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# METHOD OF ENTROPY-CONSISTENT TIME SEGMENTATION OF COMPLEX SIGNAL ENSEMBLES

## Introduction

In modern telecommunication systems, signal processing is performed under conditions of nonlinear dynamics, temporal and spectral nonstationarity, structural heterogeneity, and intensive noise interference, which significantly complicates the formation of stable and informative signal represent-tations. Under such conditions, ensemble-based processing of complex signals has become increasingly important, as it enables improved noise robustness, reduced sensitivity to random distortions, and enhanced discrimination between different dynamic regimes.

The formation of ensembles of complex signals can be achieved through permutations and decompositions in both the time and frequency domains, as well as by combining time–frequency representations. Frequency-domain and spectral permutations are widely used to improve orthogonality, reduce correlation properties, and optimize energy character-ristics of signals. At the same time, time-domain permutations and segmentation play a crucial role when signals exhibit local structural transitions, changes between dynamic regimes, and non-uniform distribution of complexity over time.

The effectiveness of ensemble-based methods strongly depends on the temporal segmentation strategy, which determines the ensemble structure and directly affects its statistical, correlation, and information characteristics. In most existing approaches, the parameters of temporal segmentation are specified in a fixed or empirical manner, without considering the local structural complexity of the signal or variations in its dynamic behavior. As a result, segmentation may become inconsistent with the actual temporal organization of the signal, leading to reduced sensitivity to structural transitions and degraded noise robustness of the resulting ensembles.

In recent years, entropy-based methods have been widely applied for analyzing the complexity and irregularity of signals, with permutation entropy and its extensions being among the most commonly used measures. These approaches have demonstrated high efficiency as quantitative indicators of structural complexity in time series. However, in the majority of studies, entropy measures are employed as passive, post hoc descriptors, rather than being directly involved in controlling the segmentation or ensemble formation process.

Therefore, a transition from using entropy solely as a descriptive complexity measure toward its application as an active control mechanism is highly relevant. Such an approach enables the coordination of temporal segmentation parameters with the local structural heterogeneity of the signal, even under conditions of nonlinear dynamics and intensive noise interference.

## Analysis of recent research and publications

Analysis of recent research [1–15] shows that entropy-based approaches to evaluating the complexity of time realizations and signal ensembles are actively developing and are widely used across a broad range of applied problems.

In studies devoted to ensemble permutations in signal formation problems [1,2], entropy-oriented evaluation of signal ensembles using LPT-τ permute-tions and Markov models has been proposed [1], and the formation of ensemble properties of complex signals based on frequency filtering of pseudorandom sequences has been investigated [2]. However, in these works the parameters of time segmentation and its scale are treated as fixed or auxiliary, without formalizing a mechanism for their adaptive adjustment.

Studies [3, 4] demonstrate that signal complexity can change significantly depending on the system regime and observation conditions; nevertheless, these results are mainly applied to dynamic interpretation or state classification rather than to adaptive signal formation.

The fundamental basis of entropy-based time series analysis is formed by ordinal approaches and permutation entropy [11, 12], as well as survey studies on the application of PE in biomedical and techno-economic problems [14]. To improve metric informativeness, extensions accounting for amplitude weights or specific data structures have been proposed [10, 13]. However, in these works entropy metrics are considered as static indicators intended for complexity evaluation or classification, rather than as elements of a segmentation control mechanism.

In the direction of advanced entropy-based methods, approaches proposed in [5, 6] improve robustness to parameter selection and demonstrate better discrimination of dynamic regimes under noisy conditions [5]. A similar ensemble-averaging ideology aimed at reducing bias and increasing stability is developed in the ensemble entropy framework [8]. Modified multiscale entropy measures for real-world signal analysis have also been proposed [7]. Nevertheless, even in these studies the focus remains on improving the evaluation metric itself, while the relationship between entropy and parameter control in ensemble formation problems is not formalized.

Classical complexity measures justify the possibility of assessing signal regularity and irregularity using information-theoretic indicators [9], and applied studies on entropy-based classification (e.g., EEG analysis) confirm the practical effectiveness of such features [15]. At the same time, these approaches are primarily oriented toward recognition, classification, or diagnostics rather than toward optimizing the ensemble formation process through adaptive temporal decomposition.

