A Constrained GLRT Framework for Blind Spectrum Sensing in OFDM Based Cognitive Radio Systems

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Abstract – *Cognitive radio (CR) technology has emerged as a promising solution to address spectrum scarcity by enabling opportunistic access to licensed frequency bands. This paper presents novel blind spectrum sensing algorithms for orthogonal frequency division multiplexing (OFDM) based cognitive radio systems using the constrained generalized likelihood ratio test (C-GLRT) framework. We demonstrate that the existing cyclic prefix correlation coefficient (CPCC) based detection algorithm is a special case of C-GLRT in additive white Gaussian noise (AWGN) channels. However, the performance of CPCC based sensing degrades significantly in multipath fading environments, which are typical for OFDM applications. To address this limitation, we propose a multipath correlation coefficient (MPCC) based C-GLRT algorithm that exploits the inherent structure of the OFDM channel matrix. Furthermore, we develop a combined CPCC-MPCC detection algorithm that leverages both cyclic prefix and multipath correlations to achieve superior detection performance. The proposed algorithms operate without requiring prior knowledge of the primary user signal, channel state information, or noise variance, making them truly blind detection schemes. Simulation results demonstrate that the proposed MPCC based C-GLRT and combined algorithms significantly outperform conventional energy detection and CPCC based methods, particularly in low signal-to-noise ratio (SNR) regimes and rich multipath environments. The combined algorithm achieves near-optimal detection performance while maintaining computational efficiency suitable for practical CR implementations.*

Keywords: *Cognitive radio, spectrum sensing, OFDM, generalized likelihood ratio test, cyclic prefix, multipath fading, blind detection*

I. Introduction

The exponential growth of wireless applications and devices has created unprecedented demand for radio spectrum, leading to severe spectrum congestion in many frequency bands [1], [2]. Paradoxically, extensive measurements by regulatory bodies such as the Federal Communications Commission (FCC) have revealed that the licensed spectrum remains underutilized for significant periods of time, with utilization rates as low as 15% in some bands [3]. This disparity between spectrum scarcity and underutilization has motivated the development of cognitive radio (CR) technology, which enables unlicensed secondary users (SUs) to opportunistically access licensed spectrum bands without causing harmful interference to primary users (PUs) [4], [5].

Cognitive radio, first conceptualized by Mitola and Maguire in 1999 [6], refers to an intelligent wireless communication system capable of sensing its environment, learning from past experiences, and dynamically adapting its transmission parameters to optimize spectrum utilization [7]. The fundamental capability that enables this opportunistic spectrum access is spectrum sensing—the process of detecting spectrum holes or white spaces where PUs are inactive [8], [9].

Among various transmission technologies, orthogonal frequency division multiplexing (OFDM) has emerged as the preferred modulation scheme for cognitive radio systems due to its inherent advantages: high spectral efficiency, robustness against multipath fading, flexible spectrum shaping capabilities, and natural compatibility with spectrum sensing through FFT operations [10]-[12]. The ability to deactivate individual subcarriers where PUs are present makes OFDM particularly suitable for non-contiguous spectrum access in CR networks [13].

Spectrum sensing techniques can be broadly classified into three categories: transmitter detection, cooperative sensing, and interference-based detection [14], [15]. Transmitter detection methods include matched filter detection, energy detection, and feature detection. While matched filter detection provides optimal performance, it requires complete knowledge of the PU signal characteristics, which is often unavailable in practical scenarios [16]. Energy detection, despite its simplicity and low computational complexity, suffers from significant performance degradation under noise uncertainty and low SNR conditions [17], [18]. Feature detection methods, particularly cyclostationary feature detection, exploit the inherent periodicity in modulated signals to distinguish them from noise, but at the cost of high computational complexity [19], [20].

For OFDM signals, the presence of cyclic prefix (CP) introduces correlation between the head and tail portions of each OFDM symbol, which can be exploited for detection. The CPCC-based algorithm proposed in [21] utilizes this correlation for blind spectrum sensing without requiring knowledge of the PU signal or channel state information. However, this algorithm was originally designed for AWGN channels and its performance degrades in multipath fading environments where OFDM is typically deployed.

The generalized likelihood ratio test (GLRT) provides a systematic framework for composite hypothesis testing problems where certain parameters are unknown [22], [23]. By exploiting the structure of the OFDM signal covariance matrix, constrained GLRT (C-GLRT) algorithms can be developed that are both computationally efficient and robust to channel impairments.

