DOI: 10.18372/2310-5461.63.18953
УДК 621.396.967

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ADAPTIVE METHOD OF FORMING COMPLEX SIGNALS ENSEMBLES BASED ON MULTI-LEVEL RECURRENT TIME-FREQUENCY SEGMENT MODELING

Introduction

A major challenge in cognitive telecommunication networks (CTN) is the efficient utilization of the frequency spectrum, which is a limited resource under modern conditions. To achieve maximum throughput and minimize interference, cognitive networks must dynamically adapt to variations in the spectral environment. Another critical challenge is ensuring reliable data transmission, as factors such as interference, delays, and signal fluctuations necessitate adaptive solutions to maintain a high quality of service. The application of novel approaches to signal ensemble formation facilitates the development of advanced coding and modulation algorithms, enhancing signal resilience to these factors.

This is especially important in scenarios involving user mobility and fluctuating channel conditions. Additionally, the rapid increase in data volumes within CTNs necessitates efficient management of network resources. The use of methods for forming complex signal ensembles facilitates the development of models to optimize resource allocation, including transmitter power, frequency, and transmission time, thereby reducing energy consumption and enhancing network efficiency. This task becomes even more critical given the continuous rise in the number of connected devices.

Finally, data security remains a crucial aspect of cognitive telecommunication networks. The use of complex signal ensembles in increased volumes facilitates the development of methods to protect information from unauthorized access and attacks. The flexible and adaptive properties of such signal ensembles ensure effective information security under conditions of uncertainty and changing environmental parameters.

Thus, the application of advanced methods and models for forming complex signal ensembles addresses a wide range of scientific and practical challenges in wireless cognitive telecommunication networks, including efficient spectrum utilization, enhanced transmission reliability, optimized resource management, and data security. This opens up new opportunities for the development of cognitive networks and improved efficiency amid modern technological challenges.

Significant volumes of signals can be formed using time-frequency decomposition methods to create signal ensembles at various levels of frequency and temporal detail, which increases system throughput and improves data transmission reliability. The use of data fusion methods from different sources and processing based on artificial intelligence also allows the creation of highly complex signal ensembles and ensures stable communication in rapidly changing and dynamic radio frequency environments [1–3].

The formation of large signal ensembles is also achievable through the use of multichannel signal aggregation, which enhances interference resistance and improves communication quality. In this study, the proposed method of multilevel recurrent time-frequency segmentation utilizes adaptive filters and signal processing algorithms that consider the specific network parameters, enabling effective recognition and compensation of various types of interference and noise. Additionally, the proposed method involves continuous adjustment of the time segment duration and the use of time segments of varying lengths. [4–7].

Analysis of recent research and publications

Recent research efforts have aimed to enhance signal processing and spectrum sensing in cognitive radio networks, yet several challenges remain unresolved. [1] introduced multiscale adaptive signal representations to enhance computational efficiency, focusing on multi-scale frameworks that improve coding accuracy. However, their approach does not fully address the dynamic adaptability required for cognitive radio applications, particularly under rapidly changing spectral conditions. [2] explored stochastic resonance in high-order degradation systems for noise reduction and fault diagnosis, demonstrating potential in specific applications, but their methods do not extend to the real-time signal processing complexities found in telecommunications.

[3] and [4] has contributed to the understanding of spectrum sharing and quality parameter evaluation in cognitive networks. These studies emphasize resource allocation and performance metrics but fall short in addressing adaptive filtering and segmentation techniques critical for managing dynamic interference and maintaining robust communication.

[5] explored deep learning-based signal analysis, presenting methods that improved noise reduction in wireless networks, while [6] investigated spectrum analysis techniques that focus on minimizing interference. However, neither study incorporates adaptive multi-level time-frequency segmentation crucial for real-time adaptability, which remains a significant gap in their methodologies.

[7] examined the cross-correlation properties of complex signal ensembles, emphasizing the importance of frequency element permutations for improved signal formation, while Haykin [8] discussed cognitive radio concepts that support dynamic spectrum management. Nevertheless, these approaches do not integrate recursive segmentation methods capable of dynamically adjusting to changing signal conditions, limiting their practical adaptability in cognitive environments.

Here is the revised text with improved style:

Furthermore, the studies by Indyk and Lysechko [9–11] examined the formation of complex signal ensembles through the filtering of pseudo-random sequences and the adjustment of frequency bands, providing valuable insights into the management of signal properties. However, these studies do not incorporate multilevel recurrent time-frequency segmentation, which allows for dynamic adjustments in segment duration and frequency—an approach that is crucial for reducing interference and enhancing signal quality in cognitive networks.

