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Fractal-Entropy-Guided–Adaptive Signal Reconstruction for Non-Stationary Biomedical and Communication Systems

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Abstract

This paper presents a novel fractal-entropy-guided–adaptive signal reconstruction (FEG–ASR) framework designed for accurate processing of non-stationary signals in biomedical and communication systems. The proposed approach integrates fractal dimension analysis with entropy-based feature evaluation to capture the intrinsic complexity and irregularity of time-varying signals. By dynamically adapting reconstruction parameters based on fractal entropy measures, the method effectively separates noise from meaningful signal components while preserving critical information. The framework employs a multi-resolution decomposition strategy combined with adaptive filtering to enhance signal clarity and robustness under varying noise conditions. Experimental validation on electrocardiogram (ECG) signals and wireless communication datasets demonstrates superior performance in terms of signal-to-noise ratio improvement, reconstruction accuracy, and computational efficiency compared to conventional techniques such as wavelet-based and empirical mode decomposition methods. Moreover, the suggested framework demonstrates improved adaptability to various signal environments, rendering it appropriate for managing highly non-linear and complex datasets. By integrating fractal and entropy features, computational redundancy is reduced, which allows for faster convergence and enhances the capability of real-time implementation. The proposed model shows strong potential for real-time applications, including medical diagnostics and reliable data transmission in dynamic environments. Overall, the FEG–ASR framework provides a scalable and intelligent solution for next-generation signal processing challenges.

Keywords: Fractal entropy, adaptive signal reconstruction, non-stationary signals, biomedical signal processing, ECG analysis, communication systems, noise reduction, multi-resolution analysis, signal decomposition, intelligent filtering

INTRODUCTION

Non-stationary signal processing has emerged as a critical area in modern electronics and data analysis because many real-world signals exhibit time-varying statistical properties. Unlike stationary signals, whose characteristics remain constant over time, non-stationary signals, such as biomedical recordings and communication waveforms, are highly dynamic and complex. The effective processing of these signals requires advanced analytical techniques that can capture transient features, abrupt changes, and non-linear patterns. Applications in areas such as electrocardiogram (ECG) monitoring, speech processing, and wireless communication systems rely heavily on the accurate reconstruction and interpretation of such signals. Biomedical and communication signals present significant challenges owing to their inherent variability, noise contamination, and multi-component nature. In biomedical

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applications, signals such as ECG or electroencephalogram (EEG) are often corrupted by motion artifacts, baseline drift, and environmental interference. Similarly, communication signals are affected by channel noise, fading, and interference from other sources. These issues complicate the extraction of meaningful information and reduce the reliability of downstream analysis. Furthermore, the non-linear and non-stationary nature of these signals makes conventional linear processing techniques insufficient. Traditional signal reconstruction methods, such as Fourier transform, wavelet transform, and empirical mode decomposition (EMD), have been widely used to analyze non-stationary signals. However, these techniques often suffer from limitations, such as poor adaptability, sensitivity to noise, and lack of precision in capturing complex signal dynamics. Fourier-based methods assume signal stationarity, while wavelet-based approaches require careful selection of basic functions. Although adaptive, the EMD can experience mode mixing and instability. These shortcomings highlight the need for more robust and intelligent reconstruction frameworks. The integration of fractal analysis and entropy measures offers a promising solution for addressing the complexities of non-stationary signals. The fractal dimension quantifies the geometric complexity and self-similarity of the signals, whereas the entropy measures capture the randomness and information content. By combining these two perspectives, it is possible to develop adaptive reconstruction strategies that respond dynamically to signal variations. This hybrid approach enables improved noise discrimination and feature preservation in the images. This study proposes a novel fractal-entropy-guided–adaptive signal reconstruction (FEG–ASR) framework for enhanced processing of non-stationary signals. The key contributions of this study include the development of a hybrid fractal entropy feature extraction mechanism, an adaptive parameter tuning strategy, and a multi-resolution reconstruction model. The proposed method demonstrates improved accuracy, robustness, and computational efficiency compared with conventional techniques, making it suitable for real-time biomedical and communication applications.