The remainder of this paper is organized as follows. Section II presents the system model and problem formulation. Section III reviews the GLRT framework and develops the proposed C-GLRT-based spectrum sensing algorithms. Section IV provides simulation results and performance analysis. Section V concludes the paper with discussions on future research directions.

II. System Model and Problem Formulation

II.1. OFDM Signal Model

Consider a primary OFDM system employing L subcarriers with a cyclic prefix of length L_p. The n-th transmitted OFDM block, denoted as $\mathbf{s}_n$, consists of L complex data symbols modulated onto orthogonal subcarriers through inverse discrete Fourier transform (IDFT):

$$s_{n,m} = \frac{1}{\sqrt{L}} \sum_{k=0}^{L-1} S_{n,k}\, e^{j2\pi mk/L}, \quad m = 0,1,\dots,L-1 \quad (01)$$

where $S_{n,k}$ represents the complex symbol transmitted on the k-th subcarrier during the n-th OFDM symbol, with $\mathbb{E}\left[\left|S_{n,k}\right|^2\right] = \sigma_s^2$.

The cyclic prefix is formed by copying the last L_p samples of the OFDM symbol to the beginning:

$$\mathbf{s}_n = \left[s_{n,L-L_p}, \dots, s_{n,L-1}, s_{n,0}, s_{n,1}, \dots, s_{n,L-1}\right]^T \quad (02)$$

resulting in an extended symbol of length $L + L_p$.

II.2. Channel Model

The transmitted signal propagates through a multipath fading channel with discrete-time baseband impulse response $\mathbf{h} = \left[h_1, h_2, \dots, h_{L_c}\right]^T$, where L_c denotes the number of channel taps. The channel is assumed to be frequency-selective but time-invariant during the sensing period (block fading model). The received signal vector $\mathbf{x}_n$ of length $L + L_p$ is given by:

$$\mathbf{x}_n = \mathbf{H}\mathbf{s}_n + \mathbf{v}_n \quad (03)$$

where $\mathbf{H}$ is the $\left(L + L_p\right) \times \left(L + L_p + L_c - 1\right)$ Toeplitz channel matrix constructed from $\mathbf{h}$:

$$\mathbf{H} = \begin{bmatrix} h_1 & h_2 & \cdots & h_{L_c} & 0 & \cdots & 0 \\ 0 & h_1 & h_2 & \cdots & h_{L_c} & \cdots & 0 \\ \vdots & \ddots & \ddots & \ddots & \ddots & \ddots & \vdots \\ 0 & \cdots & 0 & h_1 & h_2 & \cdots & h_{L_c} \end{bmatrix} \quad (04)$$

and $\mathbf{v}_n$ is the additive white Gaussian noise (AWGN) vector with $\mathbf{v}_n \sim \mathcal{CN}(\mathbf{0}, \sigma_v^2\mathbf{I})$.

II.3. Spectrum Sensing Problem Formulation

The spectrum sensing problem is formulated as a binary hypothesis test:

$$\begin{cases} \mathcal{H}_0: \mathbf{x}_n = \mathbf{v}_n & \text{(PU absent)} \\ \mathcal{H}_1: \mathbf{x}_n = \mathbf{H}\mathbf{s}_n + \mathbf{v}_n & \text{(PU present)} \end{cases} \quad (05)$$

where $\mathcal{H}_0$ represents the null hypothesis (spectrum hole available) and $\mathcal{H}_1$ represents the alternative hypothesis (PU signal present).

The detection performance is characterized by two probabilities: - Probability of detection: $P_d = \Pr(\text{decide } \mathcal{H}_1 | \mathcal{H}_1 \text{ true})$ - Probability of false alarm: $P_f = \Pr(\text{decide } \mathcal{H}_1 | \mathcal{H}_0 \text{ true})$

For reliable spectrum sensing, we aim to maximize P_d while maintaining P_f below a specified threshold, typically $P_f \leq 0.1$ [24].

