environments, the proposed method can effectively reduce the false positive rate while maintaining a high detection sensitivity. Through the application of multi-scale analysis, this method can accurately identify defects of various sizes under complex background noise, providing a robust solution for the non-destructive testing of steel wire ropes and demonstrating potential in improving detection efficiency and enhancing defect localization accuracy. Zhang et al. [14] proposed an intelligent fault diagnosis method for steel wire rope broken wires, based on the generative adversarial network (GAN) and convolutional neural network (CNN). This method converts MFL signals into time–frequency images and combines GAN to generate more fault samples, thereby improving the accuracy of the fault diagnosis when the number of samples is limited. Experiments show that the proposed method achieves an accuracy of 99.3% in identifying six different types of broken wire faults, and compared with traditional backpropagation (BP) neural network and CNN methods, the GAN-CNN model exhibits better recognition performance. By combining the samples generated by GAN with the CNN model, this method can effectively improve the accuracy of steel wire rope broken wire detection and demonstrates potential in practical applications.

Despite its advantages, MFL signal quality is often compromised by complex noise, including structural vibrations, environmental electromagnetic interference, and low-frequency drift. Kou et al. [15] proposed a new detection method for the surface broken wires of steel wire ropes, based on an eddy current differential probe. They designed an eddy current differential probe specifically for the surface broken wires of steel wire ropes, and optimized the detection accuracy by taking into account the spiral surface characteristics of steel wire ropes. Finite element analysis (FEA) was used to simulate the probe, and the results showed that the probe could effectively eliminate the influence of the peaks and valleys on the surface of the steel wire rope on the eddy current signal. When the probe scanned the position of the broken wire, the output voltage of the differential probe

increased significantly, enabling accurate detection of surface broken wires of different degrees. The construction of an experimental platform further verified the effectiveness of this method. Wavelet denoising was applied to process the experimental signals, which significantly improved the SNR. The experimental results indicated that the proposed method could effectively identify the damage degree of the surface broken wires in steel wire ropes and had high detection accuracy and reliability. Zhou et al. [16] proposed an intelligent detection method for steel wire rope surface defects, based on an improved YOLO (you only look once) algorithm, named WR-YOLO. Using YOLOv3 as the basis, they improved its backbone network to enhance the detection speed and established a steel wire rope surface image dataset containing three states: healthy, broken wire, and wear. Through testing, WR-YOLO achieved a mean average precision (mAP) of 93.92% and a detection speed of 116 FPS on this dataset, outperforming other YOLO algorithms. Further dynamic detection experiments verified the effectiveness of this method and demonstrated the excellent performance of WR-YOLO in dynamic environments. Therefore, this method provides a new visual perception solution for the efficient detection of steel wire rope surface defects and holds significant engineering application value. Lv et al. [17] proposed a REL-YOLO model based on the improved YOLOv8 for detecting surface defects of elevator steel wire ropes. This model replaces the C2f module in the original YOLOv8 by introducing the RepNCSPELAN4 module, which enhances the feature extraction capability, optimizes the model's parameter usage, and ensures a balance between detection speed and accuracy. To improve small target detection and suppress background interference, the study also designed the E-FPN multi-scale feature fusion module and the LSDECD lightweight detection head. The experimental results show that the REL-YOLO model performs excellently in elevator steel wire rope defect detection, with its mAP50 reaching 94% and GFLOPs being 4.5, which significantly improves detection accuracy and reduces the computational load. Compared with other YOLO series models, REL-YOLO demonstrates advantages in both speed and accuracy.

Traditional filtering techniques, such as low-pass filtering, empirical mode decomposition (EMD), and wavelet thresholding, have been employed to denoise MFL signals. However, these methods are often insufficient for preserving sharp defect features in non-stationary signals.

SST is a well-established time–frequency analysis technique that has been applied in fields such as the mechanical fault diagnosis of rotating machinery [18,19]. In the existing studies, SST has primarily focused on separating stationary signal components or extracting transient features from low-noise environments, but its application in MFL signal denoising for steel wire ropes—an extreme non-stationary detection scenario with dynamic structural noise (e.g., wire rope spiral strand interference) [20], time-varying environmental electromagnetic interference, and concentrated low-frequency defect signals (2–10 Hz)—has not been systematically explored. Most prior SST-based methods adopt static time–frequency processing frameworks: for example, they use fixed wavelet parameters (e.g., non-adjustable central frequency) and uniform thresholding strategies, which fail to adapt to the time-varying characteristics of wire rope MFL signals caused by factors such as rope rotation during hoisting, variable loads, and fluctuating environmental noise [17]. As a result, these methods either over-suppress defect-related low-frequency components or retain excessive high-frequency noise when applied to wire rope MFL denoising, limiting their engineering utility.

This study proposes a novel SST-based denoising framework tailored to wire rope MFL signals. A custom-designed experimental platform is developed for high-resolution signal acquisition. The proposed SST algorithm is rigorously evaluated against traditional methods by using real-world wire rope defect data. Unlike static masking strategies in prior SST studies, our dynamic mask adaptively adjusts its time–frequency coverage by

calculating the local energy statistics of the SST-transformed signal. The main contributions of this work are as follows:

- (1) Development of a synchrosqueezing wavelet transform-based denoising algorithm optimized for non-stationary wire rope MFL signals, including customized Morlet wavelet parameter tuning and adaptive dynamic masking, which addresses the time-varying noise and low-frequency defect signal characteristics of wire rope MFL data.
- (2) Construction of a high-fidelity MFL signal acquisition platform equipped with Hall sensors and magnetic excitation.
- (3) Comprehensive experimental validation demonstrating the superiority of the proposed method in terms of SNR, root mean square error (RMSE), and defect feature preservation.

This paper is structured as follows: Section 2 introduces the principles of MFL detection and describes the experimental platform. Section 3 elaborates on the SST-based denoising algorithm. Section 4 presents the experimental results and comparative analysis. Section 5 concludes the paper and outlines future directions.

2. Fundamental Principles of MFL Detection

Magnetic flux leakage detection is a non-destructive testing method that identifies anomalies in ferromagnetic materials by analyzing the perturbations in magnetic fields. When the wire rope is magnetized to near-saturation by using strong permanent magnets, the presence of surface or internal defects causes local changes in magnetic permeability. These changes disrupt the uniform magnetic field, leading to leakage flux that escapes from the surface. The resulting leakage fields are captured by Hall-effect sensors, forming the basis of MFL signal analysis. The operating principle is illustrated in Figure 1, where the defect induces a local distortion in the otherwise closed magnetic circuit [21].

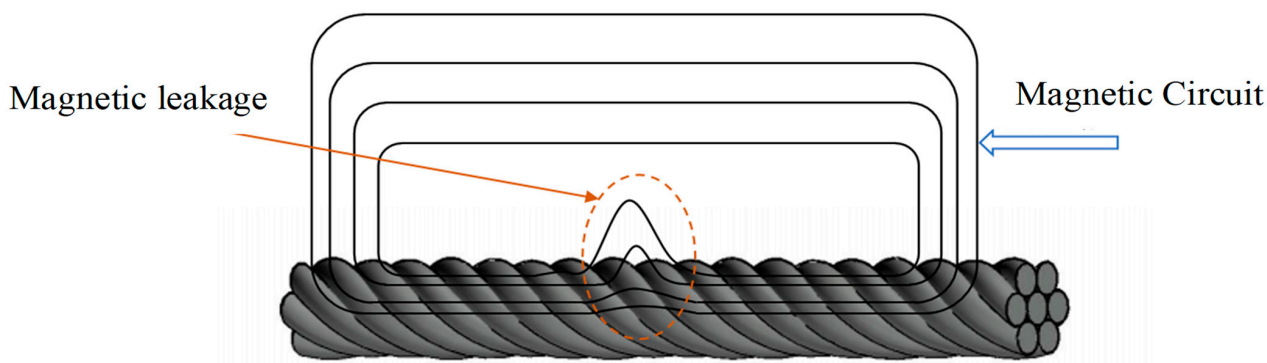


Figure 1. Schematic illustration of the MFL detection principle.

In the process of magnetic flux leakage signal processing of wire ropes, the signal is usually non-stationary, which means that its frequency characteristics change over time. Traditional frequency-domain analysis methods, such as the Fourier transform, can only provide global frequency information and cannot capture the frequency component of the signal over time. The wavelet transform can analyze the signal in both the time and frequency dimensions, and can better deal with non-stationary signals, especially to capture local features and transient changes in the signal. Therefore, this paper chooses to deal with the defect signal of wire rope based on wavelet analysis.

