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Spectrum Sensing Using Wavelet Transforms and Filtering Under Signal Frequency Distortion and Fading Conditions

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ABSTRACT This article explores improving the accuracy and reliability of spectrum sensing methods within cognitive radio networks. The primary focus is on how signal fading and frequency distortion influence the results of spectral analysis. These issues can severely impact the precision of signal detection, making adaptive methods and filters indispensable for accurately detecting changes in the spectral landscape. The purpose of the paper is to evaluate the effectiveness of various adaptive methods and filters – such as wavelet transforms, along with Butterworth, Chebyshev, and Kaiser filters—in improving the detection of changes within the spectral environment across different signal-to-noise ratio (SNR) levels. The research spans a broad frequency range, concentrating on pivotal technologies like 5G NR, Wi-Fi 6, DVB-T2, and GPS, each having unique requirements for signal precision and dependability. The spectrum sensing approach described in the article achieves high signal detection accuracy under favorable conditions, particularly when the SNR is strong. Experiments revealed that with SNR values above 1 dB, the signal detection accuracy (True Positive Rate, or TPR) for all technologies examined remains at or above 0.90. For instance, the TPR for 5G NR is 0.92 at an SNR of 1 dB, while for Wi-Fi 6, it stands at 0.90. However, the effectiveness of the method declines as the SNR decreases. For example, with 5G NR, the TPR drops to 0.70 at an SNR of -21 dB, indicating a heightened probability of false signal detection. Similar patterns are observed with Wi-Fi 6, where the TPR falls to 0.65, with DVB-T2 to 0.68, and GPS to 0.66. Additionally, the average noise level rises as SNR diminishes, making accurate signal detection increasingly challenging and emphasizing the need for further refinement of these methods. The findings underscore the need for ongoing advancements in spectrum monitoring, especially under low SNR conditions. Future research should prioritize developing new or refining existing adaptive algorithms capable of operating effectively in complex spectral environments. Exploring the impact of other filtering and transformation methods could also yield valuable insights. Moreover, the incorporation of machine learning techniques offers a promising path for boosting the adaptability and accuracy of spectrum monitoring in real-world telecommunication systems.

KEYWORDS wavelet transforms, Morlet or Daubechies, signal-to-noise ratio, Butterworth filters, Chebyshev filters.

I. INTRODUCTION

The paradigm of cognitive radio networks must embed effective sensing and at the same time be responsive to the dynamism in the environment. These are actively accessed parts of the radio spectrum, where dynamics are important, through accurate spectrum sensing, for the purposes of reliable communication. There are many problems with spectrum sensing, especially in conditions where signal fading and frequency distortions are common.

Effective spectrum sensing determines how well a network could detect and access available frequency bands. The signal-to-noise ratio (SNR), in general, is mainly critical in determining the extent of signal detection performance realized with respect to fluctuating SNR in cognitive radio systems. High SNR performance ensures robust detection of the signal so that the network can attain the said signal, thus allowing the network to operate and access the spectrum effectively. But, with the decrease in SNR, the probability of false detection increases; this will cause interference with communications, eventually lowering the network efficiency.

In response to these challenges, this paper investigates the appropriateness of adaptive methods and filters in increasing the accuracy of spectrum sensing. The research is primarily concerned with wavelet transforms and Butterworth, Chebyshev, and Kaiser filters, how they perform in varying frequency ranges and technologies: 5G NR, Wi-Fi 6, DVB-T2, and GPS. Since all these technologies necessitate the ultimate highest possible precision, reliability in the filtering method to be selected, this has been major criteria in selection.

The results of this article suggest that research on the enhancement of spectrum sensing methods must be continued in the future, especially under low SNR conditions. Further development of the concept of cognitive radio networks warrants an upgrade and enhancement of adaptive algorithms so that the communication is kept reliable in ever-changing spectrum environments.

II. REVIEW OF THE LITERATURE

Reference [1] considers application wavelet transforms in the analysis of digital signals, thus establishing a foundation for using wavelet-based techniques in the spectrum sensing process. The research is focused on the efficiency of wavelet transforms in complicated signal environments, which is a crucial factor for effective spectral analysis. This research leads to understand how wavelet-based methods can improve signal detection and processing under varied and difficult conditions.