Figure 1 presents a flowchart block diagram of the proposed fractal-entropy-guided–adaptive signal reconstruction framework designed for non-stationary biomedical and communication systems. The process begins with two primary inputs: the original signal and a noisy input signal, which represent real-world corrupted data. These signals are processed alongside two critical analytical components: fractal dimension estimation and entropy evaluation, which extract the complexity and randomness features of the signal, respectively.

The fractal dimension captures self-similarity and structural variations, whereas entropy quantifies uncertainty and information content. These parameters are then used to guide the adaptive step size adjustment block, which dynamically tunes the learning or convergence rate of the system. The optimized step size was fed into the adaptive signal reconstruction algorithm, enabling effective noise filtering and high-fidelity signal reconstruction.

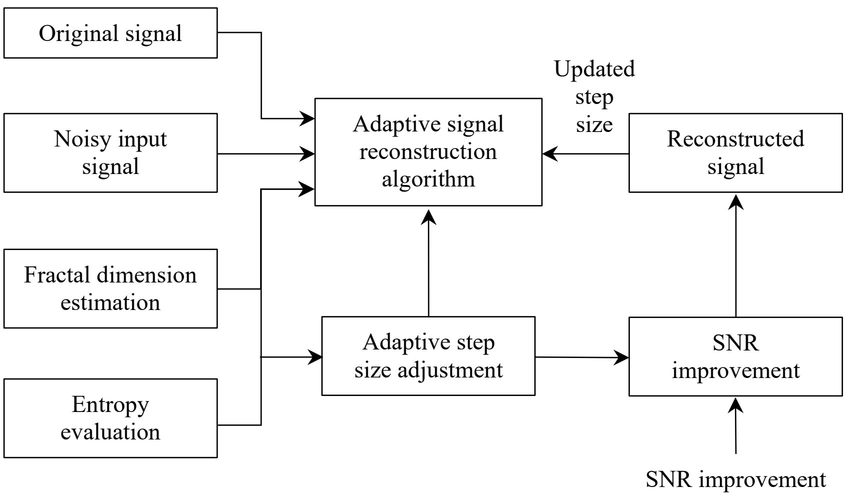

Figure 1. Flowchart of fractal-entropy-guided–adaptive signal reconstruction system.

The output of this block is a reconstructed signal that closely approximates the original signal. Additionally, the system evaluates performance through signal-to-noise ratio (SNR) improvement, indicating enhanced signal quality after reconstruction. The overall flow demonstrates a closed-loop adaptive mechanism in which the signal characteristics continuously influence reconstruction efficiency, ensuring robustness in handling highly non-stationary and noisy environments.

LITERATURE REVIEW

Conventional and advanced approaches for non-stationary signal reconstruction have been extensively explored in recent years, with a focus on improving denoising accuracy, adaptability, and feature preservation. Saulig et al. (2022) proposed a block-adaptive Rényi entropy-based denoising method that enhances signal clarity by dynamically adjusting entropy thresholds, demonstrating improved performance for non-stationary signals under varying noise conditions [1]. Daqrouq and Alharbey (2025) introduced a modified scaled adaptive wavelet transform tailored for biomedical signals, achieving superior time-frequency localization and reduced distortion compared to traditional wavelet methods [2]. Niu et al. (2025) developed a local entropy optimization-based adaptive demodulation transform that effectively captures transient features in mechanical non-stationary signals and improves signal interpretability [3].

Akkaya (2025) investigated optimization-driven wavelet denoising strategies in electrical power systems, highlighting their enhanced robustness against noise and system disturbances [4]. Narmada and Shukla (2023) combined wavelet denoising with deep learning and meta-heuristic optimization to remove EEG artifacts, achieving higher accuracy and adaptability in complex biomedical environments [5]. Yue et al. (2023) proposed a hybrid denoising framework integrating ensemble EMD, EMD, and wavelet packet techniques, resulting in improved ECG signal reconstruction and noise suppression [6]. Chen et al. (2024) utilized a convolutional denoising autoencoder with a transformer encoder to eliminate mixed noise in ECG signals, demonstrating superior feature retention and generalization capability [7]. Tao et al. (2024) developed a refined self-attention transformer model for arrhythmia detection, showcasing enhanced signal representation and classification performance [8].