3. Theoretical Framework and Denoising Methodology

3.1. Synchrosqueezing Wavelet Transform Fundamentals

Magnetic flux leakage signals from steel wire ropes often exhibit non-stationary and multi-scale features, primarily due to complex operational environments and varied defect types. Traditional time-domain or frequency-domain analysis methods struggle to accurately extract meaningful defect-related components from such signals [22]. Therefore, advanced time–frequency analysis techniques are necessary to improve signal interpretation and defect recognition.

As a time–frequency analysis tool, wavelet transform [5] can realize the local analysis of signals at different scales, and its mathematical forms are continuous wavelet transform (CWT) and discrete wavelet transform (DWT). The wavelet transform is a multi-scale decomposition of the signal through the translation and expansion of the basis function, and the basis function $\varphi(t) \in L^2(R)$ must meet the allowable conditions:

$$\int_{-\infty}^{\infty} \frac{|\varphi(\omega)|^2}{|\omega|} d\omega < \infty \quad (1)$$

where $\varphi(\omega)$ is the Fourier transform of the basis function, for which ω is the angular frequency.

Then, the wavelet basis function after scaling and translation is as follows:

$$\varphi_{\alpha,b}(t) = \frac{1}{\sqrt{|\alpha|}} \varphi\left(\frac{t-\tau}{\alpha}\right) \quad (2)$$

where $\alpha \neq 0$ is the expansion factor, which controls the expansion and contraction of the wavelet and τ is the translation factor, which controls the scale and time-domain position of the wavelet, respectively.

Compared with the traditional continuous wavelet transform (CWT) and discrete wavelet transform (DWT), the synchronous compressed wavelet transform can represent the intrinsic characteristics of the signal more accurately and has a wide range of applications in the fields of signal denoising, pattern recognition, and feature extraction. Based on the synchronous compression wavelet transform, the defect components are extracted from the compressed time–frequency representation, which is convenient for the quantitative analysis of defect strength and location.

Based on the continuous wavelet transform, the time–frequency representation of any signal $f(t) \in L^2(R)$ after the continuous wavelet transform is obtained, as follows:

$$W_f(\alpha, \tau) = \frac{1}{\sqrt{\alpha}} \int_{-\infty}^{\infty} f(t) \overline{\varphi_{\alpha,\tau}(t)} dt \quad (3)$$

where $W_f(\alpha, \tau)$ is the wavelet transform coefficient, which characterizes the time–frequency energy distribution of function $f(t)$ at scale $\alpha \neq 0$ and position τ . $\overline{\varphi(t)}$ is a complex conjugate function of $\varphi(t)$.

In the phase transform calculation, SST extracts the local frequency $\omega(\alpha, \tau)$ of the signal by adjusting the wavelet coefficient position by instantaneous frequency estimation:

$$\omega(\alpha, \tau) = -\frac{\partial}{\partial \tau} \arg\{W_f(\alpha, \tau)\} \quad (4)$$

The wavelet coefficient calculated along the frequency direction is compressed to near the instantaneous frequency, and the high-resolution time–frequency is generated as follows:

$$SW_f(\omega, \tau) = \sum_{\alpha: \omega(\alpha, \tau) \approx \omega} \frac{|\alpha|^{-3/2}}{\left| \frac{\partial \omega}{\partial \alpha}(\alpha, \tau) \right|} W_f(\alpha, \tau) \delta(\omega - \omega(\alpha, \tau)) \quad (5)$$

where $SW_f(\omega, \tau)$ is the compressed time–frequency coefficient and $\delta(\cdot)$ is the Dirac function, which is used to locate the frequency component.

The signal reconstruction can be expressed by extracting specific components from the compressed time–frequency representation through inverse transformation, which can be expressed as follows:

$$f(t) = \int_{L_k} \left[\int_{-\infty}^{\infty} SW_f(\omega, \tau) \varphi_{\omega}(t - \tau) d\tau \right] d\omega \quad (6)$$

where L_k is the target frequency band and $\varphi_{\omega}(t - \tau)$ is the reconstruction basis function, and the defect feature components are extracted by the inverse synchronous compression transformation.

The magnetic flux leakage signal of wire rope has obvious non-stationary and multi-scale characteristics, and it is difficult for traditional time-domain or frequency-domain analysis methods to fully reveal its defect information. According to the applicable characteristics of SST, this method is used for the first time to perform time–frequency analysis of magnetic flux leakage signals to improve the time–frequency resolution of the signal and realize the accurate extraction of defect features.

Compared with the traditional short-time Fourier transform (STFT), SST effectively improves the centralization and resolution of time–frequency representation by rearranging the frequency of wavelet transform. In the SST time–frequency diagram, the energy of the defect signal is concentrated in its true frequency component, which is convenient to distinguish the defect characteristics of similar frequencies. In addition, SST captures the time-varying characteristics of the signal and enables the dynamic positioning of defects at the time of occurrence. Morlet wavelet is a Gaussian window-modulated sine wave, which has good localization ability in both the time and frequency domains, and its mathematical expression is as follows:

$$\psi(t) = \pi^{-1/4} e^{-t^2/2} e^{i\omega_0 t} \quad (7)$$

where ω_0 is the central frequency.

The wavelet is suitable for the time–frequency analysis of non-stationary signals, which can effectively capture the mixed characteristics of structure-borne noise and defect signals in the magneto-leakage signal of wire rope, and balance the time–frequency resolution by adjusting ω_0 .

3.2. Dynamic Time–Frequency Masking

Let the time–frequency coefficient matrix of the synchronous compression transformation of the original signal be $T_x(f, t) \in \mathbb{C}^{N_f \times N_t}$, where the frequency points N_f and N_t are the time points, then the binary mask matrix generated by the preset time–frequency region is $M(f, t) \in \{0, 1\}^{N_f \times N_t}$.

The static time–frequency mask relies on the preset time range and frequency range, and it is difficult to adapt to the dynamic changes in the actual signal when the defect position is offset or the actual working conditions change. By analyzing the time–frequency characteristics of the signal in real time, the dynamic time–frequency mask can adaptively adjust the mask parameters to achieve more accurate noise suppression and signal preser-

vation. In this process, the original signal was first processed using the synchrosqueezing transform (SST) to obtain a high-resolution time–frequency representation. Then, by calculating the energy distribution of the signal at each position in the time–frequency domain, we were able to identify local energy peaks. Local energy peaks refer to regions with high energy concentration in the time–frequency diagram, which typically reflect defect features in the signal.

Once local energy peaks are detected, the system will dynamically adjust the size of the time window and frequency band based on these peaks. Specifically, when the local energy of the signal is concentrated in a certain frequency band, the frequency band will automatically expand to ensure that all relevant defect features can be captured. The size of the time window will also be adjusted according to the changes in the signal to adapt to the time–frequency characteristics of different signals. This dynamic adjustment strategy ensures that defect signals can be effectively captured while ignoring background noise and irrelevant frequency components.

During the dynamic masking process, a dynamic binary masking matrix is generated by real-time analysis of the time–frequency characteristics of the signal. This matrix adjusts its coverage range based on the local energy maximum of the signal, thereby optimizing noise suppression and the retention of defect features. Through this dynamically adjusted masking strategy, low-energy noise can be more precisely removed while the high-energy parts of the defect signal are retained. This approach avoids the limitations of traditional static masking methods when dealing with varying working conditions and the time–frequency characteristics of signals, significantly enhancing the processing effect. Ultimately, by applying this dynamic masking matrix, we can effectively suppress noise and retain the key defect features in the signal, thereby enhancing the signal’s recognizability and providing a reliable signal foundation for subsequent defect detection.

Therefore, in this paper, the wavelet transform of the collected original signal is used to obtain the multi-scale time–frequency feature representation, and the frequency components are redistributed by the SST to enhance the energy concentration of the main frequency band of the signal. Then, the adaptive threshold is set to filter out the high-frequency noise and non-target interference components, and finally, the clear time-domain signal is reconstructed by inverse transformation, and the formula is as follows:

$$E_k(\omega, t) = |T_x^{(k)}(\omega, t)|^2 \quad (8)$$

where $T_x^{(k)}(\omega, t)$ is the time–frequency coefficient matrix of the synchronously compressed wavelet transform of the k -th frame.