This analysis underscores that, while previous research has made significant contributions, it lacks the integration of real-time adaptability, dynamic segmentation, and advanced filtering techniques, all of which are essential for cognitive telecommunication networks. This highlights the need for the development and implementation of a multilevel recurrent time-frequency segmentation method that not only improves the accuracy of signal processing but also enhances system robustness in highly variable radio environments, effectively addressing the limitations identified in earlier studies.

Problem Statement

Ensuring efficient signal processing in cognitive telecommunication networks under dynamic radio frequency environments and high levels of interference is a complex task that traditional spectral analysis methods fail to fully address. Static approaches to signal processing do not account for rapid changes in spectral characteristics and environmental parameters, leading to significant interference between frequency components, low signal analysis accuracy, and reduced communication quality [1].

Here is the revised text with improved style:

Unlike traditional methods, the proposed multilevel recurrent time-frequency segmentation method enables the dynamic adjustment of time segment durations and the use of segments with varying lengths, allowing for adaptive signal processing based on the current characteristics of the signals. Long time segments are optimal for analyzing low-frequency components, while short segments are effective for high-frequency ones, significantly reducing frequency interference and enhancing analysis accuracy [4, 7].

Moreover, the use of segments with different durations enables optimal distribution of the signal's energy spectrum, reducing inter-channel and inter-symbol interference, which is critical for maintaining stable communication in high-density and high-activity network conditions [8]. Due to its adaptability, the method also enhances the flexibility of system parameter settings, allowing for rapid response to environmental changes and optimization of spectral resources.

Thus, the proposed method not only enhances data transmission quality but also offers high resistance to noise and interference, capabilities that traditional signal processing methods cannot reliably provide. This opens opportunities for the advancement of cognitive telecommunication networks, enhancing their efficiency in complex and variable radio frequency environments [11, 12].

The purpose of the article

The purpose of the article is to test the algorithm for the implementation of the method of forming complex signal ensembles using multi-stage recurrent time-frequency segmentation. It is presented in Fig. 1.

