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Enhanced Fault Detection in Rolling Element Bearings Using Kurtogram-Driven Spectral Kurtosis for Optimal Band Selection

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Abstract – **This paper introduces a robust methodology aimed at improving the detection and diagnosis of rolling element bearing faults, particularly in settings where other machinery components create masking signals that complicate fault identification. The proposed approach integrates advanced signal processing techniques with a straightforward classification method to achieve precise fault diagnosis. The methodology involves signal preprocessing, which includes wavelet transform-based denoising and normalization to enhance the signal-to-noise ratio and standardize signal amplitude. Subsequent Kurtogram analysis visualizes and quantifies transient features within the signal across various frequency bands using Short-Time Fourier Transform (STFT), highlighting impulsive and non-Gaussian characteristics indicative of faults. Spectral Kurtosis further isolates frequency bands with significant fault-related transients by identifying deviations from Gaussian behavior. Optimal frequency bands are selected based on a combined assessment of kurtosis and spectral kurtosis, followed by band-pass filtering to isolate these bands. Fault detection is performed using Envelope Spectrum Analysis to extract fault-specific frequencies from the filtered signal. A rule-based classifier, utilizing the log ratio of BPFI to BPFO amplitudes, is introduced for fault classification. Validation with test data shows consistent distributions and perfect accuracy, demonstrating the approach's effectiveness. Implemented and simulated in MATLAB, this integrated methodology enhances fault detection accuracy and lays the groundwork for future research involving advanced classification algorithms and additional diagnostic features.**

Keywords – **BPFI, BPFO, Kurtogram, Spectral Kurtosis, STFT, etc.**

I. INTRODUCTION

Rolling element bearings are critical components in a wide range of rotating machinery, from automotive engines to industrial equipment. Their primary function is to support and guide rotating shafts, facilitating smooth and precise movement between fixed and moving parts. Despite their robustness, these bearings are susceptible to wear and tear, which can lead to failures if not detected and addressed promptly. Given their importance, the accurate detection and diagnosis of bearing faults are crucial for maintaining machinery reliability and preventing costly downtime.

Traditionally, fault detection in bearings has relied on time-domain and frequency-domain analysis techniques. However, these methods often struggle to identify subtle fault signals, particularly in noisy environments where vibrations from other machine components can mask the signs of degradation. As machinery becomes more complex and operational environments more demanding, there is a growing need for advanced diagnostic methods that can effectively isolate and identify fault-related signals.

Recent advancements in signal processing have introduced new techniques for enhancing fault detection. One such approach involves the integration of Kurtogram-driven Spectral Kurtosis for optimal frequency band selection. The Kurtogram is a powerful tool that visualizes the frequency bands most likely to contain fault-related transients. Spectral Kurtosis, on the other hand, measures deviations from Gaussian behavior in the frequency domain, providing a quantitative assessment of signal anomalies.

This paper explores the application of these advanced techniques to improve fault detection in rolling element bearings. By employing wavelet transform techniques for signal denoising and normalization, the study aims to enhance the quality of vibration signals, making it easier to identify potential faults. The combination of Kurtogram and Spectral Kurtosis enables a more refined analysis of frequency bands, which is critical for isolating fault signals from noise.

The proposed methodology focuses on optimizing frequency band selection to balance sensitivity and

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specificity in fault detection. A frequency band that is too narrow may overlook critical fault information, while one that is too broad may be overwhelmed by noise. By leveraging Kurtogram-driven Spectral Kurtosis, this paper aims to identify the most informative frequency bands, thereby improving diagnostic accuracy and reliability.

The anticipated outcomes of this paper include improved fault detection accuracy, reduced false alarms, and earlier identification of potential faults compared to conventional methods. The integration of these advanced techniques seeks to develop a more effective and reliable bearing monitoring system, which is essential for maintaining the operational integrity of critical machinery across various industries.

The remainder of this paper is organized as follows: Section II reviews existing literature on fault detection methods for rolling element bearings, focusing on traditional and advanced techniques. Section III presents the proposed methodology, detailing the processes of signal processing, Kurtogram analysis, and Spectral Kurtosis. Section IV describes the experimental setup and results of the proposed approach. Finally, Section V concludes the paper and suggests directions for future research in bearing fault detection and diagnostic systems.

II. Literature Review

Recent research into fault detection for rolling element bearings has highlighted significant advancements and identified ongoing challenges. A study by [1] explores the integration of Spectral Kurtosis with adaptive Wavelet Transform techniques. This approach enhances fault detection sensitivity by aligning the wavelet analysis more closely with transient fault signals. However, it introduces the complexity of precise parameter tuning, which increases computational demands and complicates practical implementation. Complementarily, the research by [2] investigates combining Kurtogram with deep learning frameworks for automated fault classification. This innovative approach leverages deep learning's capacity to handle large datasets and complex fault patterns. Yet, the need for extensive labeled data poses a significant limitation, particularly in scenarios where data is scarce or difficult to label.

Further advancements are seen in the adaptive Spectral Kurtosis methods, as detailed by [3]. This study presents a method that dynamically adjusts its parameters based on real-time signal characteristics, improving fault detection accuracy under varying conditions. However, the increased computational complexity and the continuous need for parameter adjustments can challenge real-time applications. Similarly, the work by [4] combines Spectral Kurtosis with Empirical Mode Decomposition (EMD) to analyze non-stationary signals, enhancing fault detection capabilities. Despite this, EMD's sensitivity to noise and potential mode mixing can impact the accuracy of fault detection.

