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OPTIMIZATION OF PROBABILITY OF DETECTION FOR WIRELESS REGIONAL AREA NETWORK USING EMPIRICAL MODE DECOMPOSITION

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ABSTRACT.
Sensing of frequency spectrum is a critical component in designing and optimizing cognitive radio-based wireless regional area networks (WRANs). The effectiveness of frequency spectrum sensing directly influences the performance of the communication network, which can be quantitatively assessed through the probability of detection. Traditional approaches to frequency spectrum sensing, such as the Fast Fourier Transform (FFT) and wavelet transformation, have been widely used. Previous studies have typically evaluated the spectrum sensing capabilities of WRANs theoretically, focusing on the probability of detection. In this study, we present the first experimental validation of this phenomenon within a wireless communication system, wherein empirical mode decomposition (EMD) is implemented within a WRAN. We optimized spectrum sensing based on the probability of detection and conducted a comparative experimental analysis with FFT.

Keywords-
Spectrum sensing, Probability of detection, WRAN, EMD

I. Introduction:

It is important to note that, due to the growing demand for wireless applications, such as 5G and Beyond 6G [1,2] Internet of things [3], Wireless networks are progressively incorporating machine learning (ML) to optimize resource allocation, improve spectrum sensing, and strengthen network security[4] .The use of wireless systems has increased recently and is expected to increase significantly in the near future. When developing a wireless system, it is crucial to address two questions: first, how to use the available spectrum efficiently for other applications, and second, how to optimize the spectrum sensing capacity of the network. By borrowing certain frequency bands, networks known as WRAN, which are cognitive networks, may communicate with one another. By borrowing some spectrum bands from one another, particularly when there is an extra band that is not being used or underutilized (TV white space), networks of different types of wireless networks—referred to as cognitive networks—can communicate with one another. This communication is possible between the primary and secondary users depending on the spectrum sensing capacity of the network. A detailed investigation is done on spectrum sensing using fast Fourier transform and wavelet transformation methods. The authors of [5] discuss the applicability of FFT for real-time spectrum sensing as well as its processing efficiency. The technique is tested in various noisy environments, and its efficacy is contrasted with that of other traditional techniques. Another research addresses the application of FFT for effective spectrum sensing in cognitive radio networks [6] The capacity to handle huge bandwidths and computational efficiency are two key benefits of employing FFT that are highlighted in the research. the wavelet-based spectrum sensing method that makes use of wavelets' ability to perform multi-resolution analysis. The technique is demonstrated to efficiently identify spectral edges, which makes it appropriate for cognitive radio networks to find unoccupied spectrum bands. [7] A novel approach to analyzing non-stationary and nonlinear data has been developed [8] The fundamental component of the approach is the "empirical mode decomposition" method, which allows for the decomposition of any complex data set into a limited number of "intrinsic mode functions" that admit well-behaved Hilbert transforms. This decomposition process is quite effective since it is adaptive. The decomposition is suited to nonlinear and non-stationary processes since it is based on the local characteristic time scale of the data. The "intrinsic mode functions," when subjected to the Hilbert transform, produce instantaneous frequencies as functions of time that allow for precise identification