The cited study [2] detailed methods for localizing unauthorized sources of radiation and noted that, fundamentally, accurate signal processing is important for preserving the integrity of cognitive radio networks. The ideas considered in their work are close to a more general framework that aims at attaining accuracy in spectrum sensing by controlling the interference and effects of unauthorized signals.

The paper [3] focuses on the use of adaptive algorithms with cognitive radio networks and finds that, in general, the use of adaptive methods for signal processing greatly improves the reliability and performance of the mentioned networks. Their findings support the necessity of employing adaptable filters and algorithms, particularly in environments with fluctuating signal-to-noise ratios (SNRs).

Spectrum sensing techniques in cognitive radio networks have been researched and recently reviewed in various works [4-6]. This includes information criteria in spectrum monitoring; Fast Fourier Transform in spectrum analysis; and signal robustness studies in wireless access systems. All these underline the importance of adaptive filtering and signal processing methods to ensure stably reliable sensing of the spectrum under diversified network conditions. While the results from these studies have been largely positive, a literature gap exists in terms of the basic rationale regarding the selection of filter techniques to maximize spectrum sensing efficiency in cognitive radio networks.

III. THE MATERIALS AND METHODS

Steps of the Adaptive Algorithm for Spectrum Monitoring in Conditions of Distortion and Fading Using Variable Time Segments, Wavelet Transform, and Butterworth, Chebyshev, and Kaiser Filters (Figure 1):

1. **Signal Acquisition**: The goal of this stage is to ensure accurate signal collection for further analysis.

1.1. **Signal Source Identification**: Specialized equipment is used to reduce noise levels. The collected signal is represented as $x(t)$.

1.2. **Receiver Selection**: Receivers are chosen based on the characteristics of the signal and environmental conditions, requiring high sensitivity S and the ability to operate in environments with high levels of noise and interference I. Let Pr represent the received signal power; then the condition $Pr>S+I$ must be met.

1.3. **Environmental Conditions Analysis**: This involves analyzing potential sources of interference, noise levels, and other factors that affect signal quality. Moving objects and weather conditions can cause signal fading and distortion. If $H(t)$ is the fading coefficient, then $y(t)=H(t)\cdot x(t)$.

1.4. **Signal Recording**: The collected signal is recorded and stored for further analysis. If $d(t)$ is the recorded signal, then $d(t)=y(t)+n(t)$, where $n(t)$ is the measurement noise.

1.5. **Accounting for Fading and Distortion**: The overall signal model, taking into account fading and distortion, is represented as follows:

$$y(t)=\mathrm{H}\cdot\mathrm{x}(t)\cdot\exp(j\Omega\mathrm{t}+\mathrm{j}\Theta)+\mathrm{V}(t) \quad (1)$$

For modeling fading, the Rayleigh distribution is used, considering σ_H^2 as the variance of the channel attenuation coefficient.

$$p_H(h)=\frac{h}{\sigma_H^2}\exp\left(\frac{-h^2}{2\sigma_H^2}\right) \quad (2)$$

2. **Signal Sampling.** The signal is divided into short segments (frames), allowing real-time spectral analysis and enabling the tracking of changes in the spectral composition of the signal over time.

2.1. **Signal Segmentation**: The signal is divided into short frames of duration T. These frames may overlap to reduce information loss at the edges of the frames.

2.2. **Weighted Multiplication**: Each frame is subjected to weighted coefficients (a window function) to minimize discretization effects and ensure smoother transitions between frames. This is expressed by the formula:

$$y_t(n)=\mathrm{x}_t(n)\cdot\mathrm{w}(n),\mathrm{n}=0,1,\dots,\mathrm{N}-1 \quad (3)$$

3. **Signal Preprocessing**: remove noise and enhance the signal quality for subsequent spectral analysis. Modified Butterworth filters are used for this purpose, offering maximum smoothness in the frequency response. This reduces signal distortion and minimizes the filtering impact on the useful signal [7, 8].

Analog Prototype of the Modified Butterworth Filter:

$$H_a(s)=\frac{1}{\sqrt{1+\left(\frac{s+\Delta s}{\omega_c}\right)^{2m}}}\cdot\mathrm{H}_0\cdot\exp(\mathrm{j}\theta), \quad (4)$$

where s is the complex variable; Δs is the frequency shift; ω_c is the cutoff frequency; m is the filter order.

