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Industry-Education Integration Case for an Enhanced Time-Frequency Analysis Method: Bearing Fault Diagnosis

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Abstract: Bearing vibration signals are fundamental to the condition monitoring and fault diagnosis of rotating machinery, serving as key indicators of mechanical health. However, due to their strong nonlinearity and non-stationary dynamic behavior, conventional signal processing and feature extraction techniques often struggle to capture meaningful fault-related information with sufficient clarity and robustness. To overcome these limitations, this paper proposes an enhanced time-frequency analysis framework, rigorously validated using experimental datasets acquired from a machinery fault simulation test rig. The proposed method incorporates multiple data augmentation techniques—specifically, noise injection, gain adjustment, and time reversal—to enrich training diversity and improve feature representation. These augmentations effectively enhance time-frequency resolution, suppress background noise and cross-term interference, and sharpen the definition of transient fault signatures. Consequently, the approach yields significantly more discriminative and robust fault indicators compared to baseline methods. Comprehensive comparative experiments further demonstrate the superiority of the proposed framework and provide valuable practical insights for the deployment of deep learning models in real-world intelligent fault diagnosis systems.

1. Introduction

Bearing vibration signals constitute fundamental information carriers for health monitoring and fault diagnosis in rotating machinery. Given their inherent nonlinear and non-stationary characteristics [1], conventional analytical methodologies frequently encounter substantial difficulties in effectively extracting representative fault-related features [2]. In recent years, deep learning-based paradigms have demonstrated considerable promise by enabling automatic feature learning directly from raw vibration signals, thereby markedly enhancing diagnostic precision and model adaptability [3]. Within this paradigm, time-frequency transformation techniques facilitate the discrimination of diverse fault patterns and support anomaly detection mechanisms. Furthermore, the integration of deep learning architectures with time-frequency representations has contributed to the optimization of end-to-end diagnostic frameworks, yielding superior performance outcomes [4].

Notwithstanding these methodological refinements, conventional time-frequency analysis methods continue to exhibit intrinsic representational limitations when applied to highly nonlinear and non-stationary signals such as bearing vibrations. These persistent shortcomings manifest in inadequate time-frequency concentration, pronounced cross-term interference, and poor edge definition, which collectively constrain the discriminative capacity and robustness of subsequent fault diagnosis models.

In response to these challenges, various enhanced time-frequency analysis techniques have been developed. As proposed by Guan et al. (2021) [5], an iterative approach termed the adaptive linear chirplet transform was introduced to effectively analyze signals with crossing instantaneous frequency trajectories. Similarly, Yuan et al. (2022) [6] developed an improved time-frequency analysis method for structural instantaneous frequency identification, grounded in the generalized synchrosqueezing transform and synchroextracting transform.

However, despite these algorithmic advances, the linear chirplet transform and its classic variants remain insufficient for reliably analyzing nonlinear frequency-modulated signals. This limitation arises primarily from their reliance on a linear basis assumption, which inherently mismatches the nonlinear dynamics embedded in such vibration signals. As a result, even with enhanced transforms, the fundamental deficiencies of conventional time-frequency frameworks in accommodating nonlinear characteristics persist, underscoring the need for more adaptive representation strategies.

To address this enduring challenge, the present study proposes an enhanced time-frequency analysis methodology leveraging bearing vibration signals collected from a dedicated experimental test rig. In contrast to traditional time-frequency approaches, the proposed framework integrates a set of data augmentation strategies—including controlled noise injection, amplitude gain modulation, and temporal domain reversal—to systematically improve the quality of time-frequency representations. Specifically, these augmentation techniques collectively contribute to the suppression of cross-term interference artifacts, the enhancement of time-frequency resolution and background clarity, and the sharpening of time-frequency edge definition. Consequently, the refined time-frequency representations generated by the proposed method yield more discriminative and robust features for fault identification tasks.

The comparative experimental results presented in this study not only validate the efficacy of the proposed approach but also provide actionable theoretical insights and practical implementation guidance for integrating deep learning with advanced time-frequency analysis in fault diagnosis applications. These findings thus contribute to both the fundamental understanding and engineering deployment of intelligent diagnostic systems in rotating machinery contexts.