Thus, the analysis of publications [1–15] indicates that the use of entropy estimation as a control indicator for the coordinated selection of time segmentation scale during the formation of complex signal ensembles remains insufficiently investigated.

**Problem Statement**

Despite the widespread use of complex signal ensemble formation methods in the time, frequency, and time–frequency domains, the problem of consistent selection of temporal segmentation parameters remains insufficiently formalized. In most existing approaches, the segmentation scale is fixed a priori or selected empirically, without accounting for local variations in the structural complexity of the signal or the specifics of its nonlinear dynamics.

In the presence of structural transitions between irregular and regularized regimes, as well as under intensive noise conditions, fixed temporal segmentation leads to the loss of informative features, smoothing of local dynamic reconfigurations, and degradation of the noise robustness of the formed ensembles. This significantly limits the effectiveness of subsequent signal analysis, reconstruction, and optimization procedures.

At the same time, existing entropy-based approaches, including permutation entropy and its modifications, although capable of providing quantitative measures of time-series complexity, do not offer mechanisms for active control of the ensemble formation process. These measures are typically used as static post hoc indicators and are not involved in adaptive regulation of temporal decomposition parameters.

Therefore, a scientific and practical problem arises in the development of a method that enables entropy-consistent control of temporal segmentation during the formation of complex signal ensembles, taking into account local structural heterogeneity and noise influence. Solving this problem is a necessary condition for improving the noise robustness of ensemble characteristics and ensuring stable analysis results under nonlinear dynamics and noisy environments.

**The purpose of the article**

The aim of this study is to develop an entropy-consistent temporal segmentation method for forming complex signal ensembles, which ensures alignment of temporal decomposition with the local structural complexity of the signal and improves the noise robustness of the formed ensemble.

**Summary of the main material**

The proposed Entropy-Aligned Temporal Segmentation for Complex Signal Ensemble Formation (EATS) method is based on the use of an entropy indicator simultaneously as an integral measure of signal complexity and as a control variable for the adaptive selection of temporal decomposition parameters.

In the proposed framework, the entropy indicator (EIPE) serves as an internal feedback signal, whereas the EATS method defines the adaptive temporal segmentation strategy itself.

Unlike classical entropy-based approaches, such as permutation entropy (PE) and weighted permutetion entropy (WPE), which are computed using fixed segmentation parameters and applied exclusively for a posteriori complexity assessment, the proposed method introduces an entropy-aligned adjustment of the temporal segmentation scale according to the local structural heterogeneity of the signal (Table 1).

*Table 1*

**Comparative characteristics of entropy-based methods**

| Comparison feature | PE | WPE | EATS |
|---|---|---|---|
| Type of entropy estimation | Ordinal | Ordinal with amplitude weighting | Entropy-aligned |
| Consideration of amplitude information | No | Partial | Yes |
| Fixed segmentation scale | Yes | Yes | No |
| Adaptation to local structural changes | No | Limited | Yes |
| Sensitivity to regime transitions | Limited | Moderate | High |
| Noise robustness | Medium | Medium | Enhanced |
| Role of entropy | Complexity estimation | Complexity estimation | Control indicator for segmentation |
| Suitability for adaptive ensemble formation | Limited | Limited | High |

As shown in Table 1, the principal distinction of the proposed method lies in the use of an entropy indicator as a feedback mechanism that ensures a coordinated algorithmic response to local structural rearrangements of the signal, particularly during transitions between irregular (quasi-chaotic) and regularized dynamical regimes, even in the presence of intensive noise disturbances.

Within the proposed framework, the entropy indicator is not treated as a static integral measure of signal complexity; instead, it is employed as a control variable that determines the appropriate temporal decomposition scale during the formation of complex signal ensembles.

The main stages of the proposed method implementation are outlined below.

Stage 1. Temporal segmentation

Let a discrete-time signal realization be given as:

$$x(t),\ t = 1,2,3 \dots N. \tag{1}$$

At the initial stage, the signal is partitioned into temporal segments of length $L$, where the segmentation scale is selected from a predefined admissible range:

$$L \in [L_{min},\ L_{max}]. \tag{2}$$

This initial segmentation provides a baseline representation of the signal structure prior to entropy-based adaptation.