For the Digital Butterworth Filter, the analog prototype is transformed into digital form using bilinear transformation of the z-variable [8]:

$$\mathrm{s}=\frac{2}{T}\frac{1-z^{-1}}{1+z^{-1}}, \quad (5)$$

where T is the sampling period.

This results in a low-pass Butterworth filter [8] with order m, accounting for the effects of fading $H_0\cdot\exp(\mathrm{j}\theta)$distortion $\exp(j\Omega\mathrm{t}+\mathrm{j}\Theta)$ and noise $V(t)$, represented as:

$$H_d(z)=\frac{B(z)}{A(z)}\cdot\mathrm{H}_0\cdot\exp\big(j(\Omega\mathrm{t}+\theta+\Theta)\big)+\mathrm{V}(t), \quad (6)$$

$$\frac{B(z)}{A(z)}=\frac{\sum_{\mathrm{k}=0}^{m}a_k z^{-k}}{\sum_{\mathrm{k}=0}^{m}b_k z^{-k}}$$

4. **Recurrent Time Segmentation**: involves re-segmenting the signal while accounting for dynamic changes in the spectral environment as well as the effects of fading and distortion.

4.1. **Adaptive Segmentation**: The signal is divided into segments of varying durations Ti, allowing for a more precise consideration of changes in the signal's characteristics. For each segment, the current values of the fading coefficient $H(t)$ and frequency distortion $\Omega(t)$ are calculated.

4.2. **Frame Correction**: Each frame is corrected to account for fading and distortion. The correction formula is as follows:

$$y_i(t)=\mathrm{H}_i(t)\cdot\mathrm{x}(t)\cdot\exp(j\Omega_i t), \quad (7)$$

where $y_i(t)$is the corrected signal for the *i-th* frame, $H_i(t)$is the fading coefficient for the *i-th* frame, and $\Omega_i$is the frequency distortion for the *i-th* frame.

4.3. **Recursive Filtering**: Adaptive filtering is applied to each segment, considering the current values of fading and distortion, which helps to reduce the impact of these factors on signal quality. For example, an adaptive Butterworth filter can be used for each segment, with parameters that change according to the values of $H_i(t)$and Ωi. In cases where high precision in the passband is required, a Chebyshev filter may be appropriate. If minimizing signal delay is critical, a Kaiser filter can be employed [1, 9].

4.4. **Analysis and Integration of Results**: The results of processing each frame are integrated to obtain an overall result. This integration allows for constructing a comprehensive picture of spectral changes in the signal over time.

5. **Wavelet Transform (WT)**: The wavelet transform decomposes the signal into its constituent frequencies, revealing the amplitude and phase of each frequency in the spectrum, allowing for a detailed analysis of the time-frequency characteristics of the signal. The wavelet transform, considering distortions and fading, is calculated using the following formula [10-12]:

$$WT(t,f)=\int_{-\infty}^{\infty} H\cdot x(t)\cdot \exp\left(j\left(\Omega t+\theta+\Theta\right)\right)+V(t)\,\psi^{*}\left(\frac{t-\tau}{a}\right)\cdot dt, \quad (8)$$

where τ is the scaling parameter, a is the shift parameter, $\psi(t)$ is the mother wavelet function, and $\psi(t)$is the complex conjugate of the wavelet function.

6. **Filtering WT Results**: At this stage, the wavelet transform results undergo additional filtering using Chebyshev filters to improve resolution and reduce interchannel interference. The power of the frame and its spectral density are described by the formula [1, 9, 12]:

$$P_x(f) = |\mathrm{WT(t,f)}|^2. \quad (9)$$

7. **Calculation of Power Spectral Density** (PSD) of T Frames: This step is necessary to obtain the information about the distribution of signal power in the frequency domain over a prolonged period. The PSD $P_f$indicates how the signal power is distributed across frequencies

$$P_f = \frac{1}{T}\sum_{\mathrm{t}=0}^{T-1} P_x(f). \quad (10)$$

8. **Calculation of Average Spectral Power**, which provides an overall assessment of the signal's power in the frequency domain. The formula for calculating it is:

