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TIME-DOMAIN SEGMENTATION METHODS FOR COMPLEX SIGNAL ANALYSIS

This article analyzes modern time-domain segmentation methods used in complex signal analysis. Fixed-scale, adaptive, and multiscale approaches, as well as structural analysis and change detection methods, are considered. It is shown that in existing approaches the segmentation scale is mainly treated as an auxiliary parameter rather than a controlled factor in signal ensemble formation.

A comparative experimental study is performed for different scenarios of signal structural nonstationarity, including stationary conditions, local degradations, gradual structural changes, and impulsive interference. The evaluation focuses on degradation localization accuracy, segmentation-scale stability, and over-segmentation effects.

The results demonstrate inherent limitations of existing time-domain segmentation methods in ensemble formation tasks and motivate the development of approaches with controlled segmentation-scale selection based on local signal structure and ensemble requirements.

Keywords: time-domain segmentation; complex signals; structural nonstationarity; time–frequency analysis; signal ensembles; multiscale methods; degradation localization.

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МЕТОДИ ЧАСОВОЇ СЕГМЕНТАЦІЇ У ЗАДАЧАХ АНАЛІЗУ СКЛАДНИХ СИГНАЛІВ

У статті виконано систематизований аналіз сучасних методів часової сегментації, що застосовуються у задачах аналізу складних сигналів у часовій та часово-частотній областях. Розглянуто підходи з фіксованим і адаптивним масштабом сегментації, багатомасштабні методи, ентропійні та фрактальні підходи, методи виявлення точок структурних змін, а також методи формування ансамблів на основі перестановки часових інтервалів.

Обгрунтовано, що в більшості існуючих методів часова сегментація використовується як допоміжний інструмент аналізу або оцінювання структурних властивостей сигналу, тоді як масштаб сегментації не розглядається як керований параметр у задачах формування ансамблів складних сигналів. Встановлено, що методи з фіксованим масштабом забезпечують стабільність сегментації, проте мають обмежену здатність до локалізації короткочасних деградацій, тоді як адаптивні та багатомасштабні підходи характеризуються підвищеною чутливістю до змін, але супроводжуються надмірною фрагментацією та нестабільністю масштабу сегментації.

Для кількісного порівняння розглянутих методів проведено експериментальні дослідження на сигналах за різних сценаріїв структурної нестаціонарності. Оцінювання виконано за показниками кількості сегментів, похибки локалізації деградацій, варіативності довжин сегментів та рівня надмірної сегментації. Отримані результати дозволили виявити характерні обмеження кожного класу методів у контексті узгодженого формування ансамблів у часовій області.

Таким чином, проведений аналіз підтверджує актуальність подальших досліджень, спрямованих на розробку підходів, у яких масштаб часової сегментації визначається керовано з урахуванням локальної структури сигналу та вимог до ансамблевих властивостей у складних завадових умовах.

Ключові слова: часова сегментація; складні сигнали; структурна нестаціонарність; часово-частотний аналіз; ансамблі сигналів; багатомасштабні методи; локалізація деградацій.

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INTRODUCTION

In modern methods of complex signal analysis, time-domain segmentation plays a significant role as a fundamental tool for localizing nonstationarity, constructing time–frequency representations, estimating structural characteristics, and detecting changes in signals. Depending on the specific task, segmentation is applied in combination with Fourier transforms, wavelet analysis, entropy-based, fractal, and statistical methods [1-16].

Despite the wide variety of approaches to time-domain segmentation presented in recent studies, most of them treat segmentation as an auxiliary processing stage rather than as an independent object of analysis. This motivates the need for a systematic review of contemporary time-domain segmentation methods from the perspective of their underlying principles, scale properties, and inherent limitations, especially in the context of structurally nonstationary signals.

GENERAL STATEMENT OF THE PROBLEM AND ITS CONNECTION WITH IMPORTANT SCIENTIFIC OR PRACTICAL TASKS

In practical complex signal analysis, the choice of the time-domain segmentation scale directly affects the ability of processing methods to detect local structural changes, degradations, and transient regimes. The use of fixed time intervals leads to an inherent trade-off between the localization of short-term variations and the preservation of the signal's structural integrity, whereas multiscale and adaptive approaches are often accompanied by segmentation instability and excessive fragmentation.