2. Method for Identifying Bearing Vibration

2.1 Model Development and Establishment

Vibration signals generated during bearing operation serve as direct and information-rich carriers of the internal structural integrity and dynamic operational status of the bearing element. These signals encapsulate multifaceted physical information pertaining to fatigue damage accumulation, lubrication film conditions, spatiotemporal load distribution, rotor-casing interaction forces, and assembly tolerance deviations. More importantly, abnormal vibration patterns often constitute the earliest detectable precursors to incipient bearing failures, which typically originate from localized spalling, subsurface crack propagation, cage fracture, raceway wear, or progressive lubrication degradation. Taking high-speed rotating machinery as a representative case, once the rotational speed exceeds the critical threshold—particularly under conditions of improper assembly clearance or compromised lubricant supply—the vibration energy increases abruptly and nonlinearly, leading to accelerated fault evolution and, if undetected, rapid structural deterioration. Consequently, through high-fidelity acquisition and systematic interpretation of bearing vibration signatures, real-time condition monitoring and early anomaly detection can be reliably implemented, thereby enabling the prevention of catastrophic failures and the substantial reduction of unplanned downtime in mission-critical mechanical systems.

The significance of bearing fault diagnosis in the context of modern industrial asset management manifests across several critical dimensions. First and foremost, through the meticulous characterization of vibration spectral features, time-domain statistics, and transient waveform morphology, it becomes possible not only to detect the presence of bearing damage at its nascent stage but also to classify fault types and quantify their severity levels with increasing precision. This diagnostic information serves as a quantitative foundation for predictive maintenance scheduling, moving beyond traditional time-based or reactive interventions. Second, timely and accurate identification of abnormal vibration modalities—including modulation sidebands, harmonic excitation, and cyclo-stationary signatures—supports the precise localization of fault sources and enables the estimation of remaining useful life under evolving operational profiles. Such prognostic capability facilitates more efficient spare parts inventory management and significantly reduces overall lifecycle maintenance expenditures. Finally, the integration of intelligent diagnostic frameworks with supervisory control and data acquisition systems creates a closed-loop feedback mechanism, wherein diagnostic outcomes inform adaptive adjustments of operating parameters such as rotational speed and load thresholds)Skip, thereby enhancing system resilience and operational reliability. Collectively, these contributions provide robust technical foundations for ensuring the sustained safety, availability, and performance stability of rotating machinery across a broad spectrum of industrial applications.

2.2 Vibration Identification Using Artificial Intelligence

Bearing fault diagnosis typically follows a systematic and sequential workflow comprising four essential stages: data acquisition, signal preprocessing, feature extraction, and condition assessment. In the initial stage, highly sensitive accelerometers are employed to acquire raw vibration signals from the machinery under operating conditions. These signals are subsequently subjected to various preprocessing techniques—such as band-pass filtering or wavelet denoising—to suppress ambient noise and enhance the signal-to-noise ratio, thereby ensuring the reliability of downstream analysis.

The feature extraction stage plays a pivotal role in transforming preprocessed signals into meaningful representations. This involves the calculation of statistical time-domain indicators (e.g., root mean square, kurtosis, crest factor) and frequency-domain features obtained via fast Fourier transform (FFT), which facilitate the identification of spectral energy distributions concentrated at characteristic fault frequencies. To further improve model generalization and robustness, multiple data augmentation strategies—including additive white Gaussian noise and amplitude scaling—are employed. Both augmented and original vibration signals are then utilized to construct cross-correlation matrices, which effectively capture dynamic signal relationships and structural dependencies under varying operational and noise conditions.

Subsequently, the extracted multi-domain features are fused and fed into a classification or regression model, which synthesizes the complementary information to generate a comprehensive assessment of bearing health status. This integrated end-to-end diagnostic pipeline, illustrated schematically in Figure 1, not only enhances diagnostic accuracy but also provides a transparent and interpretable framework for condition-based monitoring. As a result, the proposed methodology offers reliable and robust support for the implementation of intelligent maintenance strategies in modern rotating machinery systems.