Stage 2. Entropy indicator computation.

For each temporal segment $x_k(t)$, an entropy indicator is computed as:

$$E_k = \varepsilon(x_k), \tag{3}$$

where $\varepsilon(\cdot)$ – denotes an entropy function that accounts for both ordinal relationships and amplitude-related information of the signal.

Within the proposed framework, the resulting sequence of entropy indicators can be represented as:

$$\{E_k\}_{k=1}^{K}. \tag{4}$$

This sequence characterizes the local structural complexity of the signal in the time domain and serves as the basis for adaptive control of the segmentation process.

Stage 3. Entropy-aligned control of the segmentation scale.

Based on the obtained entropy indicator $E_k$ the segmentation scale is adjusted according to:

$$L_k = \Phi(E_k), \tag{5}$$

where $\Phi(\cdot)$ is a monotonic control function that ensures a reduction of the segmentation scale in regions exhibiting abrupt structural changes of the signal, and an increase of the scale in quasi-stationary and regularized signal segments.

As a result, temporal decomposition is aligned with the local signal dynamics rather than being fixed or empirically predefined.

Stage 4. Formation of complex signal ensembles.

Using the entropy-aligned segmented fragments, a complex signal ensemble is formed as:

$$X = \{x_1,\ x_2, x_3, \dots x_M\}. \tag{6}$$

In this ensemble, the segments may have different temporal lengths; however, they remain structurally consistent in terms of entropy-based complexity.

This approach provides a simultaneous enhancement of contrast between different dynamical regimes, a reduction of noise influence on ensemble characteristics, and an improvement in the robustness of subsequent analysis and signal processing procedures.

The aforementioned features of the proposed method necessitate its experimental verification under conditions of variable nonlinear signal dynamics and intensive noise disturbances.

To verify EATS method, a series of experimental studies was conducted. The simulations employed nonlinear signals with controllable dynamics, in which structural transitions between irregular (quasi-chaotic) and regular operating regimes occur as the governing parameter varies. This class of signals enables the investigation of changes in the structural complexity of time-domain realizations and allows assessment of the proposed method's capability for local detection of dynamical rearrangements.

To evaluate the noise robustness of the method, additive white Gaussian noise was superimposed on the signals, modeling the impact of external and internal disturbances under realistic operating conditions. The experiments were performed for different signal-to-noise ratio (SNR) levels, namely SNR = 20, 10, 0, and −10 dB.

For a comparative assessment of sensitivity to nonlinear dynamics and robustness to noise, entropy characteristics were computed using classical approaches–permutation entropy (PE) and weighted permutation entropy (WPE), as well as the proposed entropy indicator (EIPE) employed within the entropy-aligned segmentation framework.

The results of the experimental modeling are presented in Table 2 and in Figures 1 and 2. The table and figures show control values of the governing parameter μ corresponding to characteristic regimes of nonlinear signal dynamics: $\mu_1$ = 3,56 for the chaotic regime, $\mu_2$ = 3,75 for the transition region, and $\mu_3$ = 3,85 for the regularized regime.

*Table 2*

**Control values of entropy indicators (%)**

| μ | SNR, dB | PE, % | WPE, % | EATS, % |
|---|---|---|---|---|
| 3,56 | Clean | 43,23 | 43,52 | 23,15 |
| | 10 | 43,05 | 43,24 | 23,44 |
| | 0 | 42,84 | 43,03 | 23.82 |
| | −10 | 42,56 | 42,74 | 24,23 |
| 3,75 | Clean | 58,42 | 57,63 | 53.22 |
| | 10 | 58,13 | 57,31 | 53,51 |
| | 0 | 57,88 | 57,02 | 54,16 |
| | −10 | 57,21 | 56.64 | 55,03 |
| 3,85 | Clean | 67,95 | 66,82 | 57,41 |
| | 10 | 67,61 | 66,41 | 57,92 |
| | 0 | 67,12 | 66,02 | 58,63 |
| | −10 | 66,37 | 65,26 | 59,43 |