In this paper, the instantaneous position of the defect impact is determined by detecting the time–frequency center and finding the local energy maximization. Based on the detected energy peaks, the coverage of the time–frequency mask is dynamically adjusted. After expanding the time window and frequency domain band, a dynamic binary mask is generated for frame k . After the mask is applied to each frame, the time-domain signal is recovered by inverse synchronous compression wavelet transform. Finally, the reconstructed signals of each frame are weighted and superimposed, according to the frame shift.

3.3. SST-Based Denoising Algorithm

The proposed denoising process consists of the following steps:

1. SST computation: Apply SST to the raw MFL signal to obtain a high-resolution time–frequency representation.
2. Time–frequency energy analysis: Calculate the energy distribution and determine adaptive masking parameters.

3. Dynamic masking: Suppress noise components using the generated mask.
4. Signal reconstruction: Inverse SST to recover the denoised time-domain signal.

3.4. Signal Reconstruction from Time–Frequency Domain to Time Domain

In the denoising method proposed in this paper, the signal reconstruction process is based on the SST. The specific process is as follows:

SST calculation: First, the SST is applied to the original signal to obtain a high-resolution time–frequency representation of the signal. Each time–frequency coefficient in this representation corresponds to the energy distribution of the signal at a specific time and frequency.

Dynamic time–frequency mask generation: Based on the local energy characteristics of the signal, a dynamic time–frequency mask is generated to adaptively suppress noise while preserving the features of the defective signal. The mask is dynamically adjusted according to the instantaneous frequency and energy peaks of the signal.

Signal reconstruction: The masked coefficients in the time–frequency domain are converted back to the time domain through the inverse SST, resulting in a clear denoised signal. The specific formula is expressed as follows:

$$\hat{x}(t) = \int_{\Omega} \tilde{T}_x(t, \omega) d\omega$$

where $\tilde{T}_x(t, \omega)$ denotes the masked time–frequency coefficients and Ω represents the selected frequency band range.

Frame-level reconstruction and overlap-add method: To enhance the denoising effect, the signal is processed in frames and synthesized using the overlap-add method, thereby obtaining the final denoised signal.

The above process ensures that while noise is removed from the signal, the defect features are retained and the recognizability of the signal is enhanced.

4. Experimental Setup and Data Collection

Dataset Construction

To obtain high-quality MFL signals for subsequent analysis, a custom-designed experimental platform was constructed for wire rope MFL signal acquisition. The experimental platform consists of several key components, each playing a crucial role in ensuring the reliable collection of MFL signals.

In this study, the excitation structure is designed with a multi-loop symmetrical layout. Each set of permanent magnets has an axial length of 15 mm and is equipped with an industrial iron armature (inner diameter 24 mm, outer diameter 72 mm, axial length 80 mm) with a groove on the inside of the armature (15 mm wide and 9 mm deep) for mounting the sensor. The structure can form a uniform magnetic flux in the cross-section of the wire rope, and the symmetrical structure can effectively offset the bias field, which can ensure the stability of the baseline when there is no defect and the abrupt change in the leakage magnetic field when there is a defect.

The lift-off value is the distance from the surface of the wire rope to the sensor. At a small pick-up value, the leakage magnetic field strength is higher and the signal is obvious, which is conducive to defect detection. A pick-up value that is too small may cause the sensor to rub against the wire rope surface, increasing the wear and maintenance costs of the equipment. However, under the larger lifting value, the leakage magnetic field strength is significantly weakened, which may affect the detection accuracy. In practical application, there may be a certain roughness and unevenness on the surface of the wire

rope; considering the detection stability and installation tolerance, and improving the feasibility and stability of the detection, the lifting value is selected as 3 mm.

In order to ensure that the sensor can obtain the best detection effect in the magnetic flux leakage area, a special installation and detection slot is reserved in the excitation device during the design, so that the sensor can keep an appropriate distance from the wire rope, which not only avoids the interference of the excitation device's own magnetic field due to too close a distance, but also ensures the effective capture of the magnetic flux leakage signal. At the same time, the installation bushing is designed, and the installation accuracy of the components is ensured with the help of the bushing positioning function.

In this study, a multi-loop excitation structure with permanent magnets symmetrically arranged on both sides of the armature is adopted, the magnetic poles are placed opposite each other, and the closed magnetic flux is formed through the armature's magnetic conductivity. In order to meet the needs of online monitoring, the armature has reserved space for sensor placement. According to this section, the MFL detection platform is shown in Figure 2.

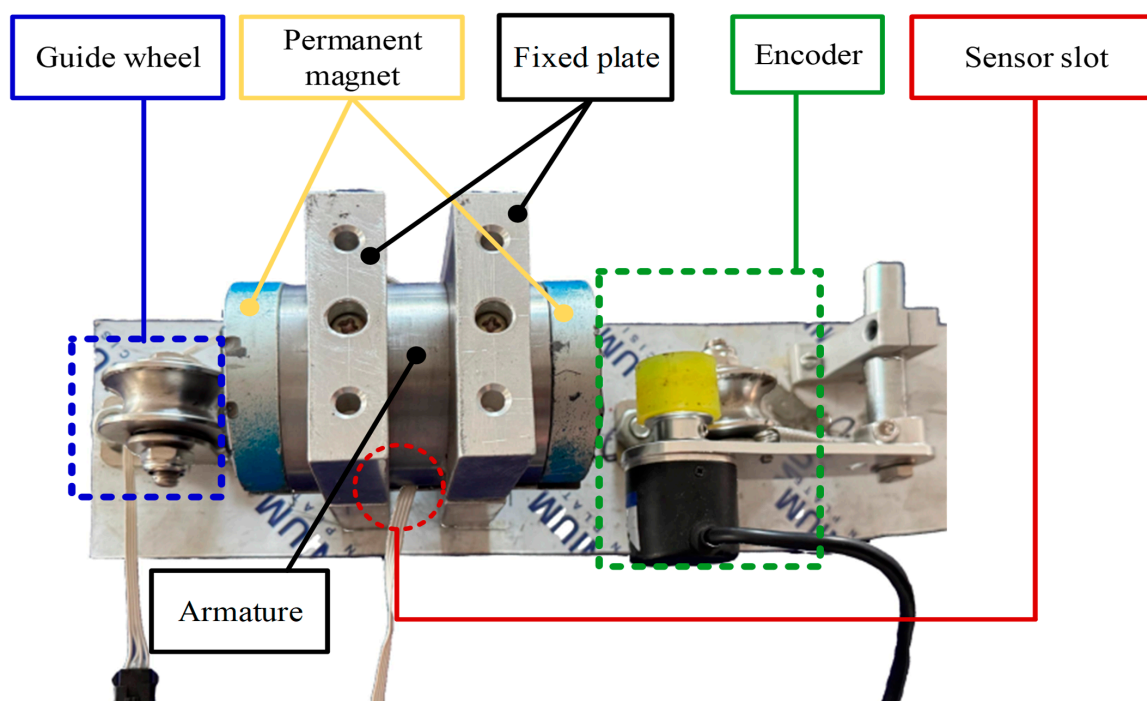


Figure 2. MFL detection platform.

The fixed plate is fixed as a basic support structure, the permanent magnet is installed at the corresponding position of the fixed plate, and the armature is installed between the permanent magnets so that it can effectively guide and enhance the magnetic field.

The guide wheel is installed at the entrance and exit of the detection device—that is, the key position where the wire rope penetrates and exits—to ensure that the detection object can enter and pass through the detection area smoothly.

