

Extracting Sparse Periodic Fault Signatures from Noisy Signals in Rolling Element Bearings

Gürültülü Rulman Sinyallerinden Seyrek ve Periyodik Arıza Verilerinin Çıkarılması

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Öz

Bu çalışmada, rulmanlarda meydana gelen arızalara ait seyrek ve periyodik sinyal bileşenlerinin gürültülü gözlem verilerinden geri kazanımı incelenmektedir. Hedef sinyallerin darbeselliğini ve seyrekliğini artırmak amacıyla, yüksek mertebeden istatistiklerin (çarpıklık ve basıklık) optimizasyonu ile L_1 -normu minimizasyonu yöntemleri karşılaştırılmıştır. İlgilenilen sinyal, harmonik olarak ilişkili sinüs dalgalarının toplamı şeklinde modellenmiştir; bu optimizasyon fonksiyonlarının performansları, beyaz gürültü ve lineer bozulmanın bulunduğu ve bulunmadığı durumlarda değerlendirilmiştir. Elde edilen bulgular, gradyan tabanlı optimizasyonun istenmeyen bileşenleri bastırarak arıza kaynaklı periyodik darbeleri başarıyla geri kazandığını göstermektedir. Ayrıca sayısal deneyler, L_1 -normu minimizasyonunun, çarpıklık ve basıklık maksimizasyonuna kıyasla, seyrekliği artırmada daha üstün bir performans ve daha hızlı yakınsama sergilediğini doğrulamaktadır.

Anahtar kelimeler: Seyrek sinyal geri kazanımı, Gradyan arama optimizasyonu, Arıza teşhisi, Öznelik çıkarımı

Abstract

This study investigates recovering sparse, periodic fault signatures from noisy observations in rolling-element bearings. We compare optimizing higher-order statistics (skewness and kurtosis) with L_1 -norm minimization to enhance the impulsiveness and sparseness of the target signals. By modeling the signal of interest as a sum of harmonically related sinusoids, these objective functions are evaluated in the presence and absence of additive noise and linear distortion. The results demonstrate that gradient-based optimization successfully recovers defect-related periodic impulses by suppressing undesired components. Furthermore, numerical experiments confirm that L_1 -norm minimization provides superior performance and faster convergence in promoting sparsity compared to skewness- and kurtosis-maximizing methods.

Keywords: Sparse signal recovery, Gradient search optimization, Fault diagnosis, Feature extraction

1. Introduction

Periodic and sparse impulse trains, representing either periodic excitation or a response to such an event, carry valuable information about phenomena occurring in the process being monitored. Such impulsive appearances are studied in seismic wave propagation [1], acoustic signals [2], power-line communications [3-4], mechanical vibrations [5-6], and teletraffic and hydrology [7]. For example, such sparse signals could arise from high-energy impacts due to a defect in a rolling bearing as an almost-periodic event [8] or be generated and transferred via a modulator to excite a system, as in ultrasound [9-12].

In an experimental setting where random noise and disturbances corrupt the source signal, extracting impulsive events from noisy observations remains challenging. By exploiting the side information at hand - the hypothesis imposed on the physical or statistical characteristics of the source signal - the undesired components can be suppressed to recover the information-rich signal. After recovery, the resulting output may indicate a fault in the observed system, for instance, in rolling bearings widely used in rotating machinery [13-14]. These fault signatures possess certain characteristics, such as impulsiveness and sparseness, that can be enhanced by optimizing measures of merit (objectives) such as higher-order statistics (HOS) and the L_1 -norm, respectively.

The periodic impulses are modeled and simulated to study and compare recovery methods for vibration analysis of rolling bearings, thereby building a robust predictive maintenance scheme [15]. A periodic impulse train representing an outer race defect will be the signal of interest, which is disturbed by an unknown linear propagation path (transfer function) and additive noise. Such a sparse spike train can be extracted by enhancing impulsiveness via skewness- and kurtosis-maximization [6] or by promoting sparseness via L_1 -norm minimization [16]. In addition to this, modeling the periodic impulses as a sum of harmonically related sinusoids will enable a comparison of the ability of these measures as sparsity-promoting functions on a real Fourier basis consisting of mutually orthogonal components [17].

The main contribution of this study is the comparative evaluation of higher-order statistics (skewness and kurtosis)

and L_1 -norm minimization, conducted strictly within the framework of a real Fourier basis specifically designed for bearing fault diagnosis. While previous studies have independently explored HOS and sparsity for signal recovery, this paper uniquely models the fault-induced periodic impulses as a weighted sum of harmonically related sinusoids to benchmark these objective functions. Specifically, this study contributes by demonstrating that L_1 -norm minimization not only yields a better approximation of the pristine sparse signal by enforcing a more rapid decay of harmonic weights, but it also achieves significantly faster convergence compared to traditional skewness and kurtosis maximization in the presence of noise and linear distortion.

2. Extracting Fault Signatures by Optimizing a Measure of Merit

2.1. Background And Prior Work

In a problem setting without access to the signal of interest or a training signal, impulsive signatures can be extracted using a *blind adaptation* scheme. In this approach, a linear filter is adapted stepwise to optimize an objective that promotes a specific measure of merit of the source signal while suppressing the undesired components that mask it. In condition-based maintenance (CBM) of rolling element bearings, the underlying failures manifest as sparse, periodic impacts with (trivially) asymmetric or heavy-tailed probability density functions (PDFs). These statistical attributes can be quantified by scale-invariant 3rd and 4th order moments, respectively. By maximizing these objectives, periodic impulses can be recovered blindly from noisy vibration signals [5-6, 18]. Because these measures involve multi-model surfaces that can cause local convergence issues, previous studies have investigated their convergence properties for different signal classes [6, 19-21].