of embedded structures. The Hilbert spectrum, also known as the energy-frequency-time distribution, is the final resultant presentation. The introduction of "intrinsic mode functions" based on local signal properties, which gives the instantaneous frequency meaning, and the introduction of instantaneous frequencies for complex data sets, which do away with the need for spurious harmonics to represent nonlinear and non-stationary signals, are the two main conceptual innovations of this method [9].
The advent of cognitive radio and the concept of opportunistic spectrum access have introduced new complexities to the spectrum sensing problem. Spectrum sensing remains one of the most challenging aspects of cognitive radio systems. The study presented in [10] provides a comprehensive overview of cognitive radio spectrum sensing techniques. It introduces a multi-dimensional spectrum sensing framework and explores various aspects of the spectrum sensing challenge from the cognitive radio perspective. Additionally, the study identifies key challenges in spectrum sensing and examines multiple techniques designed to address these challenges.
This study elucidates the concept of cooperative sensing and its various adaptations, discussing a range of sensing techniques as well as external sensing algorithms. Additionally, it delves into the statistical modeling of network traffic and the application of these models to predict primary user behavior. A critical challenge in cognitive radio technology is spectrum sensing, which involves detecting the presence of primary users within licensed frequency bands. Consequently, spectrum sensing has become a highly active area of research despite its extensive historical background. The study reviews several spectrum sensing methodologies, including joint space-time sensing, eigenvalue-based sensing, energy detection, matched filtering detection, cyclostationary detection, robust sensing techniques, and the optimal likelihood ratio test. Additionally, the study explores cooperative spectrum sensing, utilizing multiple receivers with an emphasis on sensing techniques that require minimal a priori knowledge of the propagation channel and source signal. The analysis addresses practical challenges such as noise power uncertainty and proposes potential solutions to mitigate these issues.
In the context of cognitive radio (CR) technology, dynamic spectrum allocation is examined, with particular attention to various aspects of spectrum sensing as discussed in [12]. CR systems, which are designed to adaptively exploit their environment to enhance capacity and spectral efficiency, present a promising approach for the efficient and dynamic utilization of the existing communication spectrum. This technology advocates for secondary users to optimally utilize the frequency bands allocated to primary users, which are often underutilized, thereby improving overall spectrum efficiency.
The primary objective of the IEEE 802.22 standard is to identify vacant spectrum bands allocated for Digital Television (DTV) channels and repurpose them for wireless broadband connectivity in rural areas. Cognitive radio technology aims to optimize the utilization of available radio spectrum while accommodating the increasing demand for wireless network services and applications. For cognitive radio networks to function effectively, Secondary Users (SUs) must be capable of accessing unused radio spectrum without interfering with Primary Users (PUs). Thus, spectrum sensing is a crucial component of cognitive radio. When a primary user reclaims a channel, the secondary user must efficiently sense the spectrum, exploit transmission opportunities, and vacate the channel promptly [13].
The research work [13] outlines various simulation scenarios designed to evaluate spectrum sensing by a single SU (local sensing) and multiple SUs in a cooperative framework. Through MATLAB simulations, the study details the detection accuracy and performance of the proposed algorithms, utilizing performance metrics such as the probability of detection and the probability of false alarm.
The research in [14] provides a classification of primary spectrum sensing methodologies, based on radio characteristics, and reviews previous works that apply these methods to various categories, including wideband, narrowband, cooperative, and non-cooperative sensing. Practical implementation considerations for different techniques and the latest standards relying on the interweave network model are also discussed. The study highlights recent advancements in applying traditional spectrum sensing methods.