II.4. Covariance Matrix Structure

Under $\mathcal{H}_1$, the received signal $\mathbf{x}_n$ is a zero-mean complex Gaussian random vector with covariance matrix:

$$\mathbf{R}_x = \mathbb{E}[\mathbf{x}_n\mathbf{x}_n^H] = \mathbf{H}\mathbf{R}_s\mathbf{H}^H + \sigma_v^2\mathbf{I} \quad (06)$$

where $\mathbf{R}_s = \mathbb{E}[\mathbf{s}_n\mathbf{s}_n^H]$. For OFDM signals with independent subcarriers and sufficiently large L, $\mathbf{s}_n$ can be approximated as a circularly symmetric complex Gaussian vector with $\mathbf{R}_s \approx \sigma_s^2\mathbf{I}$, leading to:

$$\mathbf{R}_x = \sigma_s^2 \mathbf{H}\mathbf{H}^H + \sigma_v^2 \mathbf{I} \quad (07)$$

The matrix $\mathbf{R}_x$ exhibits specific structural properties due to the OFDM signal characteristics and channel structure, which we exploit in developing the C-GLRT algorithms.

III. Constrained GLRT-Based Spectrum Sensing Algorithms

III.1. Generalized Likelihood Ratio Test Framework

For composite hypothesis testing where the parameters $\boldsymbol{\theta}_0$ under $\mathcal{H}_0$ and $\boldsymbol{\theta}_1$ under $\mathcal{H}_1$ are unknown, the GLRT replaces the unknown parameters with their maximum likelihood estimates (MLEs) [22]:

$$\Lambda_G(\mathbf{Y}) = \frac{\max_{\boldsymbol{\theta}_1 \in \Theta_1} f_{\mathbf{Y}|\mathcal{H}_1}(\mathbf{y}|\mathcal{H}_1, \boldsymbol{\theta}_1)}{\max_{\boldsymbol{\theta}_0 \in \Theta_0} f_{\mathbf{Y}|\mathcal{H}_0}(\mathbf{y}|\mathcal{H}_0, \boldsymbol{\theta}_0)} \underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\gtrless}} \eta \quad (08)$$

where $\mathbf{Y} = [\mathbf{y}_1, \mathbf{y}_2, \dots, \mathbf{y}_N]$ contains N received signal blocks, and η is the decision threshold.

When the parameter spaces Θ_0 and Θ_1 have specific structures (constraints), we obtain the constrained GLRT (C-GLRT), which can provide improved performance by incorporating prior knowledge about the signal structure [25].

III.2. Basic GLRT for OFDM Sensing

Consider the scenario where both the noise variance σ_v^2 and signal covariance matrix $\mathbf{R}_x$ are unknown. The MLE of σ_v^2 under $\mathcal{H}_0$ is:

$$\hat{\sigma}_v^2 = \frac{1}{NM}\mathrm{tr}(\mathbf{Y}\mathbf{Y}^H) = \frac{1}{M}\mathrm{tr}(\widehat{\mathbf{R}}_y) \quad (09)$$

where $M = L + L_p$ is the observation dimension and $\widehat{\mathbf{R}}_y = \frac{1}{N}\mathbf{Y}\mathbf{Y}^H$ is the sample covariance matrix.

Under $\mathcal{H}_1$, the unconstrained MLE of $\mathbf{R}_x$ is simply $\widehat{\mathbf{R}}_y$. Substituting these estimates into the GLRT yields the basic GLRT statistic [26]:

$$T_G(\mathbf{Y}) = \frac{\frac{1}{M}\mathrm{tr}(\widehat{\mathbf{R}}_y)}{\det(\widehat{\mathbf{R}}_y)^{1/M}} \underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\gtrless}} \gamma \quad (10)$$

This test compares the ratio of the arithmetic mean to the geometric mean of the eigenvalues of $\widehat{\mathbf{R}}_y$. However, this basic GLRT does not exploit the specific structure of OFDM signals.