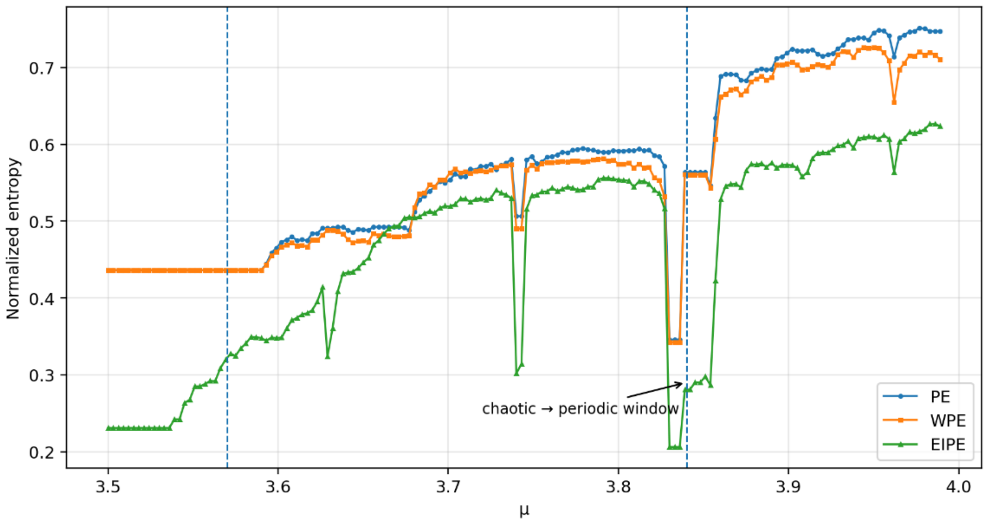


Fig. 1. Comparative entropy-based assessment of nonlinear signal dynamics

As can be seen from Fig. 1, classical entropy-based approaches (PE, WPE) exhibit a smoothed response to changes in the dynamic regime and demonstrate limited sensitivity in the transition region from chaotic to periodic behavior. In contrast, the entropy-consistent method provides a more pronounced local decrease in entropy, which corresponds to structural changes in the temporal organization of the signal.

The results presented in Fig. 2 and Table 1 quantitatively confirm the high noise robustness of the proposed entropy-consistent method. In particular, when transitioning from a clean signal to intensive noise conditions with SNR = −10 dB, the decrease in PE values at the control point μ = 3,56 is 1,6 %, while for WPE it reaches 1,8 %. At the same time, for the proposed method (EIPE), the relative change of the entropy indicator does not exceed

4,7 %, and moreover exhibits an opposite trend, reflecting an increase in sensitivity to structural changes rather than degradation of the entropy estimate.

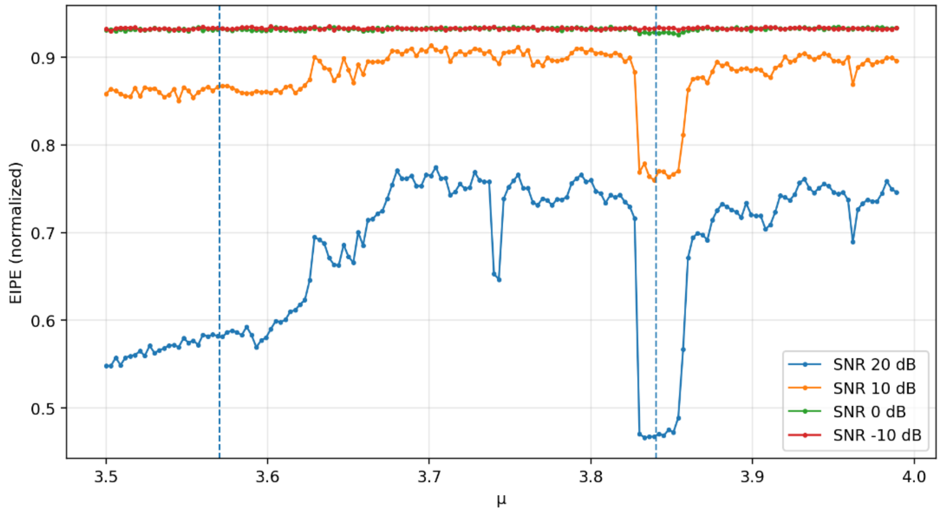


Fig. 2. Noise robustness of entropy-based evaluation

In the transition region μ = 3,75, when the SNR decreases to -10 dB, the entropy reduction for PE and WPE reaches 2,1 % and 1,7 %, respectively. In contrast, for EIPE a controlled increase of 3,4 % is observed, indicating preservation of the method's ability to locally detect structural rearrangements of the signal under noise influence.