In an effort to improve the Kurtogram methodology, [5] introduces refinements to better handle non-stationary signals, resulting in more accurate fault detection in diverse conditions. However, these enhancements come with increased computational requirements and complexity. The review by [6] offers a comprehensive overview of Spectral Kurtosis applications in gearbox fault diagnosis, summarizing various methodologies and advancements. While valuable for understanding current trends, this review lacks new experimental results and methodological innovations.

Research by [7] integrates Kurtosis with machine learning techniques to enhance fault classification accuracy. This hybrid approach benefits from the ability of machine learning to classify features identified by Kurtosis. Nonetheless, the reliance on substantial datasets and computational resources limits practical implementation. The study by [8] improves fault detection by combining Kurtogram with statistical signal processing methods, which enhances sensitivity and specificity. However, this combination increases analysis complexity and computational load.

The work by [9] explores the integration of Spectral Kurtosis with Convolutional Neural Networks (CNNs), enhancing feature extraction and classification accuracy. Yet, this approach demands significant computational resources and large datasets, which may not be feasible in all practical scenarios. In a similar vein, [10] demonstrates the use of hybrid machine learning models with Kurtogram for fault diagnosis, showing improved performance but also requiring extensive training data and computational resources.

Another notable contribution comes from the study by [11], which combines Spectral Kurtosis with Genetic Algorithms (GAs) to optimize fault diagnosis. While GAs help fine-tune parameters, they can be slow to converge and computationally intensive. The integration of Spectral Kurtosis with Principal Component Analysis (PCA), as explored by [12], improves fault detection by reducing dimensionality, though PCA's potential failure to capture non-linear relationships may affect diagnostic accuracy.

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Research by [13] combines Kurtogram with Extreme Learning Machines (ELMs) to enhance classification speed and accuracy. However, ELMs are sensitive to data quality and generalization to new fault types. Additionally, [14] integrates Spectral Kurtosis with Variational Mode Decomposition (VMD), which improves fault detection by decomposing signals into intrinsic modes. Yet, VMD's performance is sensitive to decomposition parameters, which can influence accuracy.
Finally, the study by [15] combines Kurtogram with Ensemble Empirical Mode Decomposition (EEMD) to address non-stationary signals more effectively. While this method enhances fault detection, it introduces computational demands and potential mode mixing artifacts.

A. Research Gaps

Despite these advancements, several critical research gaps persist. Current methods often struggle to handle the complexities introduced by variable operating conditions and masking signals from other components, which can reduce fault detection accuracy. There is also a lack of comprehensive solutions that integrate real-time processing with high sensitivity and specificity across diverse fault types. Existing methodologies frequently exhibit limitations in scalability and adaptability, particularly in large-scale or highly dynamic industrial environments. To address these gaps, there is a need for more robust and versatile diagnostic tools that can better manage intricate signal characteristics and operational variations, enhancing accuracy, efficiency, and applicability in practical settings.

III. Proposed Methodology

The proposed methodology aims to enhance the detection and diagnosis of rolling element bearing faults, especially when strong masking signals from other machine components are present. By integrating Kurtogram analysis and Spectral Kurtosis for optimal frequency band selection, this approach isolates the most informative frequency bands containing fault-related signals. The methodology involves several key stages: signal preprocessing, Kurtogram analysis, Spectral Kurtosis computation, optimal band selection, fault detection using envelope spectrum analysis, and diagnosis. Figure 1 shows the flow diagram for proposed research work. To ensure the effectiveness and generalizability of this methodology, it relies on a comprehensive dataset [16] that captures a wide range of operating conditions and fault scenarios. Rest of the stages are detailed below with relevant mathematical formulations.

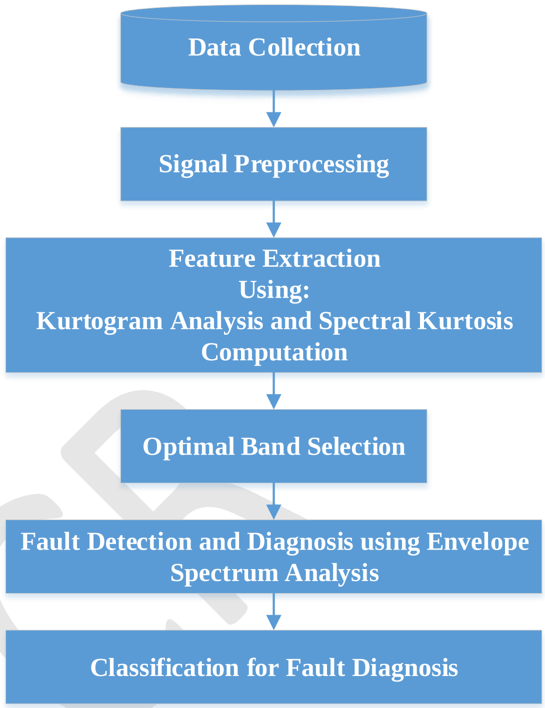

Figure 1: Flow diagram for proposed research work

A. Signal Preprocessing

In this paper, signal preprocessing involves techniques aimed at enhancing the quality of raw vibration signals collected from rolling element bearings. The main objectives are to improve the signal-to-noise ratio (SNR) and ensure accurate fault detection. This is achieved by using a combination of wavelet transform for denoising and normalization for standardization.