III.3. CPCC-Based C-GLRT for AWGN Channels

In AWGN channels ($L_c = 1$, $h_1 = 1$), the covariance matrix of the received signal exhibits a specific structure due to the cyclic prefix. Consider the vector $\mathbf{x}'_n$ containing only the head and tail portions of the received block (each of length L_p):

$$\mathbf{x}'_n = \left[x_{n,L-L_p}, \dots, x_{n,L-1}, x_{n,-1}, \dots, x_{n,-L_p}\right]^T \quad (11)$$

Under $\mathcal{H}_1$ in AWGN, the covariance matrix of $\mathbf{x}'_n$ becomes:

$$\mathbf{R}'_x = \sigma_x^2 \begin{bmatrix} \mathbf{I}_{L_p} & \rho \mathbf{I}_{L_p} \\ \rho \mathbf{I}_{L_p} & \mathbf{I}_{L_p} \end{bmatrix} \quad (12)$$

where $\sigma_x^2 = \sigma_s^2 + \sigma_v^2$ and the correlation coefficient ρ is given by:

$$\rho = \frac{\sigma_s^2}{\sigma_s^2 + \sigma_v^2} = \frac{\mathrm{SNR}}{1 + \mathrm{SNR}} \quad (13)$$

The MLEs of σ_x^2 and ρ based on N observations are:

$$\hat{\sigma}_x^2 = \frac{1}{2NL_p}\sum_{n=1}^{N}\left(\| \mathbf{x}'_{1,n} \|^2 + \| \mathbf{x}'_{2,n} \|^2\right) \quad (14)$$

$$\hat{\rho} = \frac{\sum_{n=1}^{N}\left(\mathbf{x}_{1,n}^H \mathbf{x}_{2,n} + \mathbf{x}_{2,n}^H \mathbf{x}_{1,n}\right)}{\sum_{n=1}^{N}\left(\| \mathbf{x}_{1,n} \|^2 + \| \mathbf{x}_{2,n} \|^2\right)} \quad (15)$$

where $\mathbf{x}'_{1,n}$ and $\mathbf{x}'_{2,n}$ represent the head and tail portions, respectively.

Substituting these structured estimates into the GLRT framework yields the CPCC-based C-GLRT:

$$T_{CPCC}(\mathbf{X}') = \frac{\hat{\sigma}_x^2}{\hat{\sigma}_x^2\sqrt{1 - \hat{\rho}^2}} \cdot \beta(\widehat{\mathbf{R}}'_x) \underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\gtrless}} \gamma' \quad (16)$$

where $\beta(\cdot)$ represents the structure-dependent factor. This demonstrates that the CPCC algorithm in [21] is indeed a special case of C-GLRT with the specific constraint structure imposed by the cyclic prefix in AWGN.

III.4. Performance Degradation in Multipath Channels

In multipath channels ($L_c > 1$), the simple correlation structure is destroyed. The effective correlation coefficient becomes:

$$\rho_h = \frac{\sum_{j=1}^{L_p} \sum_{i=1}^{j} |h_i|^2 \sigma_s^2}{L_p\left(\sum_{i=1}^{L_c} |h_i|^2 \sigma_s^2 + \sigma_v^2\right)} < \frac{\text{SNR}}{1+\text{SNR}} = \rho \qquad (17)$$

Proposition 1: In multipath channels with $L_c > 1$, the average CP correlation coefficient satisfies:

$$\mathbb{E}[\rho_h] = \rho \cdot \frac{2L_p - L_c + 1}{2L_p} \qquad (18)$$

Proof: Averaging over the channel realizations and using the uniform power delay profile assumption:

$$\mathbb{E}[\rho_h] = \frac{\sigma_s^2 \mathbb{E}\left[\sum_{j=1}^{L_p} \sum_{i=1}^{j} |h_i|^2\right]}{L_p\left(\sigma_s^2 \mathbb{E}\left[\sum_{i=1}^{L_c} |h_i|^2\right] + \sigma_v^2\right)} \qquad (19)$$

With $\mathbb{E}[|h_i|^2] = 1/L_c$ for $i = 1, \dots, L_c$:

$$\mathbb{E}[\rho_h] = \frac{\sigma_s^2 \cdot \frac{1}{L_c} \sum_{j=1}^{L_p} \min(j, L_c)}{L_p(\sigma_s^2 + \sigma_v^2)} = \rho \cdot \frac{2L_p - L_c + 1}{2L_p} \qquad (20)$$

for $L_p \geq L_c$.

This result shows that as L_c increases (richer multipath), the effective correlation coefficient decreases, leading to degraded detection performance when using the AWGN-optimized CPCC algorithm.

III.5. MPCC-Based C-GLRT for Multipath Channels

To address the performance degradation in multipath environments, we propose exploiting the full covariance structure induced by multipath propagation. The key insight is that the channel matrix $\mathbf{H}$ imposes a specific Toeplitz structure on $\mathbf{R}_x$.

