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Application of the SCSSA-VMD Denoising Method in Natural Gas Pipeline Leakage Detection

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Abstract: The decomposition performance of variational mode decomposition (VMD) on natural gas pipeline leakage pressure signals is highly sensitive to the subjective selection of its key parameters: the number of modes K and the penalty factor α. To address this issue, this paper proposes an enhanced sparrow search algorithm (SSA) that integrates sine/cosine searching and Cauchy mutation strategies, referred to as SCSSA, for optimizing the VMD parameter combination. Experimental results demonstrate that the SCSSA-optimized VMD method significantly outperforms denoising approaches based on the standard SSA and particle swarm optimization (PSO) in optimizing VMD parameters. Specifically, the proposed method achieves a higher signal-to-noise ratio (SNR) and a lower root mean square error (RMSE) in the denoised signal, effectively enhancing the denoising performance.

Keywords: Natural gas pipeline; Leakage detection; Sparrow search algorithm (SSA); Variational mode decomposition (VMD); Signal denoising

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1. Introduction

The detection of pipeline leakage signals serves as a crucial element in ensuring the safety and integrity of oil and gas transportation systems. These leakage signals generally display highly non-stationary and nonlinear behavior, making them inherently complex and difficult to analyze. Moreover, they are frequently contaminated by multiple forms of noise arising from diverse sources. Key contributors include internal fluid dynamic phenomena, such as turbulence induced by high-velocity flows and irregular pressure fluctuations, as well as external environmental disturbances, for instance, mechanical vibrations from pumping equipment or electromagnetic interference from nearby industrial activities. Additionally, sensor-related inaccuracies and instrumental limitations further contribute to the overall noise profile. The convergence and superposition of such noise components often mask the intrinsically weak and transient characteristics of leakage signals, which in turn substantially undermines the reliability of subsequent feature extraction processes and degrades the performance of leakage detection algorithms. As a result, the development of efficient, robust, and adaptive denoising techniques is an essential prerequisite for enhancing the discernibility of leakage signatures and improving the accuracy of detection models when handling complex real-world pipeline data.

In this context, variational mode decomposition (VMD) has emerged as a prominent technique for processing such signals since its introduction [1]. VMD is a fully non-recursive, adaptive signal decomposition method. Its core principle involves constructing and solving a constrained variational optimization problem to adaptively decompose the original signal into a set of sub-signal components with specific center frequencies and limited bandwidth, known as intrinsic mode functions (IMFs). Compared to methods like empirical mode decomposition (EMD), VMD is grounded in a rigorous mathematical framework, which effectively suppresses mode mixing and offers excellent time-frequency localization properties. This makes it particularly suitable for extracting transient components of non-stationary signals from an intensely noisy background [2,3]. In the processing of pipeline leakage pressure signals, VMD can separate the weak pressure fluctuations induced by a leak from the complex noise background, providing a high-quality data foundation for subsequent fault diagnosis [4].

However, the performance of VMD is highly contingent upon the preset values of its key parameters, primarily the number of decomposition modes, K and the penalty factor (or bandwidth constraint parameter), α. An inappropriately small K value leads to insufficient decomposition, causing different signal components to alias within the same mode. Conversely, an excessively large K value results in redundant and spurious modes, leading to over-decomposition [5]. The parameter α controls the estimated bandwidth of each IMF, influencing the smoothness of the mode's center frequency and bandwidth. Suboptimal parameter configuration can significantly degrade the decomposition efficacy of VMD, thereby impacting the accuracy of denoising and feature extraction [6].

To address this limitation, researchers have proposed multiple strategies for VMD parameter optimization and hybrid denoising. For instance, Xiao *et al.* proposed an improved VMD method combined with a threshold algorithm for partial discharge signal denoising. By optimizing the parameters, they enhanced the decomposition specificity and effectively eliminated noise-dominant modes through subsequent thresholding [7]. Wu *et al.*, focusing on surface electromyography (sEMG) signal noise, introduced an improved sparrow search algorithm (ISSA) to adaptively optimize VMD parameters. This was combined with a second-generation wavelet threshold applied to the IMFs. This approach enhanced the parameter self-adaptation capability of VMD and achieved favorable denoising results [8]. These research ideas also provide valuable references for pipeline leakage signal processing. Furthermore, some scholars have employed fitness functions such as sample entropy and envelope entropy, combined with swarm intelligence optimization algorithms (e.g., particle swarm optimization, genetic algorithm) to automatically determine the optimal parameter combination for VMD, further improving its performance in specific applications [9,10].