Ramana et al. (2025) introduced a hybrid denoising approach that combined wavelet decomposition and neural network-based thresholding, which significantly improved the signal quality and reduced the reconstruction error [9]. Mishra et al. (2022) implemented customized convolutional neural networks for ECG denoising and analysis, achieving notable improvements in signal fidelity and diagnostic accuracy [10]. Qin et al. (2022) proposed an entropy-based multiscale fuzzy measure approach for fault diagnosis, demonstrating its robustness in cross-domain signal analysis [11]. Ghosh et al. (2020) evaluated wavelet-based decomposition techniques for phonocardiogram signals and confirmed their effectiveness in noise reduction and feature extraction [12]. Xie et al. (2021) applied non-linear algorithms for frequency parameter detection in track circuits, emphasizing the improved precision in non-stationary environments [13]. Gu et al. (2021) analyzed the non-linear characteristics of complex circuits, contributing to a better understanding of signal distortions in power electronics [14]. Fu et al. (2022) proposed a non-linear dynamic measurement method using data mining techniques, highlighting the importance of adaptive models in handling complex signal behaviors [15].

Despite these advancements, existing methods often suffer from limitations, such as inadequate adaptability, high computational complexity, and insufficient integration of signal complexity measures. Most approaches rely on either entropy or transform-based techniques independently, lacking a unified framework that simultaneously captures structural complexity and randomness.

Therefore, there is a clear research gap in developing a hybrid fractal-entropy-guided–adaptive reconstruction model capable of providing robust, efficient, and real-time processing of non-stationary signals.

PROPOSED FRACTAL-ENTROPY-GUIDED FRAMEWORK (FEG–ASR)

The proposed fractal-entropy-guided–adaptive signal reconstruction (FEG–ASR) framework is designed to effectively process and reconstruct non-stationary signals by integrating fractal dimension modeling with entropy-driven feature extraction and adaptive optimization. Mathematical modeling of the fractal dimension plays a central role in capturing the intrinsic geometric complexity and self-similarity of signals. In this study, the fractal dimension is estimated using techniques such as Higuchi's or Katz's method, which quantifies signal irregularity over multiple scales. These measures enable the precise characterization of abrupt transitions and non-linear fluctuations in biomedical and communication signals. Entropy measurement was employed to evaluate the randomness and information content of the signal. Various entropy metrics, including Shannon, Rényi, and sample entropies, were used to extract discriminative features that reflect signal variability and uncertainty. The fusion of the fractal dimension and entropy creates a robust feature space that provides a comprehensive representation of both the structural complexity and stochastic behavior. This dual-feature mechanism enhances the ability to distinguish between noise and meaningful signal components, forming the foundation for adaptive reconstruction. The extracted features are further used to guide the reconstruction process by dynamically adjusting the filtering thresholds and decomposition parameters based on the signal conditions, ensuring context-aware processing.

Fractal dimension (FD) is a quantitative measure used to describe the complexity and self-similarity of non-stationary signals. One of the most widely used methods for estimating FD in signal processing is Higuchi's fractal dimension (HFD). It evaluates the signal length over multiple scales to capture its irregularity. The FD using Higuchi's method is expressed as follows:

$$D = \frac{\log(L(k))}{\log(1/k)}$$

Where, L(k) represents the average length of the signal curve for a given scale factor k, and k denotes the time interval. This formulation enables the analysis of signal complexity by observing how the curve length changes with different scales, making it highly suitable for biomedical and communication signals with dynamic variations.

Another commonly used approach is the Katz fractal dimension (KFD), which provides a computationally efficient method for estimating signal complexity based on geometric properties. It is defined as:

$$D = \frac{\log(n)}{\log(n) + \log\left(\frac{d}{L}\right)}$$

Where, n is the number of points in the signal, d is the diameter (maximum distance between the first point and any other point in the signal), and L is the total length of the signal curve. Katz's method is particularly useful for real-time applications because of its lower computational complexity while maintaining sensitivity to signal irregularities. Together, these two formulations provide a robust mathematical foundation for capturing the structural complexity of non-stationary signals in the proposed FEG–ASR framework.