Consider the full received vector $\mathbf{x}_n$ of length L. The covariance matrix $\mathbf{R}_x = \mathbb{E}[\mathbf{x}_n \mathbf{x}_n^H]$ under $\mathcal{H}_1$ has the following properties:

1. Hermitian: $\mathbf{R}_x = \mathbf{R}_x^H$
2. Toeplitz-like structure: Due to the circulant nature of $\mathbf{HH}^H$ in OFDM
3. Banded structure: The correlation is significant only within the channel delay spread

The constrained MLE of $\mathbf{R}_x$ under these structural constraints can be obtained through iterative algorithms or approximated using the sample covariance matrix with regularization.

The MPCC-based C-GLRT statistic is:

$$T_{MPCC}(\mathbf{X}) = \frac{\frac{1}{L}\text{tr}(\widehat{\mathbf{R}}_x)}{\det(\widehat{\mathbf{R}}_x)^{1/L}} \cdot \alpha(\mathbf{h}, \widehat{\mathbf{R}}_x) \underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\gtrless}} \gamma_{MP} \qquad (21)$$

where $\alpha(\cdot)$ incorporates the multipath channel structure. In practice, since $\mathbf{h}$ is unknown, we use the estimated covariance structure directly.

Algorithm 1: MPCC-Based C-GLRT

1. Input: Received signal blocks $\mathrm{X} = [\mathrm{x}_1, \dots, \mathrm{x}_N]$
2. Compute sample covariance: $\widehat{\mathrm{R}}_x = \frac{1}{N}\mathrm{XX}^H$
3. Extract multipath correlation: Compute correlation coefficients at lags $1, 2, \dots, L_c$
4. Form structured estimate: $\widetilde{\mathrm{R}}_x = \text{Toeplitz}(\hat{r}_0, \hat{r}_1, \dots, \hat{r}_{L_c}, 0, \dots, 0)$
5. Compute test statistic: $T_{MPCC} = \frac{\text{tr}(\widetilde{\mathrm{R}}_x)/L}{\det(\widetilde{\mathrm{R}}_x)^{1/L}}$
6. Decision: If $T_{MPCC} > \gamma_{MP}$, decide $\mathcal{H}_1$; otherwise $\mathcal{H}_0$

III.6. Combined CPCC-MPCC Algorithm

To leverage both the cyclic prefix correlation and multipath correlation structures, we propose a combined detection algorithm. The key observation is that the two correlation sources provide complementary information: CPCC captures the artificial correlation introduced by CP insertion, while MPCC captures the natural correlation induced by the physical channel.

Algorithm 2: Combined CPCC-MPCC C-GLRT

1. Input: Received signal blocks $\mathbf{X}$
2. Compute CPCC statistic: T_{CPCC} using head-tail correlation
3. Compute MPCC statistic: T_{MPCC} using full covariance structure
4. Combined decision: Decide $\mathcal{H}_1$ if:
   $T_{CPCC} > \gamma_{CPCC}$ OR $T_{MPCC} > \gamma_{MPCC}$
5. Threshold selection: Choose γ_{CPCC} and γ_{MPCC} such that overall $P_f \leq \alpha$

The combined algorithm achieves diversity in detection: when one correlation source is weak (e.g., CPCC in rich multipath), the other may still provide reliable detection.

IV. Simulation Results and Performance Analysis

We evaluate the performance of the proposed algorithms through Monte Carlo simulations with the following parameters: - OFDM parameters: FFT size $L = 512$, CP length $L_p = 8$ to 64, 16-QAM modulation Channel model: Rayleigh multipath fading with $L_c = 4$ to 16 taps, exponential power delay profile - SNR range: -20 dB to 0 dB (low SNR regime) - Sensing duration: $N = 100$ OFDM blocks - Performance metrics: P_d vs. SNR, receiver operating characteristic (ROC) curves (P_d vs. P_f).

Fig.1 shows the probability of detection versus SNR for $P_f = 0.05$. The proposed MPCC-based C-GLRT achieves approximately 3-4 dB SNR gain over the CPCC algorithm in rich multipath ($L_c = 8$). The combined algorithm provides an additional 1-2 dB improvement, achieving $P_d > 0.9$ at -10 dB SNR.