In summary, when confronting the challenges posed by the non-stationary, nonlinear, and noise-contaminated nature of pipeline leakage signals, VMD demonstrates significant application potential due to its solid theoretical foundation and adaptive decomposition capability. Integrating VMD with other optimization algorithms and signal processing techniques (e.g., threshold denoising, wavelet transform) to construct intelligent, parameter-optimized VMD hybrid denoising models represents a crucial research direction for improving the accuracy and reliability of pipeline leakage detection.

Despite extensive research on pipeline signal denoising, existing methods still have limitations. This study aims to develop a more efficient and robust leakage signal denoising algorithm by leveraging an optimized VMD approach, thereby improving detection accuracy and reliability, and providing enhanced technical support for the safe operation of natural gas pipelines.

2. Theoretical background and methodology

2.1. Principle of variational mode decomposition

VMD, introduced in 2014, is a fully non-recursive signal processing technique. Its core principle involves iteratively searching for the optimal solution of a variational model to adaptively decompose a complex signal into a discrete number of mode components a discrete set of band-limited (IMFs) with specific sparsity properties and central frequencies. The VMD method effectively overcomes endpoint effects and mode mixing problems common in other decomposition techniques. For a detailed mathematical formulation, readers are referred to the seminal work [1].

2.2. Enhanced sparrow search algorithm

The standard sparrow search algorithm (SSA) mimics the foraging behavior and anti-predation strategies of sparrows. While SSA benefits from a simple structure, few parameters, and rapid convergence, it often suffers from diminished population diversity in the later stages of optimization, leading to a high probability of converging to local optima [11].

To overcome these limitations, a multitude of enhanced variants of the salp swarm algorithm (SSA) have been put forward in recent years. These modifications generally concentrate on augmenting population diversity via mechanisms like adaptive parameter adjustment, hybrid operators combined with other meta-heuristic algorithms, or the incorporation of local search strategies. For example, certain studies have integrated chaotic mapping into the initialization stage to generate more uniformly distributed initial solutions. In contrast, others have incorporated mutation operators inspired by genetic algorithms to perturb stagnant populations and evade local optima. Moreover, adaptive weight strategies that dynamically balance exploration and exploitation capabilities during the optimization procedure have demonstrated potential in enhancing the algorithm's global search performance.

Notwithstanding these advancements, numerous existing improved SSA versions still encounter challenges when dealing with complex high-dimensional optimization problems or maintaining stable convergence rates across various types of objective functions. Consequently, further research is necessary to develop more robust and versatile SSA variants that can effectively address the diverse optimization requirements of real-world applications, such as engineering design, machine learning parameter tuning, and resource allocation problems.

To mitigate these limitations, this paper employs an enhanced SSA (SCSSA) that incorporates a sine/cosine search strategy and a Cauchy mutation operator, as proposed [12]. The SCSSA procedure is outlined as follows:

(1) Step 1: Initialization: Initialize the sparrow population size N, maximum iterations $Iter_{max}$, discoverer proportion P_D, vigilance proportion P_S, vigilance threshold R_2, safety value ST. Randomly generate the initial positions of the sparrows as follows:

$$X_{i,j}(i = 1,2,\cdots,N;\ j = 1,2,\cdots,D,\ D \text{ is the problem dimension})$$

(2) Step 2: Fitness evaluation: Calculate the fitness value for each sparrow based on the objective function. Identify the best fitness f_g(best position X_{best}) and the worst fitness f_w(worst position X_{worst}) in the current population;

(3) Step 3: Discoverer update: The discoverers (the best $P_D \times N$ Nsparrows) update their positions using a strategy incorporating a nonlinear weight and a sine/cosine mechanism:

If $R_2 < ST$(no threat from natural predators):

$$X_{i,j}^{t+1} = \omega \cdot X_{i,j}^{t} + r_1^{'} \cdot \sin r_2 \cdot \left| r_3 \cdot X_{\text{best}} - X_{i,j}^{t} \right| \quad (1)$$

where ω is a nonlinear decreasing weight factor $r_1^{'} = 1 \times \left(1 - \left(\frac{t}{Iter_{max}}\right)^{\eta}\right)^{\frac{1}{\eta}} (\eta = 1.5)$, $r_2, r_3 \in [0,2\pi]$ are random numbers.