A similar tendency is observed in the regularized regime μ = 3,85, where the relative decrease in entropy for PE and WPE at SNR = -10 dB amounts to 2,3 % and 2,4 %, respectively, whereas for EATS (EIPE) an increase of 3,5 % is recorded. This demon strates that the proposed method not only maintains robustness to noise but also enhances the contrast between different dynamic regimes of the signal.

The conducted simulations confirm the feasibility of using the entropy indicator not only as a measure of signal complexity but also as an informational basis for subsequent control of temporal segmentation parameters. Therefore, at the next stage of the experiment, entropy estimation is employed for adaptive selection of the temporal decomposition scale during the formation of complex signal ensembles. Quantitative values of the entropy indicators for the segmentation scale $L = 6$ are presented in Table 3, while the corresponding dependencies for different SNR levels are shown in Fig. 3.

*Table 3*

**Entropy indicators at different SNR levels ($L$ = 6)**

| SNR, дБ | PE, % | WPE, % | EIPE, % |
|---|---|---|---|
| Clean | 69,82 | 68,94 | 74,36 |
| 20 | 69,55 | 68,61 | 74,12 |
| 10 | 69,01 | 67,94 | 73,85 |
| 0 | 68,14 | 66,88 | 72,97 |
| −10 | 66,93 | 65,41 | 71,84 |

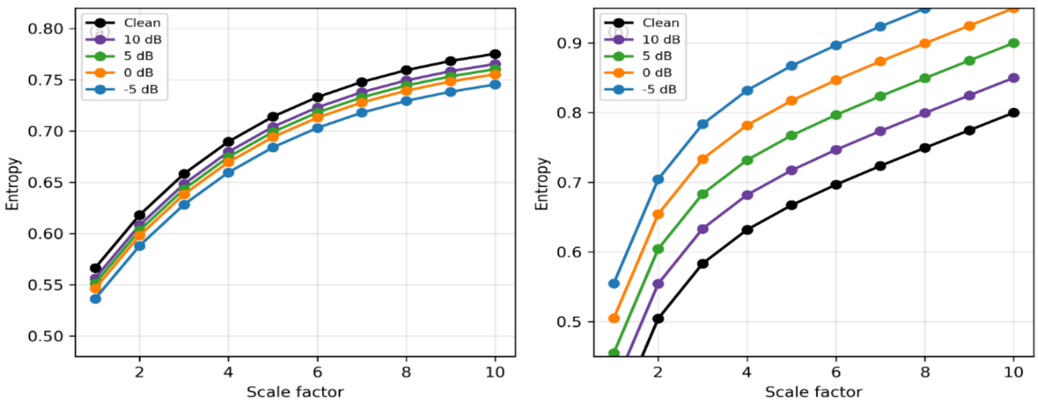


Fig. 3. Entropy characteristics of the signal

The segmentation scale $L = 6$ was chosen as a compromise providing stable entropy curves and sufficient separation between different SNR levels, ensuring both sensitivity to structural signal changes and robustness to noise. As shown in Fig. 3, increasing the segmentation scale leads to higher entropy values for all SNR levels, reflecting increased structural complexity under coarser temporal decomposition, while noise causes a reduction in absolute entropy values, most pronounced for the classical PE and WPE methods.

At $L = 6$, the entropy decrease when transitioning from a clean signal to SNR = −10 dB reaches 3,9 % for PE and 4,1 % for WPE, whereas for the entropy-consistent method EATS (EIPE) it does not exceed 2, 2 %, indicating enhanced noise robustness compared to classical approaches. To further validate these results, a statistical analysis of entropy distributions was performed for $L = 6$ (Fig. 4), enabling assessment of variability, outlier sensitivity, and stability under noisy conditions.