In another attempt to recover fault signatures by enhancing sparsity, local convergence issues associated with the above-mentioned objectives can be avoided under certain circumstances. Sparseness in a discrete-time vector $\mathbf{x}_n \in \mathbb{R}^N$ can be quantified by L_0 -norm $\|\mathbf{x}_n\|_0 = \#\{i: x_i \neq 0\}$ that can be approximated (convex relaxation) in a signal recovery framework (from noisy observations) by L_1 -norm $\|\mathbf{x}_n\|_1 = \sum_{i=1}^N |x_i|$ allowing linear programming [22-23]. Then, by minimizing the L_1 -norm of an observed signal that is defined on a proper basis, sparseness, and therefore the temporal resolution of spikes can be enhanced to reveal fault signatures [16].

The methods briefly mentioned so far are all implemented via gradient search: maximizing HOS is steepest ascent [24], whereas L_1 -norm minimization is steepest descent. Sparsity enhancement is generally studied under basis pursuit (BP) [25-27], with sufficient conditions for successful recovery of sparse signals given in [28], where the uniqueness of sparse representation [27] on orthonormal bases was discussed in [29] and objectives promoting sparsity stronger than L_1 were given in [30].

It is worth mentioning recovering sparse spike trains buried in noise [23, 31], for instance, using a wavelet packet dictionary and comparing against matching pursuit (MP) at varying levels of defect severity for inner and outer races [16]. L_1 -norm minimization was utilized to reveal the impulse

response of flaws in non-destructive evaluation (NDE) of materials [32], in deconvolution of seismic traces in the presence of noise [33], and in recovering lamb waves to remove multipath interference in ultrasonic testing [34]. In [35], impulsive signatures were enhanced using a normalized objective L_1/L_2 and compared with kurtosis maximization, and in [36], L_1 -norm minimization was employed on a subset of the spectrum of noisy vibrations from defective structures. Since the geometry of rolling bearings is known a priori [37], defect frequencies (given the rotational speed) can be estimated and used in [38] to detect mechanical faults.

2.2. Notation and Signal Model

This study focuses on outer-race defects to simplify the presentation. The deterministic, non-stationary, and periodic

discrete-time source signal $s_n \triangleq \sum_{m=-\infty}^{\infty} \delta[n - mT]$ with period

T , discrete-time index n , and the Kronecker delta function $\delta[n]$ is a sparse impulse train representing the impacts [38-40] arising from defective rolling bearings. This signal (picket fence) can be represented as a sum of harmonically related sinusoids [41] by a model with an implicit Fourier series expansion. By expanding the Fourier series to separate the DC component, the model then becomes

$$s_n = \frac{1}{T} + \frac{2}{T} \sum_{r=-\infty}^{\infty} \cos[r\omega_0 n], \text{ where } \omega_0 = \frac{2\pi}{T} \text{ is the ball pass}$$

frequency of a defect. In practical vibration analysis, piezoelectric sensors (accelerometers) are inherently AC-coupled and naturally reject the DC component ($1/T$). Furthermore, to ensure algorithmic stability and eliminate any static drift, the observed signals are explicitly pre-processed to be zero-mean. Consequently, the DC term is safely omitted from the analytical dictionary, and the basis matrix $\Psi[n, \omega_0]$ is constructed starting from the first fundamental harmonic ($r=1$). In practice, the physical sensor used for data acquisition has a finite bandwidth, limiting the observable high-frequency components. Consequently, the maximum number of harmonics N that can be accurately captured is strictly bounded by the Nyquist limit associated with the system's sampling frequency ω_s , formulated as $N < \omega_s/2\omega_0$, where ω_0 is the fundamental ball-pass frequency of the defect. This will produce a signal with a sparse representation in the given (orthogonal) real Fourier basis containing a certain number of impacts within an observation window. Through the mechanical structure represented by a linear time-invariant (LTI) system with impulse response h_n , the fault impacts s_n undergo amplitude and phase distortion, producing the distorted signal $\mathbf{x}_n$. The final observed signal $\mathbf{u}_n$ is then formed by the addition of measurement noise $\mathbf{z}_n$, expressed mathematically as $\mathbf{u}_n = \mathbf{x}_n + \mathbf{z}_n$. As established, this can be represented in matrix form as $\mathbf{u}_n = \mathbf{\Theta} + \mathbf{z}_n$. A more detailed analysis of the modeling and construction is available in [6]. Here, the emphasis (and thus novelty) is on the matrix notation that will be given now for the sparse enhancement of fault-related periodic impulses.

Assuming the source signal is sufficiently sparse, a concise representation in the proper basis enables sparse reconstruction of the fault impacts from noisy vibrations. Here, an asymmetric or heavy-tailed distribution (impulsiveness) does not necessarily imply sparseness; however, it aligns with this signal model.