If $R_2 \geq ST$(existence of predator threat), the r_2 in **Eq. (1)** is replaced by the r_2.

(4) Step 4: Follower update: The remaining sparrows (followers) update their positions using a Cauchy mutation strategy to enhance global search ability and escape local optima:

$$X_{i,j}^{t+1} = X_{\text{best}}^{t} + \text{Cauchy}(0,1) \otimes X_{\text{best}}^{t} \quad (2)$$

where Cauchy(0,1) is a random number from the standard Cauchy distribution, and ⊗ denotes element-wise multiplication.

(5) Step 5: Vigilantes update: For vigilantes (sparrows with fitness values at the tail of the population $P_S \times N$), position updates are performed under different scenarios:

If $f_i > f_g$(sparrow is at the edge of the group):

$$X_{i,j}^{t+1} = X_{\text{best}}^{t} + \beta \cdot \left| X_{i,j}^{t} - X_{\text{best}}^{t} \right| \quad (3)$$

where β is a step size control coefficient following a normal distribution.

If $f_i = f_g$(sparrow is in the center of the group):

$$X_{i,j}^{t+1} = X_{i,j}^{t} + k \cdot \frac{\left| X_{i,j}^{t} - X_{\text{worst}}^{t} \right|}{(f_i - f_w) + \varepsilon} \quad (4)$$

where $k \in (0,1)$, $\varepsilon = 10^{-50}$, is the minimum value to avoid a denominator of 0.

(6) Step 6: Population update: Merge the updated positions of discoverers, followers, and vigilantes. Recalculate the fitness of all sparrows and select the best N sparrows to form the new population;

(7) Step 7: Termination check: If the maximum iteration count $Iter_{max}$ is reached, output the optimal solution; otherwise, return to Step 2.

2.3. SCSSA-optimized VMD parameter selection

Selecting an appropriate fitness function is critical for guiding the SCSSA towards optimal VMD parameters (K, α). Pipeline leakage signals are typically nonlinear and non-stationary. Envelope entropy is highly sensitive to impulse components within such signals, making it a suitable candidate [13]. However, relying solely on envelope entropy can lead to IMFs with high purity but potential frequency aliasing. To address this, an orthogonal index is incorporated into the fitness function penalize mode mixing, effectively avoiding frequency overlapping problem and ensuring the rationality of decomposition structure.

The orthogonal index quantifies the degree of orthogonality between different IMFs, with higher values indicating less mode mixing. By combining envelope entropy and the orthogonal index, the fitness function can simultaneously minimize the complexity of the decomposed signals and maximize the independence between IMFs. This hybrid fitness function not only enhances the sensitivity to the impulse characteristics of pipeline leakage signals but also ensures the structural integrity of the decomposition results, laying a solid foundation for the subsequent accurate extraction of leakage features. In practical applications, the weights assigned to envelope entropy and the orthogonal index in the fitness function can be adjusted according to the specific characteristics of the pipeline and the environmental noise level, allowing the SCSSA to adaptively search for the optimal VMD parameters under different working conditions.

3. Experimental setup and analysis

3.1. Experimental data and parameters

The experimental pipeline was constructed from seamless steel with an outer diameter of 108 mm, a wall thickness of 4.5 mm, and a total length of approximately 100 meters. The operating pressure ranged from 0.5 MPa to 2.0 MPa. A leakage orifice with a diameter of 1 mm was simulated [14]. The leakage pressure signals used in this study are derived from the publicly available dataset provided by. The parameter search spaces for VMD were set as K∈ [2, 10] and α∈ [500, 5000]. The SCSSA population size was set to 30, with a maximum of 50 iterations.