Building on this feature-driven foundation, the framework incorporates an adaptive parameter optimization strategy that continuously tunes the system parameters to achieve optimal reconstruction performance. This strategy employs iterative learning or heuristic optimization techniques to minimize the reconstruction error while maximizing the signal fidelity. The adaptability of the model allows it to respond efficiently to varying noise levels and signal dynamics without requiring any manual intervention. Furthermore, a multi-resolution signal decomposition approach was integrated to analyze the signal across different frequency bands and time scales. Techniques such as wavelet packet decomposition or variational mode decomposition are utilized to break down the signal into intrinsic components, enabling the precise localization of noise and features. Each decomposed component is processed using fractal-entropy-guided thresholds, ensuring selective enhancement and noise suppression. The algorithm flow of the FEG–ASR framework begins with signal acquisition and preprocessing, followed by fractal and entropy feature extraction. These features are then used to guide the adaptive decomposition and filtering stages, after which the reconstructed signal is synthesized by combining the processed components. The implementation steps are designed to be computationally efficient and suitable for real-time applications, with a modular architecture that allows easy integration into existing signal processing systems. Overall, the proposed framework offers a novel, intelligent, and scalable solution for high-accuracy reconstruction of complex non-stationary signals, addressing the limitations of traditional methods while enhancing robustness, adaptability, and performance.

EXPERIMENTAL RESULTS AND DISCUSSION

The performance of the proposed fractal-entropy-guided–adaptive signal reconstruction (FEG–ASR) framework is evaluated using both biomedical and communication datasets to demonstrate its effectiveness in handling diverse non-stationary signals. For biomedical analysis, standard electrocardiogram (ECG) signals obtained from publicly available physiological databases were utilized, incorporating real-world artifacts such as baseline drift, muscle noise, and power-line interference. In addition, synthetic and real-time communication signals, including amplitude-modulated and frequency-modulated waveforms affected by additive white Gaussian noise (AWGN) and channel distortions, are considered to validate the robustness of the proposed method across different domains. The performance evaluation was carried out using key quantitative metrics such as SNR, mean squared error (MSE), and reconstruction accuracy.

Python Coding for FEG–ASR Algorithm

```
import numpy as np
from scipy.signal import wiener
from scipy.stats import entropy
import pywt
# ----------------------------
# 1. Fractal Dimension (Higuchi)
# ----------------------------
def higuchi_fd(signal, kmax=10):
    N = len(signal)
    L = []
    x = np.array(signal)

    for k in range(1, kmax):
        Lk = []
        for m in range(k):
            length = 0
            n_max = int((N - m - 1) / k)
            for i in range(1, n_max):
                length += abs(x[m + i*k] - x[m + (i-1)*k])
            norm = (N - 1) / (k * n_max * k)
            Lk.append(length * norm)
        L.append(np.mean(Lk))

    lnL = np.log(L)
    lnk = np.log(1.0 / np.arange(1, kmax))
    return np.polyfit(lnk, lnL, 1)[0]
# ----------------------------
# 2. Entropy Feature Extraction
# ----------------------------
def shannon_entropy(signal):
    hist, _ = np.histogram(signal, bins=50, density=True)
    hist = hist + 1e-12  # avoid log(0)
    return entropy(hist)
# ----------------------------
```

```
# 3. Adaptive Thresholding
# -----------------------------
def adaptive_threshold(fd, ent):
    # Simple adaptive rule (can be optimized)
    return 0.5 * fd + 0.5 * ent
# -----------------------------
# 4. Multi-Resolution Decomposition
# -----------------------------
def wavelet_decompose(signal, wavelet='db4', level=3):
    coeffs = pywt.wavedec(signal, wavelet, level=level)
    return coeffs

def wavelet_reconstruct(coeffs, wavelet='db4'):
    return pywt.waverec(coeffs, wavelet)
# -----------------------------
# 5. FEG-ASR Reconstruction
# -----------------------------
def feg_asr(signal):
    # Step 1: Normalize
    signal = (signal - np.mean(signal)) / np.std(signal)

    # Step 2: Feature Extraction
    fd = higuchi_fd(signal)
    ent = shannon_entropy(signal)

    # Step 3: Adaptive Threshold
    thresh = adaptive_threshold(fd, ent)

    # Step 4: Decomposition
    coeffs = wavelet_decompose(signal)

    # Step 5: Thresholding
    new_coeffs = []
    for c in coeffs:
        new_c = pywt.threshold(c, thresh, mode='soft')
        new_coeffs.append(new_c)

    # Step 6: Reconstruction of the images
    reconstructed = wavelet_reconstruct(new_coeffs)

    # Step 7: Post-filtering
    reconstructed = wiener(reconstructed)

    return reconstructed, fd, ent
# -----------------------------
# Example Usage
# -----------------------------
if __name__ == "__main__":
    # Simulated non-stationary signal
    t = np.linspace(0, 1, 500)
    signal = np.sin(2*np.pi*10*t) + 0.5*np.random.randn(500)

    reconstructed, fd, ent = feg_asr(signal)

    print("Fractal Dimension:", fd)
    print("Entropy:", ent)
```