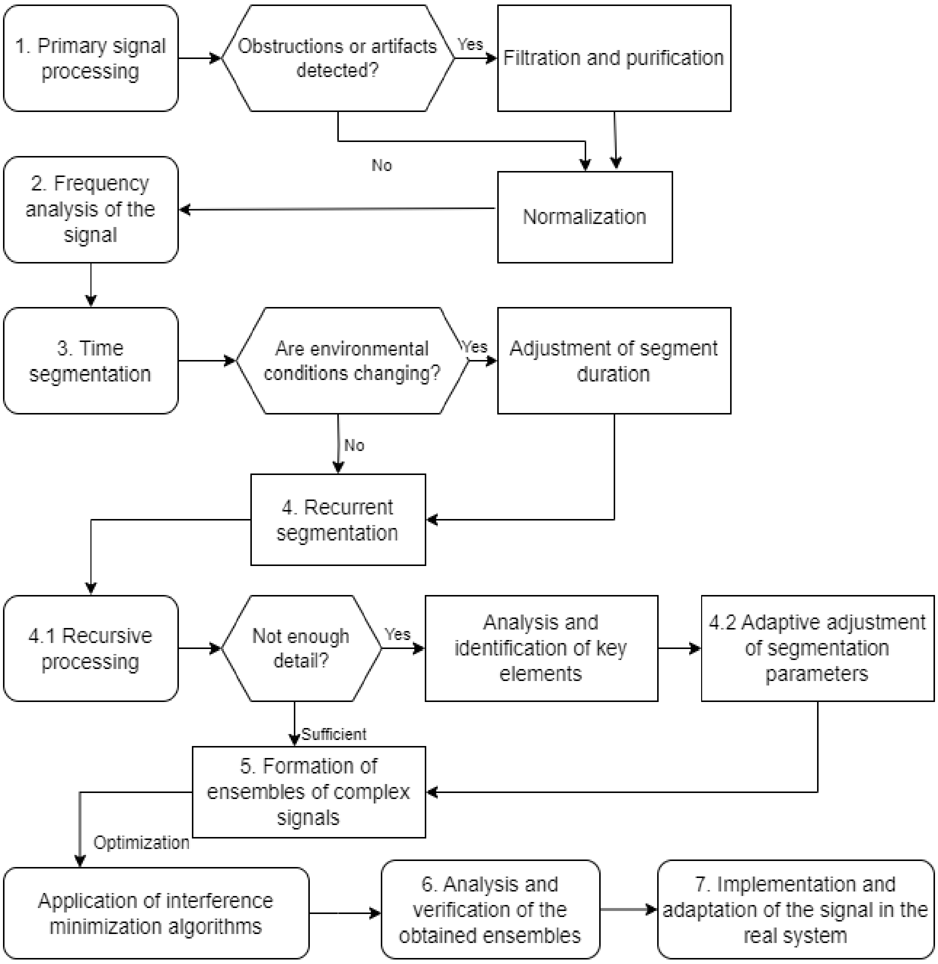

Fig. 1. The algorithm of the improved multilevel recurrent method

Summary of the main material

Let's examine in more detail the final stages of the algorithm depicted in Fig. 1 to conduct an experimental evaluation of the proposed algorithm's performance. To reduce noise, inter-channel, and inter-symbol interference before creating new ensemble signal formations, adaptive filters should be applied as they automatically adjust to changes in cognitive radio conditions, effectively separating the useful signal from noise and interference. It is effective to use the LMS (Least Mean Squares) adaptive filter [12, 14]:

$$y(n) = \sum_{k=0}^{M-1} \omega_k (n) \cdot x(n-k), \qquad (1)$$

where $y(n)$, $x(n)$ – are output and input signals, respectively; $\omega_k (n)$ – weight coefficients of the filter at time n; M – is the length of the filter.

The update of the weight coefficients is performed using the formula [10, 14]:

$$\omega_k (n+1) = \omega_k (n) + \mu \cdot e(n) \cdot x(n-k), \qquad (2)$$

where μ is the learning rate; $e(n) = d(n) - y(n)$ – is the error between the desired signal $d(n)$ and the output signal $y(n)$.

Applying Short-Time Fourier Transform (STFT) or wavelet transform at the stage of generating complex signal ensembles is justified as these transforms allow precise analysis of frequency components in each time segment before combining them into an ensemble.

To optimize newly formed ensembles of complex signals, adaptive filters can be employed to reduce the impact of interference on useful signals, thus enhancing the quality of signal transmission and processing. Adaptive filters are capable of adjusting their parameters according to changes in the radio environment. One such filter is the Recursive Least Squares (RLS) filter, calculated as follows [3, 11]:

$$\begin{gathered} K(n) = \frac{P(n-1)x(n)}{\lambda + x^T(n)P(n-1)x(n)} \\ P(n) = \frac{1}{\lambda}\left(P(n-1) - K(n)x^T(n)P(n-1)\right) \\ w(n) = w(n-1) + K(n)(d(n) - x^T(n)w(n-1)) \end{gathered} \qquad (3)$$

where $K(n)$ – is the Kalman gain vector; $x(n), w(n)$ – are the input signal vector and weight coefficients, respectively; $P(n)$ – is the covariance matrix; λ – is the forgetting factor; $d(n)$ – is the desired signal.

The Hilbert transform at this stage of the proposed method helps detect amplitude modulations of the signal, enhancing data transmission quality. This transform also aids in better distinguishing useful signals from noise, improving the accuracy of analysis and processing of complex signals.

At the verification stage of the multi-level recurrent time-frequency segmentation method, it is appropriate to apply specific filters and transformations, particularly the Richard Klein adaptive filter and independent component methods. These techniques are essential for refining the performance of the algorithm, ensuring that it effectively handles the complex and dynamic nature of cognitive radio environments by enhancing signal stability and minimizing interference from noise and other distortions.

The Richard Klein adaptive filter demonstrates high efficiency under the dynamic conditions of cognitive radio, enhancing both signal accuracy and stability. It is calculated using the formula [6, 12, 15]:

$$w_{n+1} = w_n + \mu \frac{e(n)x(n)}{x^T(n)x(n)}, \tag{4}$$

where μ – learning step.

The methods of independent components effectively isolate useful signals from noise, disturbances and distortions, are calculated according to the formula [5]:

$$S = W \cdot x(n), \tag{5}$$

where W – matrix of weighting factors; S – independent components

At the stage of the algorithm where the formed ensembles of complex signals are integrated into real systems and tested under empirical conditions to evaluate their effectiveness, it is advisable to apply specific adaptive optimization filters and transformations.