Energy detection is one of the most widely used spectrum sensing techniques, as it does not require prior knowledge of the primary user's signal characteristics. However, this method struggles to distinguish between signal and noise, performs poorly at low signal-to-noise ratios (SNRs), and is sensitive to noise uncertainty, making threshold selection problematic. In [15], a blind technique is employed to measure the noise power in the received signal, enabling a dynamic threshold selection for spectrum sensing.
The study [16] proposes a sensing technique based on cyclic prefix, matched filtering, and energy detection. It investigates the optimal combination of these detectors, along with Equal Gain Combining (EGC), in both cooperative and non-cooperative spectrum sensing scenarios. The proposed method leverages more samples than individual detectors in packet-based transmission systems, such as Orthogonal Frequency Division Multiple Access (OFDM) systems. These samples include cyclic prefix, training or pilot samples, and data payload samples. Compared to standalone detectors, the combined sensing technique achieves a lower false alarm probability and a higher detection probability over the same frame time. To meet the sensing requirements ($Pf \leq 0.1$ and $Pd \geq 0.9$) and improve sensing performance, the authors of [17] determine the optimal threshold selection at low SNRs, outperforming conventional constant false alarm rate and constant detection rate (CDR) threshold approaches.
Spectrum sensing and sharing between two cognitive networks are simulated in [11], where the study evaluates the performance in terms of probability of detection (Pd), SNR, and false alarm probability (Pf) using FFT. The results suggest that increased spectrum-sharing requests correlate with longer sharing procedure durations and lower error rates at low SNRs. Another significant contribution to spectrum sensing is presented in [12], where the authors investigate FFT-based multiband spectrum sensing over multipath Rayleigh frequency-selective fading channels in single-input multiple-output (SIMO) in-band full-duplex (FD) cognitive radio networks (FDCRNs) under residual self-interference (RSI). The study first proposes multiband energy detection using the Neyman-Pearson criterion in FDCRNs under RSI, where the secondary user utilizes multiple receive antennas to exploit spatial diversity. Two-dimensional averaging is then applied to mitigate spectrum leakage caused by FFT operations in OFDM systems.
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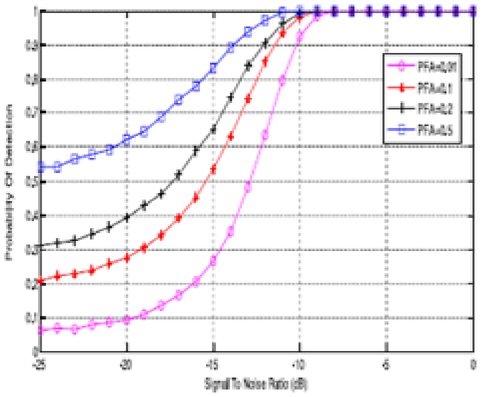
Finally, in [20], a transmitter and receiver section is implemented for effective spectrum sensing using FFT in a cognitive radio environment. The study examines the impact of message length on primary user detection using an energy detector-based spectrum sensing technique. Input messages of varying lengths are modulated using Quadrature Phase Shift Keying (QPSK) and Binary Phase Shift Keying (BPSK) before transmission. Additive White Gaussian Noise (AWGN) is introduced due to its wide frequency range across the channel. The presence or absence of the primary user is determined by measuring the energy amplitude of the received signal using a power spectral density technique based on the Welch Periodogram. However, the precision of spectrum sensing remains an unexplored area of research.

In the study [21], the Empirical Mode Decomposition (EMD) technique is utilized to evaluate the performance of Wireless Regional Area Networks (WRANs). The findings are presented graphically, illustrating the probabilities of detection and miss detection as functions of the probability of false alarm. The results demonstrate that the EMD technique significantly enhances the spectrum sensing capabilities of WRANs when compared to Fast Fourier Transform (FFT) and wavelet-based detection methods. This improvement is evident from the comparative analysis depicted in Figures 1 and 2 [21].



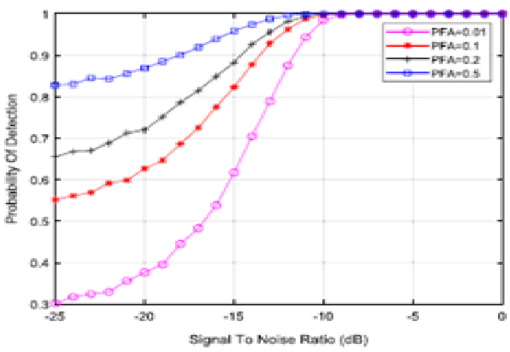


Figure 1: ROC plot for Pd Vs. SNR using FFT

Figure 2: ROC plot for Pd Vs. SNR using EMD

A thorough literature review reveals that Empirical Mode Decomposition (EMD) remains largely unexplored for spectrum sensing in Wireless Regional Area Networks (WRANs). The implementation of the EMD technique holds the potential to enhance the overall performance and spectrum sensing capabilities of WRANs. Furthermore, improving the reliability of spectrum detection is identified as a critical area of focus. Numerical investigations conducted in a MATLAB environment suggest that EMD can lead to significant improvements in spectrum detection, as indicated by higher probabilities of detection across various false alarm rates.

The FFT and wavelet transformation methods employed in frequency spectrum sensing require large data samples, which can negatively impact detection potential and sensing accuracy. To address these limitations, integrating the Empirical Mode Decomposition (EMD) technique with Wireless Regional Area Networks (WRANs) may enhance overall spectrum sensing capabilities.

The research paper is organized into five sections. Section 3 provides a concise overview of the EMD technique. The practical implementation of the EMD technique is detailed in Section 4 under the headings of Materials and Methods. Section 5 presents the results and discussion, comparing the sensing performance of EMD and FFT techniques across various probabilities of detection. The conclusion and potential future research directions are outlined in Section 6.