1. Denoising Using Wavelet Transform

We employ the discrete wavelet transform (DWT) for denoising, which is particularly effective for non-stationary signals such as those from rotating machinery. The DWT decomposes the signal into different frequency components, making it easier to identify and suppress noise.
The discrete wavelet transform of the signal $x(t)$ is defined as:

$$W_x(j,k) = \sum_n x(n)\psi_{j,k}(n) \qquad (1)$$

Where,

- $W_x(j,k)$ represents the wavelet coefficients at scale j and position k,
- $\psi_{j,k}(n)$ is the discrete wavelet function for scale j and position k,
- n is the discrete time index.

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For denoising, we apply a thresholding technique to the wavelet coefficients. The coefficients are processed through a threshold function T to suppress noise while preserving significant signal features:

$$\widehat{W}_x(j,k) = \begin{cases} W_x(j,k), & if\ |W_x(j,k)| > \tau \\ 0, & otherwise \end{cases} \quad (2)$$

Where τ is the threshold value, typically set using methods such as Stein's unbiased risk estimate (SURE) or universal thresholding.

The thresholded wavelet coefficients are then used to reconstruct the denoised signal:

$$x_{denoised}(t) = \sum_{j,k} \widehat{W}_x(j,k)\psi_{j,k}(t) \quad (3)$$

This approach effectively reduces noise while retaining important signal characteristics related to bearing faults.

2. Normalization

Normalization is applied to the denoised signal to standardize its amplitude, ensuring consistency for further analysis. This step is crucial to ensure that variations in signal amplitude do not affect the fault detection process.

The denoised signal $x_{denoised}(t)$ is standardized using the following formula:

$$s(t) = \frac{x_{denoised}(t) - \mu_{x_{denoised}}}{\sigma_{x_{denoised}}} \quad (4)$$

Where,

- $\mu_{x_{denoised}}$ is the mean of the denoised signal:

$$\mu_{x_{denoised}} = \frac{1}{N}\sum_{i=1}^{N} x_{denoised}(t_i) \quad (5)$$

$\sigma_{x_{denoised}}$ is the standard deviation of the denoised signal:

$$\sigma_{x_{denoised}} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(x_{denoised}(t_i) - \mu_{x_{denoised}}\right)^2} \quad (6)$$

Here, N represents the number of data points in the signal, and t_i are the discrete time points.

The resulting standardized signal $s(t)$ is now ready for further analysis, ensuring that the subsequent steps focus on detecting fault-related features rather than being biased by variations in signal amplitude.

B. Kurtogram Analysis

In this paper, Kurtogram analysis is employed as a crucial technique for detecting transient or non-Gaussian behavior in vibration signals from rolling element bearings, which can indicate underlying faults. The Kurtogram visualizes kurtosis values across various frequency bands and scales, allowing for the precise identification of fault-related signals embedded within noise.

1. Short-Time Fourier Transform (STFT)

To create the Kurtogram, the Short-Time Fourier Transform (STFT) is applied to the preprocessed signal $s(t)$. This method provides a detailed time-frequency representation of the signal, which is essential for analyzing the non-stationary characteristics of bearing fault signals.

The STFT of the signal $s(t)$ is calculated using the following equation:

$$S(t,f) = \int_{-\infty}^{\infty} s(\tau)\omega(t-\tau)e^{-j2\pi f\tau}d\tau \quad (7)$$

Where:

- $S(t,f)$ represents the STFT of the signal at time t and frequency f,
- $s(\tau)$ is the input signal,
- $\omega(t-\tau)$ is the window function centered at time t, specifically a Hamming window, which is chosen for its effective balance between time and frequency resolution.

By sliding the window $\omega(t-\tau)$ across the entire signal, the signal is segmented into short intervals. Each segment undergoes a Fourier transform, resulting in a time-frequency map $S(t,f)$. This map is crucial for identifying frequency components that vary over time, which is essential for detecting the non-stationary characteristics of bearing faults.

2. Calculation of Kurtosis

After applying the STFT, the kurtosis $\kappa(f)$ for each frequency band is calculated to measure the "peakedness" of the signal distribution. This step is focused on identifying sharp transients or impulsive features, which are typical indicators of bearing faults.

Kurtosis $\kappa(f)$ is calculated using the following formula:

$$\kappa(f) = \frac{\frac{1}{N}\sum_{n=1}^{N}(S(t_n,f)-\mu_S)^4}{\left(\frac{1}{N}\sum_{n=1}^{N}(S(t_n,f)-\mu_S)^2\right)^2} \quad (8)$$

Where:

- $S(t_n,f)$ denotes the STFT magnitude at frequency f and time t_n,
- μ_S is the mean value of $S(t_n,f)$ across the time window, calculated as:

$$\mu_S = \frac{1}{N}\sum_{n=1}^{N} S(t_n,f) \quad (9)$$

- N represents the number of time samples within the window.

This kurtosis calculation is applied across sliding windows on the STFT output, targeting the detection

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of non-Gaussian features in the signal. High kurtosis values are indicative of impulsive, fault-related events characterized by high amplitude and short duration, which are easily identifiable through elevated kurtosis.