Spectral filtering using second-order wavelets improves signal quality by accurately extracting useful components from noise. This is calculated as [13]:

$$S = \sum_{i=1}^{N} c_i \, \psi_i(t), \tag{6}$$

where S – is the filtered signal; c_i – are the wavelet transformation coefficients; $\psi_i(t)$ – are second-order wavelets.

The adaptive filter based on fast gradient descent achieves high signal accuracy and stability through rapid adaptation to changing conditions. It is calculated using the formula:

$$w_{n+1} = w_n + \mu \nabla J(w), \tag{7}$$

where $\nabla J(w)$ – is the gradient of the error function.

To substantiate the effectiveness of the aforementioned filters and transforms, a comparative evaluation was conducted using software implementation in Python. We consider that Ensemble 1 consists of 3 signals with frequencies of 50 Hz – 300 Hz and amplitudes of 0,4 V–1 V, which are accompanied by white noise with an amplitude of 0.5 V, impulse noise with an amplitude of 0,3 V and Gaussian noise with an amplitude of 0,2 V. The results of the calculations are presented in the tab. 1.

Table 1

Calculations for Ensemble 1 before and after filtering and transformation

Metric	Before	After filtering		After Transformation		
		LMS	RLS	STFT	Wavelet	Hilbert
MA, B	0,802	0,781	0,813	0,783	0,802	0,793
RMS,B	0,85	0,75	0,732	0,74	0,76	0,75
DC, %	0,12	0,08	0,07	0,08	0,06	0,07
PSNR, dB	26,00	30,00	31,00	29,50	32,00	31,52
SNR, dB	22,00	26,00	27,00	25,50	28,00	27,51
CCC	0,89	0,95	0,97	0,94	0,98	0,96
SC	0,70	0,80	0,82	0,78	0,84	0,83
NRC	0,45	0,50	0,52	0,49	0,54	0,53
ACF	0,88	0,902	0,911	0,893	0,922	0,913
MaxA, B	1,10	1,05	1,07	1,06	1,09	1,08
MedA,B	0,75	0,73	0,74	0,73	0,75	0,74
EE, %	78,02	80,00	82,03	79,04	84,08	83,07
MaxPCCF	0,015	0,012	0,010	0,011	0,008	0,009

The reduction in average amplitude after filtering is 2,53 %, indicating the effective performance of filtering methods without significantly impacting signal amplitude. All filtering and transformation methods provide nearly identical results. A significant reduction in RMS after filtering is approximately 11,82 %, demonstrating a decrease in overall signal amplitude, as filtering effectively reduces noise but may also weaken part of the signal. The distortion coefficient decreased by 33,35 % after filtering and up to 50,2 % after transformation, showing a substantial reduction in signal ensemble distortion levels and high transformation efficiency, particularly with wavelet transforms. The SNR and PSNR metrics increased by 22,7 % and 15,4 %, respectively, proving effective noise reduction in the signal ensemble. Wavelet and Hilbert transforms exhibited the highest improvements in SNR and PSNR, demonstrating their high efficiency in enhancing signal quality. The CCC increased by 7,9 % after filtering and up to 10,1% after transformation, indicating moderate levels that prevent signal overlay. MaxPCCF decreased by 33,3 %, suggesting reduced peak noise correlation after processing, with wavelet transformation being the most effective in this regard.

Calculation of the metrics after filtering and transformation for Ensemble 2 is presented in Tab. 2.

Table 2

Calculations for Ensemble 2 before and after filtering and transformation

Metric	Before	After filtering		After Transformation		
		LMS	RLS	STFT	Wavelet	Hilbert
MA, B	0,78	0,75	0,77	0,76	0,78	0,77
RMS,B	0,83	0,72	0,70	0,71	0,73	0,72
DC, %	0,11	0,072	0,065	0,07	0,05	0,06
PSNR, dB	25,00	29,00	30,00	28,50	31,00	30,50
SNR, dB	21,00	25,00	26,00	24,50	27,00	26,50
CCC	0,87	0,94	0,96	0,93	0,97	0,95
SC	0,68	0,79	0,81	0,77	0,83	0,82
NRC	0,42	0,48	0,50	0,47	0,52	0,51
ACF	0,87	0,89	0,90	0,88	0,91	0,90
MaxA, B	1,05	1,00	1,02	1,01	1,04	1,03
MedA,B	0,73	0,70	0,72	0,71	0,72	0,73
EE, %	76,00	79,00	81,00	78,00	83,00	82,00
MaxPCCF	0,014	0,011	0,009	0,010	0,007	0,008

In fig. 2 presents the analysis of indicators before and after filtering and transformations for Ensemble 1 and Ensemble 2.