$$P_{\mathrm{avg}} = \frac{1}{N}\sum_{\mathrm{f}=0}^{N-1} P_f. \quad (11)$$

9. **Calculation of the Decision Statistic** *r(k)*, which is resistant to background noise levels, is calculated to identify signals that exceed the noise level. This enables the identification and analysis of useful signals in noisy conditions [11]

$$r(k) = \frac{P_f(k)}{P_{\mathrm{avg}}}. \quad (12)$$

10. **Threshold Value Calculation**: determines the threshold level to distinguish between useful signals and interference, i.e., to detect the presence or absence of a signal at a specific frequency. It is calculated as [11]:

$$\lambda = \frac{1}{N}\sum_{\mathrm{k}=0}^{N-1} r(k). \quad (13)$$

11. **Spectrum Analysis**: The results of spectrum analysis are used to determine the frequency components of the signal. At this stage, Kaiser adaptive filters are effectively used to fine-tune the filtering parameters and increase analysis accuracy [3]. The formulas are:

– Kaiser window function:

$$w(n) = \frac{I_0\left(\beta\sqrt{1-\left(\frac{2n}{N-1}\right)^2}\right)}{I_0(\beta)}; \quad (14)$$

– Modified Bessel function of the first kind (zero-order):

$$I_0(x) = \sum_{\mathrm{k}=0}^{\infty} \frac{\left(\frac{x}{2}\right)^{2k}}{(\mathrm{k}!)^2}, \quad (15)$$

where *w(n)* is the value of the Kaiser window at point *n*, $I_0$is the modified Bessel function of the first kind (zero-order), β is the window shape parameter, and N is the window length.

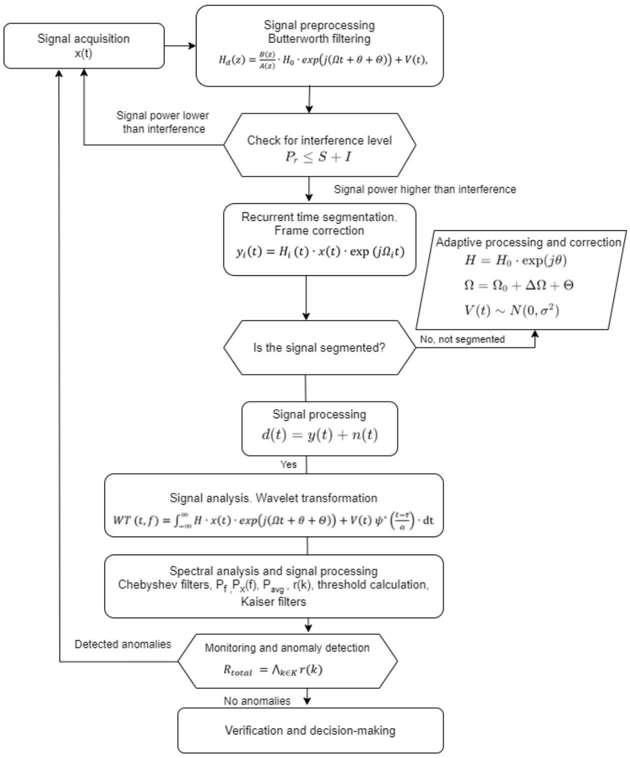

FIG. 1. Adaptive Algorithm for Spectrum Monitoring Using Wavelet Transform and Filtering.

12. **Monitoring and Anomaly Detection**: This stage includes accounting for modern spectrum monitoring conditions, such as high dynamics of changes, multiple signal sources, and high levels of interference. Based on the WT results, threshold values for frequency amplitudes are established, and spectrum changes are monitored. Comparing the current spectrum with the baseline allows for accurate detection of unusual events or anomalies in the spectrum. The decision conditions are:

$$\begin{aligned} r(k) > \alpha &\Rightarrow \text{channel is occupied,} \\ r(k) < \alpha &\Rightarrow \text{channel is free,} \end{aligned} \quad (16)$$

or

$$\begin{aligned} P_f(k) - \alpha\cdot \mathrm{P_{avg}} > 0 &\Rightarrow \text{channel is occupied,} \\ P_f(k) - \alpha\cdot \mathrm{P_{avg}} < 0 &\Rightarrow \text{channel is free.} \end{aligned} \quad (17)$$

After analyzing the detected anomalies in frequency data, a decision is made on further actions, which may include adjusting spectrum monitoring settings, recollecting data, excluding anomalies from the analysis, or taking measures to mitigate the consequences.

