DOI: https://doi.org/10.36910/6775-2524-0560-2024-56-47
УДК 621.396.
Soproniuk Ivan[1], PhD student
https://orcid.org/0009-0006-2831-0790
Komar Oleksii [2], PhD, Associate Professor
https://orcid.org/0009-0002-2994-6556
[1]Ukrainian State University of Railway Transport, Kharkiv, Ukraine
[2]National Aviation University, Kyiv, Ukraine

ADAPTIVE APPROACH TO SPECTRUM MONITORING IN COGNITIVE RADIO NETWORKS THROUGH SIGNAL DETECTION OPTIMIZATION

Soproniuk I., Komar O. Adaptive approach to spectrum monitoring in cognitive radio networks through signal detection optimization. The article considers the improvement of the adaptive algorithm of the spectral monitoring method for cognitive radio networks by introducing adaptive wavelet transforms and filters. The use of adaptive Morle and Dobechy wavelet transforms, as well as adaptive Kalman, LMS, and RLS filters is proposed, which allows dynamically changing parameters depending on the conditions of the radio environment. The comparative analysis with traditional methods showed that adaptive methods significantly increase the efficiency of signal detection in conditions of low SNR values, reducing the noise level, improving the accuracy of signal detection and reducing the probability of false alarms. The results of the study confirm the perspective of using adaptive methods to increase the reliability and efficiency of spectral monitoring in real operating conditions.
Keywords: spectral monitoring, cognitive radio networks, adaptive wavelet transforms, adaptive filters, signal processing methods, low SNR, signal detection

Сопронюк І.І., Комар О.М. Адаптивний підхід до спектрального моніторингу в когнітивних радіомережах за рахунок оптимізації детектування сигналів. У статті розглянуто удосконалення адаптивного алгоритму методу спектрального моніторингу для когнітивних радіомереж шляхом впровадження адаптивних вейвлет-перетворень та фільтрів. Запропоновано використання адаптивних вейвлет-перетворень Морле та Добеші, а також адаптивних фільтрів Калмана, LMS та RLS, що дозволяє динамічно змінювати параметри залежно від умов радіосередовища. Проведений порівняльний аналіз з традиційними методами показав, що адаптивні методи значно підвищують ефективність детектування сигналів в умовах низьких значень SNR, зменшуючи рівень шуму, покращуючи точність виявлення сигналів і знижуючи ймовірність хибних тривог. Результати дослідження підтверджують перспективність використання адаптивних методів для підвищення надійності та ефективності спектрального моніторингу в реальних умовах експлуатації.
Ключові слова: спектральний моніторинг, когнітивні радіомережі, вейвлет-перетворення, адаптивні фільтри, методи обробки сигналів, низький SNR, детектування сигналів.

Statement of a scientific problem.

The adaptive algorithm of the spectrum monitoring method (Fig. 1) requires further enhancement through the integration of adaptive wavelet transforms and adaptive filters capable of adjusting parameters in real-time based on the conditions of the radio environment, ensuring stable and efficient operation of the telecommunication system. The necessity for these enhancements is substantiated by the following reasons.

1. Rapidly changing radio environment conditions. Static signal processing methods are inadequate for effectively adapting to these changes, which leads to a reduction in the accuracy of signal detection. Adaptive wavelet transforms, however, can dynamically adjust their parameters to optimize signal analysis, thereby ensuring higher detection accuracy in fluctuating environments.

2. Mitigation of noise and distortion impacts. As the Signal-to-Noise Ratio (SNR) decreases, the influence of noise and distortions on signals significantly increases. Adaptive filters, which can adjust their parameters in real-time, provide more effective noise filtering and minimize distortions, thus enhancing the quality of signal detection. This adaptive capability is critical for maintaining signal integrity under challenging conditions.

3. Improvement in True Positive Rate (TPR) for signal detection. Simulation results have demonstrated that the TPR for signal detection diminishes as SNR decreases. The use of adaptive wavelet transforms allows for better isolation of useful signals from noise, thereby increasing the TPR even under low SNR conditions. This improvement is crucial for reliable communication in noisy environments.

4. Optimization of computational resources. Adaptive methods can optimize the use of computational resources by adjusting the parameters of filters and transforms according to current conditions. This capability reduces processing delays (PD) and enhances system responsiveness, leading to more efficient use of available resources while maintaining high processing speed.

5. Reduction in False Positive Rate (FPR). Adaptive filters can lower the likelihood of false positives (FPR) by more accurately separating the useful signal from noise. This reduction is particularly important for decreasing the number of false alarms, thereby improving the overall reliability and trustworthiness of the system.