The average amplitude (MaxA) Ensemble 2 decreased by 3,85 %, indicating noise amplitude reduction. The root mean square (RMS) decreased by 13,25 %, reflecting increased signal stability. The distortion coefficient (DC) decreased by 36,36 %, confirming a reduction in distortion levels. Peak signal-to-noise ratio (PSNR) increased by 16,33 %, indicating improved signal quality, particularly at high amplitudes. Overall signal-to-noise ratio (SNR) increased by 19,05 %, showing enhanced noise resistance.

The cross-correlation coefficient (CCC) Ensemble 2 increased by 8,05 %, indicating moderate growth in mutual correlation between signals. The smoothing coefficient (SC) increased by 16,18 %, showing improved signal smoothing. The noise reduction coefficient (NRC) increased by 14,29 %, demonstrating effective noise reduction. Autocorrelation function (ACF) increased by 2,30 %, preserving the internal signal structure. Maximum amplitude (MaxA) decreased by 4,76 %, indicating reduced peak noise amplitude.

The comparative analysis of the calculations in Tables 1 and 2 demonstrated that the application of filtering and transformation methods at the generation and optimization stages of complex signal ensembles for Ensemble 2 yielded better results than the calculated metrics obtained for Ensemble 1. This improvement is attributed to the fact that the signals in Ensemble 2 contained modulated components and more complex spectral characteristics, which complicate the process of distortion detection and correction. Despite these challenges, the overall enhancement of signal quality was achieved due to the effective processing of amplitude-modulated signals and the reduction of additive white Gaussian noise (AWGN).

In fig. 2 shows that ensembles of complex signals, which have a smaller number of modulated components and simpler spectral characteristics, such as experimental Ensemble 1 (blue line in the graphs), are better amenable to filtering and transformation processes. This is especially noticeable when applying the wavelet transform for Ensemble 1, which provides the greatest reduction in distortion and noise, and the RLS filter for Ensemble 2 (orange line), which effectively reduces signal dispersion. This is because Ensemble 1 has a more uniform signal structure, which facilitates the processing process and improves the filtering results.

Fig. 2. Analysis of indicators after filtering and transformations

Conclusions

The proposed adaptive method for analyzing and processing complex signal ensembles, based on specific transformations and optimized filters applied at various stages of multistage recursive time-frequency segmentation, has demonstrated high efficiency in the experimental calculations presented in this study. The analysis of different types of transformations – such as Fourier, Short-Time Fourier Transform (STFT), wavelet, cosine, and Hilbert – reveals that their application at various stages of multilevel time-frequency segmentation provides high precision and adaptability in signal processing. This approach enables more accurate identification of key signal elements, including amplitude peaks and frequency variations, which are essential for maintaining signal stability and quality.

At the stages of the algorithm–formation, optimization, verification, and implementation of signal ensembles – the adaptive method incorporating specific transformations and filters demonstrated high effectiveness in reducing noise levels by 21,7–29,6 % and improving signal quality by 14,3–24,5 %. The use of adaptive filters, such as LMS and RLS, as well transformations like STFT, wavelet, and Hilbert, significantly enhanced signal interference resistance and energy efficiency by 9,8–18,9 %.

The experimental results thus confirm that the proposed method ensures consistently high-quality processing of complex signal ensembles, even in the dynamic environment of cognitive radio. Future research will aim to further enhance the adaptive capabilities of the proposed method, particularly under more complex and rapidly changing signal conditions, to improve robustness and adaptability across diverse telecommunication applications.

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АДАПТИВНИЙ МЕТОД ФОРМУВАННЯ АНСАМБЛІВ СКЛАДНИХ СИГНАЛІВ НА ОСНОВІ БАГАТОРІВНЕВОГО РЕКУРЕНТНОГО ЧАСОВО-ЧАСТОТНОГО СЕГМЕНТНОГО МОДЕЛЮВАННЯ

У статті досліджено впровадження адаптивного методу формування ансамблів складних сигналів, заснованого на багаторівневому рекурентному часово-частотному сегментуванні. Розглянуто основні проблеми в когнітивних безпроводових мережах в умовах динамічних радіочастотних середовищах з високим рівнем інтерференції, що потребує швидкої адаптації до змін у спектральних характеристиках сигналів.