3.2. Signal decomposition and denoising process

The SCSSA (Slime Cossinidae Swarm Algorithm) was utilized to determine the optimal parameter combination for the VMD process, which was identified as K = 8 and α = 1496. By applying VMD with these specifically optimized parameters to the noisy pipeline leakage signal, the method adaptively and effectively decomposed the original signal into eight distinct Band-Limited Intrinsic Mode Functions (BLIMFs). As clearly illustrated in **Figure 1**, each of these eight BLIMF components captures and represents information from different and specific frequency ranges present within the complex noisy signal, thereby facilitating a more detailed and structured analysis of the underlying data characteristics.

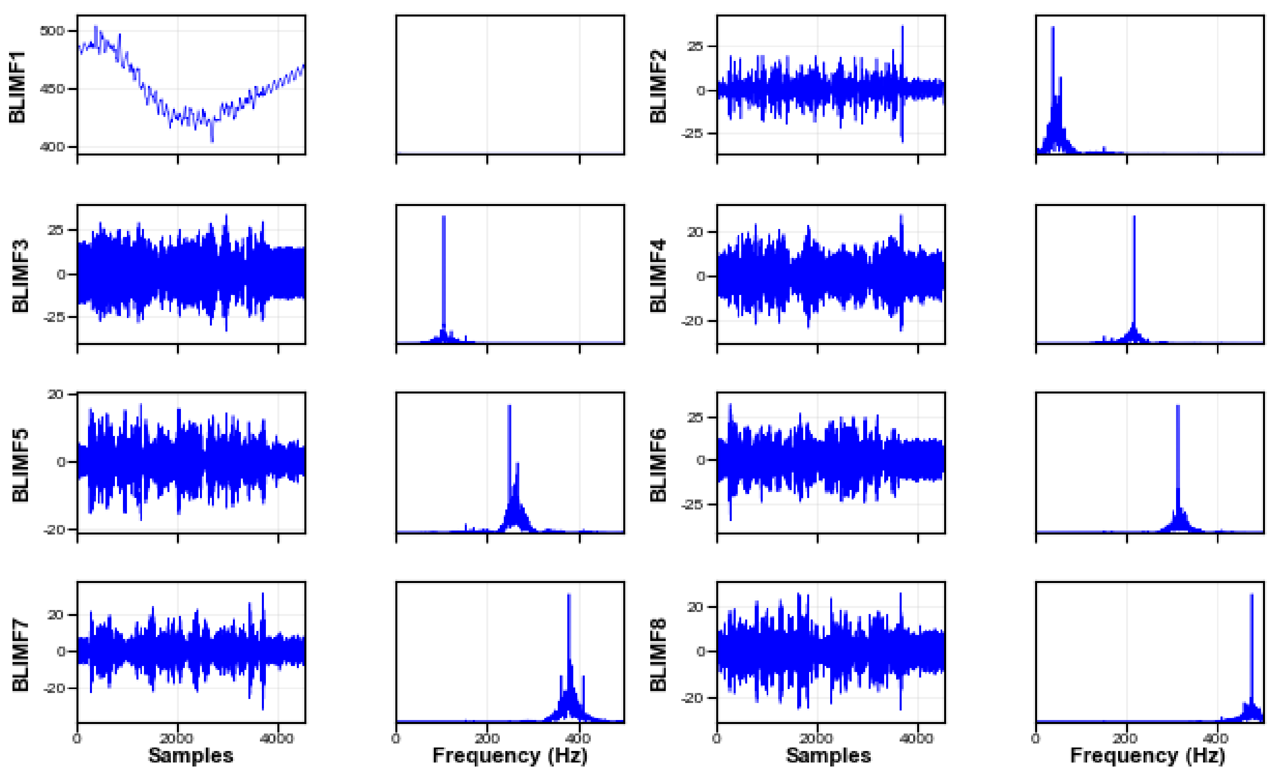

Figure 1. Time-frequency representations of BLIMF component.

Subsequent filtering of these BLIMFs was performed based on their correlation with the original signal, energy distribution, and frequency characteristics. BLIMFs strongly correlated with leakage features (e.g., representing pressure transient events) and possessing significant energy were retained. BLIMFs dominated by high-frequency noise were discarded. The denoised signal was reconstructed by summing the selected relevant BLIMFs. The comparison between the original signal and the denoised signal is shown in **Figure 2**. The visual comparison between the original signal and the denoised signal further confirms the effectiveness of the proposed method, showing a smoother waveform that retains the essential leakage-induced pressure variations.