3. Construction and Interpretation of the Kurtogram

After computing the kurtosis values for all frequency bands, the Kurtogram is constructed by plotting these values against frequency. The resulting Kurtogram visually represents the kurtosis distribution across different frequency bands and scales, helping to identify specific frequencies where transient events occur.

Kurtogram Construction: The Kurtogram plots the kurtosis values $\kappa(f)$ on a two-dimensional plane, with the x-axis representing frequency and the y-axis representing kurtosis. Peaks in this plot correspond to frequency bands with high kurtosis, suggesting the presence of faults.

Kurtogram Interpretation: Interpreting the Kurtogram involves identifying significant peaks, which indicate frequencies exhibiting pronounced transient or non-Gaussian behavior. These peaks are directly associated with potential bearing faults, such as spalls, cracks, or other defects in the rolling elements or races. By focusing on these peaks, fault-related signals can be isolated from surrounding noise, leading to more accurate fault diagnosis.

C. Spectral Kurtosis Computation

In the proposed work, the computation of Spectral Kurtosis (SK) is a critical step aimed at identifying non-Gaussian components within the vibration signals of rolling element bearings. This step specifically targets the detection of transient events that are often indicative of bearing faults. The methodology employs Spectral Kurtosis to distinguish frequency bands that contain fault-related transients from those dominated by Gaussian noise.

1. Fourier Transform of the Preprocessed Signal

The starting point for Spectral Kurtosis computation is the preprocessed signal $s(t)$, which has been denoised and normalized in the earlier stages of the methodology. To analyze the frequency content of $s(t)$, we apply the Fourier Transform, which converts the time-domain signal into its frequency-domain representation:

$$X(f) = \int_{-\infty}^{\infty} s(t) e^{-j2\pi f t} dt \quad (10)$$

Where $X(f)$ represents the complex spectrum of the signal at frequency f. This transformation is crucial because it allows us to examine how the energy of the signal is distributed across different frequencies, which is key to identifying the presence of fault-related transients.

2. Computation of Spectral Kurtosis

The Spectral Kurtosis $SK(f)$ at each frequency f is then computed using the following formula:

$$SK(f) = \frac{E[|X(f)|^4]}{(E[|X(f)|^2])^2} - 2 \quad (11)$$

In this expression:

- $E[|X(f)|^2]$ is the expected value of the squared magnitude of the Fourier transform, representing the power spectral density at frequency f.
- $E[|X(f)|^4]$ is the fourth-order moment of $X(f)$, which captures the extremity of variations in the signal's energy at that frequency, highlighting the presence of sharp transients or non-Gaussian behavior.

The term -2 is subtracted to adjust the kurtosis so that a purely Gaussian process would have a Spectral Kurtosis of zero. Higher values of $SK(f)$ indicate a higher likelihood of transient, non-Gaussian events, which are typically associated with bearing faults.

3. Application and Interpretation in the Research Context

In the context of this research, the computed Spectral Kurtosis values $SK(f)$ serve as a criterion for identifying the most informative frequency bands. The goal is to isolate those bands that contain significant fault-related transients, which are often masked by other, stronger signals from the machine's normal operation. The process can be summarized in the following steps:

Segmentation: The signal $s(t)$ is divided into overlapping segments $s_k(t)$ to ensure that transient events are not overlooked. For each segment k, the Fourier transform $X_k(f)$ is calculated as:

$$X_k(f) = \int_{t_k}^{t_k+T} s_k(t) e^{-j2\pi f t} dt \quad (12)$$

Where t_k denotes the start time of the k^{th} segment, and T is the segment length.

Averaging: To obtain a stable estimate of $SK(f)$, the Spectral Kurtosis is averaged over all segments:

$$SK(f) = \frac{1}{K} \sum_{k=1}^{K} \left[\frac{|X_k(f)|^4}{\left(\frac{1}{K} \sum_{k=1}^{K} |X_k(f)|^2\right)} - 2 \right] \quad (13)$$

Here, K is the total number of segments. This averaging process mitigates the impact of random noise, ensuring that the resulting $SK(f)$ values accurately reflect the presence of fault-related transients.

Frequency Band Identification: Frequency bands with high $SK(f)$ values are identified as potential candidates for containing fault-related signals.

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These bands are then prioritized in the subsequent analysis, particularly in the optimal band selection stage.

The application of Spectral Kurtosis in this paper is integral to enhancing the accuracy of fault detection. By focusing on non-Gaussian behavior, which is often indicative of faults, the methodology reduces the likelihood of false positives and improves the detection of subtle, early-stage faults that might otherwise be missed. This step ensures that only the most relevant frequency bands are considered for further analysis, leading to a more targeted and effective diagnostic process.

D. Optimal Band Selection

In this proposed methodology, the optimal band selection integrates insights from Kurtogram analysis and Spectral Kurtosis computation to isolate the most informative frequency bands for detecting rolling element bearing faults. This process aims to enhance fault detection accuracy by focusing on frequency bands that are most likely to contain fault-related signals, thus minimizing the impact of masking noise from other machine components. The optimal band selection is performed in two main stages: evaluating band significance and applying band-pass filtering.

1. Band Selection Criteria

The proposed methodology for optimal band selection integrates Kurtogram analysis and Spectral Kurtosis to isolate the most relevant frequency bands for fault detection in rolling element bearings. This approach ensures that the selected frequency bands emphasize fault-related signals while minimizing the impact of masking noise. The optimal band selection involves evaluating band significance and applying band-pass filtering.