Обґрунтовано необхідність використання адаптивних фільтрів та специфічних перетворень для покращення якості обробки сигналів, зокрема у середовищах з високою варіативністю частотних характеристик і наявністю потужних завад.

Запропонований метод багаторівневого рекурентного часово-частотного сегментування дозволяє змінювати тривалість часових сегментів і використовувати сегменти неоднакової довжини, що забезпечує гнучкість у процесі обробки сигналів та їх адаптацію до поточних умов. Така адаптивність дозволяє оптимально налаштовувати обробку для кожного окремого випадку, враховуючи короткочасні імпульси, довготривалі коливання, а також різноманітні типи завад та спотворень. Це забезпечує ефективне розділення частотних компонентів і зниження рівня інтерференції між ними, що є особливо важливим для забезпечення високої якості сигналу та стабільності зв'язку в когнітивних мережах.

Доведено, що застосування адаптивних фільтрів, таких як LMS та RLS, а також швидкого перетвореня STFT Фур'є, вейвлет і Гільберта на різних етапах багаторівневої часово-частотної сегментації значно підвищує завадостійкість та енергетичну ефективність обробки сигналів. Проведений порівняльний аналіз показників до та після фільтрації та перетворень демонструє збільшення якості сигналів на 14,3–24,5 % та зниження рівня шуму на 21,7–29,6 %. Особливо ефективним виявилося використання вейвлет-перетворення, яке дозволяє точно виділяти корисні частотні компоненти з шумового фону, покращуючи параметри сигналу за рахунок динамічного налаштування під конкретні умови радіосередовища.

Експериментальні результати підтверджують ефективність запропонованого методу, показуючи його здатність забезпечити стабільно високу якість обробки ансамблів складних сигналів навіть у динамічному когнітивному радіосередовищі.

Ключові слова: ансамблі складних сигналів, когнітивне радіосередовище, часово-частотне сегментування, багаторівневий рекурентний метод, міжканальна та міжсимвольна інтерференція, підвищення завадостійкості, фільтри, перетворення.

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ADAPTIVE METHOD OF FORMING COMPLEX SIGNALS ENSEMBLES BASED ON MULTI-LEVEL RECURRENT TIME-FREQUENCY SEGMENT MODELING

The article investigates the implementation of an adaptive method for forming ensembles of complex signals based on multilevel recurrent time-frequency segmentation. It addresses the key challenges faced by cognitive wireless networks operating in dynamic radio frequency environments with high levels of interference, necessitating rapid adaptation to changes in the spectral characteristics of signals. The study substantiates the need for adaptive filters and specific transformations to enhance signal processing quality, particularly in environments with high variability in frequency characteristics and significant noise interference.

The proposed method of multilevel recurrent time-frequency segmentation allows for the modification of time segment durations and the use of segments of varying lengths, providing flexibility in signal processing and adaptation to current conditions. This adaptability enables optimal signal processing for each individual case, taking into account short-term impulses, long-term fluctuations, and various types of noise and distortions. This approach effectively separates frequency components and reduces interference between them, which is crucial for maintaining high signal quality and communication stability in cognitive networks.

It has been proven that the use of adaptive filters such as LMS (Least Mean Squares) and RLS (Recursive Least Squares), as well as fast Fourier Transform (STFT), wavelet, and Hilbert transforms at different stages of multilevel time-frequency segmentation, significantly enhances signal interference resistance and energy efficiency. Comparative analysis of signal metrics before and after filtering and transformation shows an increase in signal quality by 14,3–24,5% and a reduction in noise levels by 21,7–29,6%. The wavelet transform, in particular, proved to be highly effective, allowing for precise extraction of useful frequency components from the noise background and improving signal parameters through dynamic adjustment to specific radio environment conditions.

Experimental results confirm the effectiveness of the proposed method, demonstrating its ability to ensure consistently high-quality processing of complex signal ensembles even in dynamic cognitive radio environments.

Keywords: complex signal ensembles, cognitive radio environment, time-frequency segmentation, multilevel recurrent method, inter-channel and inter-symbol interference, interference resistance enhancement, filters, transformations.

Стаття надійшла до редакції 05.08.2024 р.
Прийнято до друку 11.09.2024 р.