IV. EXPERIMENTS

To verify the accuracy of the developed algorithm of spectrum monitoring under distorted and faded conditions, with the use of time segments having various lengths, a wavelet transform, Butterworth, Chebyshev, and Kaiser filters, a software realization was made within the Python programming language. The input data for the experiments are given in Table 1.

TABLE 1. Input Data.

Parameter	Value
Signal Types	4G LTE, 5G NR, Wi-Fi 6, DVB-T2, GPS
Sensitivity, dBm	-94, -116, -107, -95, -100
SNR, dB	1, -5, -12, -15, -21
Channel Type	AWGN
Number of Primary Users	50
Probability of False Alarm	0.005
FFT Size (N)	512
Number of Frames (T)	250
Wavelet Transform	Morlet or Daubechies
Butterworth Filter	Cutoff Frequency: 0.1, Filter Order: 4
Chebyshev Filter	Filter Order: 5, Allowable Ripple: 0.5 dB
Kaiser Filter	Parameter β: 5.0, Window Length: 51

For the realization of effective spectral analysis on signals under rough conditions, the selected wavelet transforms for this algorithm are Morlet and Daubechies.

The registered signals of interest are 4G LTE, 5G NR, Wi-Fi 6, DVB-T2 and GPS, to be detected at a low SNR level of 1, -5, -12, -15, -21 dB.

To evaluate the effectiveness of the proposed method, it is necessary to calculate the following indicators (Tables 2-6):

1. **True Positive Rate (TPR)**: This metric shows how well the method identifies useful signals.
2. **Average Noise Level (ANL)**: This assesses the efficiency of filtering in reducing noise.
3. **Fading Attenuation Factor (FAF)**: This evaluates how well the method handles signal fading.
4. **Filtering Efficiency Factor (FEF)**: This evaluates the overall effectiveness of filtering through the application of multiple filters at different stages.
5. **False Positive Rate (FPR)**: This metric indicates how often the method incorrectly identifies a missing signal as present. It is crucial for assessing the reliability of the method and reducing false alarms.
6. **Processing Delay (PD)**: This is calculated to assess the speed of the method.
7. **Frequency Distortion (FD)**: This is a measure of the change in the signal's frequency after processing and is calculated to evaluate the preservation of the signal's frequency characteristics.

TABLE 2. Calculation Results for 4G LTE.

Parameter	SNR = 1	SNR = -5	SNR = -12	SNR = -15	SNR = -21
True Positive Rate	0.95	0.88	0.85	0.80	0.75
Average Noise Level	0.10	0.11	0.12	0.14	0.15
Fading Attenuation Factor	0.05	0.06	0.07	0.09	0.10
Filtering Efficiency Factor	0.02	0.02	0.03	0.03	0.04
False Positive Rate	0.01	0.01	0.02	0.02	0.03
Processing Delay	0.5 s	0.5 s	0.6 s	0.7 s	0.7 s
Frequency Distortion	0.1	0.12	0.15	0.18	0.2

TABLE 3. Calculation Results for 5G NR.

Parameter	SNR = 1	SNR = -5	SNR = -12	SNR = -15	SNR = -21
True Positive Rate	0.92	0.85	0.80	0.75	0.70
Average Noise Level	0.11	0.12	0.13	0.14	0.16
Fading Attenuation Factor	0.06	0.07	0.08	0.09	0.11
Filtering Efficiency Factor	0.03	0.03	0.04	0.04	0.05
False Positive Rate	0.01	0.02	0.03	0.03	0.04
Processing Delay	0.5 s	0.5 s	0.6 s	0.7 s	0.8 s
Frequency Distortion	0.1	0.13	0.16	0.19	0.22

TABLE 4. Calculation Results for Wi-Fi 6.