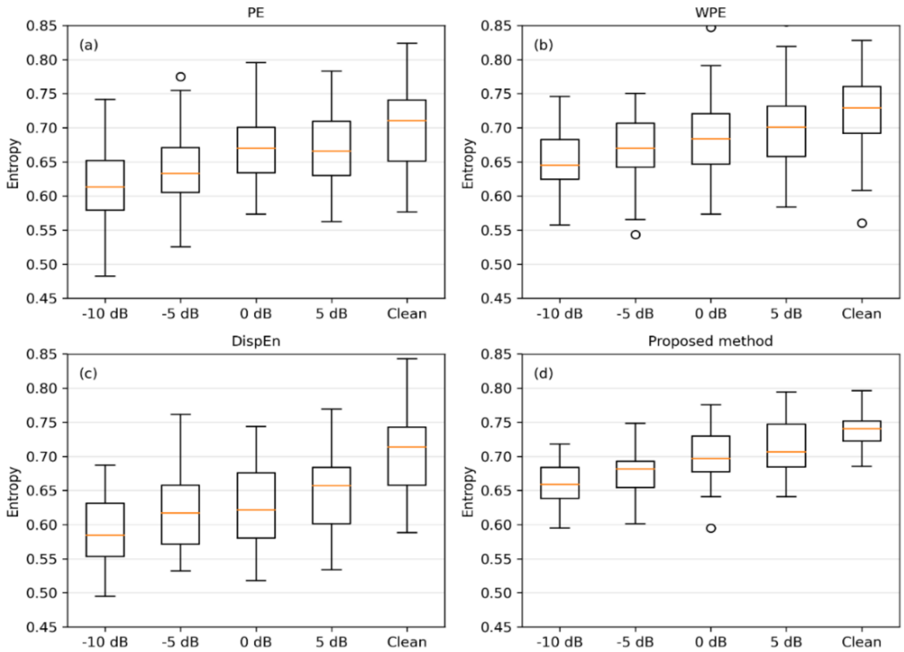


Fig. 4. Statistical comparison of entropy indicators

As shown in Fig. 4, for the classical methods PE, WPE, and DispEn, decreasing SNR leads to both a reduction in median entropy values and a significant expansion of the interquartile range, indicating increased sensitivity of these approaches to noise. In particular, when transitioning from a clean signal to SNR = -10 dB, the relative decrease in the entropy median reaches 3,9 % for PE and 4,1 % for WPE.

Thus, the results presented in Fig. 4 are consistent with the conclusions drawn from the analysis of mean entropy values (Figs. 2 and 3) and further confirm the advantage of entropy-consistent temporal segmentation in terms of noise robustness and result reproducibility.

**Conclusions**

Based on the results of experimental modeling, quantitative evidence has been obtained confirming the effectiveness of the entropy-consistent temporal segmentation method for forming complex signal ensembles compared to classical entropy-based approaches for time-series analysis.

The proposed method provides enhanced sensitivity to structural signal rearrangements, particularly in transition regions between irregular and regularized dynamic regimes. This is confirmed by a more pronounced local response of the entropy indicator compared to classical permutation entropy (PE) and weighted permutation entropy (WPE) methods.

Under conditions of intensive noise influence (SNR = −10 dB), the relative change of the entropy indicator for the proposed method does not exceed 2,2 %, whereas for the classical PE and WPE methods the corresponding decrease reaches 3,9 % and 4,1 %, respectively. This demonstrates the increased noise robustness of the entropy-consistent approach.

The use of the entropy indicator as a control variable for adaptive selection of the temporal segmentation scale enables alignment of the temporal decomposition with local structural inhomogeneity of the signal and improves the reproducibility of ensemble characteristics under noisy conditions.

Thus, the proposed entropy-consistent temporal segmentation method ensures a simultaneous increase in sensitivity to nonlinear signal dynamics and robustness to noise, making it suitable for applications related to the formation and adaptive processing of complex signal ensembles in uncertain and interference-intensive environments.

Future research directions include extension of the method to multivariate signals, integration with time–frequency and nonlinear analysis models, as well as application of entropy-consistent segmentation for controlling spectral reconstruction parameters and multi-criteria optimization of ensemble signal properties.