The noisy observations will be synthesized as a weighted sum of harmonics. Let M denote the number of samples in the observation window, and N denote the number of considered harmonics. For a discrete-time index $n=0, 1, \dots, M-1$ spanning the observation window, we define the harmonic basis row vector $\Psi[n, \omega_0] \in \mathbb{R}^{1 \times N}$ evaluated at time n as defined in Eq. 1:

$$\Psi[n, \omega_0] = [\cos(\omega_0 n), \cos(2\omega_0 n), \dots, \cos(N\omega_0 n)] \quad (1)$$

The signal of interest, $\mathbf{s}_n$, representing the equally spaced and scaled periodic impacts, can be expressed in vector-matrix notation as defined in Eq. 2:

$$\mathbf{s}_n = \Psi[n, \omega_0] \mathbf{c} \text{ where } \mathbf{c} = \left[\frac{2}{T}, \frac{2}{T}, \dots, \frac{2}{T} \right]^T \in \mathbb{R}^N \quad (2)$$

As the signal travels through the mechanical structure, it is convolved with the linear time-invariant (LTI) system characterized by the impulse response h_n . The frequency response of this transmission path is mathematically defined by its Discrete-Time Fourier Transform (DTFT) as $H(e^{j\omega}) = \sum_{m=-\infty}^{\infty} h_m e^{-j\omega m}$. This system introduces linear distortion, filtering the harmonic components. Consequently, the parameter vector $\boldsymbol{\theta} = [\alpha_1, \alpha_2, \dots, \alpha_N]^T \in \mathbb{R}^N$ represents the modified weights of the harmonics, such that the initial amplitude of each r -th harmonic is scaled by the magnitude response of the transmission path at that specific harmonic frequency, yielding $\alpha_r = \frac{2}{T} |H(e^{jr\omega_0})|$. The resulting distorted signal $\mathbf{x}_n = \Psi[n, \omega_0] \boldsymbol{\theta}$ and the final noisy observation $\mathbf{u}_n$ are modeled as defined in Eq. 3:

$$\mathbf{u}_n = \mathbf{x}_n + \mathbf{z}_n \quad (3)$$

where the parameter vector $\boldsymbol{\theta} = [\alpha_1, \alpha_2, \dots, \alpha_N]^T \in \mathbb{R}^N$ represents the modified weights of the harmonics such that $\alpha_r = \frac{1}{T} |H(e^{jr\omega_0})|$. The term $\mathbf{z}_n$ represents the additive background noise inherent to the measurement environment, bounded by $\|\mathbf{z}_n\|_2 \leq \epsilon$.

This mathematical model with an implicit dictionary is the analytical approach that will allow us to seek the $\tilde{\boldsymbol{\theta}} = [\tilde{\alpha}_1, \dots, \tilde{\alpha}_N]^T$ one that produces the sparsest signal in both the absence and presence of noise. By doing so, we will assess the optimized functions for their ability to increase sparsity. Then, the aim will be to extract the impulses corrupted by an LTI transfer function and additive noise. The following section presents a simulation experiment to compare the methods for extracting fault signatures.

The proposed analytical approach uses a fixed, predefined dictionary constructed from the bearing's known kinematics. Specifically, the basis matrix $\Psi[n, \omega_0]$ serves as a deterministic dictionary of harmonically related sinusoids. Unlike "dictionary learning" frameworks, where atoms are adaptively learned from data, our dictionary is analytically constructed to reflect the physical periodicity of expected fault signatures, ensuring that the optimization process focuses solely on finding the sparsest weight vector $\boldsymbol{\theta}$ within this established physical basis.

The processing has been performed in the context of blind deconvolution, treating mechanical vibration as a sum of harmonics to analyze the convergence properties of skewness [6, 42]. A similar study on seismic data used a normalized sparsity measure [43]. In addition to extracting impulses from the given signal model, this application can also be seen as a harmonic content enhancement by L_1 -regularization [44], as it was done by skewness maximization in [45].

3. Sparse Enhancement of Fault Signatures

3.1. Comparison of Sparsity-Enhancing Functions in the Absence of Noise and Linear Distortion

This section compares functions optimized to enhance sparse fault signatures. As a sparsity measure, the expectation of the functions is to produce weights that are rapidly decreasing in the parameter vector $\boldsymbol{\theta}$, imposing a quick decay on them [46]. In other words, the more evenly distributed the total energy among the α -coefficients, the less sparse the signal is produced.

The following analyses are primarily fundamental and theoretical. Rather than proposing a competitive algorithm to outperform current state-of-the-art diagnostic tools, the aim is to investigate the mathematical behavior, coefficient decay, and convergence properties of specific sparsity-promoting functions when applied strictly to a real Fourier basis representation.

3.1.1. Maximizing HOS via Gradient Ascent on $\Psi[n, \omega_0] \boldsymbol{\theta}$

The scale-invariant p^{th} order moment of a zero-mean discrete-time signal $\mathbf{u}_n$ is mathematically defined as

$$M_p(\mathbf{u}_n) = \frac{E[\mathbf{u}_n^p]}{(E[\mathbf{u}_n^2])^{p/2}}. \text{ Based on this general definition,}$$

Skewness (S) and Kurtosis (K) correspond to the 3rd-order ($p = 3$) and 4th-order ($p = 4$) moments, respectively. Thus, substituting $p=3$ into Eq. 4 yields Skewness $S(\mathbf{u}_n) = M_3(\mathbf{u}_n)$, whereas substituting $p=4$ into Eq. 5 yields Kurtosis $K(\mathbf{u}_n) = M_4(\mathbf{u}_n)$:

$$S(\mathbf{u}_n) = \frac{E\{\mathbf{u}_n^3\}}{(E\{\mathbf{u}_n^2\})^{3/2}} \quad (4)$$

$$K(\mathbf{u}_n) = \frac{E\{\mathbf{u}_n^4\}}{(E\{\mathbf{u}_n^2\})^2} \quad (5)$$

The complete mathematical derivations of the gradients for Skewness and Kurtosis, including their step-by-step formulations and local convergence proofs, have been extensively established in prior work [6]; therefore, they are omitted here for brevity. However, for the practical numerical implementation of the simulation experiments, it is crucial to explicitly define how the statistical expectation operator $E[\cdot]$ is computed. In our discrete-time finite sample versions, the expectation is calculated as an unbiased time average over the observation window of length M . Specifically, the p^{th} order expectation of a discrete-time signal vector $\mathbf{v}$ is defined as in Eq. 6:

$$E[v^p] \approx \frac{1}{M} \sum_{n=0}^{M-1} v_n^p \quad (6)$$

Algorithmic Presentations

While highly efficient, state-of-the-art algorithms such as FastICA or the Fast Kurtogram exist in the literature for HOS maximization, we deliberately chose standard steepest ascent/descent algorithms with fixed step sizes for all objective functions in this study. The primary goal is not to benchmark the computational sophistication of the solvers, but rather to conduct a controlled, baseline comparison of the inherent mathematical topography (e.g., convexity, gradient steepness, and local optima) of the objective functions themselves. By confining all methods to the same basic gradient-based search mechanism within the fixed Fourier basis, the inherent convergence behavior and coefficient-decay properties dictated strictly by the chosen metrics (HOS vs. L_1 -norm) can be isolated and evaluated fairly.