Kurtosis Maximization: The Kurtogram, generated from the Short-Time Fourier Transform (STFT) of the preprocessed signal $s(t)$, is used to identify frequency bands exhibiting high kurtosis values. Kurtosis $\kappa(f)$ is computed for each frequency band to detect transient features indicative of faults. Bands with the highest kurtosis values are considered significant for containing fault-related transients.

Spectral Kurtosis Significance: Spectral Kurtosis (SK) is calculated for each frequency band $[f_1, f_2]$ to measure the deviation of the signal from Gaussian behavior. Higher SK values indicate the presence of non-Gaussian components, suggesting that these frequency bands are more likely to contain fault-related signals.

Integration of Kurtosis and Spectral Kurtosis: The optimal frequency band $[f_1, f_2]$ is determined by maximizing the product of kurtosis $\kappa(f)$ and Spectral Kurtosis $SK(f)$:

$$[f_1, f_2] = \arg\max_{f}\{\kappa(f) \cdot SK(f)\} \quad (14)$$

This criterion ensures that the selected frequency band exhibits both strong transient features and significant non-Gaussian behavior, enhancing the likelihood of detecting fault-related signals while minimizing noise interference.

2. Band-Pass Filtering

Following the identification of the optimal frequency band $[f_1, f_2]$, a band-pass filter is applied to isolate this band from the preprocessed signal $s(t)$. The band-pass filter operation is defined as:

$$s_{filtered}(t) = \text{BandPass}(s(t), f_1, f_2) \quad (15)$$

Where $\text{BandPass}(s(t), f_1, f_2)$ denotes the application of a band-pass filter that retains frequency components within the range $[f_1, f_2]$ and attenuates others. The resulting filtered signal $s_{filtered}(t)$ emphasizes the frequency band where fault-related information is expected to be most prominent.

The methodology for optimal band selection involves:

- ***Kurtosis Analysis:*** Identifying frequency bands with high kurtosis to capture transient fault features.
- ***Spectral Kurtosis Assessment:*** Evaluating frequency bands for non-Gaussian behavior to confirm the presence of fault-related signals.
- ***Combining Metrics:*** Selecting the frequency band $[f_1, f_2]$ that maximizes the product of kurtosis and Spectral Kurtosis.
- ***Filtering:*** Applying a band-pass filter to isolate the identified frequency band for focused analysis.

This approach ensures that the most relevant frequency bands are selected, leading to improved fault detection and diagnosis capabilities.

E. Fault Detection and Diagnosis

In this research work, fault detection and diagnosis are performed using Envelope Spectrum Analysis on the filtered signal. This stage is designed to identify characteristic fault frequencies, which are indicative of defects in rolling element bearings. The methodology includes computing the envelope of the filtered signal and analyzing its spectrum to detect fault-specific signatures.

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Envelope Spectrum Analysis is utilized to reveal characteristic fault frequencies hidden within the noise and other signal components. This technique is particularly effective for detecting faults such as spalls, cracks, and other anomalies in rolling element bearings by analyzing the amplitude modulation of the signal.

1. Envelope Extraction

The envelope of the filtered signal $s_{filtered}(t)$ is computed using the Hilbert transform. The Hilbert transform provides a method to obtain the analytic signal $s_{analytic}(t)$ from which the envelope can be derived.

The analytic signal $s_{analytic}(t)$ is given by:

$$s_{analytic}(t) = s_{filtered}(t) + j.\mathcal{H}\{s_{filtered}(t)\} \quad (16)$$

Where $\mathcal{H}\{\cdot\}$ denotes the Hilbert transform. The envelope $E(t)$ is then computed as the magnitude of the analytic signal:

$$E(t) = |s_{analytic}(t)| \quad (17)$$

This envelope $E(t)$ emphasizes the modulation patterns in the signal, highlighting fault-related features that are modulated at characteristic fault frequencies.

2. Envelope Spectrum Computation

The Fourier transform of the envelope signal $E(t)$ yields the envelope spectrum $E(f)$. This spectrum provides a frequency-domain representation of the modulating components in the signal.

The envelope spectrum is computed as:

$$E(f) = \mathcal{F}\{E(t)\} \quad (18)$$

Where $\mathcal{F}\{\cdot\}$ denotes the Fourier transform operation. The resulting spectrum $E(f)$ reveals peaks at frequencies corresponding to fault-related modulation.

3. Fault Frequency Identification

The envelope spectrum $E(f)$ is analyzed to identify significant peaks, which correspond to characteristic fault frequencies. These frequencies are associated with specific defects in rolling element bearings, such as:

- Outer Race Fault Frequency:

$$f_{outer} = \frac{N_{race}}{2} \cdot f_{rpm} \quad (19)$$

- Inner Race Fault Frequency:

$$f_{inner} = \frac{N_{race-1}}{2} \cdot f_{rpm} \quad (20)$$

- Rolling Element Fault Frequency:

$$f_{rolling} = \frac{N_{rolling}}{2} \cdot f_{rpm} \quad (21)$$

- Cage Fault Frequency:

$$f_{cage} = \frac{N_{cage}}{2} \cdot f_{rpm} \quad (22)$$

Where N_{race}, $N_{rolling}$, and N_{cage} are the number of rolling elements, races, and cage respectively, and f_{rpm} is the rotational frequency of the bearing.