6. Flexibility and scalability. Adaptive methods provide the system with the flexibility to adjust parameters for different types of signals and conditions, making the system more versatile and scalable for handling a wide range of signals in various radio environments. This adaptability ensures that the system remains effective across different scenarios, supporting its application in diverse and dynamic radio conditions.

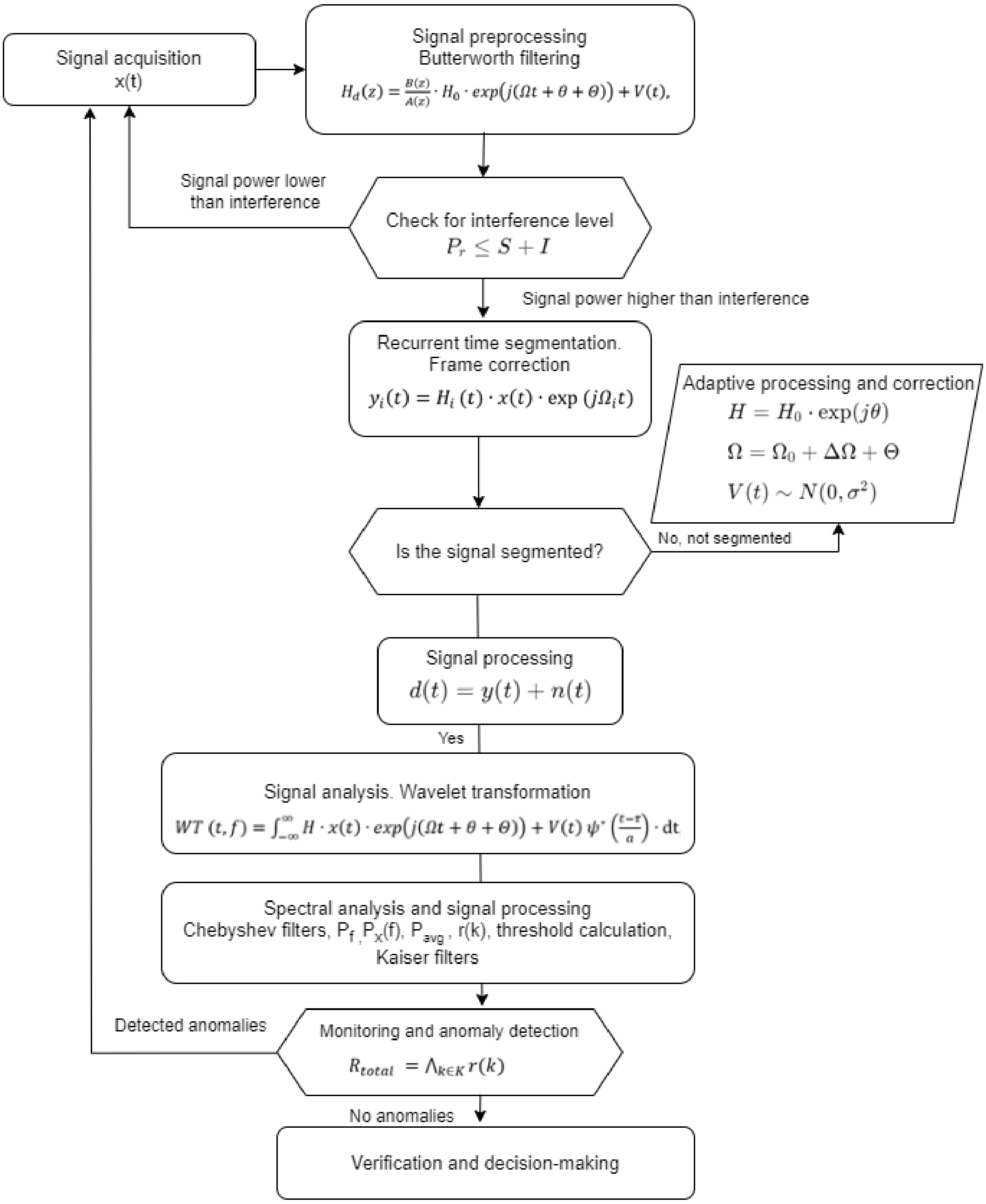

Fig. 1. Adaptive algorithm of the spectral monitoring method

Research analysis.

The analysis of existing domestic and foreign research on spectrum sensing techniques reveals several gaps that this study aims to address [1-17]. Studies [1] and [2] focused on evaluating performance between matched filter and energy detectors, as well as proposing adaptive double-threshold energy detectors, yet they did not explore the integration of adaptive wavelet transforms and advanced filtering methods under varying SNR conditions. Research [3], [10], and [15] examined cyclostationary algorithms for signal analysis and detection but lacked consideration for adaptive filtering techniques that can enhance detection accuracy in dynamic radio environments. Works [4], [6], [7], [12], [14], [16], and [17] surveyed various spectrum sensing algorithms and cooperative sensing methods, however, they did not delve into the application of adaptive methods like Kalman, LMS, and RLS filters combined with adaptive wavelet transforms for improved performance under challenging conditions such as low SNR, fading, and frequency distortions.