In this regard, an important scientific and practical problem is the analysis of existing time-domain segmentation approaches in terms of their behavior under different nonstationarity scenarios, as well as the identification of their limitations in tasks where segmentation scale consistency is critical. Addressing this problem is essential for improving the effectiveness of signal analysis, monitoring, and ensemble-related processing in modern telecommunication and signal processing systems.

ANALYSIS OF RESEARCH AND PUBLICATIONS

An analysis of recent research and publications [1–16] shows that existing approaches to time-domain segmentation of complex signals are primarily focused on auxiliary processing tasks such as time–frequency representation, structural complexity evaluation, and detection of nonstationary behavior, rather than on controlled ensemble formation.

A significant group of studies addresses fixed-scale segmentation and classical time–frequency analysis methods, where the segmentation scale is predefined and selected based on general resolution trade-offs without explicit consideration of local signal structure [1, 5]. Adaptive time–frequency approaches attempt to improve sensitivity to nonstationary behavior by modifying the window length according to local signal properties; however, such adaptation is typically heuristic and aimed at enhancing representation quality rather than regulating ensemble characteristics [2].

Multiscale signal analysis methods, including wavelet-based, multiscale entropy, and fractal approaches, exploit predefined or scale-invariant representations to characterize signal complexity and irregularity [3, 6, 10, 14]. In these methods, segmentation is implemented implicitly through decomposition or coarse-graining procedures and is not treated as a controllable parameter for ensemble construction.

Change-point detection techniques focus on identifying structural transitions by partitioning signals into statistically homogeneous intervals [11, 12, 15]. Although these methods provide accurate localization of regime changes, they are sensitive to noise and are not designed for controlled segmentation with predefined ensemble properties.

Ensemble formation methods based on time-interval permutation and multilevel time–frequency processing demonstrate the potential for improving mutual correlation characteristics and robustness [7, 8, 16]. However, in these approaches, the segmentation scale is either fixed in advance or determined by the algorithmic structure, which limits adaptability to local signal nonstationarity.

Overall, the analysis of publications [1–16] indicates the absence of approaches in which the time-domain segmentation scale is explicitly formulated as a controlled optimization parameter for complex-signal ensemble formation under structurally nonstationary conditions.

MATHEMATICAL FORMULATION OF THE PROBLEM

In modern methods for the formation and analysis of complex signals, time-domain segmentation is mainly used as an auxiliary processing tool; however, approaches in which the segmentation scale is treated as a controlled optimization parameter of the ensemble under conditions of structural signal nonstationarity are still lacking.

An analysis of recent studies [1–16] shows that, in general, time-domain segmentation can be defined as the transformation of a continuous (or discrete) signal $x(t)$ into a set of fragments or windows $\{xk(t)\}$, each of which is processed independently for the purposes of analysis, filtering, transformation, correlation or entropy estimation, and interval permutation.

The practical role of time-domain segmentation in complex-signal ensemble formation lies in the localization of nonstationary regions, increased sensitivity to short-term degradations, and the ability to perform coordinated decision-making in spectrum or channel monitoring tasks and time-domain ensemble formation. The general problem of selecting an appropriate segmentation scale is illustrated in Fig. 1.