2. Empirical Mode Decomposition: The EMD technique breaks down a signal x(t) into IMFs imf i(t) and a residual rN(t) by an iterative screening technique

An IMF was originally defined by Huang et al. [21] as a function with two properties:

First, the number of local maxima and minima, and the number of zero crossings, differ by no more than one and the second, The lower and upper envelopes generated from the extrema have a mean value of zero. In an iterative process, the EMD algorithm decomposes a signal x(t) into various intrinsic mode functions (IMFs) and a residual. The algorithm's basic component includes sifting a function x(t) to generate a new function Y(t):

determine the local maxima and minima of x(t) first.

Then, using the local extrema, prepare the lower and upper envelopes s(t) & s+(t) of x(t). Calculate the mean of the envelopes, m(t).

To get the residual Y(t), subtract the mean from x(t).

The decomposition algorithm is as follows [22]

1. let $a_1(t) = x(t)$, where $x(t)$ is the initial signal, and let $i = 0$.
2. Before sifting, check $b_i(t)$:
   a. Determine the local extrema(X) of $b_i(t)$.
   b. Find the energy ratio (Y) of $b_i(t)$
3. If (Y > Maximum energy ratio) or (X < Maximum extrema) or (number of IMFs > Max IMF) then stop the decomposition.
4. Let $b_{i,\mathrm{Prev}}(t) = b_i(t)$.
5. Sift $b_{i,\mathrm{Prev}}(t)$ to obtain $b_{i,\mathrm{Cur}}(t)$.
6. Check for $b_{i,\mathrm{Cur}}(t)$
   a. Determine the relative tolerance (A) of $b_{i,\mathrm{Cur}}(t)$
   b. find current sift iteration number (B).
7. If (A < Sift Relative Tolerance) or (B > Sift Max Iterations) then stop sifting. An IMF will be found: $\mathrm{IMF}_i(t) = b_{i,\mathrm{Cur}}(t)$. Otherwise, let $b_{i,\mathrm{Prev}}(t) = b_{i,\mathrm{Cur}}(t)$ and repeat Step 5.
8. Let $b_{i+1}(t) = b_i(t) - b_{i,\mathrm{Cur}}(t)$.
9. Let $i = i + 1$. back to Step 2.

