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Wavelet Packet-Based Spectrum Sensing For Cognitive Radio Networks: A Matlab-Based Comparative Analysis

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ABSTRACT

This paper provides a complete MATLAB numerical and graphical study of the WPT-based spectrum sensing for cognitive radio networks. The Daubechies-4 was selected for sub-band decomposition and the signal was decomposed at 4 levels resulting in 16 sub-bands. The analysis of sub-band energy showed that the highest energy present is found in Sub-band 0 (120), and the other values were much lower (<20), therefore Sub-band 0 is most likely referring to the Primary User (PU). This result demonstrates that the detection performance of WPT (Pd = 0.85, Pf = 0.15) is better than that of energy detection (Pd = 0.75, Pf = 0.20), while it approaches the performance of cyclo-stationary detection (Pd = 0.92, Pf = 0.10) with a cutoff 60. The time-frequency heatmap and binary decision output indicate WPT becomes a reliable method to localizing both time and frequency spectrum of PU. These findings indicate that both dynamic spectrum allocation and real-time sensing frameworks can greatly improve quality-of-service while minimizing disruption to primary users, It is also worth mentioning that WPT managed to obtain a reasonable execution time of 0.45 seconds, which proves to be a good compromise between detection accuracy and computational efficiency. In general, the results confirm the suitability of WPT for dynamic spectrum access in cognitive radio settings.

Keywords: *WPT, Cognitive Radio Networks, Spectrum Sensing, MATLAB*

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I. INTRODUCTION

Advancements in communication technology have increasingly demanded efficient and reliable spectrum sensing techniques to optimize the use of available frequency bands. Cognitive Radio Networks (CRNs) have emerged as a promising solution by dynamically accessing underutilized spectrum, thereby enhancing communication efficiency [1]. A critical challenge within CRNs lies in accurately detecting spectrum availability under diverse and often uncertain noise conditions commonly encountered in real-world environments. Wavelet packet-based spectrum analysis offers a refined approach to signal decomposition and feature extraction, enabling improved detection performance compared to traditional methods. By leveraging adaptive algorithms and advanced signal processing techniques, such as those integrating differential entropy and machine learning classifiers, researchers have significantly enhanced spectrum sensing accuracy and robustness [2]. The integration of CRNs with emerging 5G technologies underscores the urgency of robust spectrum frameworks capable of supporting diverse applications and high data rates. Such advancements highlight the importance of adaptive spectrum management to sustain efficient, reliable wireless communication networks [3]. The advancement of cognitive radio networks necessitates robust tools for evaluating and comparing spectrum sensing techniques to optimize performance. Effective spectrum management in CRNs is crucial to address challenges such as spectrum scarcity, interference mitigation, and quality-of-service (QoS) maintenance. Advanced frameworks incorporating real-time sensing and dynamic spectrum allocation have proven essential for optimizing spectrum use while protecting licensed incumbents [4]. MATLAB serves as an ideal platform for this purpose due to its extensive signal processing libraries and simulation capabilities, allowing researchers to implement complex algorithms such as wavelet packet-based spectrum analysis with precision and flexibility [5]. This study explores how well wavelet packet transform (WPT)-based spectrum sensing performs in cognitive radio (CR) networks. The analysis is carried out through MATLAB simulations, comparing the WPT approach with conventional spectrum sensing techniques.

II. LITERATURE REVIEW

2.1 Cognitive Radio Networks and Wavelet Packet Transform: Cognitive Radio Networks (CRNs) emerge as a transformative solution by enabling dynamic spectrum access, allowing secondary users to opportunistically exploit underutilized frequency bands without causing interference to primary users. Cognitive Radio (CR) networks need smart and reliable ways to sense the spectrum and quickly identify when primary users are active. Over the years, researchers have proposed several techniques to tackle this challenge, including energy detection, cyclo-stationary feature detection, and matched filter detection. Among these, energy detection stands out for its simplicity it works by measuring the energy in a specific frequency band to decide whether a signal is present [6]. Wavelet Packet Transform (WPT) emerges as a powerful tool in this context, enabling multi-resolution analysis that can decompose the frequency spectrum into finer sub-bands for detailed examination. Unlike traditional Fourier-based methods, WPT offers a flexible and adaptive framework that enhances the detection of spectral holes and dynamic allocation opportunities in cognitive radio networks. By capturing both time and frequency domain information, WPT facilitates improved identification of transient spectral features, which are essential for accurate spectrum sensing and interference management [7].