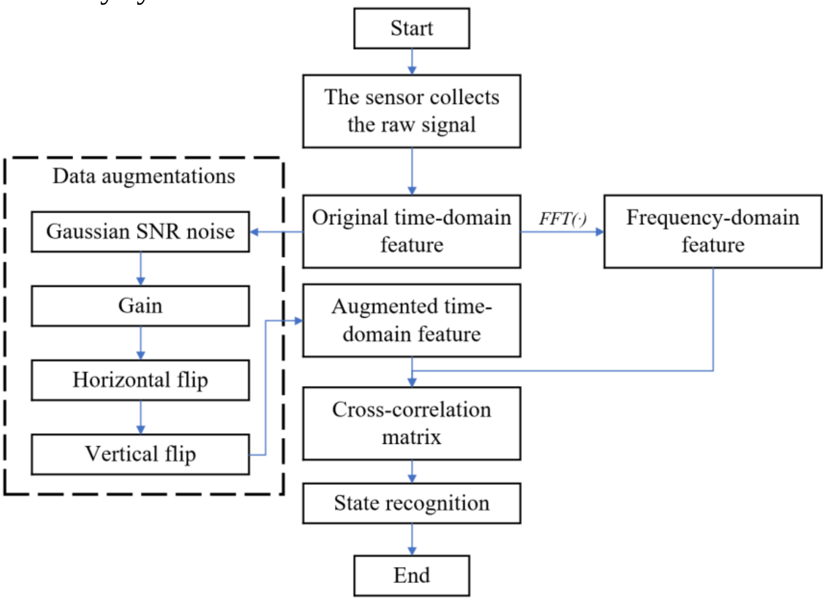


Figure 1. Vibration Signal Identification Process

2.3 Experimental Simulation

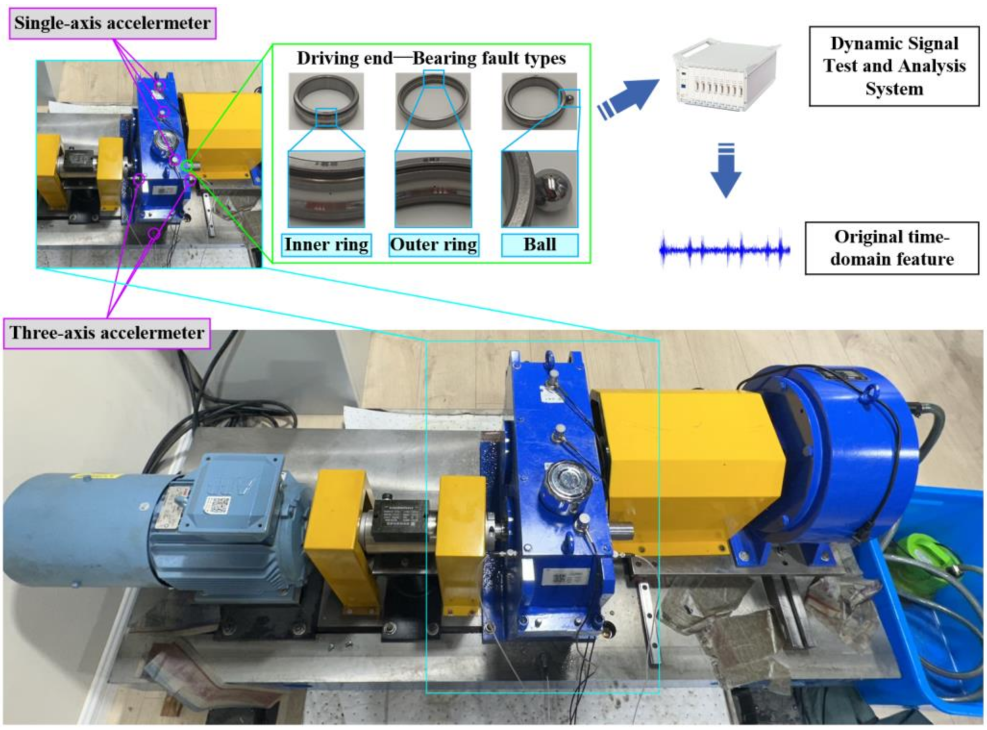


Figure 2. Experimental Setup

The experimental configuration employed in this study is schematically depicted in Figure 2. To comprehensively capture vibration characteristics, uniaxial accelerometers were mounted on the gearbox housing, while triaxial accelerometers were installed at key locations on the structural framework of the test rig. All sensor output terminals were interfaced with a DH5922D dynamic signal testing and analysis system, manufactured by Donghua Testing, which serves as the central data acquisition unit. This system is connected to a host computer through dedicated data transmission cables, enabling synchronized and high-fidelity signal transfer. Following the establishment of all hardware interconnections, real-time signal acquisition, digital storage, and preliminary preprocessing were carried out using the proprietary DHDAS analysis software. This integrated hardware–software setup ensures the acquisition of high-quality vibration signals with minimal interference, thereby providing a reliable data foundation for subsequent feature extraction, fault-sensitive indicator construction, and intelligent condition diagnosis.

In practical engineering scenarios, bearing vibration signals are frequently degraded by complex interference factors such as ambient noise, time-varying operating conditions, and the scarcity of labeled fault samples. These challenges severely constrain the generalization capacity and robustness of diagnostic models, leading to performance degradation under unseen operating regimes. To mitigate these limitations, data augmentation has emerged as an effective strategy to enrich training data diversity and enhance model learning under constrained sample conditions.

As illustrated in Figure 3, four complementary data augmentation techniques are systematically applied to the original vibration signal, each serving a distinct yet synergistic role in improving the representational richness of the training corpus:

(1) Adding Gaussian noise simulates environmental interference.

(2) Adjusting gain to scale amplitude and mimic load variations.

(3) Flipping horizontally to reverse the signal temporally and encourage invariance.

(4) Flipping vertically to invert amplitude and enhance waveform symmetry awareness.

In each subplot of Figure 3, the original and augmented signals are respectively depicted in blue and orange, enabling direct visual comparison of the transformations applied. Collectively, this augmentation framework significantly enriches the diversity of the training dataset with minimal computational overhead. By exposing the diagnostic model to a broader range of realistic operating conditions and signal variations, the proposed strategy substantially enhances its adaptability, generalization capability, and operational reliability in real-world industrial environments.