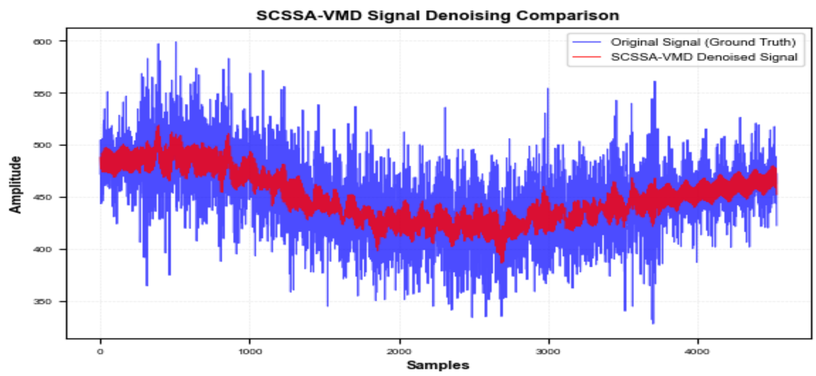

Figure 2. Comparison of original and denoised signals.

3.3. Results and comparative analysis

The denoising performance was quantitatively evaluated using signal-to-noise ratio (SNR) and root mean square error (RMSE). Higher SNR and lower RMSE values indicate superior denoising performance. The proposed SCSSA-VMD method was compared against two established optimization algorithms for VMD parameter tuning: the standard SSA-VMD and PSO-VMD.

As shown in **Table 1**, the SCSSA-VMD method achieved the highest SNR value of 24.490 dB and the lowest RMSE of 0.0996 among the three algorithms. In contrast, the SSA-VMD method obtained an SNR of 24.1588 dB and an RMSE of 0.1035, while the PSO-VMD method had the lowest SNR of 23.914 dB and the highest RMSE of 0.1065. These results clearly demonstrate that the proposed SCSSA-VMD method outperforms both the standard SSA-VMD and PSO-VMD in terms of denoising performance. The superior performance of SCSSA-VMD can be attributed to its enhanced ability to optimize the VMD parameters K and α. Specifically, the SCSSA-VMD method selected a K value of 8 and an α value of 1496, which are different from the values chosen by the other two algorithms. The higher K value might allow the method to better decompose the signal into more intrinsic mode functions, capturing more detailed information and thus improving the denoising effect. Meanwhile, the optimized α value could help in balancing the trade-off between the sparsity and smoothness of the decomposed components, leading to a more effective noise reduction. The quantitative comparison through SNR and RMSE metrics provides solid evidence that the SCSSA-VMD method is a more effective approach for VMD parameter tuning in denoising applications.

Table 1. Performance comparison of different denoising algorithms

Optimization algorithm	K	α	SNR (dB)	RMSE
SCSSA-VMD	8	1496	24.490	0.0996
SSA-VMD	3	3102	24.1588	0.1035
PSO-VMD	3	3652	23.914	0.1065

The SCSSA-VMD algorithm achieved the most optimal parameter combination, resulting in the highest SNR and the lowest RMSE. This indicates its superior ability to effectively separate noise from the underlying leakage signal while preserving critical diagnostic information.

4. Conclusion

This study successfully addressed the sensitivity of VMD to subjective parameter selection in pipeline leakage signal denoising by introducing an enhanced SCSSA for automatic parameter optimization. The SCSSA incorporates sine/cosine searching and Cauchy mutation to improve global exploration and avoid local optima. Experimental results demonstrate that the SCSSA-VMD method significantly outperforms traditional optimization approaches like SSA and PSO, achieving superior denoising performance quantified by higher SNR and lower RMSE. The proposed method effectively enhances the accuracy of pipeline leakage detection, contributing to improved safety and reliability in natural gas pipeline operations. Future work will focus on validating the method across a wider range of leakage scenarios and pipeline conditions.

Disclosure statement

The authors declare no conflict of interest.

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