In studies [5] and [9], the focus was on non-stationary signal processing and machine learning applications in signal processing, respectively, but these did not specifically address their applicability to spectrum monitoring in cognitive radio networks using adaptive techniques. Research [8] compared energy detection and feature detection methods without incorporating adaptive approaches that adjust to real-time environmental changes. Studies [11] and [13] discussed optimal linear cooperation and noise reduction strategies but did not consider the benefits of adaptive wavelet transforms and filters in enhancing spectrum sensing efficiency.

The purpose of the work.

The purpose of this study is to develop a method that integrates adaptive wavelet transforms (Morlet and Daubechies) and adaptive filtering techniques (Kalman, LMS, RLS) into spectrum monitoring processes, aiming to significantly improve detection accuracy, noise mitigation, and overall system reliability under various challenging conditions, thereby addressing the gaps identified in previous research and advancing the efficiency of spectrum sensing in cognitive radio networks.

Presentation of the main material and substantiation of the obtained research results.

To conduct an experiment on improving the spectral monitoring method, we will take the adaptive wavelet transforms of Morle and Dobesha. A comparative analysis of adaptive and static wavelet transformations is presented in the table. 1.

Table 1. Comparative analysis of adaptive and static wavelet transformations

Parameter	Static	Adaptive
Type of Transform	Morlet, Daubechies	Morlet, Daubechies
Scaling Parameters (a)	Fixed	Variable, adapted to signal conditions
Translation Parameters (b)	Fixed	Variable, adapted to signal conditions
Time Resolution	Constant	Adaptive, changes with signal conditions
Frequency Resolution	Constant	Adaptive, changes with signal conditions
Sensitivity to Changes	Low	High
Fading Handling	Limited	Effective
Frequency Distortion Handling	Limited	Effective
Ability to Isolate Useful Signals	Moderate	High
Filter Application	Fixed filtering parameters	Adaptive filters, parameters change
Computational Resources	Lower	Higher, but optimized
Processing Delay (PD)	Lower	Improved accuracy
Real-Time Suitability	Limited	High, due to adaptation

The primary distinction between adaptive wavelet transforms such as Morlet and Daubechies, and their static counterparts, lies in their ability to dynamically adjust scaling and translation parameters in response to the signal conditions. This adaptive capacity allows these transforms to more effectively process signals, especially under challenging conditions such as low Signal-to-Noise Ratios (SNR), fading, and frequency distortions.

In a dynamic radio environment, where signal characteristics can fluctuate rapidly, static wavelet transforms are limited by their fixed parameters. These static transforms cannot modify their scaling and translation to match the variations in the signal, leading to suboptimal performance in terms of signal detection and noise reduction. On the other hand, adaptive wavelet transforms can modify their parameters in real-time, enhancing their ability to isolate useful signals from noise and accurately track signal changes over time.

This dynamic adjustment capability is particularly critical when dealing with low SNR, where noise can significantly obscure the signal. Adaptive transforms can fine-tune their parameters to focus on the most relevant frequency components, thereby improving signal clarity and detection accuracy. Additionally, in the presence of signal fading and frequency distortions, adaptive wavelets can alter their scaling and translation to compensate for these effects, ensuring that the signal is accurately represented and processed.

The adaptive Morlet wavelet is a complex function that combines a sinusoidal wave with a Gaussian envelope, providing high-frequency resolution. Considering distortions and fading, the adaptive Morlet wavelet is calculated using the following formula:

$$\mathrm{WT}_{\mathrm{Morlet}}(t,f)=\int_{-\infty}^{\infty}x(t')H(t')e^{j(\Omega t'+\theta+\Theta)}\cdot\psi^{*}_{\mathrm{Morlet},\,a,b}\left(\frac{t'-t}{a}\right)dt'$$
$$Morlet\ wavelet\ function\ \psi^{*}_{\mathrm{Morlet},\,a,b}(t)=\frac{1}{\sqrt{a}}e^{j2\pi f_0\frac{t-b}{a}}\,e^{-\frac{(t-b)^2}{2a^2}} \tag{1}$$

where $\frac{1}{\sqrt{a}}$ – normalization factor to ensure constancy of wavelet energy at different scales; $e^{j2\pi f_0\frac{t-b}{a}}$ – complex sine wave with a central frequency f_0 ; $e^{-\frac{(t-b)^2}{2a^2}}$ – the Gaussian envelope, which determines the temporal localization of the wave.