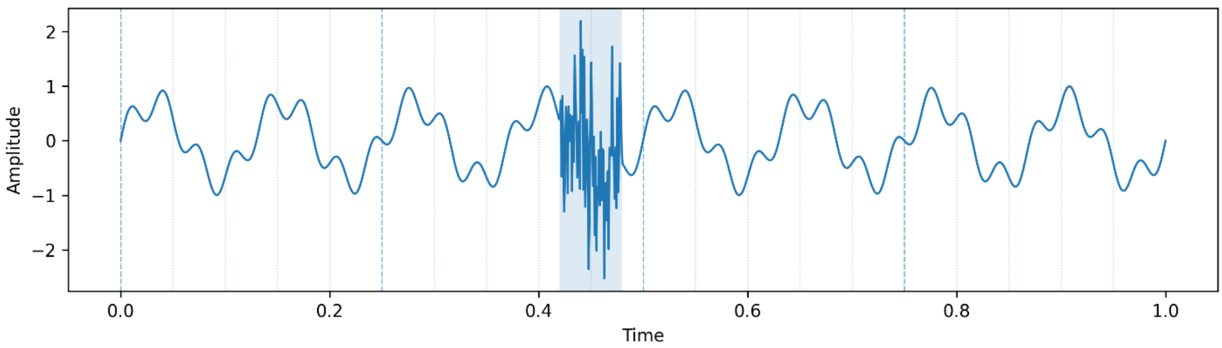

Fig. 1. Time-domain segmentation scale selection problem

As shown in Fig. 1, the use of a fixed time-domain segmentation scale leads to a fundamental trade-off between the localization of short-term degradations and the preservation of the structural integrity of the signal. Specifically, when long time intervals are applied (dashed lines), the segmentation ensures a stable and compact representation of the signal; however, it significantly reduces sensitivity to localized nonstationary variations, causing short-term degradations to be smoothed or entirely masked within a single segment. As a result, critical local changes remain undetected at the segmentation level.

Conversely, the use of excessively short time intervals (dotted lines) increases sensitivity to rapid structural changes and allows more accurate localization of degradations. At the same time, this leads to over-fragmentation of structurally stable regions, producing an excessive number of segments, increasing computational and organizational overhead, and introducing redundancy without a proportional increase in informative content. Consequently, stable signal fragments are unnecessarily subdivided, which complicates subsequent processing and ensemble formation.

This behavior illustrates that fixed-scale segmentation is inherently unable to simultaneously ensure reliable localization of local degradations and stable representation of stationary signal regions.

The main approaches to time-domain segmentation used in modern complex signal analysis methods are summarized in Table 1.

Table 1

Time-domain segmentation approaches in modern signal analysis methods

Method class	Segmentation principle	Scale definition	Main application	Key limitation
Fixed window (STFT)	Uniform time windowing	Fixed window length	Time–frequency analysis	No adaptation to local non-stationarity
Adaptive window TF analysis	Window length varies with signal properties	Heuristic / local criteria	Non-stationary signal analysis	Scale not formally optimized
Wavelet / multiwavelet	Multiresolution decomposition	Discrete predefined scales	Multiscale signal representation	No explicit time-interval control
Multiscale entropy methods	Coarse-graining over time scales	Entropy scale parameter	Structural complexity analysis	Segmentation used only for evaluation
Fractal-based methods	Scale-invariant irregularity analysis	Fractal dimension scale	Irregular time series analysis	No direct segmentation mechanism
Change-point detection	Partition at structural changes	Statistical criteria	Regime change detection	Sensitive to noise and outliers
Time-interval permutation	Fixed segmentation + interval reordering	Number of segments	Ensemble formation	Segmentation scale is fixed
Multilevel TF segmentation	Hierarchical segmentation with filtering	Algorithm-defined	Robust TF processing	No adaptive scale selection

Let us consider the time-domain segmentation methods in more detail.

1. Fixed window (uniform segmentation).

This is the most classical segmentation approach, in which the signal is divided into time windows of fixed length $L$with a specified overlap. This principle underlies the short-time Fourier transform (STFT), where the choice of L determines the trade-off between time and frequency resolution [1].

In practical applications, such as those reported in [5], this scheme is often used as a default solution, with window length and overlap selected by the user or according to general recommendations, without explicit consideration of the local signal structure.

The main limitation of this approach is that, for structurally nonstationary signals, the use of a single fixed value of L inevitably leads to a compromise: large windows reduce the localization accuracy of short-term degradations, whereas small windows cause excessive fragmentation of stable signal regions.

2. Adaptive windowing in time–frequency analysis.

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This class includes methods in which the time-window length is varied according to local signal properties in order to improve the quality of the time–frequency (TF) representation [2]. In such approaches, the segmentation scale is determined using local rules or heuristic criteria and is employed as an auxiliary parameter for time–frequency analysis.