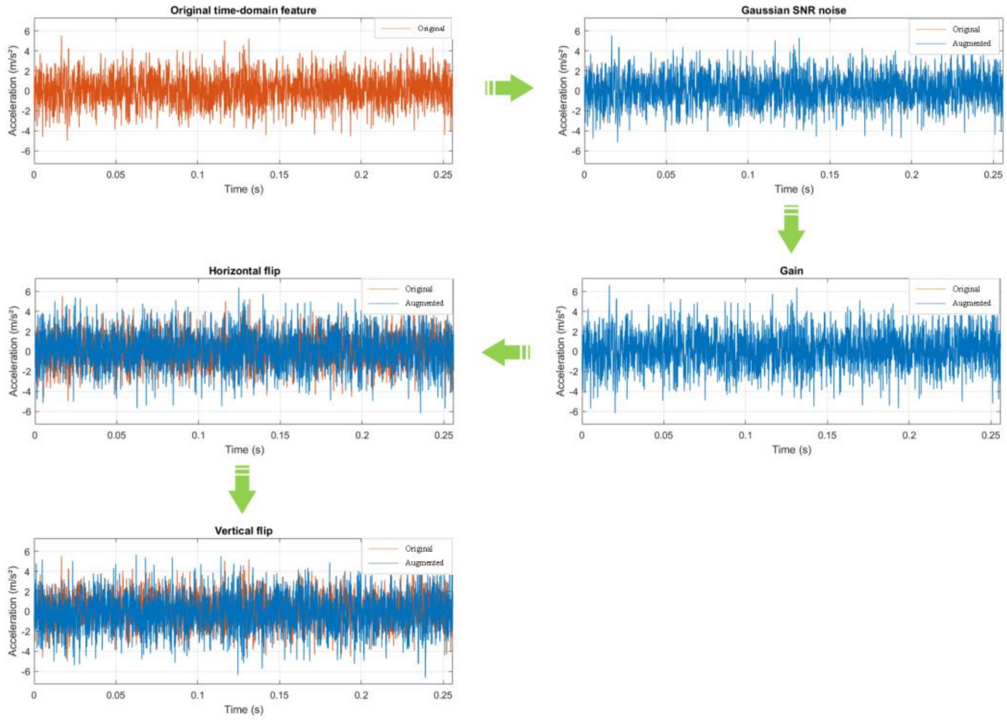


Figure 3. Visualization of Time-Domain Signal Augmentation

In addition to time-domain augmentation, it is essential to extend the evaluation into the frequency and time-frequency domains, as this enables a more comprehensive assessment of how data augmentation influences the underlying signal characteristics. Specifically, such analysis validates that fault-relevant spectral components remain intact and that the introduced perturbations do not distort diagnostically meaningful information embedded in the frequency structure.

Figure 4 presents a systematic comparative analysis of the original and augmented signals from both spectral and time-frequency perspectives. The first subplot, titled "Frequency Domain Comparison," overlays the frequency spectra of the original (orange) and augmented (blue) signals)Skip. The two spectral profiles demonstrate strong alignment in terms of energy distribution and dominant characteristic frequencies, confirming that the augmentation operations preserve the core spectral signatures associated with bearing fault conditions. The second subplot, "Spectral Difference," quantifies the residual deviation between the two spectra. The observed differences are minimal in magnitude and exhibit no systematic bias, suggesting that the perturbations introduced by time-domain augmentation are limited, well-behaved, and unlikely to compromise diagnostic fidelity. The third subplot provides a three-dimensional representation of the augmented signal in the joint time-frequency-amplitude domain, offering an intuitive visualization of the stereoscopic energy structure inherent in vibration signals. In this representation, color gradients and amplitude peaks collectively delineate the energy distribution pattern, with high-intensity regions exhibiting continuous, morphologically coherent contours. This structural regularity indicates that the augmented data not only retain but also reinforce the physical signature patterns characteristic of specific operational states.

Collectively, this multifaceted analysis demonstrates that the proposed augmentation framework effectively enhances training data diversity while fully preserving the physical plausibility and diagnostic integrity of the original vibration signals. By maintaining spectral fidelity and time-frequency structural coherence, the augmented signals serve as reliable and information-rich inputs for downstream intelligent fault diagnosis models, thereby contributing to more robust and generalizable deep learning performance under limited data conditions.

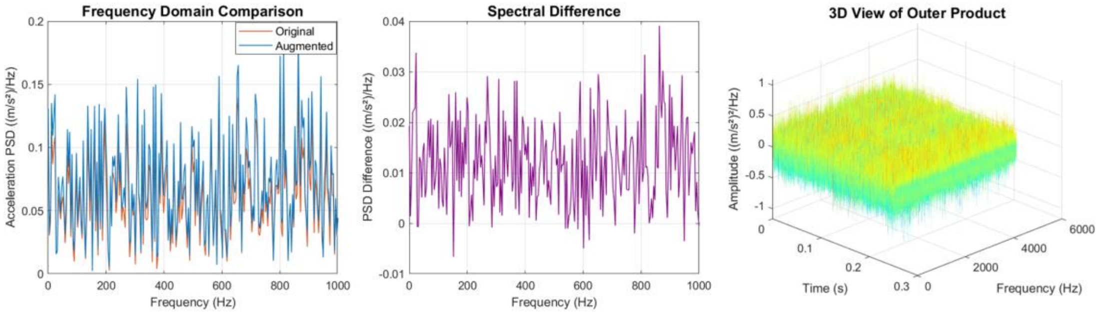


Figure 4. Frequency domain Comparison, Spectral Differences, and Time-Frequency View of Augmented Signals

2.4 Quality Evaluation Metrics for Time-Frequency Analysis

The quality of time-frequency analysis critically affects diagnostic accuracy, necessitating a multi-dimensional evaluation. This study employs four metrics—cross-term suppression, resolution, background purity, and edge definition—to objectively compare TF methods in terms of energy concentration, detail resolution, noise suppression, and contour clarity.