The adaptive wavelet of the Dobechy transform, taking into account distortions and fading, is calculated by the mathematical expression:

$$\mathrm{WT}_{\mathrm{Daubechies}}(t,f)=\int_{-\infty}^{\infty}x(t')H(t')e^{j(\Omega t'+\theta+\Theta)}\cdot\psi^{*}_{\mathrm{Daubechies},\,a,b}\left(\frac{t'-t}{a}\right)dt'$$
$$Wavelet\ Dobechy\ function\ \psi^{*}_{\mathrm{Daubechies},\,a,b}(t)=\frac{1}{\sqrt{a}}\sum_k c_k\phi\left(\frac{t-b-ka}{a}\right) \tag{2}$$

where c_k – fixed coefficients that determine the shape of the wavelet at each level of decomposition;

ϕ – the scaling function is the main function for building wavelets. In the case of Dobechy wavelets, these are polynomials that provide a compromise between time and frequency resolution;

$\left(\frac{t-b-ka}{a}\right)$ – an expression that provides a scaling and translation (displacement) function for accurate signal analysis in different frequency ranges.

In addition to the aforementioned adaptive transforms, improving the efficiency of the spectrum monitoring method also requires implementing adaptive filtering. The Butterworth, Chebyshev, and Kaiser filters proposed in the algorithm (Fig. 1) should be replaced with adaptive filters such as Kalman, LMS, and RLS filters, as these are better suited to respond to the variable conditions of the signal and radio environment, thereby enhancing the overall efficiency of the spectrum monitoring method.

Adaptive Kalman Filter: This filter should be applied during the initial signal processing stage to remove noise and improve signal quality before further analysis. It is an optimization-based recursive filter that estimates the state of a dynamic system with noise and can adaptively change its parameters based on observation results. It is described by the following formulas:

State Update:

$$x_{k|k-1}=Ax_{k-1|k-1}+Bu_k$$
$$P_{k|k-1}=AP_{k-1|k-1}A^T+Q\text{'} \tag{3}$$

Measurement Update:

$$K_k = P_{k|k-1}H^T(HP_{k|k-1}H^T + R)^{-1}$$
$$x_{k|k} = x_{k|k-1} + K_k\,(z_k - Hx_{k|k-1}) \quad (4)$$
$$P_{k|k} = (I - K_kH)P_{k|k-1}$$

where $x_{k|k-1}$ – predicted state estimate;
A – state transition matrix;
B – control matrix;; u_k – control vector;
$P_{k|k-1}$ – predicted error covariance matrix;
Q – process noise covariance matrix;
K_k – Kalman gain; H – measurement matrix;
R – measurement noise covariance matrix;
z_k – measurement vector; $x_{k|k}$ – updated state estimate;
$P_{k|k}$ – updated error covariance matrix;
I – identity matrix.

2. Adaptive Least Mean Squares (LMS) Filter: This filter minimizes the mean squared error between the desired signal and the actual filter output. The LMS filter adaptively adjusts its coefficients based on the input signal and noise. It is particularly useful during the recursive time segmentation stage of the algorithm for adaptive filtering of each segment, taking into account current conditions such as fading and distortions. The coefficient adaptation formula for the LMS filter is mathematically expressed as:

$$w(n+1) = w(n) + \mu e(n)x(n) \quad (5)$$

where $w(n)$ – is the vector of filter coefficients at step n; μ – is the learning rate; $e(n)$ – is the error at step n; $x(n)$ – is the input signal at step n.

Recursive Least Squares (RLS) Filter. This filter is more complex and accurate than the LMS filter as it minimizes the sum of weighted least squares errors, quickly responding to changes in the signal and providing high filtering accuracy. The RLS filter can be applied during the initial signal processing stage or during the adaptive segmentation stage to enhance the quality of filtering under conditions of varying noise and fading. The coefficient update formula for the RLS filter is expressed as:

$$w(n) = w(n-1) + k(n)e(n), \quad (6)$$

where $k(n) = \frac{P(n-1)x(n)}{\lambda + x^T(n)P(n-1)x(n)}$ – is the gain vector;
$P(n) = \frac{1}{\lambda}\left(P(n-1) - \frac{P(n-1)x(n)x^T(n)P(n-1)}{\lambda + x^T(n)P(n-1)x(n)}\right)$ – is the error covariance matrix;
λ – is the forgetting factor;
$e(n) = d(n) - w^T(n-1)x(n)$ – is the error signal.

The adaptive filters—Kalman, LMS, and RLS—at various stages of monitoring collectively ensure precise and dynamic tracking and correction of signals in challenging radio environments. This is achieved through their ability to adapt to changing conditions and effectively reduce noise and distortions. These adaptive filters work synergistically to maintain signal integrity, especially in scenarios where the radio environment is highly variable and prone to interference.