***REFERENCES***


[1] I. Tulenko and O. Shevchenko, "Entropy-based evaluation method of signal ensembles using LPT-τ permutations and Markov models," Computer-Integrated Technologies: Education, Science, Production. *Telecommunications and Radio Engineering*, no. 61, pp. 300–310, 2025, https://doi.org/10.26906/SUNZ.2024.1.206.

[2] S. V. Indyk and V. P. Lysechko, "Investigation of ensemble properties of complex signals obtained by frequency filtering of pseudorandom sequences with low interaction in the time domain," Collection of Scientific Works of Ivan Kozhedub Kharkiv National Air Force University, vol. 66, no. 4, pp. 46–50, 2020, DOI: 10.30748/zhups.2020.66.06.

[3] M. U. Ahmed and D. P. Mandic, "Multivariate multiscale entropy: A tool for complexity analysis of multichannel data," *Phys. Rev. E*, vol. 84, no. 6, Art. no. 061918, 2011, https://doi.org/10.1103/PhysRevE.84.061918.

[4] R. G. Andrzejak et al., "Indications of nonlinear deterministic and finite-dimensional structures in time series of brain electrical activity: Dependence on recording region and brain state," *Phys. Rev. E*, vol. 64, no. 6, Art. no. 061907, 2001, https://doi.org/10.1103/PhysRevE.64.061907.

[5] Z. Chen, X. Ma, J. Fu, and Y. Li, "Ensemble improved permutation entropy: A new approach for time series analysis," *Entropy*, vol. 25, no. 8, Art. no. 1175, 2023, https://doi.org/10.3390/e25081175.

[6] Z. Chen, Y. Li, H. Liang, and J. Yu, "Improved permutation entropy for measuring complexity of time series under noisy condition," *Complexity*, vol. 2019, Art. no. 1403829, 2019, https://doi.org/10.1155/2019/1403829.

[7] B. Deka and D. Deka, "An improved multiscale distribution entropy for analyzing complexity of real-world signals," *Chaos, Solitons & Fractals*, vol. 158, Art. no. 112101, 2022, https://doi.org/10.1016/j.chaos.2022.112101.

[8] A. Hamed, S. Saeid, and T. K. R. Tarek, "Ensemble entropy: A low-bias approach for data analysis," *Knowledge-Based Systems*, vol. 256, Art. no. 109876, 2022, https://doi.org/10.1016/j.knosys.2022.109876.

[9] S. M. Pincus, "Approximate entropy as a measure of system complexity," *Proc. Natl. Acad. Sci. USA*, vol. 88, no. 6, pp. 2297–2301, 1991, https://doi.org/10.1073/pnas.88.6.2297.

[10] D. Cuesta-Frau, M. Varela-Entrecanales, A. Molina-Pico, and B. Vargas, "Patterns with equal values in permutation entropy: Do they really matter for biosignal classification," *Complexity*, vol. 2018, Art. no. 1324696, 2018, https://doi.org/10.1155/2018/1324696.

[11] C. Bandt and B. Pompe, "Permutation entropy: A natural complexity measure for time series," Phys. Rev. Lett., vol. 88, no. 17, Art. no. 174102, 2002, https://doi.org/10.1103/PhysRevLett.88.174102.

[12] C. Bandt, "Ordinal time series analysis," Ecological Modelling, vol. 182, no. 3–4, pp. 229–238, 2005, https://doi.org/10.1016/j.ecolmodel.2004.04.003.

[13] H. Azami and J. Escudero, "Amplitude-aware permutation entropy: Illustration in spike detection and signal segmentation," *Comput. Methods Programs Biomed.*, vol. 128, pp. 40–51, 2016, https://doi.org/10.1016/j.cmpb.2016.02.008.

[14] M. Zanin, L. Zunino, O. A. Rosso, and D. Papo, "Permutation entropy and its main biomedical and econophysics applications: A review," *Entropy*, vol. 14, no. 8, pp. 1553–1577, 2012, https://doi.org/10.3390/e14081553.

***[15]*** P. Li, C. Karmakar, C. Yan, M. Palaniswami, and C. Liu, "Classification of epileptic EEG recordings using distribution entropy and sample entropy," *Frontiers in Physiology*, vol. 7, Art. no. 136, 2016, https://doi.org/10.3389/fphys.2016.00136.