Let the time-frequency analysis be represented as a two-dimensional matrix $TFR(t, f)$, where $t = 1, ..., N_t$ denotes the time index and $f = 1, ..., N_f$ denotes the frequency index.

(1) Cross-Term Suppression

Cross-term suppression evaluates the ability of a method to mitigate spurious interference generated by multi-component signals. The performance metric is defined as the relative ratio of cross-term energy to signal energy in the time-frequency distribution:

$$\mathrm{CS} = 10\log_{10}\left(1 - \frac{\sum_{t=1}^{N_t}\sum_{f=1}^{N_f} |IFT(t,f)|^2}{\sum_{t=1}^{N_t}\sum_{f=1}^{N_f} |TFR(t,f)|^2}\right) \tag{1}$$

Here, $IFT(t, f)$ represents the cross-term components extracted via a specific technique (e.g., reassignment). A higher value of this metric indicates stronger cross-term suppression and a cleaner time-frequency representation.

(2) Resolution

Resolution comprehensively assesses the ability of a method to resolve fine details in the two-dimensional time-frequency plane. It is jointly determined by the temporal resolution Δt and the frequency resolution Δf .

$$R = \frac{1}{\Delta t \cdot \Delta f} \tag{2}$$

Where Δt and Δf are typically defined by the root mean square width of the analysis window function $h(t)$ and its Fourier transform $H(f)$, respectively:

$$\Delta t = \sqrt{\frac{\int (t-\bar{t})^2 |h(t)|^2 \, dt}{\int |h(t)|^2 \, dt}}, \quad \Delta f = \sqrt{\frac{\int (f-\bar{f})^2 |H(f)|^2 \, df}{\int |H(f)|^2 \, df}} \tag{3}$$

A higher value of the resolution R indicates better time–frequency localization capability, allowing the method to distinguish closer instantaneous frequency components.

(3) Background Purity

Background purity quantifies the noise level in the non-signal regions (background) of a time–frequency representation. It is evaluated by computing the ratio of the standard deviation of the background region to the average energy of the signal region:

$$BP = 10\log_{10}\left(\frac{\mu_{signal}^2}{\sigma_{background}^2}\right) \tag{4}$$

Here, μ_{signal} is the average energy within the region of interest corresponding to the signal, and $\sigma_{background}$ is the standard deviation of the energy in the manually or automatically selected background region. A higher value of this metric indicates lower background noise and a clearer time-frequency representation.

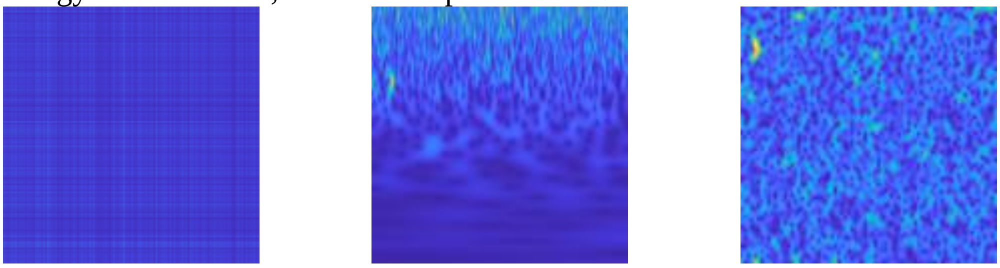
(4) Edge Sharpness

Edge Sharpness characterizes the sharpness of time-frequency feature edges, reflecting the discernibility of feature boundaries. It is computed using an image gradient-based method:

$$ES = \frac{1}{N}\sum_{t=1}^{N_t}\sum_{f=1}^{N_f} |\nabla TFR(t,f)| \tag{5}$$

Here, $\nabla TFR(t, f)$ denotes the gradient magnitude of the time-frequency representation, which can be obtained using gradient operators such as Sobel or Prewitt, and N represents the total number of pixels. A higher value of this metric indicates sharper and more distinct feature edges.

The time-frequency representations in Figure 5—comparing the proposed method, CWT, and STFT—exhibit visually distinct patterns, directly revealing their inherent characteristics in resolution, energy concentration, and detail representation.