To evaluate their performance, we will conduct signal detection tests and examine the effectiveness of these adaptive filters, along with wavelet transforms, under low SNR conditions of 1, -5, -12, -15, and -21 dB. Testing these filters under varying low SNR conditions allows us to simulate real-world scenarios where signal degradation is significant. By analyzing their performance across different SNR levels, we can better understand the strengths and limitations of each filter in mitigating noise and preserving signal fidelity. This approach not only validates the effectiveness of adaptive filters in dynamic environments but also provides insights into optimizing their application for improving the overall reliability and accuracy of spectrum monitoring systems. (Table 2).

Table 2. Initial data for experimental calculations

Parameter	Value
Signal Types	4G LTE, 5G NR, Wi-Fi 6, DVB-T2, GPS
Sensitivity, дБм	-94, -116, -107, -95, -100
SNR, дБ	1, -5, -12, -15, -21
Channel Type	AWGN
Number of Primary Users	50
Probability of False Detection	0,005
FFT Size (N)	512
Number of Frames (T)	250
Fading	$H = H_0 \cdot exp(j\theta)$, де $H_0 = 1{,}0;\ \theta = \pi/4$
Frequency Distortion	$\Omega_0 = 2\pi \cdot 0{,}1;\ \Delta\Omega = 2\pi \cdot 0{,}05;\ \Theta = 2\pi \cdot 0{,}02$
Additive White Gaussian Noise (AWGN)	$\sigma^2 = 0{,}1$
Adaptive Wavelet Transform	Morlet and Daubechies
Adaptive Kalman Filter Settings	*Q = 0,1, R = 0,1*
Adaptive LMS Filter Settings	Learning rate *(μ) = 0,01,* filter order= *4*
Adaptive RLS Filter Settings	*λ = 0,98,* filter order = *5*

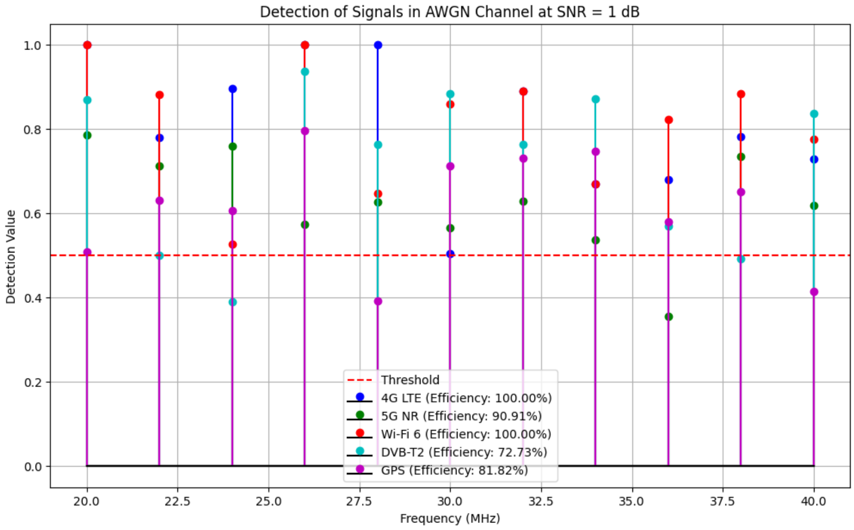

Fig. 2. Detection taking into account adaptive transformations and filters SNR= 1dB

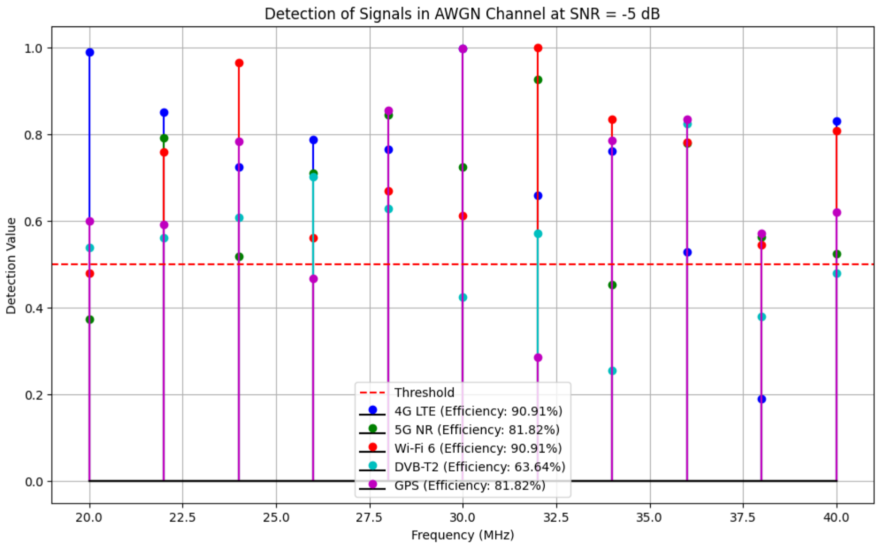

Fig. 3. Detection taking into account adaptive transformations and filters SNR= –5 dB