To maximize the higher-order statistics (HOS) and minimize the L_1 -norm, we use iterative gradient-based approaches. Algorithm 1 and Algorithm 2 summarize the procedures.

Algorithm 1: HOS (Skewness/Kurtosis) Maximization via Gradient Ascent

1. **Initialize:** Initialize: Define starting parameter vector θ_0 as a uniform weight vector $\theta_0 = [1, 1, \dots, 1]^T$. Set step size $\mu > 0$. Set iteration index $k = 0$.
2. **Normalize:** Scale the initial vector to unit norm: $\theta_0 = \frac{\theta_0}{\|\theta_0\|_2}$.
3. **Repeat** until convergence (e.g., $\|\theta_{k+1} - \theta_k\|_2 < \delta$ or maximum iterations reached):
 - a. Compute the target signal estimate: $\hat{u}_k = \Psi[n, \omega_0] \theta_k$.
 - b. Calculate the gradient of the objective function (Skewness or Kurtosis): $\nabla M(\theta_k)$.
 - c. Update the parameter vector via steepest ascent: $\theta_{k+1} = \theta_k + \mu \nabla M(\theta_k)$.
 - d. Enforce unit energy constraint: $\theta_{k+1} = \frac{\theta_{k+1}}{\|\theta_{k+1}\|_2}$.
 - e. Update iteration index: $k = k + 1$.
4. **Output:** Optimal parameter vector $\tilde{\theta} = \theta_k$.

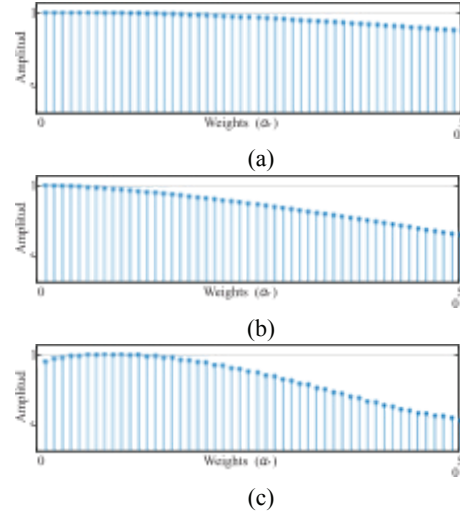


Figure 1. (a) The $\tilde{\alpha}$ -weights (scaled to have unit amplitude) in the vector $\tilde{\theta}$ after kurtosis maximization, (b) after skewness maximization, and (c) L_1 -norm minimization as formulated in (7).

For a numerically tractable algorithm, the norm of the parameter vector is constrained to be unity, which implies

$$\|\theta\|_2^2 = \theta^T \theta = \sum_{r=1}^N \alpha_r^2 = 1. \text{ Scale-invariant 3rd (skewness) and}$$

4th (kurtosis) order moments will be maximized to produce a sparse signal, both in the absence and presence of noise, to compare their performances against L_1 -norm minimization.

3.1.2. Minimizing L_1 -norm via Gradient Descent on $\Psi[n, \omega_0] \theta$

Sparseness is promoted by minimizing the L_1 -norm, which is defined as the sum of the absolute values of the vector components. For the parameter vector θ :

$$\|\theta\|_1 = \sum_{r=1}^N |\alpha_r| \quad (7)$$

Algorithm 2: L_1 -Norm Minimization via Gradient Descent / Subgradient Method

1. **Initialize:** Define starting parameter vector as a zero vector $\theta_0 = [0, 0, \dots, 0]^T$. Set step size $\mu > 0$. Set regularization parameter λ . Set $k = 0$.
2. **Formulate Lagrangian Objective:**

$$J(\theta) = \|\theta\|_1 + \frac{1}{\lambda} \sum_{n=0}^{M-1} (\Psi[n, \omega_0] \theta_k - u_n)^2.$$
3. **Repeat** until convergence:

Compute the gradient of the quadratic error term:

$$\nabla E(\theta_k) = \frac{2}{\lambda} \sum_{n=0}^{M-1} \Psi[n, \omega_0]^T (\Psi[n, \omega_0] \theta_k - u_n).$$
 - a. Compute the subgradient of the L_1 -norm: $\text{sgn}(\theta_k)$.
 - b. Update the parameter vector via steepest descent: $\theta_{k+1} = \theta_k - \mu (\text{sgn}(\theta_k) + \nabla E(\theta_k))$.
 - c. Update iteration index: $k = k + 1$.
4. **Output:** Optimal sparse parameter vector $\tilde{\theta} = \theta_k$.