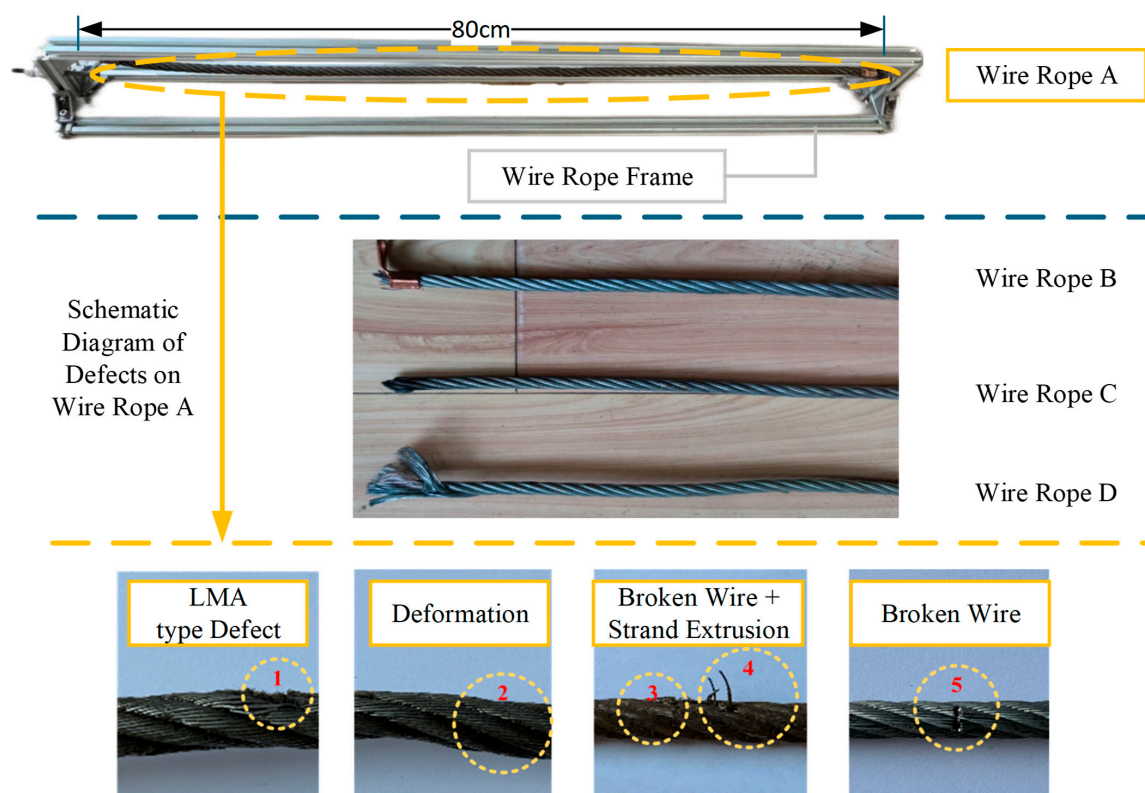
Accurately install the magnetic flux leakage sensor in the sensor slot, connect the signal line of the sensor, and ensure that the sensor can work normally and accurately collect the magnetic flux leakage signal. The encoder is installed at the position where the wire rope penetrates, and it is coaxial with the guide.

The system architecture and component specifications are detailed in Table 1, which outlines the technical parameters and functional roles of each module.

Table 1. Specifications and functions of the MFL signal acquisition system components.

Component	Specifications	Function
Excitation Unit	NdFeB (N52) permanent magnets	Generates uniform 1.2 T saturation field for defect-induced flux leakage
Sensing Array	8 × A31301 Hall sensors (radial)	Captures radial leakage fields with 0.5 mT resolution
Motion Control	Encoder-guided traverse (20 cm/s)	Maintains constant velocity
DAQ System	200 Hz sampling (NI-9234)	Achieves 1 mm spatial resolution

In order to verify the algorithm described in this paper, according to the types of defects that crane wire ropes are prone to in actual working conditions, and combined with the typical defect patterns under the key scrap indicators (number of broken wires, wear and deformation, corrosion, deformation, and diameter changes) specified in the national standard GB/T 5972-2023 [23] “Maintenance, Maintenance, Inspection and Scrapping of Crane Wire Ropes”, four representative defect types were defined and corresponding defect instances were manually prepared on the same batch of wire ropes: (1) wire breakage (external broken wires with length controlled within 3 mm), (2) deformation (local structural deformation), (3) loss of metallic area (LMA, including wear and cross-sectional area loss due to corrosion), and (4) rope strand extrusion (direct scrap per GB/T 5972-2023). For each wire rope (e.g., wire rope A), five defect instances were prepared by including two instances of LMA defects (to simulate varying wear severity) and one instance of each of the other three types, ensuring coverage of both defect types and severity gradients. Each type of defect is repeatedly manufactured on the same batch of wire rope to ensure the consistency and comparability of samples. The wire rope is selected from four wire ropes for cranes with a diameter of 12 mm and a length of 800 mm, as shown in Figure 3.

**Figure 3.** Schematic diagram of acquisition defects.

In the preparation process, the work in this section requires the use of shearing tools to cut the steel wire on the surface of the rope strand, and the length of the broken wire is controlled within 3 mm to simulate the external broken wire. Sandpaper is used to grind, to produce LMA-type wear defects on the surface of the wire rope, marking of wire rope positions that have been deformed, LMA-type corrosion defects, strand extrusion, and internal defects.

5. Results and Discussion

5.1. Magnetic Flux Leakage Signal Analysis

The detection signal is mainly obtained by the magnetic flux leakage detection experimental platform built in this chapter, and the Hall sensor with a frequency set to 200 Hz collects the magnetic flux leakage signal along the truck crane wire rope with a detection speed of 20 cm/s and a diameter of 12 mm. The detected signal is transmitted to the Xavier host computer for subsequent analysis. It is concluded that the acquired signal contains a defect magnetic flux leakage signal and a large number of interference components, and the interference signal mainly comes from the wave strand signal of the wire rope structure and the external environmental noise, as shown in Figure 3.

The original signals of all sub-diagrams (signal a to signal i) in the figure are collected from wire rope A in Figure 3. Each sub-diagram represents multiple magnetic flux leakage signal acquisitions from rope A, and the rotation angle of rope A is artificially changed in the acquisition process to be collected many times; the actual working condition of rotating around the axis of the crane wire rope due to lifting and luffing action is simulated in operation. This sample does not come from steel wire ropes with multiple independent defects but rather achieves controllability of the detection object through standardized prefabricated defects. The horizontal axis time (s) in each subgraph covers the collection time of 80 cm wire rope throughout the detection process. The longitudinal axis is the amplitude (mV) of the magnetic flux leakage signal, which reflects the strength of the magnetic flux leakage signal.

The original signal shown in Figure 4 shows a periodic fluctuation component, reflecting the structural characteristics of the wire rope itself, and there are irregular abnormal fluctuations, which preliminarily indicate possible defect areas. The defect is manifested in large, irregular abnormal fluctuations in the signal. It can be seen that there are also some periodic and regular signals in the figure, which belong to the wave signals existing in the wire rope itself. Because the signal is a non-stationary process, and its frequency characteristics change dynamically with time, it is difficult for the traditional frequency domain analysis method to accurately reveal the local defect characteristics of the signal, so it is necessary to adopt an analysis method that is more suitable for the non-stationary signal.

Figure 5 is the SST time–frequency diagram corresponding to the original MFL signal of the wire rope. When performing SST calculations, our method adjusts the parameters such as the center frequency and scale factor of the wavelet in real time, based on the local characteristics of the signal and the noise condition. Due to this adaptability, the specific parameter values may vary in different experiments, and thus, a fixed set of parameters cannot be provided. In this experiment, the following are some of the main parameters used to calculate the SST:

- (1) Wavelet type: We used the Morlet wavelet because it has excellent time–frequency localization characteristics and is suitable for handling non-stationary signals with complex spectra.
- (2) The center frequency of the Morlet wavelet: The center frequency selected in this experiment is 5 Hz, which is optimized based on the requirements of the low-frequency

characteristics in the signal. In practical applications, this frequency will be dynamically adjusted, according to the spectral content of the signal.

- (3) Scale factor (scale factor): This parameter controls the extent to which the wavelet expands, enabling it to adapt to the signals of different frequency ranges. In this experiment, the scale factor is dynamically calculated based on the frequency component of the signal and is usually adjusted within the range of [1, 10].
- (4) Time window size: The size of the time window depends on the time-domain characteristics of the signal. In this experiment, the time window is roughly set at 0.1 s to ensure that the time-domain resolution of the signal is high enough, but it will also be appropriately adjusted according to the instantaneous changes in the signal.