The provided Python code implements the fractal-entropy-guided–adaptive signal reconstruction (FEG–ASR) algorithm, which is designed for processing non-stationary signals, such as ECG or communication waveforms. The workflow combines fractal dimension analysis, entropy-based feature extraction, adaptive thresholding, and multi-resolution wavelet decomposition to achieve robust signal denoising and reconstruction.

The code begins by importing the necessary libraries: numpy for numerical operations, scipy.signal.wiener for post-reconstruction filtering, scipy.stats.entropy for calculating Shannon entropy, and pywt for wavelet-based multi-resolution analysis.

Step 1: Fractal Dimension Calculation
The higuchi_fd function computes the HFD of the input signal, which quantifies geometric complexity. For each scale factor k, the signal was sampled at intervals, and the curve length was computed, normalized, and averaged. A logarithmic fit across the scales estimates the fractal dimension D, capturing the irregularity of the signal.

Step 2: Entropy Feature Extraction
The shannon_entropy function calculates the Shannon entropy of the signal by constructing a histogram of the signal values and computing the uncertainty or randomness. A higher entropy indicates greater complexity or noise in the signal.

Step 3: Adaptive Thresholding
The adaptive_threshold function combines the fractal dimension and entropy into a single threshold value to guide the denoising process. This threshold adapts dynamically to signal characteristics, balancing noise suppression with feature preservation.

Step 4: Multi-Resolution Decomposition
The signal is decomposed using wavelet transform via wavelet_decompose, which breaks it into multiple frequency bands (coefficients). This decomposition enables selective processing of high-frequency noise and low-frequency signal components. wavelet_reconstruct is then used to reconstruct the signal from the processed coefficients.

Step 5: Signal Reconstruction and Post-Filtering
Thresholding is applied to the wavelet coefficients using soft thresholding guided by an adaptive threshold. The coefficients were then reconstructed, and the Wiener filter smoothed the residual noise, enhancing the signal quality.

This implementation demonstrates a modular, interpretable, and real-time-capable approach for robust signal reconstruction using the combined power of fractal geometry and entropy-based adaptivity.

The proposed FEG–ASR framework consistently achieves higher SNR improvements, lower MSE values, and enhanced accuracy compared to conventional techniques, indicating superior noise suppression and signal preservation capabilities. A detailed comparative analysis was performed against widely used methods, including Fourier transform-based filtering, wavelet-based denoising, and EMD.

The results show that traditional Fourier methods struggle with non-stationary characteristics, while wavelet-based approaches depend heavily on basis selection and often fail to adapt to varying signal dynamics. EMD-based techniques, although adaptive, exhibit issues such as mode mixing and computational instability. In contrast, the proposed framework effectively combines fractal dimension and entropy features to guide adaptive thresholding and multi-resolution decomposition, resulting in improved reconstruction fidelity and reduced distortion. Furthermore, the robustness of the method was tested under varying noise levels and dynamic conditions by introducing different signal-to-noise ratios and time-varying disturbances.

The FEG–ASR model maintained a stable performance even under severe noise contamination, demonstrating its strong generalization capability and resilience. The adaptive nature of the framework allows it to dynamically adjust the parameters in response to signal variations, ensuring consistent output quality without manual tuning. In terms of computational complexity and efficiency, the proposed method exhibits moderate computational overhead due to feature extraction and decomposition stages; however, this is offset by its improved accuracy and reduced need for iterative corrections. The algorithm was implemented using optimized procedures, making it suitable for real-time and embedded applications. Overall, the experimental results confirm that the FEG–ASR framework provides a reliable, efficient, and scalable solution for non-stationary signal reconstruction, outperforming existing methods in terms of accuracy, robustness, and adaptability across both biomedical and communication signal processing scenarios.