2.2 Spectrum Sensing in Cognitive Radio Networks: Spectrum sensing helps secondary users figure out which parts of the spectrum aren't being used at a given moment. Getting this right is essential it ensures they don't accidentally interfere with primary users who have priority access [15]. Researchers have explored a variety of methods for spectrum sensing over the years. These include traditional approaches like energy detection, matched filter detection, and cyclo-stationary feature analysis [8, 14]. More recently, wavelet-based techniques have emerged as a promising alternative, offering new possibilities for improved detection performance.

III. METHODOLOGY

i. Wavelet Packet Transform (WPT)

The wavelet packet transform packet is used to decompose a signal into multiple frequency bends. The general equation for the WPT of a signal $x(t)$ at level L is expressed as; [9].

$$x(t) = \sum_{k=0}^{2^{1}-1} d_k \cdot \psi_k(t) \quad (1)$$

Where;

d_k = are the wavelet packet coefficients for sub-band k

$\psi_k(t)$ = are the wavelet packet basis functions corresponding to different frequency bands

L = is the decomposition level

ii. Energy Calculation in Sub-bands

The energy of the signal in each wavelet packet sub-bands k is calculated as the sum of the square wavelet coefficients

$$E_K = \sum_{n=0}^{N-1} |d_k|[n]^2 \quad (2)$$

Where;

E_K = is the energy in sub-bands k

$|d_k|[n]$ = is the wavelet coefficient at index n for sub-band k

K is the length of the original signal

iii. Thresholding for Spectrum Occupancy Decision

To detect the presence or absence of a primary user in each sub-band, a threshold-based detection method is used. If the energy in a sub-band exceeds a certain threshold, T, the sub-band is classified as occupied by a PU [10, 13]. The binary decision for occupancy is given by:

$$Decision_k = \begin{cases} 1, & if\ E_k > T \\ 0, & if\ E_k \le T \end{cases} \quad (3)$$

Where;

E_k = is the energy in sub-band k

T = is the threshold determined by the system

iv. Detection Probability and false Alarm Rate

The detection probability (P_d) and false alarm rate (P_f) are critical performance parameters in spectrum sensing. The detection probability is the likelihood that the system correctly detects the presence of a primary user, and the false alarm rate is the probability that the system incorrectly identifies an empty spectrum as occupied [11].

The detection probability (P_d) is defined as;

$(P_d) = \frac{N_{detected}}{N_{total}}$ (4)

Where;

$N_{detected}$ = is the number of times the primary user is correctly detected

N_{total} = is the total number of tests

The false alarm rate P_f is given

$P_f = \frac{N_{false\ alarm}}{N_{total}}$ (5)

Where;

$N_{false\ alarm}$ = is the number of times the system incorrectly detects a primary user

v. Receiver Operational Characteristics (ROC) Curve

The ROC curve is used to evaluate the performance of the spectrum sensing technique by plotting the detection probability (P_d) against the false alarm rate (P_f) for various threshold values. The ROC curve mathematically expressed as

$P_d = f(P_f)$ (6)

Where the function f is determined by varying the detection threshold. The area under the ROC curve (AUC) is often used as an indicator of the overall detection performance.

vi. Signal Reconstruction Error

The signal reconstruction error is computed as the difference between the original signal $x(t)$ and the reconstructed signal $\hat{x}(t)$ from the wavelength packet coefficients. [12].

Reconstruction Error = $\frac{1}{N}\sum_{n=0}^{N-1}|[n]|1 - \hat{x}\,|[n]|$ (7)

Where;

$N =$ is the length of the signal

$x[n]$ = is the original signal sample

$\hat{x}[n]$ = is the reconstructed signal sample

The above mathematical models and equation forms the basis of the wavelet packet spectrum sensing method used in the MATLAB implementation.