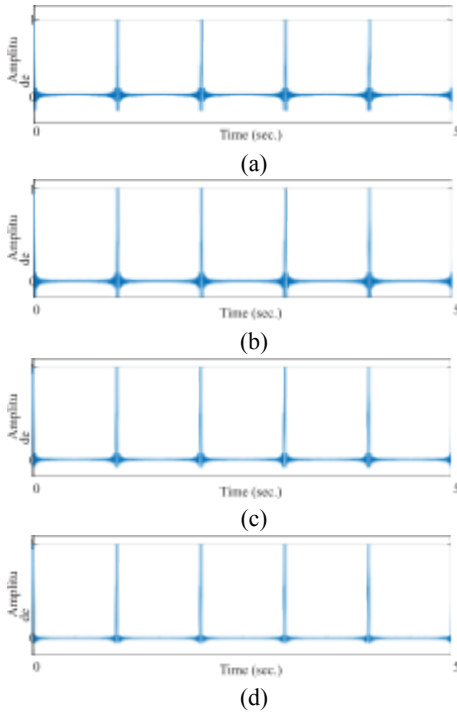


Figure 2. (a) The simulated source signal with $N = 50$ and $f_0 = 1$ Hz, (b) the generated signal after kurtosis maximization, (c) after skewness maximization, and (d) L_1 -norm minimization, where the signals are scaled to have unit amplitude. The relative improvement in time resolution after optimizing each function is evident.

3.1.3. Simulations

The performance and relevance of the functions in promoting sparsity can be compared in the absence of noise ($z_n = 0$) and linear distortion (trivial h_n) by seeking the weights producing the sparsest solution on the given signal model. The Θ that maximizes the skewness and kurtosis, or minimizes the L_1 -norm, should produce a compressible signal (or, with a stricter notion, sparse) on the basis that the atoms (columns) are scaled by $\tilde{\alpha}_r$ with a magnitude that decays according to a power law. In this context, a source signal is simulated as a sum of 50 equally strong harmonics ($N = 50$), resulting in spikes that are 1 sec. long. apart ($f_0 = 1$ Hz) as shown in Fig. 2a. Maximizing the kurtosis and skewness until convergence produced Θ settings as shown in Figure 1a and Figure 1b, respectively, whereas minimizing the L_1 -norm resulted in a setting as depicted in Figure 1c. Here, to solve problem (7) designed on the signal model in (1), CVX was utilized, a package for specifying and solving convex programs [49, 50].

3.1.4 Simulation Parameters and Practical Implications

To ensure the reproducibility of the numerical experiments, the key hyperparameters utilized in the simulations are explicitly defined and justified in Table 1. The selection of these hyperparameters directly impacts the recovery performance, computational complexity, and real-time feasibility of the methods. For instance, increasing the filter length L or the number of harmonics N improves the temporal resolution of the extracted impulses but significantly increases the computational cost per iteration.

Table 1. Summary of Simulation Parameters

Parameter	Symbol	Value	Justification
Number of Harmonics	N	50 (clean) / 15 (noisy)	Chosen based on presumed sensor bandwidth limits and required signal resolution.
Fundamental Frequency	f_0	1 Hz / 50 Hz	Selected to emulate typical outer-race bearing fault frequencies (BPFO).
Step Size (Skewness)	μ_s	10^{-2}	Empirically tuned to balance convergence speed and algorithmic stability.
Step Size (Kurtosis)	μ_k	10^{-3}	Empirically tuned; required a smaller step than skewness to prevent divergence.
Number of Iterations	k_{max}	600	Determined empirically as the threshold where HOS algorithms reached a steady-state optimum.
FIR Filter Length	L	225	Chosen to encompass enough impact periods for accurate statistical estimation.
Regularization Param.	λ	0.5	Tuned to achieve an optimal trade-off between strict sparsity and data fidelity.
Window Length	M	3 seconds (depending on the sampling frequency)	Defined to capture enough mechanical cycles within the observation timeframe.

Furthermore, the step sizes (μ) dictate the stability of the gradient search; a step size that is too large causes the adaptation to diverge, while a conservatively small step size drastically increases the required number of iterations,

delaying diagnosis. Notably, the L_1 -norm minimization demonstrated convergence in substantially fewer iterations (e.g., 9 iterations) compared to HOS maximization (600 iterations), highlighting its better computational efficiency for

potential real-time condition monitoring. Initialization also plays a critical role in these algorithms. For HOS maximization (Algorithm 1), which navigates non-convex multi-modal surfaces, the parameter vector was initialized uniformly as $\theta_0 = [1, 1, \dots, 1]^T / \sqrt{N}$ to provide an unbiased starting point with unit energy. Conversely, for the L_1 -norm minimization (Algorithm 2), the parameter vector was initialized as a zero vector ($\theta_0 = 0$). Because the L_1 -norm formulation poses a convex optimization problem, it inherently guarantees convergence to the global optimum regardless of the starting point. Furthermore, when the adaptation is shifted from the harmonic weights (θ) to a time-domain FIR filter ($\mathbf{f}$) in Section 3.2, the filter is initialized as a center-spike (Dirac delta) sequence (e.g., $\mathbf{f}_0 = [0, \dots, 0, 1, 0, \dots, 0]^T$) to pass the initial signal unaltered before gradient updates commence.

Theoretical Sensitivity and Robustness: While an exhaustive empirical robustness analysis is beyond the scope of this study, the theoretical implications of parameter variations are critical for practical implementation. In gradient-based HOS maximization, the step size (μ) is the most sensitive parameter; slight perturbations can drastically alter the convergence landscape, with excessively large values causing rapid divergence, particularly at lower Signal-to-Noise Ratios (SNR). Conversely, the L_1 -norm minimization relies heavily on the regularization parameter (λ), which strictly dictates the trade-off between absolute sparsity and data fidelity. If λ is set too high in a low-SNR environment, the algorithm may oversmooth the signal, suppressing true physical effects along with noise. Generally, as background noise increases (lower SNR), all discussed methods theoretically require larger observation windows or longer FIR filter lengths to maintain reliable gradient estimates, albeit at the cost of significantly increased computational overhead.

