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Fractal Classification Method for Complex Signals

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Abstract

The classification of complex signals, often characterized by high noise levels, non-linearity, and overlapping patterns, poses significant challenges in signal processing. Traditional methods frequently fail to address the intricate structures inherent in such signals, necessitating the adoption of advanced analytical techniques. This study explores the application of fractal methodologies, leveraging their self-similar and scale-invariant properties, for classifying complex signals. By employing tools such as the Hurst exponent and the (R/R) method, this work demonstrates how fractal analysis can effectively characterize and categorize stationary and non-stationary signals based on their probabilistic distributions and fractal dimensions. Results indicate that fractal methods provide robust descriptors for distinguishing signal types, enabling enhanced accuracy and operational efficiency. The proposed approach holds promise for developing virtual analyzers with expansive dynamic ranges, applicable in diverse fields such as diagnostics, control systems, and signal processing.

Key Words: signal processing, fractal dimension, Hurst exponent, (R/R) method

Introduction

The classification of hard signals is a critical challenge in signal processing, where the goal is to analyze and interpret complex, non-trivial datasets generated by various sources. Hard signals often exhibit characteristics such as high noise levels, overlapping patterns, non-linearity, and high dimensionality, making traditional classification approaches less effective. These signals can arise in diverse domains, including biomedical applications (e.g., EEG or ECG signals), industrial monitoring, telecommunications, and environmental systems [1].

The complexity of these signals necessitates advanced analytical techniques that can handle intricate patterns and extract meaningful features. Recent advancements in machine learning, particularly deep learning and ensemble methods, have demonstrated significant potential in addressing these challenges. These approaches leverage powerful computational models to capture subtle patterns and relationships within the data, enabling improved classification accuracy and robustness.

Fractal methods offer a promising solution for addressing these challenges by leveraging the self-similar and scale-invariant properties inherent in many complex signals. These methods utilize fractal geometry to analyze signal structures across multiple scales, revealing insights into their underlying

dynamics that are often inaccessible through conventional techniques. Key tools in this domain include fractal dimension analysis, multifractal spectra, and wavelet-based fractal approaches, which provide robust descriptors for distinguishing between signal types and classes.
The advantages of fractal methods lie in their ability to handle irregularities and noise effectively while preserving the intrinsic characteristics of the signal. By focusing on the geometric and topological aspects of signals, these methods enhance classification accuracy and robustness, even in highly complex and noisy environments. This paper explores the application of fractal methodologies to signal classification, highlighting their theoretical foundations, practical implementations, and comparative advantages over traditional approaches.

Signal Categories and Spectra

Signals can be categorized into stationary and non-stationary types, each with distinct spectral characteristics. Understanding these categories is crucial for accurate frequency analysis. Stationary signals have statistical parameters that remain constant over time, such as the overall signal level, amplitude distribution, and standard deviation. These are further classified into:
Deterministic Signals:
- Maintain relatively constant frequency and amplitude components over time.
- Subdivided into periodic signals (repeating at equal intervals) and quasi-periodic signals.
- Periodic signals exhibit discrete frequency components, known as harmonics.

Random Signals:
- Unpredictable in frequency and amplitude but exhibit constant statistical characteristics.

Non-stationary signals, on the other hand, can be divided into transient and continuous signals. Transient signals begin and end at zero levels and exist for finite durations, varying from very short to relatively long periods [1].

Literature Review

Fractal analysis has emerged as a powerful tool for understanding and characterizing complex signals. Leveraging the self-similar and scale-invariant properties of fractal structures, researchers have successfully deciphered intricate patterns and dynamics inherent in various signal types. This narrative review synthesizes recent contributions to the field, outlining the theoretical foundations, methodological advancements, and practical applications of fractal analysis in signal classification.
The exploration of fractal methodologies begins with Falconer (2013), who provides a foundational understanding of fractal geometry. This seminal work emphasizes the relevance of fractal principles in analyzing irregular and fragmented structures across multiple scales. By establishing the theoretical basis for fractal techniques, Falconer's insights form the cornerstone for subsequent applications in signal processing.
Building on this theoretical framework, Eke et al. (2002) demonstrate the practical utility of fractal measurements in physiological signal analysis. Their study illustrates how fractal dimensions can quantify complexity and distinguish between different physiological states, highlighting the potential of fractal methods in biomedical contexts such as heart rate variability and EEG analysis.