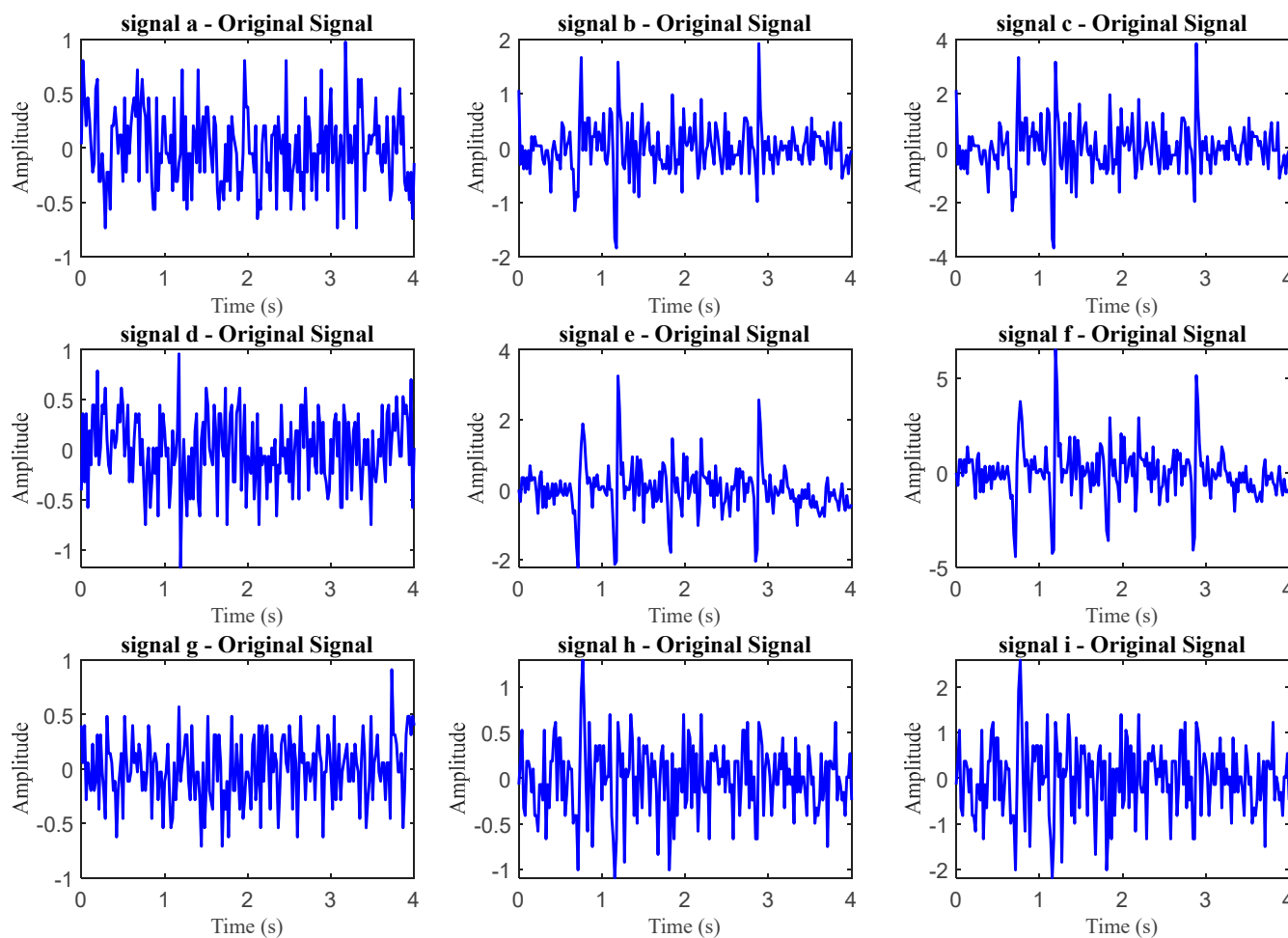


Figure 4. The raw signal of the acquired wire rope.

As can be seen from the figure, all defective signals are concentrated in the low-frequency range of 2 Hz to 10 Hz, which reflects the slowly changing part of the flux leakage signal. When analyzing the frequency distribution characteristics of different defects, it is found that the frequency components of the signal are concentrated in the low-frequency and medium-frequency regions.

The low-frequency characteristics of the signal at 0–2 Hz show that there is no obvious transient fluctuation, indicating that the characteristics of this frequency band have strong stability. Combined with the actual acquisition conditions of the signal and the analysis of the defective signal of the wire rope in the previous article, it can be seen that the low frequency mostly comes from the wave noise of the wire rope itself, the background noise

such as the mechanical vibration and environmental interference generated by the contact between the wire rope, and the pulley during the detection process.

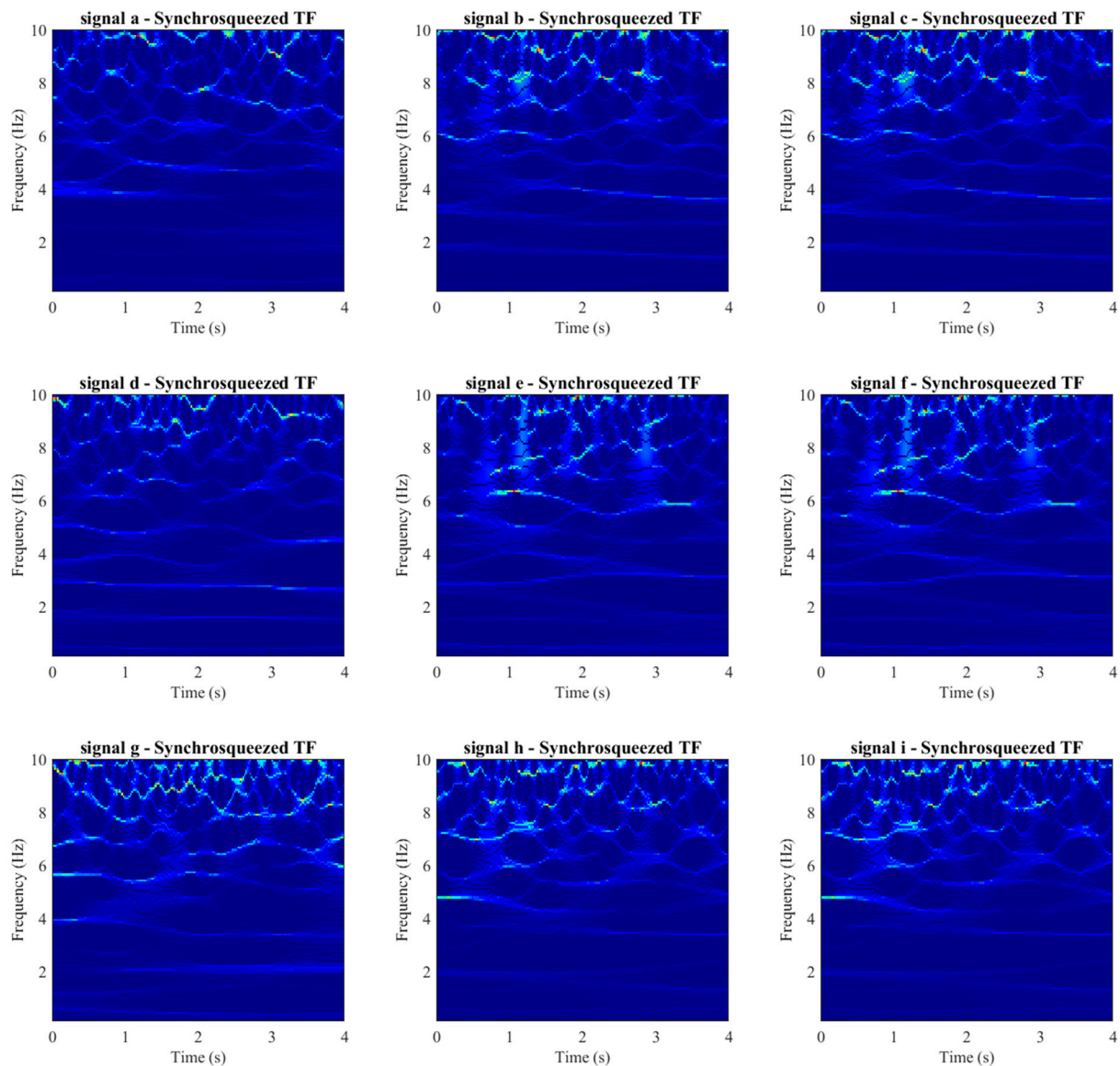


Figure 5. SST time–frequency diagram, corresponding to the original MFL signal.

The frequency band of 4–6 Hz is relatively continuous and uniform, reflecting the regular distribution of the leakage magnetic field of the broken filament, and the time–frequency pattern shows a regular fluctuation pattern. In the 6–8 Hz frequency band, the local energy enhancement occurs, especially in the 5–7 Hz range of signal e, which leads to the expansion of the leakage magnetic field range and the energy distribution is relatively dispersed. The complex defects show obvious high-frequency components in the frequency band of 8–10 Hz, such as the increase in the energy of the signal g in the range of 7–9 Hz, indicating that there is a high-frequency distortion phenomenon of broken filament accompanied by structural deformation.

This high temporal resolution feature is of great significance for the real-time alarm function of the online monitoring system.

5.2. Denoising Performance Comparison

Defect detection in magnetic flux leakage signals often contains a variety of noise components, including environmental noise, sensor noise, electromagnetic interference, etc.