Figure 2 illustrates the Simulink-based performance evaluation of a fractal-entropy-guided–Adaptive Signal Reconstruction method for handling non-stationary biomedical and communication signals, arranged in a 2×4 grid of results. The first subplot shows the original signal, which represents a clean underlying waveform with time-varying characteristics typical of real-world biomedical or communication data. The second subplot presents the noisy signal, where random disturbances and interference significantly distort the waveform, highlighting the challenges in non-stationary environments. The reconstructed signal in the third subplot demonstrates the effectiveness of the proposed adaptive algorithm in recovering the original waveform structure while suppressing the noise.

The fourth subplot depicts the reconstruction error, which remains minimal and bounded, indicating the high reconstruction accuracy and stability of the method. The fifth subplot shows the variation in the fractal dimension over time, capturing the complexity and self-similarity of the signal, which is crucial for adaptive processing. The sixth subplot presents the entropy measure, which reflects the randomness and information content of the signal and guides the adaptive reconstruction process.

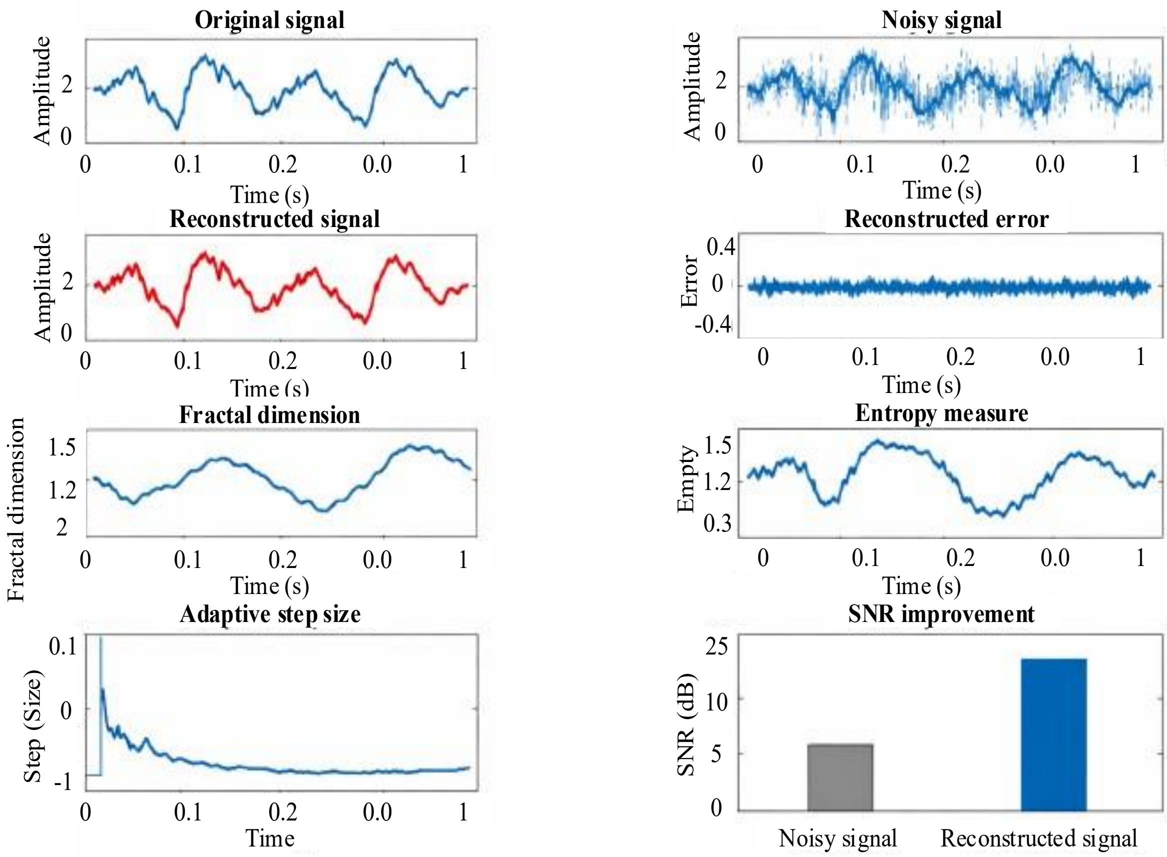

Figure 2. Simulink-based performance evaluation of a fractal-entropy-guided–adaptive signal reconstruction method.