Parameter	SNR = 1	SNR = -5	SNR = -12	SNR = -15	SNR = -21
True Positive Rate	0.90	0.83	0.78	0.72	0.65
Average Noise Level	0.10	0.11	0.13	0.15	0.17
Fading Attenuation Factor	0.04	0.05	0.07	0.09	0.12
Filtering Efficiency Factor	0.02	0.03	0.04	0.05	0.06
False Positive Rate	0.02	0.02	0.03	0.04	0.05
Processing Delay	0.4 s	0.5 s	0.6 s	0.8 s	0.9 s
Frequency Distortion	0.1	0.12	0.14	0.18	0.25

TABLE 5. Calculation Results for DVB-T2.

Parameter	SNR = 1	SNR = -5	SNR = -12	SNR = -15	SNR = -21
True Positive Rate	0.94	0.87	0.82	0.75	0.68
Average Noise Level	0.09	0.11	0.12	0.14	0.18
Fading Attenuation Factor	0.03	0.04	0.06	0.08	0.09
Filtering Efficiency Factor	0.01	0.02	0.03	0.04	0.05
False Positive Rate	0.01	0.02	0.02	0.03	0.04
Processing Delay	0.3 s	0.4 s	0.5 s	0.7 s	0.8 s
Frequency Distortion	0.1	0.12	0.15	0.18	0.2

TABLE 6. Calculation Results for GPS.

Parameter	SNR = 1	SNR = -5	SNR = -12	SNR = -15	SNR = -21
True Positive Rate	0.91	0.84	0.79	0.72	0.66
Average Noise Level	0.11	0.12	0.14	0.16	0.19
Fading Attenuation Factor	0.04	0.06	0.07	0.09	0.11
Filtering Efficiency Factor	0.02	0.03	0.04	0.05	0.06
False Positive Rate	0.02	0.02	0.03	0.04	0.05
Processing Delay	0.4 s	0.5 s	0.6 s	0.8 s	0.9 s
Frequency Distortion	0.1	0.12	0.14	0.18	0.22