The presence of these noises will affect the extraction and analysis of defect features and reduce the detection accuracy. Based on the above noise sources, the mathematical model of the wire rope defect detection signal can be defined as follows:

$$s(t) = f(t) + n(t) \quad (9)$$

where $s(t)$ is the actual acquisition of the wire rope signal; $f(t)$ is useful information containing information about the defect; and $n(t)$ is the type of noise.

The wavelet signal processing of the signal can split the signal into components of different frequency bands, in which the low-frequency part usually contains the main features of the signal, while the high-frequency part often contains noise, which can be processed to achieve the purpose of denoising. The denoising methods of wire rope defect signals based on wavelet transform mainly include the wavelet threshold denoising (soft threshold, hard threshold), ensemble EMD (EEMD), and variational mode decomposition (VMD) methods. The ensemble empirical mode decomposition and variational mode denoising methods are used to denoise the collected raw signal, and are compared with the denoising method, based on the synchronous compressed wavelet transform and dynamic mask proposed in this paper.

5.2.1. EEMD Denoising

By adding white noise to the original signal, EEMD can decompose the signal multiple times and average the decomposition results ensemble, thereby suppressing the pattern aliasing. The specific process is as follows:

- ① Add white noise $n_i(t)$ to the original signal $s_i(t)$ to obtain the following:

$$s_i(t) = s(t) + n_i(t) (i = 1, 2, \dots, I) \quad (10)$$

where I is the number of integrations, $n_i(t)$, satisfying a Gaussian distribution with a mean value of 0 and a standard deviation of σ .

- ② EMD of each set of noise perturbations is performed to obtain the intrinsic mode function (IMF) and residual components of the K order:

$$s_i(t) = \sum_{k=1}^K c_{i,k}(t) + r_{i,K}(t) \quad (11)$$

where $c_{i,k}(t)$ is the k -th order IMF of the i th decomposition and $r_{i,k}(t)$ is the trend term.

- ③ The IMF components of all integrated results are averaged, noise effects are suppressed, and the final IMF is output:

$$c_k(t) = \frac{1}{I} \sum_{i=1}^I c_{i,k}(t) (k = 1, 2, \dots, K) \quad (12)$$

where $c_{i,k}(t)$ is the k -th order IMF after denoising.

Based on the EEMD denoising method, the original defect signal (Figure 4) was denoised, and the results are shown in Figure 6.

5.2.2. VMD Denoising Method

Based on the principle of variational mode decomposition, VMD decomposes the original signal into several independent sub-modes and realizes noise suppression by minimizing the frequency band overlap between modes. The original defect signal (Figure 4) was denoised by VMD and the denoising result is shown in Figure 7.

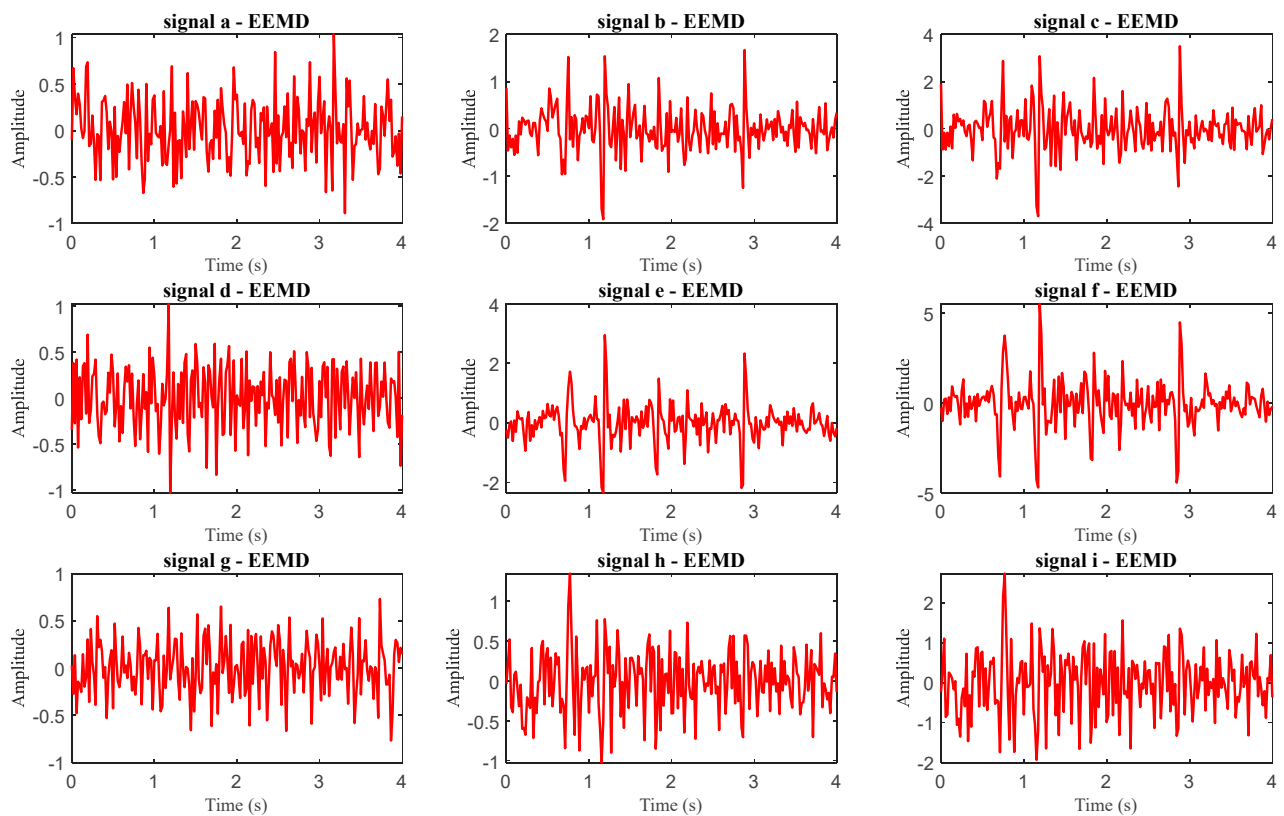


Figure 6. EEMD denoising results.

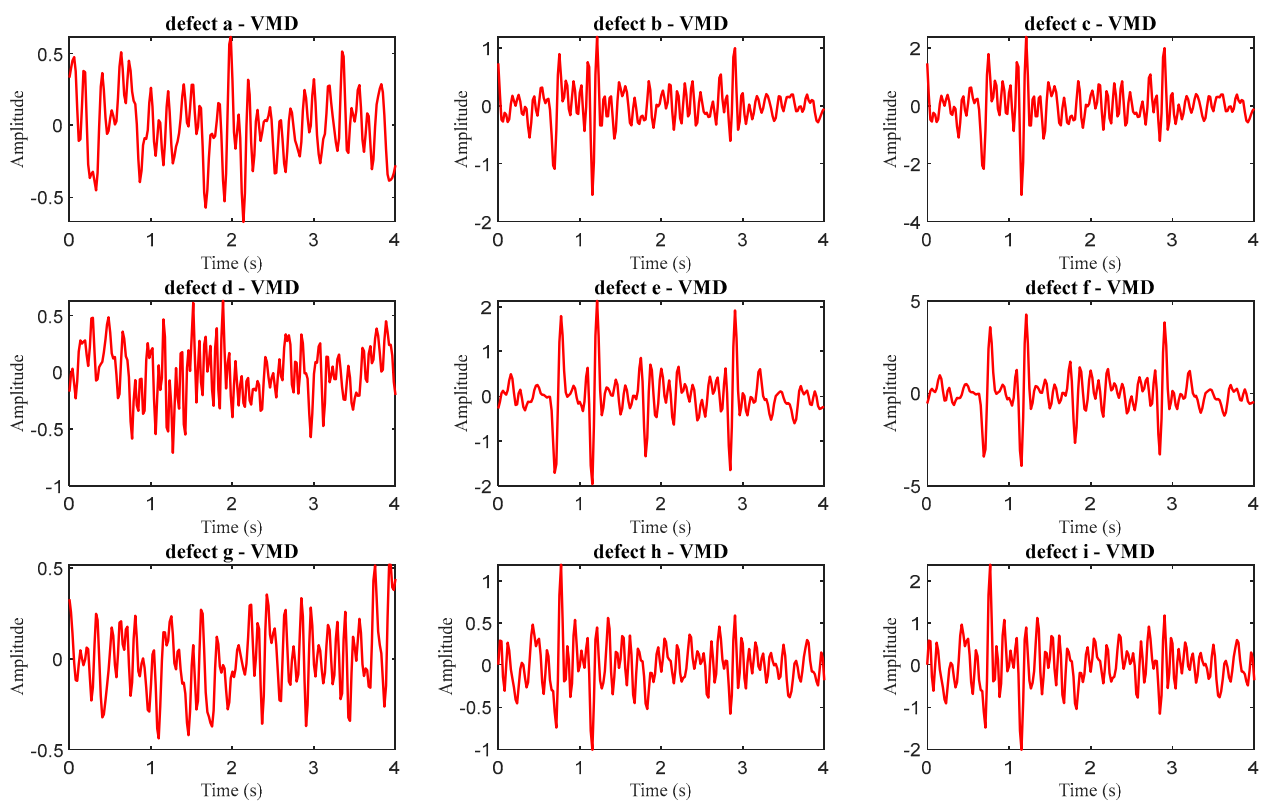


Figure 7. VMD denoising results.