In accordance with these results, it can be concluded that the coefficients α_r . Scaling the harmonics does not cause them to decay rapidly after HOS maximization; rather, the disparity between them decreases with r . On the other hand, seeking the sparsest solution as in (7) produced weights that decay relatively more quickly, making it a more proper measure of sparsity. Synthesizing the signals on the given basis with the resulting parameter vector θ^* shows the improvement in the sparsity in the output signals. The ripples due to the finite number of harmonics (limited bandwidth) are suppressed, resulting in the sparsest signal after L_1 -norm minimization as illustrated in Figure 2d. Skewness-maximizing output, as in Figure 2c, yields a better approximation than kurtosis-maximizing output, as in Figure 2b.

Such a performance assessment was also done on different functions [46], where kurtosis was normalized, satisfying more constraints than its original counterpart. As mentioned before, the purpose is to find a sparsity-enhancing function that yields a parameter setting with a few strong coefficients that characterize the entire signal on a proper basis. The method in (7) appears to better satisfy this expectation than maximizing the HOS in the model of (1). The next section will investigate the case where $z_n \neq 0$.

3.2. Comparison Of Sparsity-Enhancing Functions in the Presence of Noise and Linear Distortion

In case the source signal is subject to amplitude and phase distortion and corrupted by measurement noise, the goal is to approximately invert the disturbing system by promoting sparsity [51, 52] from noisy measurements [48, 53, 54]. To extract sparse periodic impulses arising from defects, the observed signal u_n is iteratively filtered by a finite impulse response (FIR) filter to maximize the higher-order statistics objective functions as defined in Eq. 4 and Eq. 5. Similarly, promoting sparseness is achieved by minimizing the L_1 -norm as defined in Eq. 7. The processing is accomplished as in Sec. III-A1 in an iterative manner (with index k), where the gradient is estimated with respect to the filter f_k^n instead of θ^k .

The output signal $v_n = \mathbf{f}^T \mathbf{u}_n$ is expected to provide conclusive evidence of the existence of a defect, where the adaptation process suppresses the undesired components. Here, the constraint on the filter vector is still valid $\|\mathbf{f}^k\|_2 = 1$, as was the case for the parameter vector of weights θ^k .

For the same purpose of recovering the signal of interest by restoring its structure, sparseness can also be promoted in noisy observations by minimizing the L_1 -norm, as defined in (7). To conduct experiments with these methods, the source signal was simulated as a sum of 15 harmonics ($N = 15$) with a fundamental frequency of $f_0 = 50$ Hz to form a sparse impulsive signal representing an outer race defect as shown in Figure 3a. To simulate the linear distortion introduced by the mechanical transfer function h_n , each r^{th} harmonic component of the source signal was subjected to arbitrary amplitude attenuation and phase shifts. Specifically, the intermediate distorted sequence x_n was numerically generated as

$$x_n = \sum_{r=1}^N \alpha_r \cos(r\omega_0 n + \gamma_r), \text{ where the weights } \alpha_r \in (0, 1]$$

and phase shifts $\gamma_r \in [0, 2\pi)$ represent the magnitude and phase response of the transmission path, respectively. Following this linear degradation, additive white Gaussian noise z_n was introduced to yield the final observed signal $u_n = x_n + z_n$, as illustrated in Figure 3b.

For this illustrative simulation, the additive white Gaussian noise z_n was scaled to yield a Signal-to-Noise Ratio (SNR) of approximately 8.5 dB. This noisy signal is processed by an FIR filter maximizing the kurtosis of its output iteratively with a fixed step size $\mu = 10^{-3}$, resulting in a signal as shown in Figure 6a, whereas maximizing the skewness with a fixed step size $\mu = 10^{-2}$ produced an output as in Figure 6b. In both cases, the algorithms were iterated for 600 iterations at equal filter lengths, allowing the HOS to converge.

In any sparsifying dictionary, the source signal's sparsity depends on the rotation speed, provided we use a constrained local observation window. This creates a relation between sparseness and rotation speed, which can further be analyzed for diagnostics of slowly rotating machinery.

After noting this remark, the result of promoting sparseness in u_n via the objective formulated in (7) is shown in Figure 6c, where the defect-related impulses are recovered after 9 iterations. The parameter vector θ^* forming the sparse output signal $v_n = \Psi[n, \omega_0] \theta^*$ from the real Fourier basis consisted of almost equally strong weights α_r , unlike the case in the absence of noise and linear distortion.

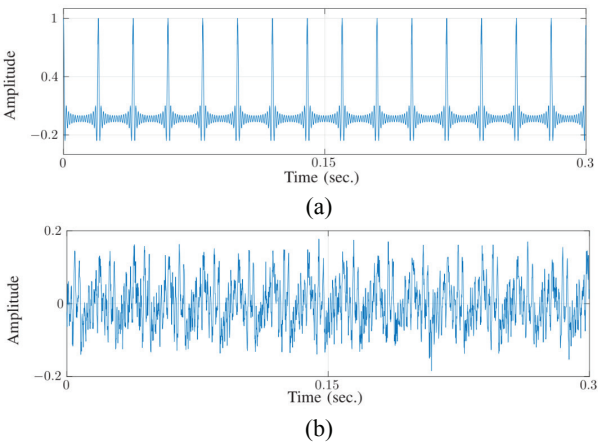


Figure 3. (a) The simulated source signal s_n as a sparse impulse train and (b) the observed signal u_n after linear distortion and additive noise.