Expanding the scope of fractal applications, Otkhozoria et al. (2023) investigate the fractal properties of network topologies and stochastic processes using the LabVIEW platform. Their work underscores the versatility of fractal techniques in modeling and analyzing real-world stochastic dynamics, providing a robust framework for understanding structural complexities in networked systems.
Further advancing the field, Otkhozoria, Otkhozoria, and Narchemashvili (2021) introduce innovative methods for quantifying fractal dimensions with a focus on the classification and diagnosis of dynamic systems. Their study emphasizes the metrological performance of fractal methods, showcasing their relevance for precision measurement and signal classification.
In addition to classification tasks, Abelashvili et al. (2024) explore the use of fractal structure analysis for diagnosing the stability of large-scale processes. By analyzing time series data, their approach facilitates real-time monitoring and diagnostics, demonstrating the applicability of fractal analysis in stability assessments and control systems.
Collectively, these studies highlight the robustness and adaptability of fractal methodologies across diverse domains. From biomedical signal analysis to network modeling and process stability diagnostics, fractal techniques provide a comprehensive framework for addressing the complexities of signal classification. This body of literature establishes a strong foundation for future advancements in the integration of fractal analysis with computational tools and machine learning approaches.

Theoretical Foundations of the (R/S) Method

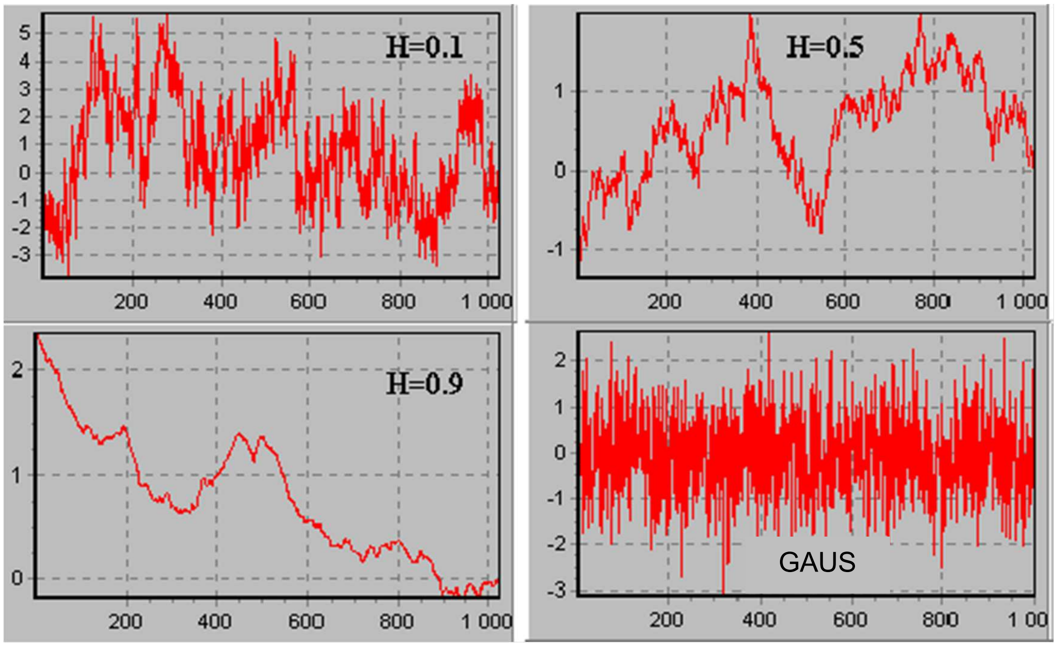
Before applying fractal methods to classify complex signals, we examine the indicator Hurst introduced for time series evaluation—the range of accumulated deviation ("R") to the standard deviation from the mean ("S"). The dependence of the (R/S) parameter on observation time, represented on a double logarithmic scale, forms the fractal function of the studied process. The linear approximation of this function determines the angular coefficient, H, or the Hurst exponent. This exponent helps calculate the fractal dimension[3]:

$$D = 2 - H$$

The fractal dimension characterizes the chaotic properties and complexity of a process. Processes with a Hurst exponent in the range:

- $0 < H < 0.5$: Antipersistent processes, indicating high noise levels and frequent trend changes.
- $0.5 < H < 1$: Persistent processes, reflecting trend preservation and relatively low noise levels.
- $H = 0.5$: Processes with no discernible trend, influenced by unpredictable noise (Fig.1).