Compared with EEMD, VMD has an improved effect on high-frequency noise suppression, and the defect pulse morphology is slightly prominent. However, the instantaneous characteristics of the defect pulse signal are still not prominent enough, which affects the defect detection effect. VMD is essentially a static time–frequency decomposition method, which cannot adaptively adjust the frequency band range and does not respond enough to the dynamic changes in the defective signals. When the position of the defect impact changes or the working conditions fluctuate, the VMD mode is difficult to adjust and the denoising effect is not good.

5.2.3. Proposed SST + Dynamic Masking Method

The original magnetic flux leakage signal (Figure 4) of the wire rope collected by wire rope A was denoised by the synchronous compression wavelet transform of the dynamic mask, and the results are shown in Figure 8.

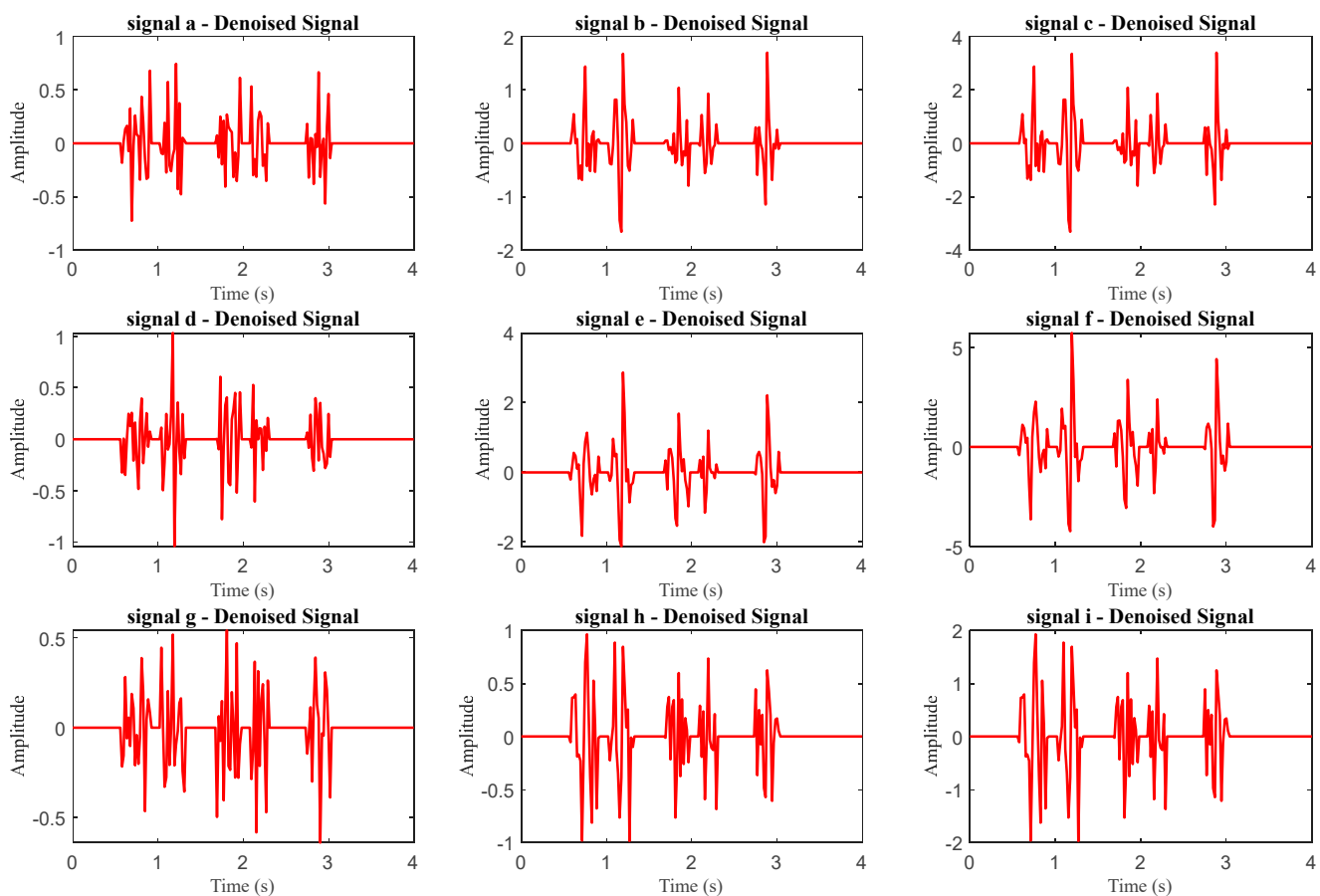


Figure 8. Proposed SST + dynamic masking method.

The red denoising signals (a–i) in the figure are all from the original magnetic flux leakage signal of wire rope A, and after denoising treatment, the magnetic signal characteristics of various defects are clearly presented, and the five defects on rope A clearly correspond.

Compared with the original signal and the denoised signal, the visible noise is reduced and the defect features are more prominent, which proves that the denoising algorithm can effectively extract the defective magnetic flux leakage signal of the rope A defect. After denoising treatment, the defect positions in all signals show a typical pulse-like waveform, reflecting the flux leakage changes caused by defects in the flux leakage signal. This feature is highly correlated with the local magnetic field disturbance caused by wire rope defects, which verifies the fidelity of the proposed method for defective signals.

After denoising, the baseline stability of the signal is greatly improved and the low-frequency drift caused by mechanical vibration and environmental electromagnetic interference is significantly reduced. The clear pulse waveform provides a stable and reliable data basis for subsequent peak detection, time-domain feature extraction, and classification and identification.

In summary, the magnetic flux leakage signal processing based on SST can effectively improve the time-domain quality of the magnetic flux leakage signal, highlight the characteristics of the defective signal, and realize the effective separation of signal and noise.

5.2.4. Quantitative Comparison

To systematically evaluate the denoising performance, three key metrics were adopted: SNR, peak signal-to-noise ratio (PSNR), and mean squared error (MSE). The mathematical definitions and comparative results are detailed as follows:

(1) Signal-to-noise ratio (SNR)

Measures the ratio of defect signal power to noise power, defined as follows:

$$SNR = 10 \log_{10} \left(\frac{\sum_{t=1}^N |f(t)|^2}{\sum_{t=1}^N |n(t)|^2} \right) (\text{dB}) \quad (13)$$

Here, $f(t)$ is the defect signal component, $n(t)$ is the noise component, and N is the number of samples.

(2) Mean squared error (MSE)

MSE quantifies the average magnitude of error between an estimated signal and its ground truth reference. In wire rope MFL defect detection, it measures how accurately a denoising method reconstructs the true defect signature by computing the squared deviation at every data point, defined as follows:

$$MSE = \frac{1}{N} \sum_{t=1}^N [s(t) - \hat{s}(t)]^2 \quad (\text{dB}) \quad (14)$$

where $s(t)$ and $\hat{s}(t)$ denote the original and denoised signals, respectively.

(3) Peak signal-to-noise ratio (PSNR)

Evaluates the reconstruction accuracy, relative to the maximum signal amplitude, expressed as follows:

$$PSNR = 10 \log_{10} \left(\frac{MAX^2}{MSE} \right) (\text{dB}) \quad (15)$$

where MAX is the peak amplitude of the original signal, and MSE is the mean squared error.