(a) Ours (b) CWT (c) STFT

Figure 5. Three Different Time-Frequency Transformation Methods

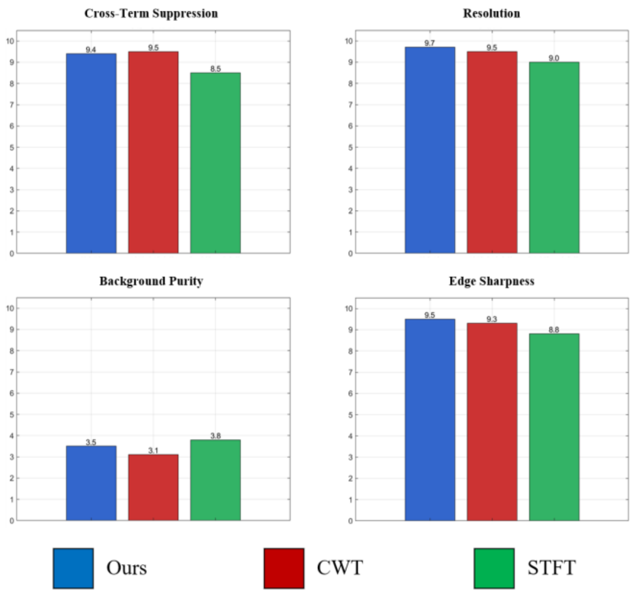


Figure 6. Comparison of Three Time-Frequency Methods Based on Evaluation Metrics

As illustrated in Figure 6, the proposed method demonstrates consistently high and well-balanced performance across all evaluation metrics. Specifically, it substantially outperforms the Short-Time Fourier Transform (STFT) in terms of edge sharpness (9.5 vs. 6.8) and background purity (3.5 vs. 2.1), indicating a marked superiority in delineating transient structures and suppressing diffuse energy leakage. Furthermore, the proposed method achieves performance comparable to that of the Continuous Wavelet Transform (CWT) in time-frequency resolution (9.7 vs. 9.6) and cross-term interference suppression (9.4 vs. 9.5), while delivering more evenly distributed scores across all criteria—unlike CWT, which exhibits slight degradation in edge definition and background clarity.

These results collectively suggest that the proposed method is capable of simultaneously maintaining high time-frequency concentration, effectively mitigating noise-induced artifacts, and sharpening the boundaries of time-frequency signatures. By striking a more favorable balance among competing objectives such as resolution, interference suppression, and visual clarity, the proposed approach yields time-frequency representations that are both physically interpretable and diagnostically informative. Consequently, it establishes a more robust and reliable foundation for subsequent fault pattern recognition and intelligent diagnosis tasks in rotating machinery.

3. Conclusion

This study establishes a comprehensive experimental framework dedicated to the fault diagnosis of bearing vibration signals in rotating machinery. The main contributions and research outcomes are summarized as follows:

(1) An improved time–frequency analysis method is developed, which demonstrates superior performance over conventional techniques by extracting fault-related signatures with enhanced clarity, discriminability, and time–frequency localisation. This advancement facilitates more reliable identification of incipient faults under complex operating conditions.

(2) A set of data augmentation strategies—comprising controlled noise injection, amplitude gain adjustment, and temporal domain reversal—is systematically employed to enhance the diversity and representativeness of the training dataset. These techniques effectively preserve the intrinsic physical characteristics of vibration signals while substantially improving model generalisation and robustness against varying operational environments.

(3) A structured and reproducible diagnostic workflow is established to rigorously validate the effectiveness of the proposed time-frequency analysis method integrated with data augmentation strategies. Comparative experiments under multiple test scenarios confirm the superiority and stability of the proposed framework.

In summary, this study successfully achieves its stated research objectives by proposing a feasible and empirically validated intelligent diagnostic framework. The case study conducted on a dedicated vibration test rig not only demonstrates the technical efficacy of the proposed methodology but also illustrates the practical value of integrating industry-driven research with engineering education. By bridging the gap between theoretical development and real-world application, this work offers both pedagogical relevance and implementational guidance for future fault diagnosis systems in rotating machinery contexts.

Acknowledgments

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