To provide an objective, quantitative assessment of recovery performance beyond visual inspection, the Mean Squared Error (MSE) and Pearson correlation coefficient (r) were calculated between the impulsive source signal (s_n) and the final reconstructed outputs (v_n). Table 2 summarizes the test-case results.

Table 2. Quantitative Performance Metrics for Signal Recovery

Optimization Method	MSE	Correlation Coefficient (r)
Kurtosis Maximization	0.00523	0.9248
Skewness Maximization	0.00519	0.9317
L_1 -norm Minimization	0.00483	0.9428

These metrics align with the visual findings, demonstrating that the L_1 -norm minimization not only converges in significantly fewer iterations but also yields a reconstructed signal that mathematically correlates more strongly with the original sparse impulse train, minimizing the residual error compared to the HOS-based approaches.

Noise Robustness and Breakdown Limits: To rigorously evaluate the noise tolerance of the compared objective functions, additional simulations were conducted across a wide range of Signal-to-Noise Ratios (SNR = [5, 0, -5, -10, -15] dB) under purely additive noise conditions. The evaluation metrics, Mean Squared Error (MSE) and Pearson correlation coefficient (r), are visually presented in Figure 4 and Figure 5, respectively. The results reveal a stark contrast in robustness between the methods. As the background noise begins to overpower the defect-induced impacts, higher-order statistics experience catastrophic breakdowns. Specifically, kurtosis maximization collapses below 0 dB, showing a sharp MSE increase (Figure 4a) and dropping to near-zero correlation (Figure 5a) because 4th-order moments exponentially amplify noise variance. Skewness maximization exhibits a similar, albeit slightly softer, degradation (Figure 4b

and Figure 5b). Conversely, the L_1 -norm minimization demonstrates exceptional resilience, maintaining a minimal MSE (Figure 4c) and a correlation coefficient above 0.82 (Figure 5c) even at extreme noise levels (-15 dB). These breakdown limits theoretically confirm that while HOS methods require strict pre-whitening in noisy environments, L_1 -norm minimization provides a vastly superior and more stable approximation of sparse fault signatures under heavy background noise.

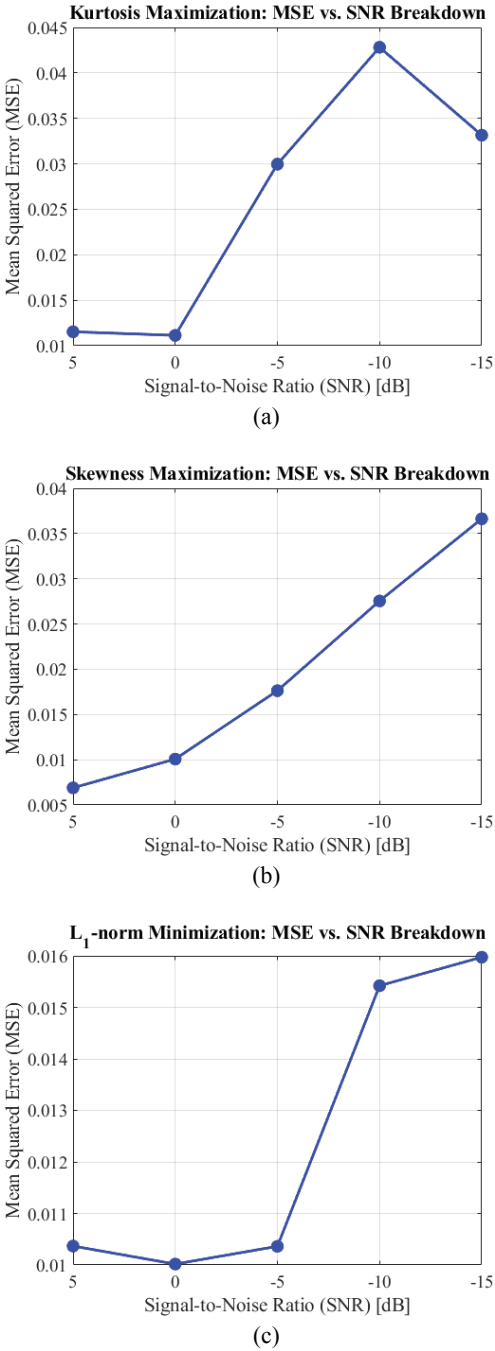


Figure 4. The breakdown limits of the objective functions evaluated by Mean Squared Error (MSE) under varying Signal-to-Noise Ratios (SNR): (a) Kurtosis maximization, (b) Skewness maximization, and (c) L_1 -norm minimization.