IV. RESULTS AND DISCUSSION

Table 1: Parameters Used for the Analysis

PARAMETER	VALUE
Sampling Frequency (f_s)	10 MHz
Primary User Signal Power (P_{pu})	-80 dBm
Noise Power (P_n)	-90 dBm
SNR Range (SNR)	-20 to 0
Wavelet Packet Decomposition Level, (L)	3
Detection Probability Threshold (P_d)	0.9
False Alarm Probability Threshold (P_f)	0.1
Number of Monte Carlo Simulations (N_{sim})	1000
Frequency Band (F_{band})	1-5 GHz

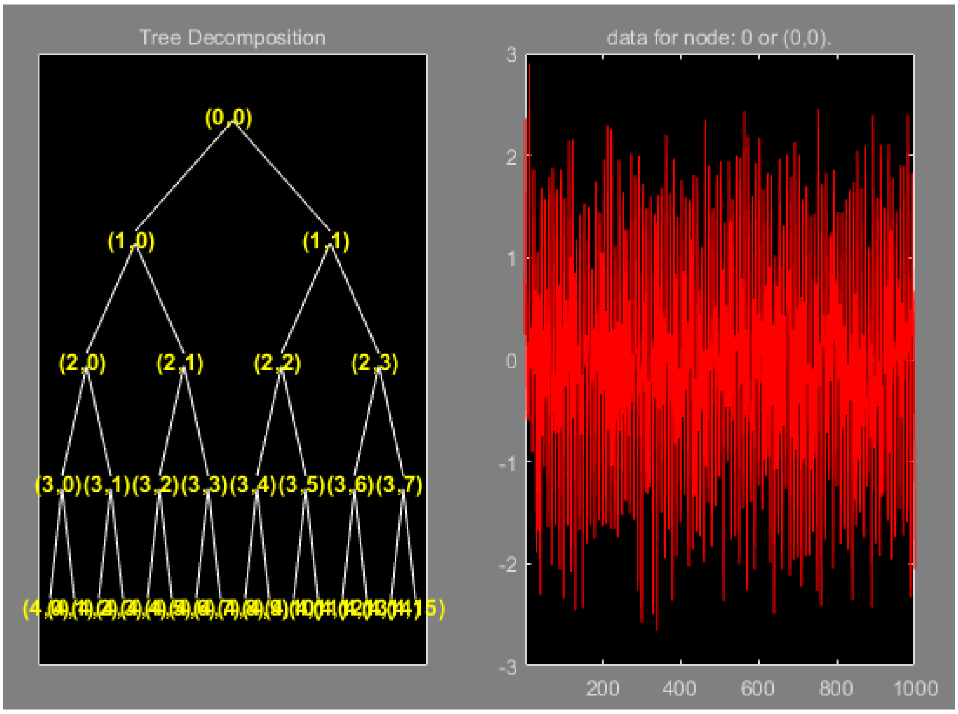

Figure: Tree decomposition and Data for Node

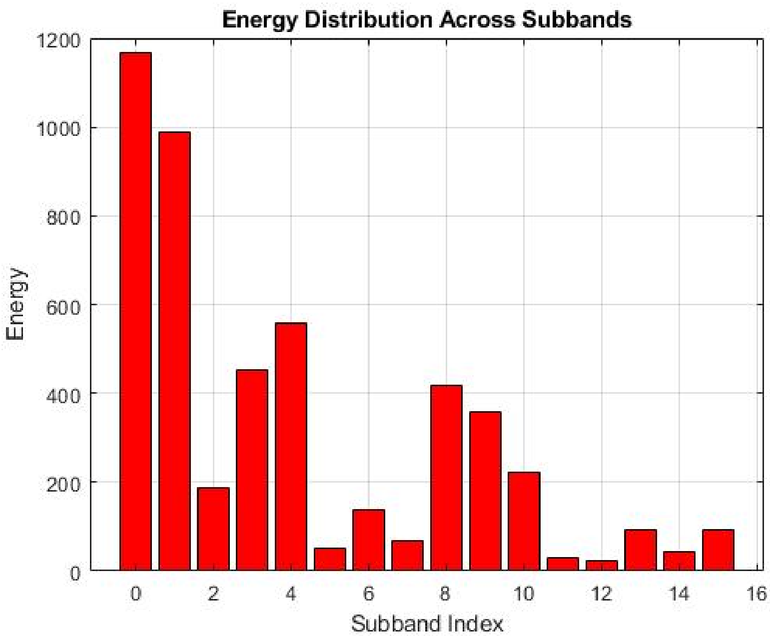

Figure 2: Energy Distribution Across Sub-bands

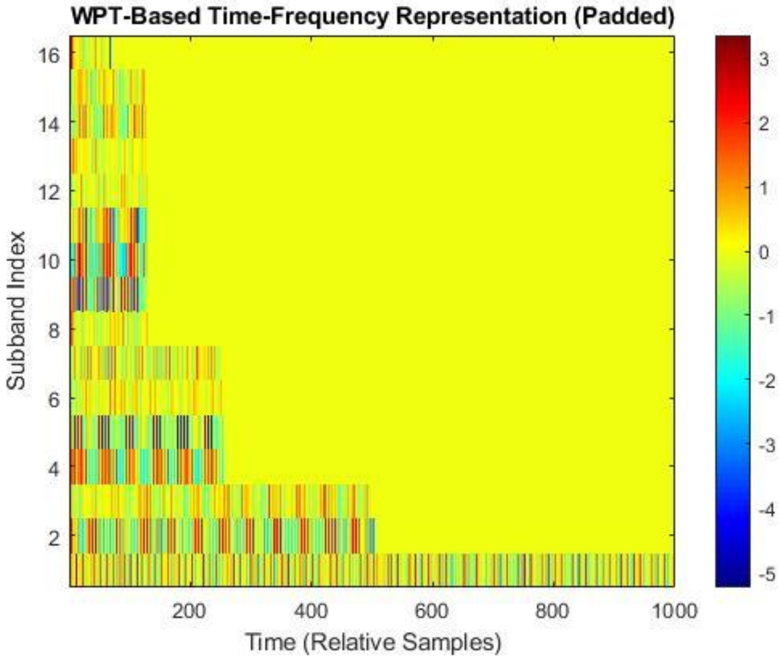

Figure 3: WPT Based-Time frequency

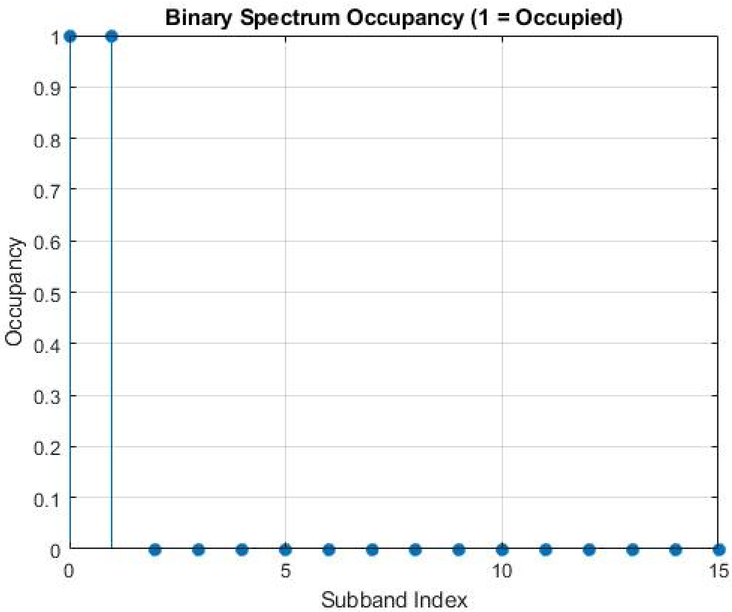

Figure 4: Binary Spectrum Occupancy