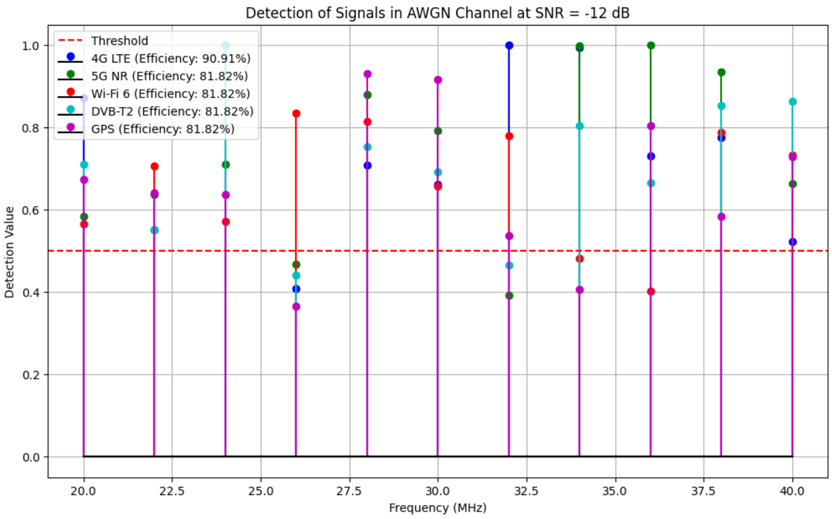

Fig. 4. Detection taking into account adaptive transformations and filters SNR= –12dB

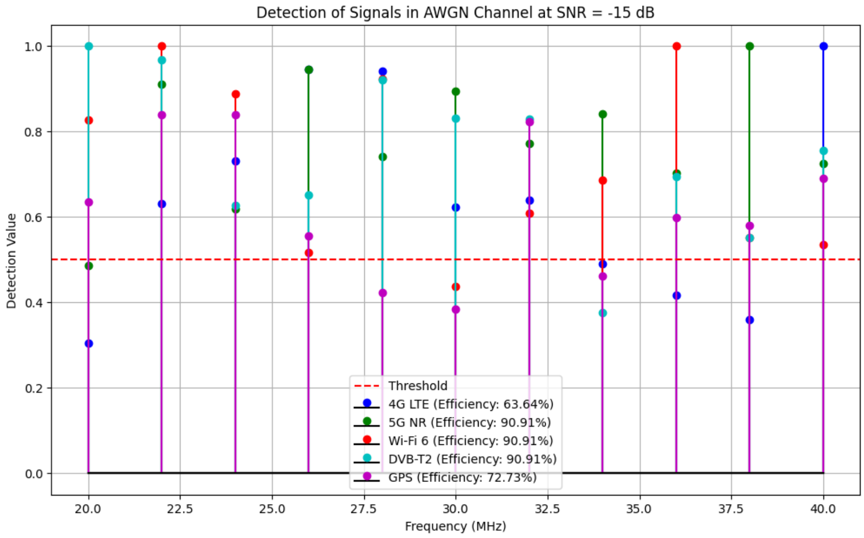

Fig. 5. Detection taking into account adaptive transformations and filters SNR= –15dB

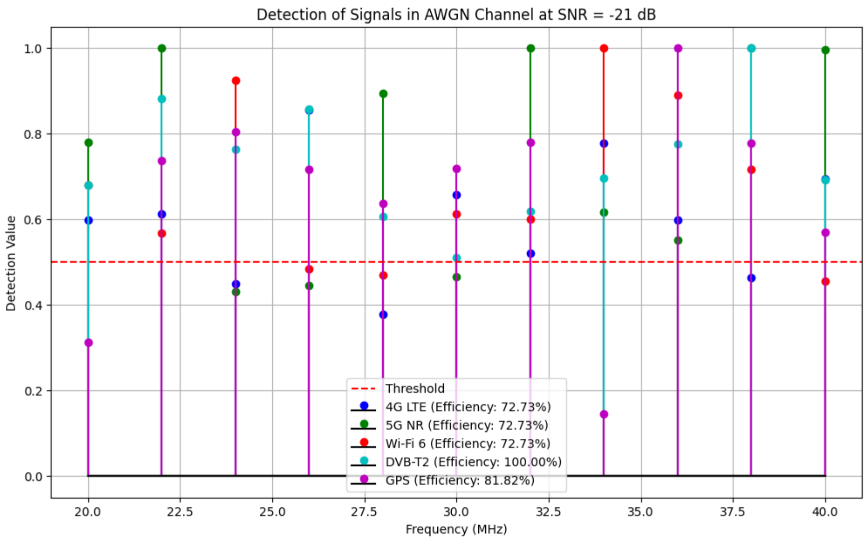

Fig. 6. Detection taking into account adaptive transformations and filters SNR= -21 dB