Fig.1. Examples of antipersistent (B) fractal lines



Measurement of Stationary Random Signals Using the (R/R) Method

The (R/R) method extends the (R/S) analysis by examining the relationship between squared deviations and mean deviations. Unlike the Hurst method, this technique separates random stationary signals based on their probability distributions, creating a practical scale for signal measurement and classification[2] [4].

Using software-generated random numbers, sets of stationary signals were analyzed. For each set, the fractal (R/R) function was calculated, and model parameters (A, B, and C) were estimated and averaged. Results indicated that the fractal (R/R) functions exhibit linear behavior within the considered sample size range (e.g., N=400), allowing the slope parameter (B) to serve as an identification metric [5].

Results and Discussion

Table 1 summarizes the metrological characteristics of the fractal identification scale (FIS) based on the (R/R) method. Key evaluation metrics include the average maximum (R/R) values, slope (B), and error estimates.

Table 1 metrological characteristics of the fractal identification scale

Distribution type	max (R/R)	B	**Absolute Error**	Relative Error (%)
2MOD	153,03	0,385	0.002	0.52
ARCS	76 959	0,194	0.002	1.03
EVEN	50 971	0,128	0.0005	0.39
SIMP	27588	0,07	0.0009	1.298
RELE	21 013	0,05	0.001	1.89
GAUS	17845	0,048	0.0008	1.78
COSH	10956	0,003	0.0001	1.99

The random error (approximately 25%) exceeds the systematic error (1.6%), enabling the rounding of max(R/R) values for practical use. For varying sample sizes, the slope parameter (B) provides a more consistent classification scale.

Conclusion

The discussed fractal classification methodology effectively categorizes complex signals based on their probabilistic and fractal properties. By integrating Hurst and (R/R) methods, the technology enables the development of virtual analyzers with broad dynamic ranges for signal shape measurement. These advancements hold potential for applications in signal processing, diagnostics, and control systems.

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კომპლექსური სიგნალების ფრაქტალური კლასიფიკაციის მეთოდი

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საქართველო ტექნიკური უნივერსიტეტი

რთული სიგნალების კლასიფიკაცია, რომელიც ხშირად ხასიათდება ხმაურის მაღალი დონით, არაწრფივობითა და გადაფარვით, მნიშვნელოვან გამოწვევებს უქმნის სიგნალის დამუშავებას. ტრადიციული მეთოდები ხშირად ვერ აანალიზებენ ასეთი სიგნალების თანდაყოლილ რთულ სტრუქტურებს, რაც მოითხოვს მოწინავე ანალიტიკური ტექნიკის გამოყენებას. სტატია იკვლევს ფრაქტალური მეთოდოლოგიების გამოყენებას რთული სიგნალების კლასიფიკაციისთვის ისეთი ინსტრუმენტებით, როგორიცაა ჰურსტის მაჩვენებლები და (R/R) მეთოდი, სტატიიდან ჩანს, თუ როგორ შეუძლია ფრაქტალურ ანალიზს ეფექტურად დაახასიათოს და დაახარისხოს სტაციონარული და არასტაციონარული სიგნალები მათი ალბათური განაწილებისა და ფრაქტალის განზომილებების საფუძველზე. მიღებული შედეგები სიგნალების კლასიფიკაციის გაუმჯობესებული სიზუსტის და ეფექტურობის საშუალებას იძლევა. შემოთავაზებული მიდგომა საინტერესოა ვირტუალური ანალიზატორების განვითარებისთვის გაფართოებული დინამიური დიაპაზონებით, რომლებიც გამოიყენება სხვადასხვა სფეროებში, როგორიცაა დიაგნოსტიკა, კონტროლის სისტემები და სიგნალის დამუშავება.

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