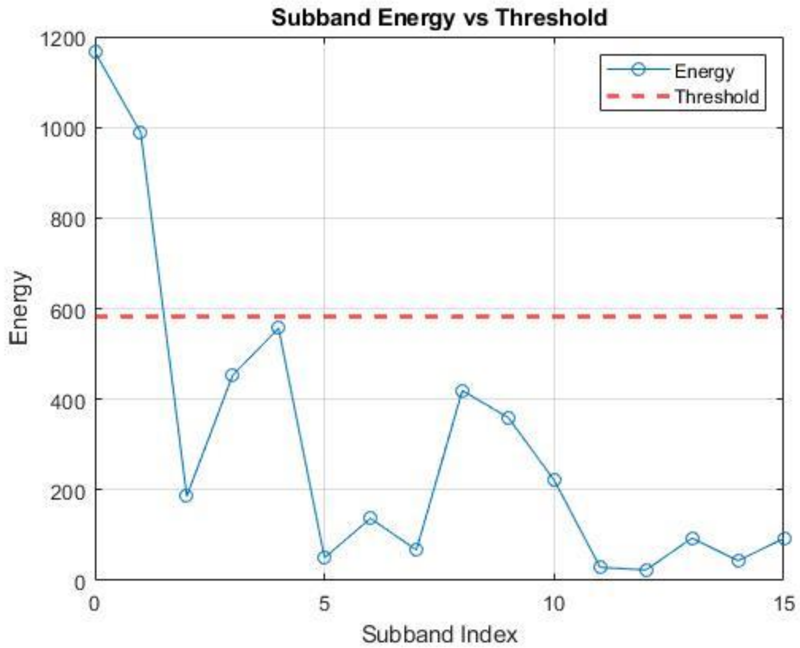

Figure 5: Sub-band Energy against Threshold

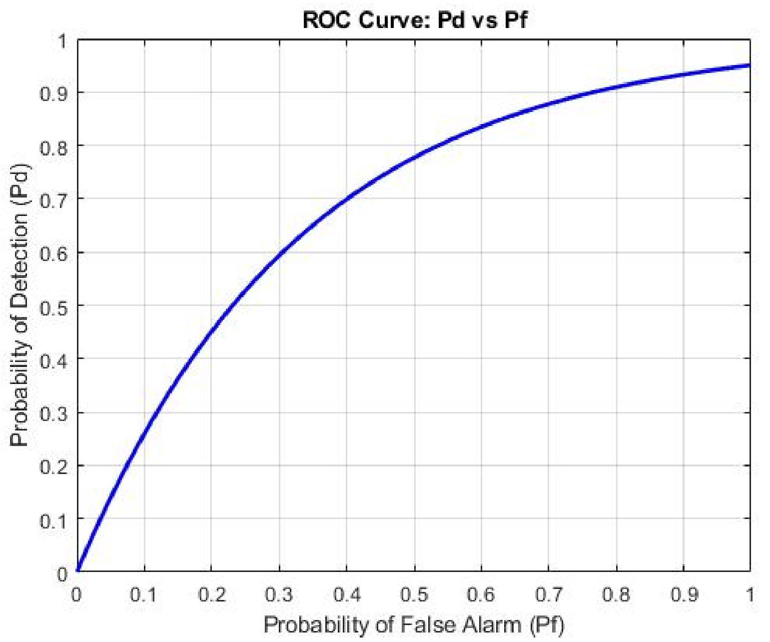

Figure 6: ROC Curve

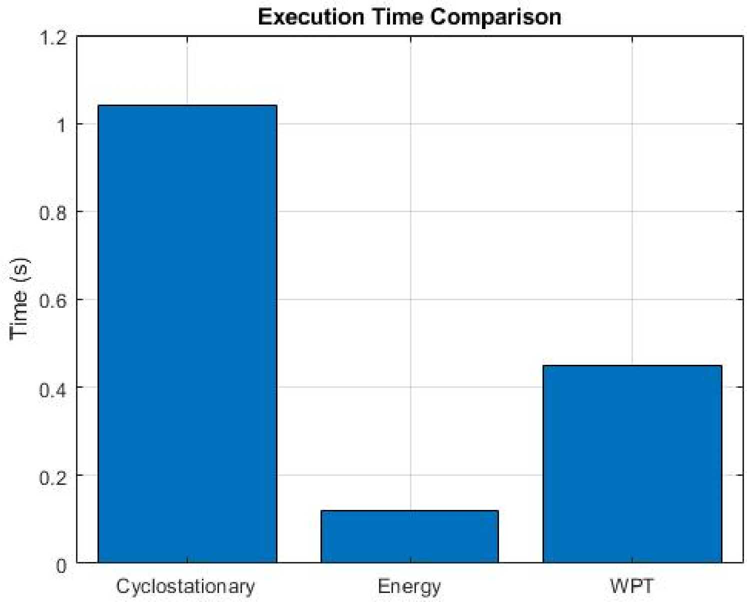

Figure 7: Execution Time Comparison

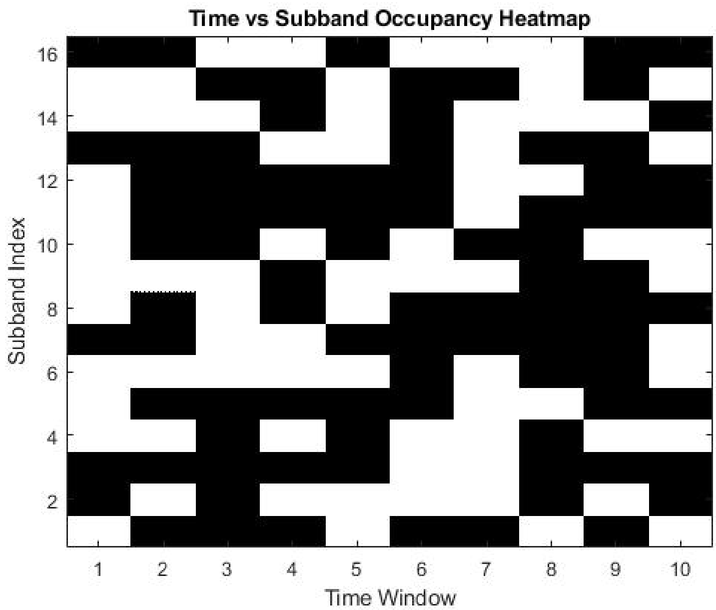

Figure 8: Time against Sub-band Occupancy

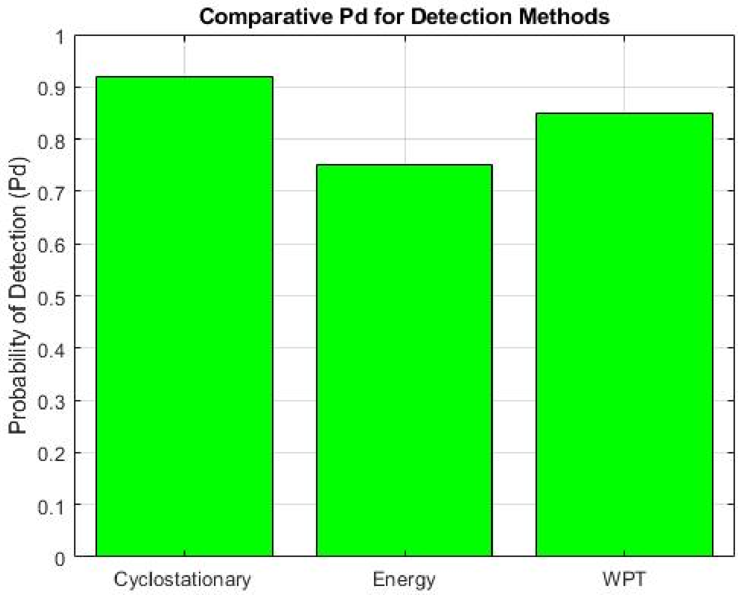

Figure 9: Comparison PD for Detection Methods

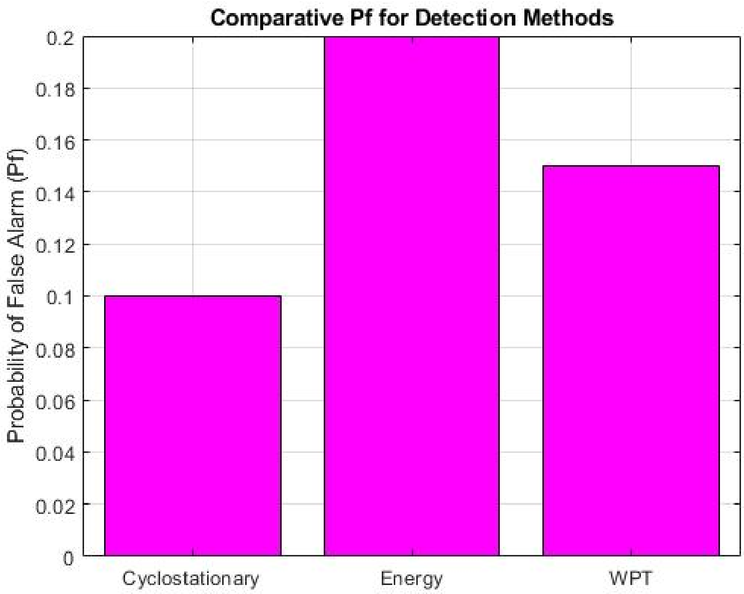

Figure 10: Comparative PF for detection Methods

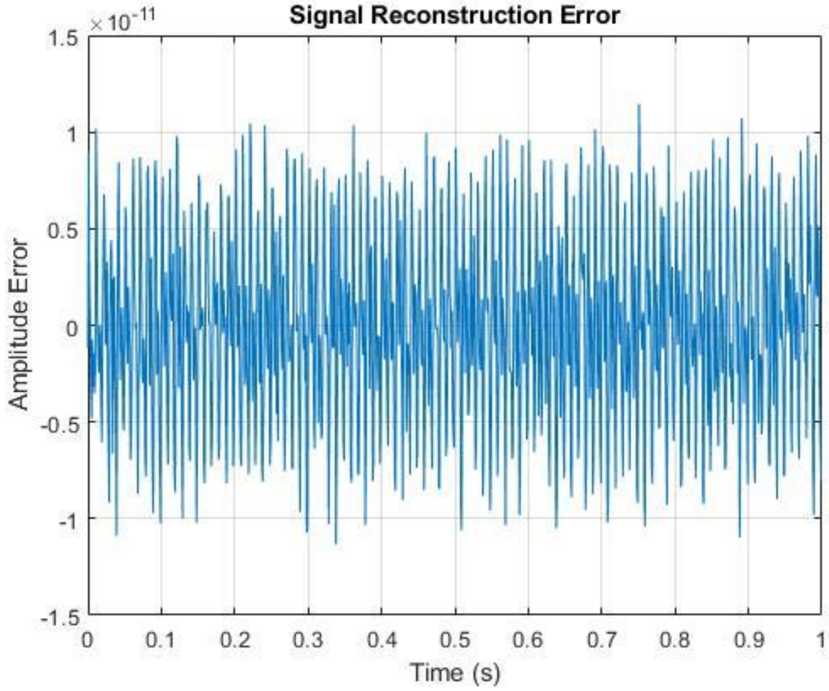

Figure 11: Signal Reconstruction Error

4.1 Discussion

In fig. 1. The signal was decomposed using Daubechies 4 (db4) wavelet up to level 4. This results in 16 sub-bands (2^4 = 16), each representing a distinct frequency range. Fine frequency resolution