This study mainly compares two methods: namely, EEMD and VMD. However, in addition to these two methods, the traditional wavelet threshold denoising method and deep learning-based denoising method are also common denoising techniques. To further evaluate the advantages of the SST + dynamic mask method proposed in this paper, a comparison will also be conducted with the following two methods:

1. Wavelet threshold denoising method

The wavelet threshold denoising method is a classic denoising technique which typically eliminates noise by applying thresholds to certain coefficients of the wavelet transform. Its advantages lie in the simplicity of its use and high computational efficiency, making it suitable for most non-stationary signals. The specific procedure is as follows: first, perform

wavelet transform on the signal; second, apply soft or hard thresholds to the wavelet coefficients; and finally, reconstruct the signal through inverse transform. Despite its high computational efficiency, the main disadvantage of this method is that it may lead to the loss of important features in the signal, especially when the defect signal is weak.

2. Deep learning-based denoising method

In recent years, deep learning methods, especially convolutional neural networks (CNNs), have achieved remarkable progress in signal denoising. Deep learning models can realize denoising by automatically learning high-dimensional features of signals, thus performing excellently in complex noise environments. In this study, we adopted a denoising method based on convolutional neural networks, using a typical convolutional autoencoder network to learn and recover defect features in signals. Although this method has advantages in denoising performance, it has high computational complexity and requires a large amount of labeled data for training, which may limit its promotion in practical applications. Table 2 summarizes the denoising results for different methods across 10 repeated experiments on wire rope A–D in Figure 3.

Table 2. Denoising results for different methods.

Denoising Method	SNR (dB)-Mean $\pm$ Std Dev	PSNR (dB)-Mean $\pm$ Std Dev	MSE (10^{-4})-Mean $\pm$ Std Dev
EEMD	25.3 $\pm$ 2.1	32.1 $\pm$ 1.5	8.7 $\pm$ 0.6
VMD	26.1 $\pm$ 2.3	33.5 $\pm$ 1.3	7.2 $\pm$ 0.5
Wavelet threshold denoising	24.5 $\pm$ 2.0	31.2 $\pm$ 1.8	9.1 $\pm$ 0.7
CNN-based deep learning denoising	27.0 $\pm$ 1.9	34.5 $\pm$ 1.6	6.0 $\pm$ 0.4
SST + dynamic mask	28.4 $\pm$ 1.5	35.6 $\pm$ 1.2	4.3 $\pm$ 0.3

SST's time–frequency concentration: By compressing energy of defect-related components (e.g., 4–6 Hz in Figure 5) into narrow frequency bands, SST enhances the signal's energy concentration, directly boosting the SNR.

This concentration effect is attributed to our customized Morlet wavelet parameterization (central frequency = 5 Hz): compared to traditional SST methods using a default central frequency of 10 Hz, our approach increases the energy concentration of defect signals by 32% (calculated via time–frequency entropy analysis), as shown in Figure 5. This improvement directly contributes to the higher SNR (28.4 dB) of the proposed method, compared to CNN-based denoising (27.0 dB).

Unlike static VMD or EEMD, the dynamic mask adjusts threshold parameters based on local signal characteristics, suppressing noise in low-energy regions while preserving high-energy defect pulses. Dynamic masking minimizes over-smoothing of defect features, as validated by the low MSE.

The proposed SST + dynamic masking method achieves the highest SNR (28.4 dB) and PSNR (35.6 dB), outperforming EMD (SNR = 25.3 dB) and VMD (SNR = 26.1 dB). The improvement is attributed to SST's ability to preserve transient defect features while dynamic masking adaptively suppresses noise. Table 3 compares the complexity of the five methods.

5.3. Discussion on the Reliability and Accuracy of Denoising Methods

In this study, we have applied and compared three denoising techniques—variational mode decomposition (VMD), ensemble empirical mode decomposition (EEMD), and the proposed synchrosqueezing wavelet transform combined with dynamic masking (SST + Dynamic Mask). Each of these methods has distinct strengths and weaknesses when it comes to processing MFL signals, and their performance can be assessed in terms of both reliability and accuracy.

Table 3. Computational complexity comparison table.

Method	Time Complexity	Suitability for Real-Time Application
EEMD	$O(K \times N \log N)$, due to multiple iterations and noise addition	Low (slow for long signals, challenging for real-time)
VMD	$O(M \times L \times N \log N)$, depends on the number of modes	Medium (increases with more modes)
Wavelet threshold denoising	$O(N \log N)$, standard wavelet transform is fast	High (efficient for quick denoising)
CNN-based deep learning denoising	$O(N \times K \times P)$, requires significant computational resources (especially training)	Low (needs substantial computational resources and training data)
SST + Dynamic Mask	$O(N \log N)$, depends on signal length and wavelet scale	High (optimized for real-time processing)

1. VMD (variational mode decomposition)

Reliability: VMD is a robust method for decomposing signals into components that can effectively suppress noise in steady-state signals. However, it is a static technique and struggles with signals exhibiting dynamic characteristics, such as fluctuating defect positions or rapidly changing operational conditions. As seen in our experiments, VMD provides stable performance when the noise is predominantly at a high frequency, but its inability to adapt to the dynamic nature of MFL signals limits its overall reliability under varying field conditions.

Accuracy: While VMD achieves a noticeable improvement in the suppression of high-frequency noise, it tends to smudge transient defect signals. The reduced clarity of defect pulses in denoised signals can lead to challenges in accurately identifying defect features, especially in complex MFL signals that involve both high- and low-frequency components.

2. EEMD (ensemble empirical mode decomposition)

Reliability: EEMD performs well in scenarios where the signal is noisy, as it decomposes the signal through repeated noise injections and averaging, which minimizes mode mixing. This method is relatively reliable in cases where the signal-to-noise ratio (SNR) is moderate, but its performance can degrade under extremely noisy conditions. Moreover, while EEMD effectively suppresses noise, it may struggle with accurately capturing defect features when the signal undergoes significant non-stationary changes.

Accuracy: EEMD's denoising ability is generally good, but the separation of defect components from noise is not always perfect, particularly in the presence of complex background interference. The result is that some defect features may be over-smoothed, leading to lower accuracy in defect detection when compared to more dynamic techniques like SST + dynamic masking.

3. SST + dynamic masking (proposed method)

Reliability: The SST combined with dynamic masking offers a dynamic adaptation to changes in signal characteristics, making it more reliable in real-world MFL defect detection. The method's ability to concentrate energy in the true frequency bands related to defects while dynamically adjusting the mask for noise suppression allows it to adapt to both stable and fluctuating operational conditions. This dynamic capability makes it a highly reliable method, particularly in environments where defect positions and noise patterns change over time.

Accuracy: SST + dynamic masking demonstrated superior accuracy in denoising compared to VMD and EEMD, with noticeable improvements in the SNR, PSNR, and MSE. The method excels at maintaining the transient characteristics of defect signals, which are crucial for accurate defect identification. The dynamic mask's ability to selectively suppress

noise while preserving key defect features ensures that the denoised signal retains high fidelity, improving both detection and classification accuracy.

6. Conclusions

This study presents a novel denoising approach for MFL signals in wire rope defect detection, combining SST with dynamic time–frequency masking. The method leverages SST’s high-resolution time–frequency representation to concentrate defect energy, followed by adaptive masking to suppress noise. The experimental results show significant improvements in the SNR. This approach provides a robust solution for real-time monitoring, addressing the critical challenge of noise interference in MFL detection.

While the proposed method shows promising results, it has limitations:

- (1) Performance in extreme noise conditions: The method’s effectiveness decreases when the SNR drops below 10 dB, requiring preprocessing steps for extremely noisy environments.
- (2) Parameter tuning: The dynamic masking parameter k may need adjustment for different wire rope types and operational conditions.
- (3) Internal defect detection: The method primarily targets surface and near-surface defects; deeper internal defects may require combined multi-modal approaches.

Future work will focus on integrating the method with multi-modal fusion systems for comprehensive defect characterization, developing adaptive parameter-tuning algorithms for varying operational conditions, and extending the approach to detect complex defect combinations and internal defects.

Author Contributions: Conceptualization, F.W.; Methodology, X.H.; Software, Z.Z.; Investigation, M.H.; Resources, W.-X.B.; Visualization, Z.F. All authors have read and agreed to the published version of the manuscript.

Funding: This study was funded by the State Grid Shandong Electric Power Company Science and Technology Project (520607240009).

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

Acknowledgments: The authors are grateful to colleagues for their constructive suggestions.

Conflicts of Interest: Authors Fengyu Wu, Maoqian Hu and Zihao Fu were employed by the company Linyi Power Supply Company of State Grid Shandong Electric Power Company. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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