A key limitation of these methods is that the adaptation of the segmentation scale is not formulated as a controlled optimization parameter and is not directly linked to ensemble-related signal characteristics, such as mutual correlation properties, ensemble size, or interference robustness.

3. Wavelet- and multiwavelet-based methods.

In wavelet and multiwavelet approaches, signal segmentation is implemented indirectly through multiscale decomposition, in which the signal is represented as a set of components corresponding to fixed discrete scales [6]. In this case, time intervals are not explicitly defined, and the analysis scale is determined by the choice of the wavelet basis and the level of decomposition.

A limitation of this approach is the lack of direct control over the time-domain segmentation intervals, as well as the discrete nature of the available scales, which complicates the alignment of multiscale representations with ensemble-related signal characteristics.

4. Multiscale entropy–based methods.

In multiscale entropy methods, time-domain segmentation is used in the form of a coarse-graining procedure applied to the signal at different scales in order to evaluate its structural complexity [10, 14]. The segmentation scale is defined by the entropy analysis parameter and is employed for quantitative complexity assessment rather than for forming time intervals as ensemble elements.

The limitation of these approaches lies in the fact that segmentation plays an auxiliary role and is not treated as a controlled parameter for complex-signal ensemble formation or for managing their mutual correlation properties.

5. Fractal-based time-series analysis methods.

Fractal-based methods are grounded in the evaluation of scale-invariant signal properties and irregularity, typically through fractal dimension or related measures [3]. The analysis scale in such approaches is determined by the method itself and is used to characterize signal complexity, without explicit formation of time-domain segmentation intervals.

A key limitation of fractal-based methods is the absence of a direct mechanism for partitioning the signal into time segments suitable for subsequent ensemble formation or structural control.

6. Change-point detection methods.

In change-point detection methods, signal segmentation is performed by partitioning the time axis into intervals corresponding to different statistical regimes of the signal [11, 12, 15]. Segment boundaries are determined based on statistical criteria and are used to identify moments of structural changes.

A limitation of these methods is their sensitivity to noise and outliers, as well as their primary focus on change detection rather than on the controlled formation of segmentation with predefined ensemble properties.

7. Time-interval permutation–based ensemble formation methods.

In methods of this class, the signal is first divided into time intervals of fixed length, after which an ensemble is formed by permuting the obtained segments [8]. The segmentation scale is predefined and remains unchanged during the ensemble formation process.

The limitation of this approach is the fixed nature of segmentation, which prevents aligning the time-interval length with local structural variations of the signal.

8. Multilevel time–frequency segmentation.

In multilevel approaches, segmentation is implemented hierarchically using successive stages of filtering and analysis in the time and frequency domains [7]. The segmentation scale is determined by the algorithm structure and the processing levels.

A limitation of these methods is the absence of an explicit mechanism for adaptive selection of the segmentation scale as a controlled parameter in the formation of complex-signal ensembles.

EXPERIMENTAL RESULTS

In view of the above, experimental studies were conducted to quantitatively compare time-domain segmentation approaches, aimed at evaluating the influence of segmentation scale selection on the processing characteristics of structurally non-stationary signals and identifying the limitations of existing methods in time-domain ensemble formation tasks.

Table 2 and Fig. 2 present the results of a comparative analysis of time-domain segmentation methods for model signals under different non-stationarity scenarios: C1 – stationary signal; C2 – short-term degradation; C3 – slow structural change; C4 – impulsive interference.

The following metrics were used for quantitative evaluation: Ns – number of segments; E_{loc} – degradation localization error; σ_L – variance of segment lengths; S_{over} – over-segmentation index.