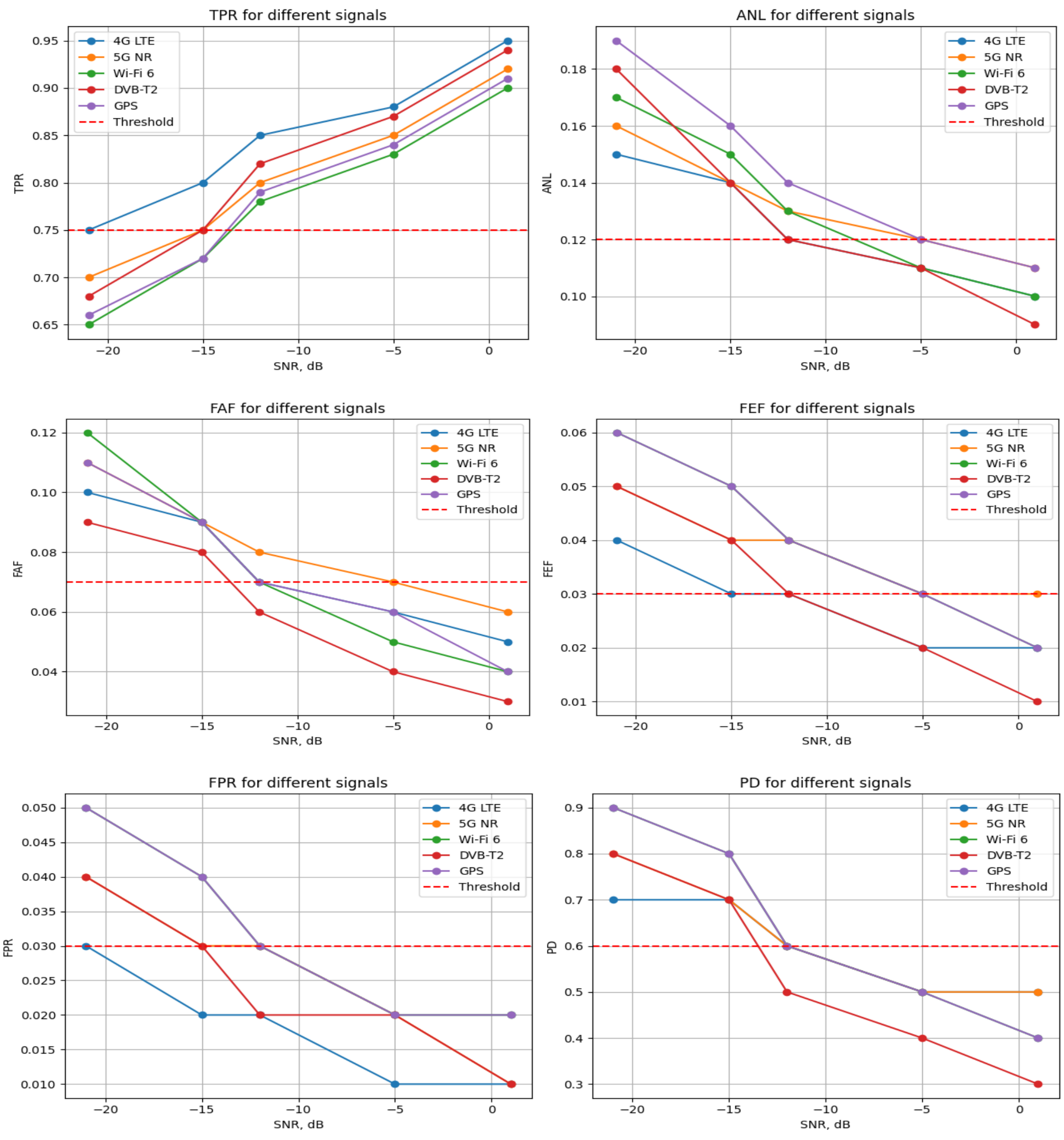

FIG. 2. Graphical Comparison of Signal Detection Efficiency Metrics.

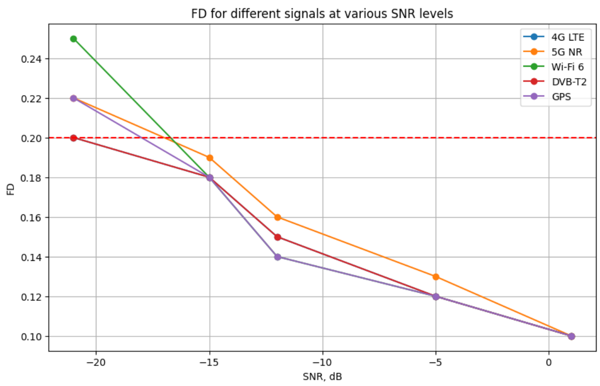

FIG. 3 Impact of SNR Levels on Frequency Distortion (FD) for Signals.

V.CONCLUSION

The analysis of the performed computer simulations makes it possible to draw a few key conclusions regarding the developed method's effectiveness in monitoring the spectrum using wavelet transforms and Butterworth, Chebyshev, and Kaiser filters at different SNR conditions. Figures 2 and 3 give a clear pictorial representation of how changes in dynamics are performed on the metrics for signal types: TPR, ANL, FAF, FEF, FPR, PD, and FD.

5G NR: For 5G NR, it can be observed from Table 3 that the TPR has been reduced with a reduction in SNR—from 0.92 to 0.70 for SNR = −21 dB. The ANL increases with decreasing SNR—from 0.11 to 0.16—meaning that noise levels are rising. FAF and FPR increase with a lower SNR, indicating rising challenges in signal detection. In this case, the FEF gradually reduces, which signifies less and less efficacy in noise elimination, as SNR reduces. The Processing Delay (PD) increases because the detection signal processing gets more and more complex; on the other hand, Frequency Distortion (FD) increases to show more and more noise affecting frequency characteristics of the signal.

Wi-Fi 6: It can be noticed from Table 4 that for Wi-Fi 6, TPR decreases with a decrease in SNR from 0.90 for SNR = 1 dB to 0.65 when SNR = -21 dB. ANL increases, suggesting an increased presence of noise in the system as SNR gets lower. Both FAF and FPR increase, suggesting increased complexity for detection. FEF decreases, implying reduced method capability to get rid of noise with SNR decrease. PD grows, meaning that it becomes larger and testifies to a longer processing time needed for signal analysis. At the same time, FD also increases, showing the increased influence of noise on the frequency characteristics of the signal.