4. Fault Diagnosis

The detected fault frequencies are compared with known fault signatures to diagnose the type and severity of the fault. This involves:

- ***Matching Peaks:*** Comparing the peaks in $E(f)$ with known fault frequencies to identify the type of defect.
- ***Amplitude Analysis:*** Evaluating the amplitude of the peaks to assess the severity of the fault.

By correlating the envelope spectrum peaks with theoretical fault frequencies and amplitudes, the fault type and severity are determined, facilitating accurate diagnosis of rolling element bearing conditions.

This methodology enhances the capability to accurately detect and diagnose faults in rolling element bearings, even in the presence of masking noise.

F. Classification for Fault Diagnosis

In addition to Envelope Spectrum Analysis, a simple classifier based on the log ratio of BPFI Amplitude to BPFO Amplitude is employed to enhance fault diagnosis. This classifier is designed to classify the type of bearing fault based on the log ratio feature derived from the vibration signals.

1. Feature Extraction for Classification

The log ratio feature is computed as:

$$IOLogRatio = \log\left(\frac{BPFI\ Amplitude}{BPFO\ Amplitude}\right) \quad (23)$$

This feature is derived from the amplitude values obtained from the training and test datasets.

2. Classifier Development and Validation

A simple rule-based classifier is used, with thresholds determined from the training data:

- If $IOLogRatio \leq -1.5$, classify as "Outer Race Fault."
- If $-1.5 < IOLogRatio \leq 0.5$, classify as "Normal."
- If $IOLogRatio > 0.5$, classify as "Inner Race Fault."

The performance of the classifier is validated using test data. Histograms of the log ratio feature for both training and test datasets are compared, showing consistent distributions and indicating effective generalization of the classifier.

3. Classification Results

The classifier shows perfect accuracy on the test data, demonstrating that the log ratio feature

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effectively distinguishes between different fault types. While this simple approach provides robust results, future work may involve more sophisticated classifiers by incorporating additional features and using advanced machine learning techniques to further enhance fault diagnosis capabilities.

IV. Simulation Results

A. Test Dataset

The test dataset used for validation consists of six files with varied bearing conditions:

- Normal Condition Data: 1 dataset representing fault-free bearings.
- Inner Race Fault Data: 2 datasets featuring faults in the inner race.
- Outer Race Fault Data: 3 datasets showcasing faults in the outer race.

This dataset [16] is processed to include additional features like BPFI Amplitude and BPFO Amplitude. The data is read, processed to extract relevant features, and assembled into a feature table for thorough evaluation of the classifier's performance. This comprehensive validation ensures the classifier's effectiveness across different fault scenarios and normal conditions.

B. Results

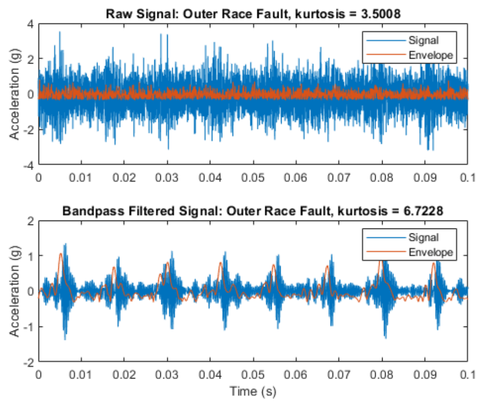

Figure 2: Effect of Bandpass Filtering on Signal Kurtosis and Envelope Spectrum

Figure 2 demonstrates the impact of bandpass filtering on the signal's kurtosis and the retrieval of modulated amplitude associated with an outer race fault. Top subplot displays the raw vibration signal and its envelope before filtering. The plot includes the raw signal and its envelope, with the kurtosis value indicated. This subplot illustrates the original characteristics of the signal and its envelope before any preprocessing. Bottom subplot shows the same signal after applying a bandpass filter, designed based on the kurtogram's optimal frequency band. The plot includes the filtered signal and its envelope, along with the updated kurtosis value. The enhancement in kurtosis indicates improved detection of the fault signature. The comparison highlights how bandpass filtering enhances the kurtosis of the signal, making the modulated amplitude of the fault more prominent and thus improving the sensitivity of envelope spectrum analysis for fault diagnosis.

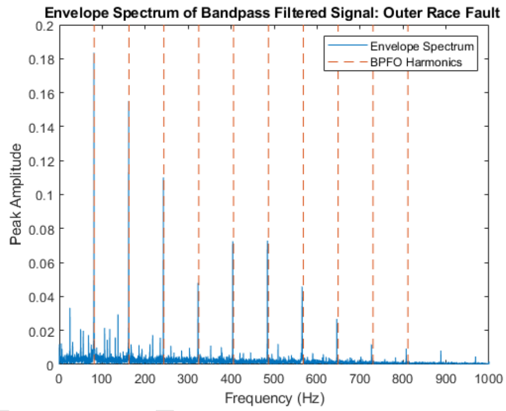

Figure 3: Envelope Spectrum of Bandpass Filtered Signal for Outer Race Fault

Figure 3 illustrates the frequency domain representation of the envelope spectrum after applying bandpass filtering to the raw signal, specifically for an outer race fault. The plot shows the envelope spectrum of the bandpass filtered signal. It displays the peak amplitude of the envelope signal against frequency, with a focus on frequencies up to 1000 Hz. The vertical lines indicate the BPFO and its harmonics. The figure demonstrates how bandpass filtering, guided by kurtogram and spectral kurtosis analysis, enhances the detection of fault-related features. The clear visibility of peaks at BPFO and its harmonics confirms the effectiveness of the preprocessing steps in isolating fault signatures from noise.