Table 2

Segmentation behavior of different methods under non-stationary conditions

Method	C1: Ns	C2: E_{loc}	C3: σ_L	C4: S_{over}
Fixed window	20	0,42	0,00	0,18
Adaptive window	28	0,21	0,37	0,31
Wavelet-based	32	0,19	0,41	0,35
Multiscale entropy	20	0,48	0,00	0,12
Fractal-based	18	0,44	0,05	0,14
Change-point	47	0,08	0,62	0,71
Time-interval permutation	20	0,39	0,00	0,09
Multilevel TF	26	0,17	0,29	0.22

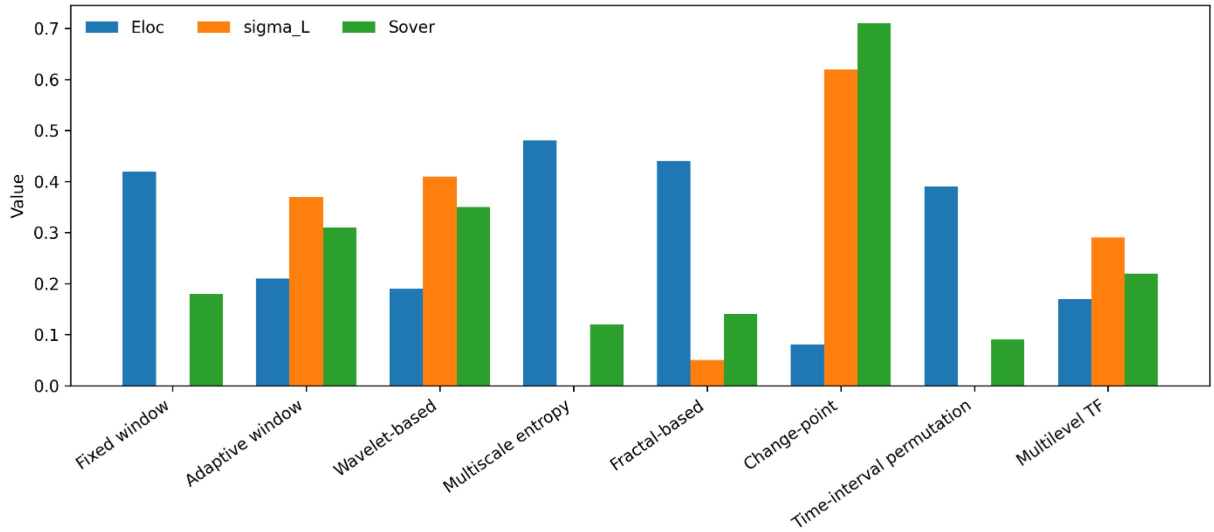

Fig. 2. Comparative analysis of time-domain segmentation methods

As shown in Table 1 and Fig. 2, different classes of time-domain segmentation methods exhibit significantly different behavior in terms of degradation localization accuracy, segmentation scale stability, and excessive fragmentation.

Fixed-scale segmentation methods are characterized by zero variance of segment lengths ($\sigma_L = 0$), which ensures structural stability of segmentation; however, this comes at the cost of increased degradation localization error (E_{loc}), especially in the presence of short-term or impulsive signal changes.

In contrast, change-point–based methods provide high sensitivity to structural variations (low E_{loc} values) but are accompanied by substantial variability in segment lengths and high values of the over-segmentation index (S_{over}), which complicates consistent ensemble formation in the time domain.

CONCLUSIONS FROM THIS RESEARCH AND PROSPECTS FOR FURTHER RESEARCH IN THIS AREA

This paper presents a comparative analysis of modern time-domain segmentation approaches used in complex signal analysis. It is shown that most existing methods are primarily focused on time–frequency analysis, structural assessment, or change detection, and generally do not consider the segmentation scale as a controllable parameter in the process of forming complex-signal ensembles in the time domain.

It has been established that fixed-scale segmentation methods provide structural stability of the partitioning but do not ensure sufficient localization of short-term degradations in structurally non-stationary signals. In contrast, adaptive and multiscale approaches increase sensitivity to structural changes; however, they are often accompanied by high segmentation variability and excessive fragmentation, which complicates coordinated ensemble formation in the time domain and degrades the stability of ensemble characteristics.

The obtained results confirm the relevance of developing methods in which the time-domain segmentation scale is determined in a controlled manner, taking into account the local signal structure and the requirements for ensemble properties, including mutual correlation characteristics and robustness to interference.

Further research will focus on the development and experimental validation of controlled segmentation-scale selection mechanisms for structurally non-stationary signals, as well as on extending the proposed approaches to multichannel and multiband scenarios and refining ensemble evaluation criteria under interference conditions.

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