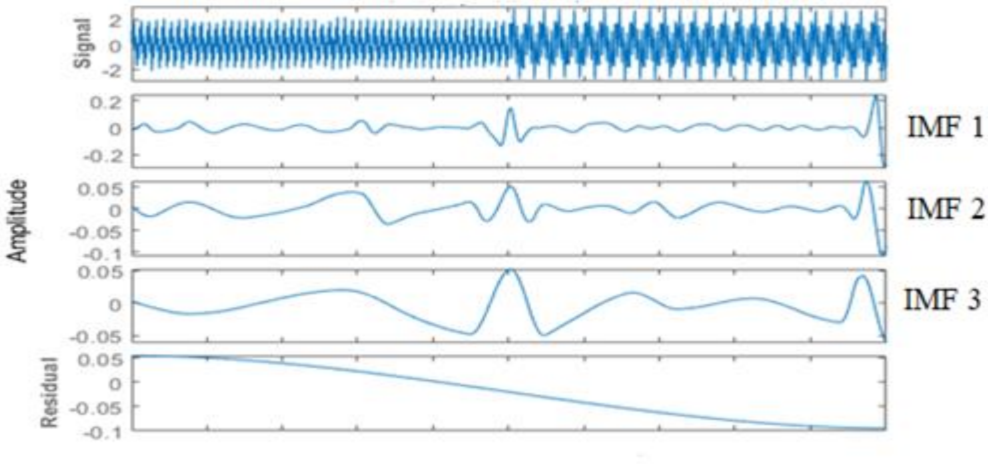


Fig 3: Intrinsic Mode functions

3. Material and Method:

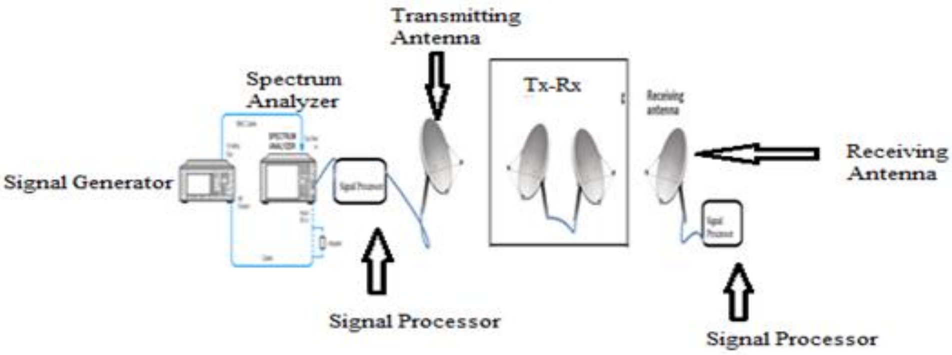


Fig 4: Schematic of Experimental set up

Fig 5: Experimental Setup to implement EMD with WRAN

As depicted in Figure 5, a Wireless Regional Area Network (WRAN) signal is generated using an RF signal generator, and its spectrum is analyzed using a spectrum analyzer. The waveform parameters obtained from the spectrum analyzer are referenced in the MATLAB code at the transmitter side. Both FFT and EMD methods are implemented within the WRAN framework, and the code is executed for various probabilities of false alarm. The resulting output signal from the code execution is transmitted via a transmitting antenna. A cognitive radio environment is established using multiple transmitters and receivers. The output from the receiving antenna is visualized on the inbuilt MATLAB/SIMULINK spectrum analyzer.

4. Result and Discussion:

4.1 Received Signal with FFT

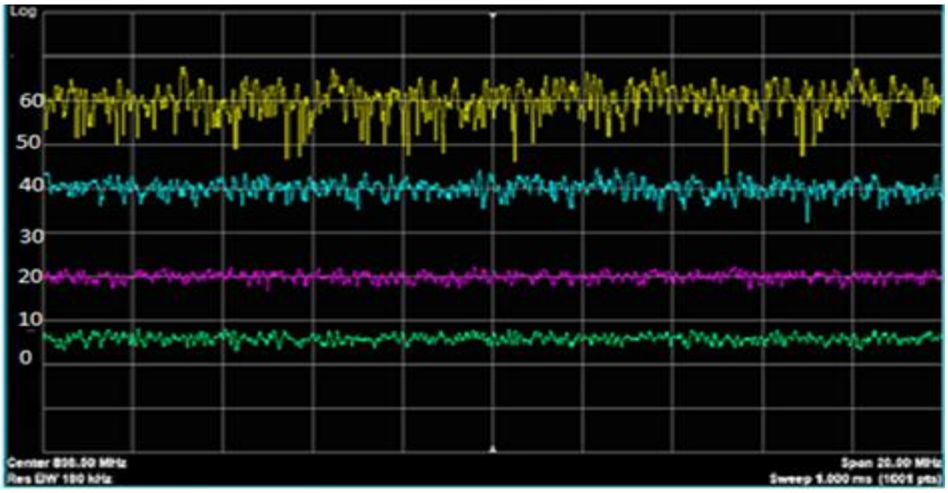


Fig 6: Output of Spectrum analyzer (Probability of detection) with FFT

As illustrated in Figure 6, the simulation results show a correlation between the probability of false alarm (Pfa) and the received signal strength. For a Pfa of 0.01, the measured received signal strength is approximately 6 (Green). Increasing the Pfa to 0.1 results in a received signal strength of 20 (Magenta). Further increasing the Pfa to 0.2 raises the received signal strength to 40 (Blue), and at a Pfa of 0.5, the received signal reaches 60 (Yellow). This analysis indicates that as the probability of false alarm increases, the probability of detection in WRAN improves, thereby enhancing the spectrum sensing capabilities.