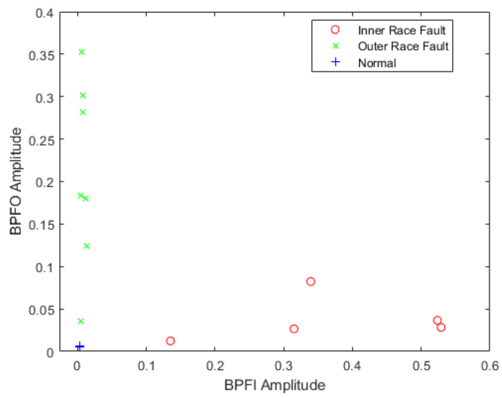

Figure 4: Feature Visualization and Histogram of Log Ratio

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Figure 4 displays a scatter plot of BPFI Amplitude versus BPFO Amplitude for various fault types, showing how these features differentiate between "Inner Race Fault," "Outer Race Fault," and "Normal" conditions. The plot reveals distinct clusters for each fault type, indicating that these amplitude features can effectively separate fault categories. To further analyze the discriminative power of these features, a new feature—the log ratio of BPFI to BPFO Amplitude—is introduced. The accompanying histogram visualizes the distribution of this log ratio across different fault types, highlighting its potential to enhance fault classification by capturing the relative strength of the BPFI and BPFO signals.

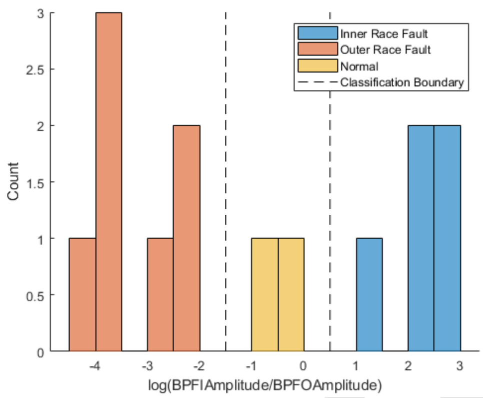

Figure 5: Histogram of Log Ratio Feature for Fault Classification

Figure 5 presents histograms of the log ratio of BPFI Amplitude to BPFO Amplitude, grouped by different fault types: "Inner Race Fault," "Outer Race Fault," and "Normal." The histograms reveal distinct distributions for each fault category, indicating that the log ratio is a useful feature for distinguishing between bearing conditions. A classification boundary is illustrated with a dashed vertical line at $\log\left(\frac{BPFI\ Amplitude}{BPFO\ Amplitude}\right)$ = -1.5 and 0.5, showing how the log ratio can be used to classify the fault type. Specifically, values ≤ -1.5 suggest an outer race fault, values between -1.5 and 0.5 indicate a normal condition, and values > 0.5 are associated with an inner race fault. This visualization demonstrates the effectiveness of the log ratio feature for bearing fault diagnosis.

Figure 6 presents histograms comparing the log ratio of BPFI Amplitude to BPFO Amplitude between training and test datasets for three bearing conditions: "Inner Race Fault," "Outer Race Fault," and "Normal." The histograms illustrate the distribution of the log ratio for each condition across both datasets, with training data shown in larger bins (0.5) and test data in smaller bins (0.1). The dashed vertical lines represent the classification boundaries used for fault diagnosis. The consistent distributions between training and test data indicate that the classifier derived from the log ratio feature effectively generalizes to unseen test data. The perfect accuracy of the naive classifier suggests that this simple feature-based approach is highly effective for fault detection in the given test scenarios. Further refinement and sophistication in classification could be achieved by incorporating additional features and advanced techniques.

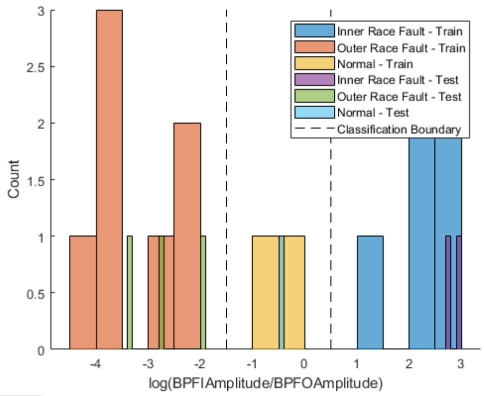

Figure 6: Comparison of Log Ratio Distribution between Training and Test Data for Bearing Fault Classification

V. Conclusion

The methodology developed in this paper marks a significant advancement in rolling element bearing fault diagnosis by effectively addressing the challenges posed by masking signals from other machinery components. The approach begins with meticulous signal preprocessing, employing wavelet transform and normalization to ensure data cleanliness and standardization, which are critical for accurate fault detection. This preprocessing step removes noise and normalizes signal amplitude, providing a solid foundation for subsequent analysis.