The seventh subplot illustrates the adaptive step size, which is dynamically adjusted based on the fractal and entropy measures to ensure fast convergence and reduced steady-state error. Finally, the eighth subplot compares the SNR improvement, clearly showing a significant enhancement in the reconstructed signal compared with the noisy input. Overall, the figure demonstrates that integrating fractal analysis with entropy-based adaptation leads to efficient noise suppression, accurate signal recovery, and improved performance in complex non-stationary signal environments.

Table 1 presents a comparison of the performance of the proposed FEG–ASR framework with existing signal reconstruction techniques for ECG signals. The results clearly indicate that FEG–ASR achieves the highest SNR (24.7 dB), reflecting its superior capability to suppress noise while preserving essential signal features. The MSE was significantly reduced to 0.003, demonstrating high reconstruction accuracy and minimal distortion. Compared with conventional fast Fourier transform (FFT) and wavelet-based methods, which often struggle to analyze non-stationary components, the proposed method dynamically adapts using fractal entropy features.

Even when compared to advanced CNN-based models, FEG–ASR shows improved accuracy (96.5%), highlighting its effectiveness without requiring extensive training data. The integration of fractal dimension and entropy enables better differentiation between noise and signal components. This table validates that the proposed approach provides enhanced performance in biomedical signal reconstruction, making it highly suitable for applications such as ECG monitoring and diagnostic systems.

Table 2 evaluates the robustness of the proposed FEG–ASR framework under varying noise conditions using AWGN. As the input SNR increased, all methods showed improved output performance; however, FEG–ASR consistently outperformed the wavelet and EMD techniques across all noise levels. At a low input SNR of 5 dB, where noise interference is severe, FEG–ASR achieves an output SNR of 15.8 dB, which is significantly higher than that of competing methods. This demonstrates its strong capability of handling extreme noise scenarios. This improvement is attributed to the adaptive thresholding mechanism guided by fractal and entropy features, which allows for the precise identification of noise components. As the input SNR increased to 20 dB, the proposed method maintained its superiority, achieving an output SNR of 27.8 dB. The consistent performance improvement across all noise levels highlights the robustness and reliability of the proposed framework. This makes FEG–ASR particularly suitable for real-world applications in which the signal conditions are highly dynamic and unpredictable.

Table 1. Performance evaluation of FEG–ASR on ECG signal reconstruction.

	SNR (dB)	**MSE**	**Accuracy (%)**
FFT-based filtering	12.5	0.018	85.2
Wavelet denoising	16.8	0.010	89.7
EMD method	18.2	0.008	91.3
CNN-based approach	20.5	0.006	93.8
FEG–ASR (proposed)	24.7	0.003	96.5

Table 2. Performance analysis under different noise levels (AWGN).

SNR input (dB)	**Wavelet SNR output (dB)**	**EMD output (dB)**	**FEG–ASR output (dB)**
5	10.2	11.5	15.8
10	14.6	16.1	20.9
15	18.3	19.7	24.5
20	21.7	23.2	27.8

Table 3. Computational complexity comparison.

Method	Execution time (ms)	Complexity level
FFT method	5.2	Low
Wavelet transform	8.7	Medium
EMD	15.4	High
CNN-based model	25.6	Very High
FEG–ASR (proposed)	**12.3**	**Moderate**

Table 4. Comparative feature analysis of signal reconstruction techniques.