DVB-T2: The TPR of DVB-T2, as seen in Table 5, decreases with SNR from 0.94 at SNR = 1 dB to 0.68 at SNR = -21 dB. ANL increases, clearly showing an increase in noise in the system. FAF increases; likewise, FPR, which shows that detection is tending to increase its complexity. FEF decreases; therefore, there is less efficiency in removing noise. The PD increases, due to increased time of processing, and FD due to increased noise in terms of magnitude increases the impact of noise on the frequency characteristics of the signal.

GPS: From Table 6, the TPR of GPS drops with reducing SNR, from 0.91 at SNR = 1 dB to 0.66 at SNR = -21 dB. ANL goes up, higher noise level for the system. Both FAF and FPR go up, which indicates difficulties in signal detection. FEF goes down, showing a lower efficiency in noise removal. PD increases and reflects longer times of processing, needed for the analysis of the signals; FD rises and means that noise impacts the frequency characteristics of the signal.

By the results of the simulation, the spectrum monitoring method with the wavelet-transform-based Butterworth, Chebyshev, and Kaiser filters can be assumed to be variable in terms of the signal detection effectiveness, depending on the level of SNR. Substantial values of ANL with increasing negative FPR and frequency distortion for low levels of SNR show that there is a need for further improvement of the method to obtain constant performance in hard SNR conditions.

AUTHOR CONTRIBUTIONS

I.S., V.L. – writing (original draft preparation), conceptualization, methodology, investigation; I.S. – methodology, investigation, writing (review and editing).

COMPETING INTERESTS

The authors declare no conflict of interest.

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Метод спектрального моніторингу з використанням вейвлет-перетворень та фільтрації в умовах спотворення та завмирання частоти сигналу

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АНОТАЦІЯ У статті розглянуто питання підвищення точності та надійності моніторингу спектру в когнітивних телекомунікаційних системах. З урахуванням динамічних умов радіочастотного середовища, основна увага приділена аналізу впливу завмирання та спотворення частоти сигналу на результати спектрального аналізу. Завмирання та спотворення можуть суттєво впливати на точність виявлення сигналів, що робить адаптивні методи і фільтри критично важливими для успішного виявлення змін у спектральному середовищі. Мета статті полягає в оцінці ефективності використання адаптивних методів і фільтрів, таких як вейвлет-перетворення, а також фільтрів Баттерворта, Чебишева і Кайзера, для покращення виявлення змін у спектральному середовищі при різних рівнях сигнал-шум (С/Ш). Дослідження охоплюють широкий спектр частот, зосереджуючи увагу на ключових технологіях, таких як 5G NR, Wi-Fi 6, DVB-T2 і GPS, що мають різні вимоги до точності та надійності сигналу. Метод моніторингу спектру, описаний у статті, дозволяє досягти високої точності виявлення сигналів у сприятливих умовах, коли С/Ш є високим. Проведені експерименти показали, що при значеннях С/Ш вище 1 дБ, показник точності виявлення сигналів (ПТВС) для всіх розглянутих технологій залишається на рівні 0,90 і вище. Наприклад, для 5G NR ПТВС становить 0,92 при С/Ш = 1 дБ, тоді як для Wi-Fi 6 цей показник досягає 0,90. Однак, зі зниженням рівня С/Ш, ефективність методу поступово знижується. Для 5G NR ПТВС знижується до 0,70 при С/Ш = -21 дБ, що свідчить про значне зростання ймовірності хибного виявлення сигналів. Аналогічні результати спостерігаються для Wi-Fi 6, де ПТВС знижується до 0,65, для DVB-T2 — до 0,68, і для GPS — до 0,66. Крім того, середній рівень шуму збільшується зі зниженням С/Ш, що додатково ускладнює процес точного виявлення сигналів, ілюструючи необхідність подальшого вдосконалення методів. Отримані результати підкреслюють важливість подальшого вдосконалення спектрального моніторингу, особливо в умовах низького С/Ш. Подальші дослідження повинні зосереджуватися на розробці нових або вдосконаленні існуючих адаптивних алгоритмів, здатних ефективно працювати в складних спектральних умовах, а також на дослідженні впливу інших типів фільтрації та перетворень.

КЛЮЧОВІ СЛОВА вейвлет-перетворення, Марле Добеши, відношення сигнал/шум, фільтри Баттерворта, фільтри Чебишева.