4.2 Received Signal with EMD

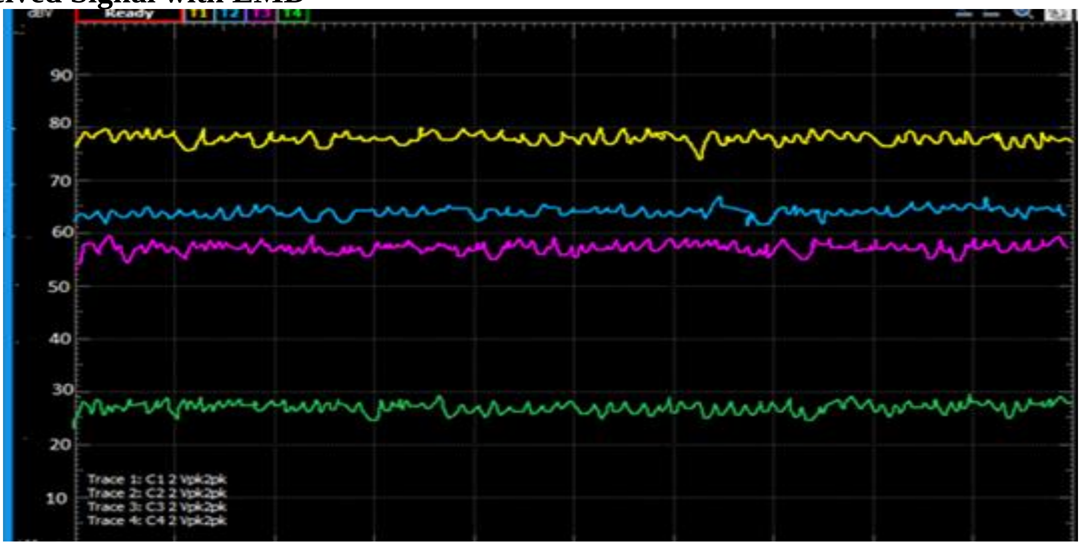


Figure 7: Output of Spectrum analyzer (Probability of detection) with EMD

As illustrated in the diagram, for a probability of false alarm (Pfa) of 0.01, the received signal strength is approximately 28 (Green). When the Pfa is increased to 0.1, the received signal strength rises to 58 (Magenta). Further increasing the Pfa to 0.2 results in a signal strength of 65 (Blue), and for a Pfa of 0.5, the signal strength reaches 80 (Yellow). These results suggest that the spectrum sensing performance of WRAN is superior when utilizing the EMD technique compared to the FFT method.

5. Comparison and Sensing outcome of WRAN with FFT and EMD

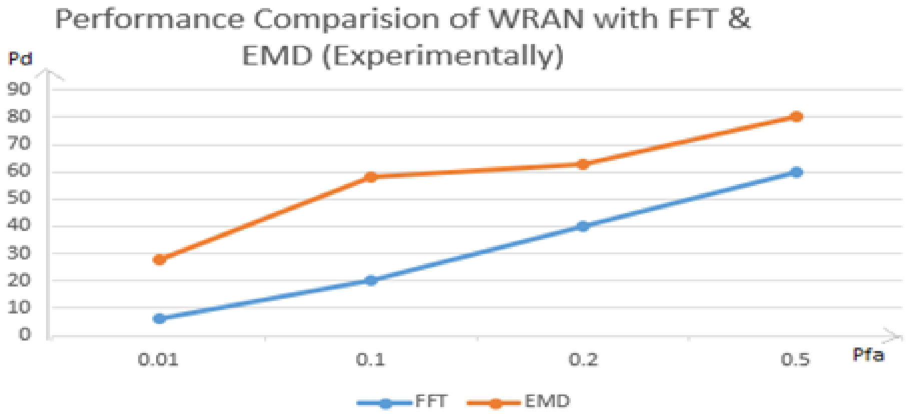


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Figure 8: Graph of performance comparison of WRAN with FFT & EMD.

The graph further corroborates that as the probability of a false alarm increases, the probability of detection also rises. Additionally, the detection probability in each scenario is consistently higher with the EMD technique compared to the FFT method.

6. Conclusion:

In this work, the performance of Wireless Regional Area Networks (WRAN) is analyzed using both Fast Fourier Transform (FFT) and Empirical Mode Decomposition (EMD) techniques. The results from various tests indicate that WRAN achieves optimal performance when EMD is incorporated. Furthermore, the detection accuracy of WRAN with EMD surpasses that of FFT. The performance analysis, based on the experimental results of the probability of detection, as well as observations from the spectrum analyzer and corresponding graphs, clearly demonstrates that WRAN performs more effectively with EMD.

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