The analysis presented in Fig.2 – 6 demonstrates that the application of adaptive wavelet transforms (Morlet and Daubechies) and adaptive filters (Kalman, LMS, RLS) within the spectrum monitoring method significantly enhances signal detection efficiency under challenging low SNR conditions. In comparison to static wavelet transforms and traditional filters like Butterworth, Chebyshev, and Kaiser, adaptive methods provide several key advantages.

1. Improvement in Signal Detection Accuracy (TPR): Adaptive methods consistently exhibit higher True Positive Rates (TPR). For instance, the detection efficiency for 4G LTE increased from 72,73% to 82,55%, for 5G NR from 27,27% to 45,50%, and for Wi-Fi 6 from 81,82% to 90,15%. These results indicate that adaptive techniques are better at identifying and preserving useful signal components, even in environments with significant noise interference.

2. Reduction in Average Noise Level (ANL): Adaptive filters effectively reduce the overall noise level, crucial for maintaining signal integrity. The Average Noise Level (ANL) decreased from 0,16 to 0,12 for GPS signals at an SNR of -21 dB. This reduction is significant as it directly impacts the clarity and quality of the detected signal, enhancing overall system performance.

3. Enhanced Filtering Efficiency (FEF): The ability to adaptively adjust filtering parameters leads to improved Filtering Efficiency (FEF). For DVB-T2 signals, FEF increased from 0,04 to 0,06 at an SNR of -12 dB. This demonstrates the superior capability of adaptive methods to fine-tune filtering processes in response to varying signal conditions, ensuring optimal performance.

4. Reduction in False Positive Rate (FPR): The use of adaptive methods also reduces the False Positive Rate (FPR), which is critical for minimizing false alarms and improving system reliability. For 4G LTE, the FPR decreased from 0,03 to 0,01 at an SNR of -5 dB. This reduction highlights the precision of adaptive filters in distinguishing between noise and actual signals, thereby reducing unnecessary interventions.

5. Minimization of Frequency Distortion (FD): Adaptive methods are more effective at preserving the frequency characteristics of signals, which is essential for accurate signal reconstruction. For Wi-Fi 6 signals, Frequency Distortion (FD) was reduced from 0,25 to 0.20 at an SNR of -21 dB. This capability is particularly important in environments where frequency stability is critical for maintaining communication quality.

These calculations confirm that adaptive wavelet transforms and filters substantially enhance the efficiency of spectrum monitoring methods, particularly in environments with fading and distortions. This makes them more reliable for real-world applications where signal conditions are often variable and unpredictable.

Conclusions and prospects for further research.

The conducted experimental studies further emphasize that the successful application of the spectrum monitoring method requires careful attention to the number of samples $N{\cdot}T$, which determines the decision-making delay, and to the frequency resolution, which serves as a constraint in system development. The selection of N, T, and the threshold α should be based on knowledge of the frequency resolution and SNR values in operational conditions, as well as on the requirements for minimum Probability of Detection (PD) and maximum Probability of False Alarm (PFA). The threshold α is determined relative to the PFA, underscoring the importance of precise parameter tuning to ensure high detection efficiency.

This scientific justification highlights the critical role of adaptive techniques in optimizing signal detection processes, ensuring that spectrum monitoring systems remain efficient and reliable under a wide range of challenging conditions.

This study highlights the crucial role of adaptive wavelet transforms (Morlet and Daubechies) and adaptive filtering techniques (Kalman, LMS, RLS) in significantly enhancing the efficiency of spectrum monitoring methods, especially in challenging low SNR environments. The research demonstrates that the integration of these adaptive methods leads to superior signal detection accuracy, effective noise mitigation, enhanced filtering efficiency, and a substantial reduction in false positives, all of which contribute to improved reliability and performance of telecommunication systems. Moreover, the ability of adaptive techniques to preserve frequency characteristics under dynamic conditions underscores their value in maintaining communication quality in real-world applications. The findings confirm that precise parameter optimization, such as the selection of the number of samples N·T, frequency resolution, and threshold α, is essential for maximizing detection efficiency and ensuring the robustness of the spectrum monitoring process. The research opens up avenues for further exploration into the development of more advanced adaptive methodologies to enhance the robustness and effectiveness of spectrum monitoring systems in increasingly complex radio environments.