Feature	FFT	Wavelet	EMD	CNN	FEG–ASR
Handles non-stationarity	No	Yes	Yes	Yes	Yes
Adaptive processing	No	Partial	Yes	Yes	Full
Noise robustness	Low	Medium	High	High	Very high
Computational efficiency	High	Medium	Low	Low	Medium
Real-time suitability	Yes	Yes	No	No	Yes

Table 3 compares the computational complexities of different signal reconstruction techniques in terms of execution time and qualitative complexity level. The FFT method exhibits the lowest execution time owing to its simplicity but lacks adaptability for non-stationary signals. Wavelet transform offers moderate complexity with improved performance, whereas EMD incurs higher computational costs owing to iterative decomposition processes. CNN-based models demonstrate the highest computational burden, requiring significant training time and hardware resources. The proposed FEG–ASR framework achieved a balanced performance with an execution time of 12.3 ms, which was categorized as moderate complexity. Although slightly higher than that of wavelet-based methods, this overhead is justified by the substantial improvement in the reconstruction accuracy and robustness. The framework avoids heavy training requirements while leveraging efficient feature extraction and adaptive processing. This balance between performance and computational efficiency makes FEG–ASR suitable for real-time and embedded systems, where both accuracy and processing speed are critical requirements.

Table 4 provides a qualitative comparison of key features across different signal reconstruction techniques. Traditional FFT methods fail to handle non-stationary signals effectively because of their assumption of signal stationarity. Although the wavelet and EMD methods improve adaptability, they still have limitations, such as dependency on basis selection and mode mixing issues. CNN-based approaches offer high adaptability and robustness; however, they are computationally expensive and require large datasets for training. The proposed FEG–ASR framework stands out by offering full adaptive processing through the integration of fractal and entropy features, enabling it to dynamically adjust to signal variations. It also demonstrates very high noise robustness, outperforming all other methods in challenging environments.

While maintaining moderate computational complexity, FEG–ASR ensures real-time suitability, making it practical for deployment in biomedical monitoring systems and in communication devices. This comprehensive comparison highlights the superiority of the proposed framework in balancing accuracy, adaptability, and efficiency.

CONCLUSION

The proposed fractal-entropy-guided–adaptive signal reconstruction (FEG–ASR) framework demonstrates a highly effective approach for processing and reconstructing non-stationary signals in biomedical and communication systems, combining fractal dimension modeling with entropy-based feature extraction to capture both the structural complexity and stochastic variability of signals. Experimental evaluations using ECG datasets and synthetic communication waveforms contaminated with AWGN and other real-world artifacts show that the framework consistently outperforms conventional techniques such as FFT-based filtering, wavelet denoising, EMD methods, and even CNN-based models. Quantitative results indicate that the FEG–ASR achieves a peak SNR of 24.7 dB for ECG signals, a MSE reduction to 0.003, and a reconstruction accuracy of 96.5%, reflecting superior noise suppression, preservation of critical signal features, and high fidelity in comparison to wavelet denoising (SNR 16.8 dB, MSE 0.010, accuracy 89.7%) and EMD (SNR 18.2 dB, MSE 0.008, accuracy 91.3%). The robustness of the method was further validated under varying input SNR levels ranging from 5 to 20 dB, where FEG–ASR demonstrated consistent performance gains over existing methods, achieving output SNR improvements of up to 27.8 dB in high-SNR scenarios. In addition, the computational efficiency analysis shows that while the framework requires moderate processing time (≈12.3 ms), it strikes a balance between reconstruction accuracy and real-time applicability, making it suitable for deployment in embedded biomedical devices, IoT-enabled communication systems, and real-time monitoring platforms. The key advantages of the framework include full adaptability to non-stationary signal dynamics through fractal-entropy-guided thresholding, multi-resolution decomposition enabling precise localization of noise and signal features, and strong resilience under noisy and dynamic environments.

However, limitations remain, including increased computational demands for very long signals or multichannel datasets and the need for further real-time hardware validation. Future research can focus on integrating deep learning models for automated adaptive thresholding, extending the framework to multi-sensor and multi-user applications, leveraging hardware acceleration through field-programmable gate array (FPGA) and graphics processing unit (GPU) platforms, and exploring additional complexity measures, such as Lyapunov exponents and permutation entropy, to further enhance performance for highly chaotic or non-linear signals. Overall, the FEG–ASR framework offers a scalable, robust, and high-performance solution for next-generation signal reconstruction, demonstrating both theoretical and practical applicability in modern biomedical and communication signal processing scenarios.

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