Following preprocessing, Kurtogram analysis reveals transient and non-Gaussian features within the signal, which are indicative of bearing faults. By utilizing Short-Time Fourier Transform (STFT) to compute kurtosis, the analysis highlights impulsive characteristics often associated with faults. Spectral Kurtosis further refines the focus on relevant frequency bands by emphasizing significant non-Gaussian behavior, isolating the most informative parts of the signal for detailed analysis.

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The methodology excels in selecting optimal frequency bands through a dual evaluation of kurtosis and spectral kurtosis, enhancing fault detection precision. Band-pass filtering isolates these critical frequency components, making them more prominent for subsequent analysis. Envelope Spectrum Analysis is then used to extract fault-specific frequencies from the filtered signal, enabling accurate diagnosis of bearing conditions. The introduction of a rule-based classifier, which uses the log ratio of BPFI to BPFO amplitudes, provides a simple yet effective method for fault classification. The classifier's validation with test data, showing consistent results and perfect accuracy, underscores the efficacy of combining traditional signal processing techniques with a straightforward classification method. This approach not only improves diagnostic accuracy but also establishes a precedent for integrating advanced signal processing with effective classification methods to tackle complex fault diagnosis challenges.

Future research should explore the inclusion of additional features and the application of more sophisticated machine learning algorithms to further enhance classification performance. Additionally, efforts to increase the robustness of the classifier and expand the methodology's applicability to a wider range of fault types and operational conditions are recommended. This work lays a solid foundation for advancing fault diagnosis in rolling element bearings, with potential for significant improvements through further refinements and innovations.

REFERENCES

[1] Gelman, L., Patel, T.H., Persin, G., Murray, B. and Thomson, A., 2023. Novel technology based on the spectral kurtosis and wavelet transform for rolling bearing diagnosis. International Journal of Prognostics and Health Management, 4(2).

[2] Udmale, S.S., Singh, S.K. and Bhirud, S.G., 2019. A bearing data analysis based on kurtogram and deep learning sequence models. Measurement, 145, pp.665-677.

[3] Hu, Y., Bao, W., Tu, X., Li, F. and Li, K., 2019. An adaptive spectral kurtosis method and its application to fault detection of rolling element bearings. IEEE Transactions on Instrumentation and Measurement, 69(3), pp.739-750.

[4] Kedadouche, M., Thomas, M. and Tahan, A.J.M.S., 2016. A comparative study between Empirical Wavelet Transforms and Empirical Mode Decomposition Methods: Application to bearing defect diagnosis. Mechanical Systems and Signal Processing, 81, pp.88-107.

[5] Plazenet, T., Boileau, T., Caironi, C. and Nahid-Mobarakeh, B., 2018, February. Signal processing tools for non-stationary signals detection. In 2018 IEEE International Conference on Industrial Technology (ICIT) (pp. 1849-1853). IEEE.

[6] Wang, Y., Xiang, J., Markert, R. and Liang, M., 2016. Spectral kurtosis for fault detection, diagnosis and prognostics of rotating machines: A review with applications. Mechanical Systems and Signal Processing, 66, pp.679-698.

[7] Sohaib, M., Kim, C.H. and Kim, J.M., 2017. A hybrid feature model and deep-learning-based bearing fault diagnosis. Sensors, 17(12), p.2876.

[8] Wang, R., Fang, H., Zhang, Y., Yu, L. and Chen, J., 2022. Low-rank enforced fault feature extraction of rolling bearings in a complex noisy environment: A perspective of statistical modeling of noises. IEEE Transactions on Instrumentation and Measurement, 71, pp.1-14.

[9] Udmale, S.S., Patil, S.S., Phalle, V.M. and Singh, S.K., 2019. A bearing vibration data analysis based on spectral kurtosis and ConvNet. Soft Computing, 23(19), pp.9341-9359.

[10] Hong, Y., Kim, M., Lee, H., Park, J.J. and Lee, D., 2019. Early fault diagnosis and classification of ball bearing using enhanced kurtogram and Gaussian mixture model. IEEE Transactions on Instrumentation and Measurement, 68(12), pp.4746-4755.

[11] Hussain, S. and Gabbar, H.A., 2014. Gearbox fault detection using real coded genetic algorithm and novel shock response spectrum features extraction. Journal of Nondestructive Evaluation, 33, pp.111-123.

[12] Mohanty, S., Gupta, K.K. and Raju, K.S., 2017. Adaptive fault identification of bearing using empirical mode decomposition–principal component analysis-based average kurtosis technique. IET Science, Measurement & Technology, 11(1), pp.30-40.

[13] Udmale, S.S., Nath, A.G., Singh, D., Singh, A., Cheng, X., Anand, D. and Singh, S.K., 2024. An optimized extreme learning machine-based novel model for bearing fault classification. Expert Systems, 41(2), p.e13432.

[14] Meng, Z., Liu, J., Liu, J., Li, J., Cao, L., Fan, F. and Yu, S., 2023. An improved variational mode decomposition method based on spectrum reconstruction and segmentation and its application in rolling bearing fault diagnosis. Digital Signal Processing, 141, p.104161.

[15] Song, S. and Wang, W., 2023. Early Fault Detection of Rolling Bearings Based on Time-Varying Filtering Empirical Mode Decomposition and Adaptive Multipoint Optimal Minimum Entropy Deconvolution Adjusted. Entropy, 25(10), p.1452.

[16] Test Dataset. Online available at: https://ieee-dataport.org/documents/bearing-dataset