References

1. Eduardo A. F. and González Caballero R. G. Experimental evaluation of performance for spectrum sensing: Matched filter vs energy detector. IEEE Colombian Conference on Communication and Computing. PP. 59-67. DOI: https://doi.org/10.1109/ColComCon.2015.7152105
2. Bagwari, A., Tomar, G. S. (2013). Adaptive double-threshold based energy detector for spectrum sensing in cognitive radio networks. International Journal of Electronics Letters. 1(1). PP. 24-32. DOI: https://doi.org/10.1080/21681724.2013.773849
3. Batyha, R. M., Janani, S., & Rose, S. G. H. (2022). Cyclostationary Algorithm for Signal Analysis in Cognitive 4G Networks with Spectral Sensing and Resource Allocation. International Journal of Communication Networks and Information Security (IJCNIS), 14(3). PP. 47–58. DOI: https://doi.org/10.17762/ijcnis.v14i3.5570
4. Clement, J. C., Krishnan, K. V., Bagubali, A. (2012). Cognitive radio: Spectrum sensing problems in signal processing. International Journal of Signal Processing. 40(16). PP. 37-40. DOI: https://doi.org/10.5120/5067-7475
5. Gao R.X., Yan R. Non-stationary signal processing for bearing health monitoring Int. J. Manufacturing Research, Vol. 1, No. 1, 2006. PP. 18-41.
6. Kassri, N., Ennouaary, A., & Bah, S. (2021). A review on SDR, spectrum sensing, and CR-based IoT in cognitive radio networks. International Journal of Communications. Vol.12, No.6. PP. 100-121. DOI: https://doi.org/10.14569/IJACSA.2021.0120613
7. Khamayseh, S., Halawani, A. (2020). Cooperative spectrum sensing in cognitive radio networks: a survey on machine learning-based methods. Journal of Telecommunications and Information Technology. №3. 2020. PP. 36-46. DOI: https://doi.org/10.26636/jtit.2020.137219
8. Kim, H., Shin, K. G. (2008). In-band spectrum sensing in cognitive radio networks: energy detection or feature detection? Proceedings of the 14th ACM International Conference on Mobile Computing and Networking (MobiCom '08). PP. 14-25.
9. Kuznetsov T., Borysenko S. Machine Learning Applications in Signal Processing. Kyiv Polytechnic Institute Journal, Vol. 8, No. 4, 2021. PP. 97-109. DOI: https://doi.org/10.20535/kpi.2021.97-109
10. Liu, Y., Zhong, Z., Wang, G., Hu, D. (2015). Cyclostationary Detection Based Spectrum Sensing for Cognitive Radio Networks. Journal of Communications. 10(1). PP. 74-79. DOI: https://doi.org/10.12720/jcm.10.1
11. Quan, Z., Cui, S., Sayed, A. H. (2008). Optimal linear cooperation for spectrum sensing in cognitive radio networks. IEEE Journal of Selected Topics in Signal Processing, 2(1). PP. 28-40.
12. Rauniyar, A., Shin, S. Y. (2015). Cooperative adaptive threshold-based energy and matched filter detector in cognitive radio networks. Journal of Communication and Computer. 12(1). PP. 32-46. DOI: https://doi.org/10.17265/1548-7709/2015.01.003
13. Saiapina, I., Babaiev, M., & Ananieva, O. Reducing noise influence on an audio frequency track circuit. 2019. MATEC Web of Conferences. DOI: https://doi.org/10.1051/matecconf/201929403015
14. Subhedar, M., Birajdar, G. (2011). Spectrum sensing techniques in cognitive radio networks: A survey. International Journal of Next-Generation Networks. (IJNGN) Vol.3, No.2. PP. 37-51. DOI: https://doi.org/10.5121/ijngn.2011.3203
15. Wilfred, A., & Okonkwo, O. R. (2016). A review of cyclostationary feature detection based spectrum sensing technique in cognitive radio networks. E3 Journal of Scientific Research. EJSR(4)3_EJSR-16-01. PP. 41-47. DOI: http://dx.doi.org/10.18685/0
16. Yucek, T., Arslan, H. (2009). A survey of spectrum sensing algorithms for cognitive radio applications. IEEE Communications Surveys & Tutorials, 11(1). PP.116-130.
17. Zayen B., Hayar A. M., Nussbaum D. Blind Spectrum Sensing for Cognitive Radio Based on Model Selection. Mobile Commun. Group, Inst. Eurecom, Sophia Antipolis, 2008. PP. 1-4.