**Голейчук Л. В., Лисечко В. П.**

**МЕТОД ЕНТРОПІЙНО-УЗГОДЖЕНОЇ ЧАСОВОЇ СЕГМЕНТАЦІЇ АНСАМБЛІВ СКЛАДНИХ СИГНАЛІВ**

*У статті запропоновано метод ентропійно-узгодженої часової сегментації для формування ансамблів складних сигналів, який ґрунтується на використанні ентропійного показника одночасно як інтегральної міри структурної складності сигналу та як керуючого індикатора для узгодженого вибору параметрів часової декомпозиції. Особливістю методу є підвищення чутливості до локальних структурних перебудов сигналу та завадостійкості ансамблевих характеристик в умовах нелінійної динаміки та інтенсивних завадових впливів.*

*На відміну від класичних ентропійних підходів, зокрема ординальної ентропії перестановок та зваженої ординальної ентропії перестановок, які обчислюються для фіксованого масштабу сегментації, запропонований метод передбачає узгодження масштабу часової сегментації з локальною структурною неоднорідністю сигналу. У межах підходу ентропійний показник використовується як механізм зворотного зв'язку, що дозволяє адаптивно змінювати часову декомпозицію при переходах між нерегулярними та регуляризованими режимами динаміки.*

*Експериментальну верифікацію методу проведено на нелінійних сигналах з керованою динамікою за наявності адитивних білих гаусівських завад із різними рівнями відношення сигнал/шум. Отримані результати показали, що запропонований ентропійно-узгоджений метод забезпечує підвищену стійкість ентропійної оцінки до завад, зменшуючи деградацію показників на 2,2 % при SNR = −10 дБ, тоді як для класичних методів PE та WPE відповідне зниження становить 3,9 % та 4,1 %. Крім того, метод забезпечує кращу контрастність між різними режимами динаміки сигналу та зменшення варіативності ентропійних оцінок при багаторазовому моделюванні.*

*Таким чином, запропонований метод ентропійно-узгодженої часової сегментації забезпечує ефективне та завадостійке формування ансамблів складних сигналів.*

**Ключові слова**: телекомунікації, сигнал, SNR; перестановки; ентропія; декомпозиція; завадостійкість; моделювання.

**Goleychuk L., Lysechko V.**

**METHOD OF ENTROPY-CONSISTENT TIME SEGMENTATION OF COMPLEX SIGNAL ENSEMBLES**

*This paper proposes an entropy-consistent temporal segmentation method for the formation of complex signal ensembles, which is based on the use of an entropy measure simultaneously as an integral indicator of the signal structural complexity and as a control variable for the coordinated selection of temporal decomposition parameters. A distinctive feature of the proposed method is the enhanced sensitivity to local structural transformations of the signal and the improved noise robustness of ensemble characteristics under nonlinear dynamics and intensive interference conditions.*

*Unlike classical entropy-based approaches, including ordinal permutation entropy and weighted ordinal permutation entropy, which are computed for a fixed segmentation scale, the proposed method provides coordination of the temporal segmentation scale with the local structural heterogeneity of the signal. Within the proposed framework, the entropy measure is employed as a feedback mechanism that enables adaptive modification of temporal decomposition during transitions between irregular and regularized dynamical regimes.*

*Experimental verification of the method was performed using nonlinear signals with controlled dynamics in the presence of additive white Gaussian noise at different signal-to-noise ratio (SNR) levels. The obtained results demonstrate that the proposed entropy-consistent method ensures enhanced robustness of entropy estimation to noise, reducing metric degradation to 2,2% at SNR = −10 dB, whereas the corresponding reductions for the classical PE and WPE methods amount to 3,9% and 4,1%, respectively. In addition, the method provides improved contrast between different dynamical regimes of the signal and reduced variability of entropy estimates under repeated simulations.*

*Thus, the proposed entropy-consistent temporal segmentation method enables efficient and noise-robust formation of complex signal ensembles.*

**Keywords:** telecommunications; signal; SNR; permutations; entropy; decomposition; noise robustness; modeling.

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