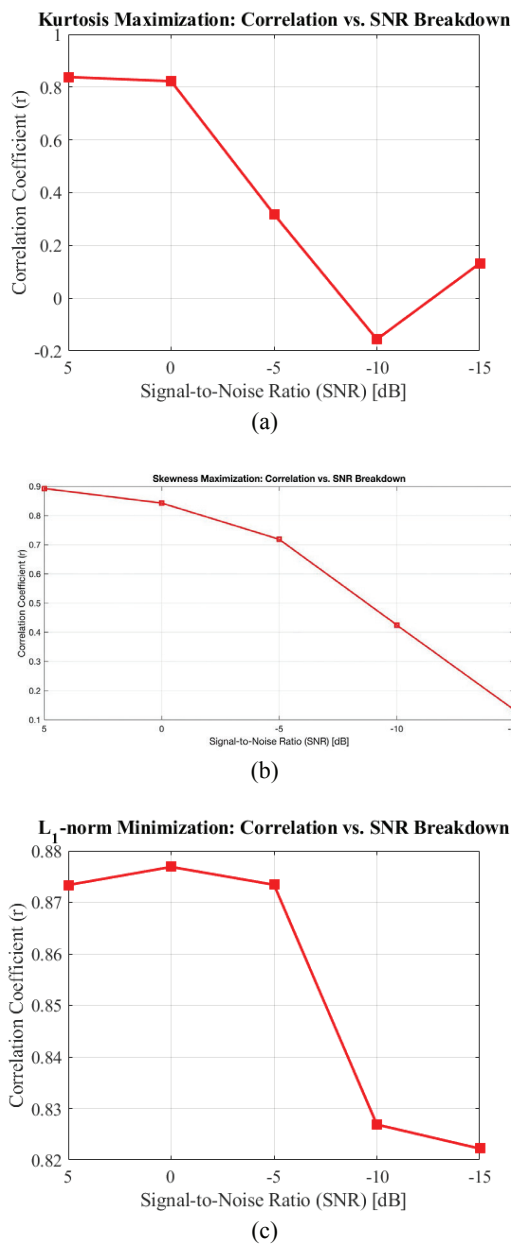


Figure 5. The breakdown limits of the objective functions evaluated by Pearson correlation coefficient (r) under varying Signal-to-Noise Ratios (SNR): (a) Kurtosis maximization, (b) Skewness maximization, and (c) L_1 -norm minimization.

3.3. Discussion on Scope and Applicability

While this study primarily uses an outer race defect model to demonstrate the theoretical framework, the underlying hypothesis of sparse, periodic impulses naturally extends to other localized faults, such as inner race or rolling-element defects. However, practitioners should note that inner race faults often exhibit amplitude modulation due to the rotating load zone. This modulation introduces sidebands that slightly deviate from the strictly uniform harmonic weights modeled in our pristine signal s_n , though the core sparsity assumptions remain valid.

Regarding the selection of optimization methods, L_1 -norm minimization is highly advantageous-and recommended-when the structural kinematics (e.g., shaft speed and bearing geometry) are known a priori. In such cases, the basis matrix $\Psi[n, \omega_0]$ can be accurately constructed, and the algorithm will robustly handle high noise levels and strong linear distortion while guaranteeing global convergence. Conversely, HOS-based blind deconvolution (such as skewness maximization) might still be preferable in purely exploratory or "blind" scenarios. If the exact machinery kinematics are unknown, an adaptive FIR filter that maximizes HOS does not require a predefined frequency basis to extract an impulsive signature, making it a flexible, albeit mathematically riskier, alternative, given the potential for local convergence issues.

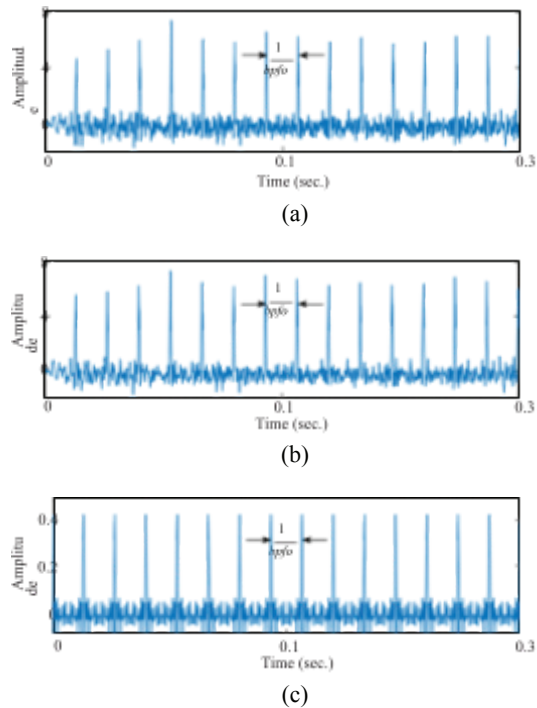


Figure 6. (a) The output signal v_n after kurtosis maximization, (b) after skewness maximization, and (c) after L_1 -norm minimization, zoomed in and marked with outer race ball-pass period, the inverse of the ball-pass frequency outer race ($1/bpfo$).

4. Conclusion

This study provided a theoretical and numerical comparison of Higher-Order Statistics (skewness and kurtosis) and L_1 -norm minimization for recovering sparse periodic fault signatures in rolling element bearings. Using a real Fourier basis as an analytical dictionary, we showed that both methods could suppress noise and compensate for linear distortion, revealing the underlying impact trains.

However, key performance differentiators were identified. Our numerical experiments L_1 -norm minimization achieves a statistically superior approximation of the true sparse signal, with a more rapid decay of harmonic weights compared to HOS-based methods. Crucially, the computational L_1 -norm approach converged in significantly fewer iterations (typically under 10) than the 600 iterations required for HOS

maximization to reach steady state. Furthermore, while HOS objectives are prone to local convergence issues depending on initialization, L_1 -norm minimization offers robust global convergence properties within the established basis. These findings suggest that for predictive maintenance regimes where bearing kinematics are known, L_1 -based sparsity enhancement provides a more efficient and mathematically sound framework for automated fault diagnosis.

A notable limitation of the current study is the absence of experimental validation using real-world measured data. To strictly isolate and mathematically compare the convergence dynamics and coefficient decay of the optimization functions on a real Fourier basis, this study relied on a controlled synthetic framework. Consequently, the performance of the proposed approach on benchmark empirical data remains untested. Validating the proposed L_1 -norm minimization framework on publicly available datasets-such as the SU RF Sensing Lab, CWRU, or Paderborn bearing datasets-constitutes a primary direction for future work. Applying this analytical dictionary approach to such real signals would be highly feasible in subsequent studies, provided that the complex, time-varying structural transfer paths and non-Gaussian mechanical background noises inherent to physical machinery can be adequately decoupled or robustly integrated into the measurement model.

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