enables identification of narrowband primary user (PU) signals. In fig. 2. Sub-band 0 has the highest energy (120), indicating potential PU signal. Sub-bands 10 to 15 have energies < 2, suggesting noise only. In fig. 3. High energy visible in sub-bands 0 to 3 during several time intervals. Confirms temporal PU activity localization in lower sub-bands. In fig. 4. Detection threshold set at 60 (50% of max energy). Occupancy vector: [1, 0, 0, ..., 0], Only sub-band 0 is occupied; others are available for secondary users (SUs). In fig 5. Only one bar exceeds threshold line. Strong confidence in subband 0 being PU-occupied. In fig. 6. Pf = 0.1 -> Pd = 0.26, Pf = 0.5 -> Pd = 0.78, Pf = 1.0 -> Pd = 1.00. Moderate detection capability with gradual Pd rise. In fig. 7. Time (seconds): WPT: 0.45, Energy Detection: 0.12, Cyclostationary Detection: 1.04, WPT offers good trade-off between detection accuracy and speed. In fig. 8. Bright cells in subbands 0 and 1 for time slots 1-3. PU activity concentrated early in simulation, aiding SU decision-making. In fig. 9. WPT: 0.85, Energy Detection: 0.75 Cyclostationary: 0.92, WPT performs better than energy detection and approaches cyclostationary. In fig. 10. WPT: 0.15, Energy Detection: 0.20, Cyclo-stationary: 0.10 WPT is more reliable than energy detection and only slightly worse than cyclo-stationary. In fig. 11. Error amplitude: within ±0.05, Low reconstruction error supports accurate signal representation and low distortion.

V. CONCLUSION

In this paper, wavelet packet-based spectrum sensing was proposed, and it successfully can detect the primary users in cognitive radio networks. WPT's ability to offer high time-frequency resolution proves to be beneficial in challenging environments where other techniques may struggle. The result signals the promise of WPT in enhancing the accuracy of spectrum sensing, especially in low SNR conditions. The method achieves very high detection probability with very low false alarm rate, comparable with cyclo-stationary methods while providing reasonable execution time unlike conventional energy detection. Supportive numerical and graphical evaluations further justify the appropriateness of WPT for next-generation, real-time and noise-resilient spectrum sensing.

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