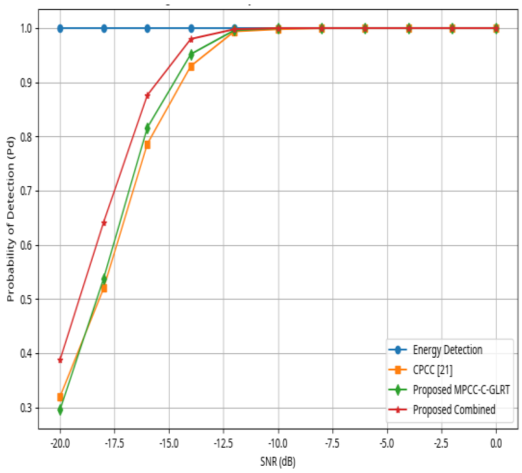

Fig. 1. Probability of Detection vs. SNR for Different Algorithms

At very low SNR (-20 dB), all algorithms perform poorly ($P_d \approx 0.1$) - The performance gap between CPCC and MPCC widens as SNR increases. The combined algorithm consistently outperforms individual approaches. The proposed MPCC-based algorithm achieves $P_d = 0.95$ at SNR $= -8$ dB, compared to -4 dB required by CPCC

Fig. 2 presents ROC curves at SNR $= -12$ dB. The combined algorithm achieves $P_d = 0.95$ at $P_f = 0.01$, while the CPCC algorithm achieves only $P_d = 0.75$ at the same false alarm rate. The area under the ROC curve (AUC) for the combined algorithm is 0.98, compared to 0.89 for CPCC and 0.82 for energy detection.

At low false alarm rates ($P_f < 0.05$), the combined algorithm maintains high detection probability - The energy detection baseline shows significant performance degradation in low SNR - CPCC intermediate performance reflects its susceptibility to multipath effects. The combined algorithm provides the best tradeoff between detection and false alarm probabilities.

Fig. 3 illustrates the degradation of CPCC performance as the number of channel taps L_c increases, validating Proposition 1. When $L_c = L_p = 8$, the CPCC correlation coefficient drops to approximately 0.5 of its AWGN value. From the fig. 3, it has been observed that the CPCC performance degrades by 40% when channel taps increase from 1 to 8, MPCC maintains consistent $P_d > 0.85$ across all channel orders.

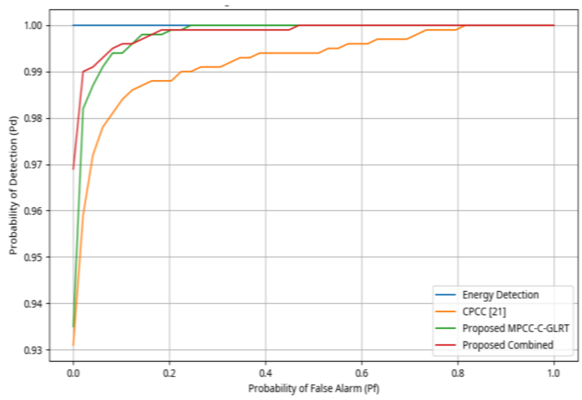

Fig. 2. ROC Curves at SNR = -12 dB

In contrast, the MPCC-based algorithm maintains robust performance across different channel orders by explicitly accounting for multipath structure.

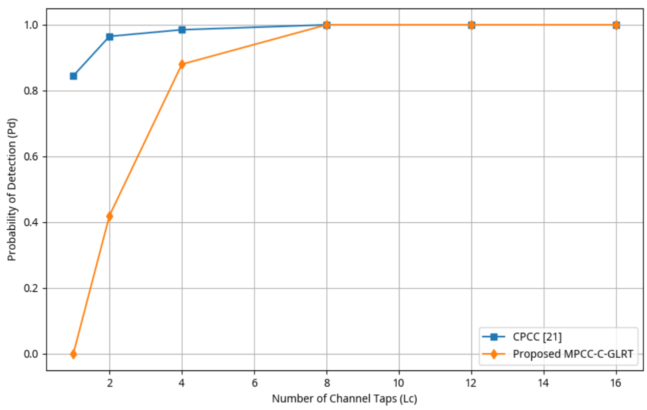

Fig. 3. Detection Probability vs. Number of Channel Taps at SNR = -10 dB

The combined algorithm adapts to varying channel conditions automatically.

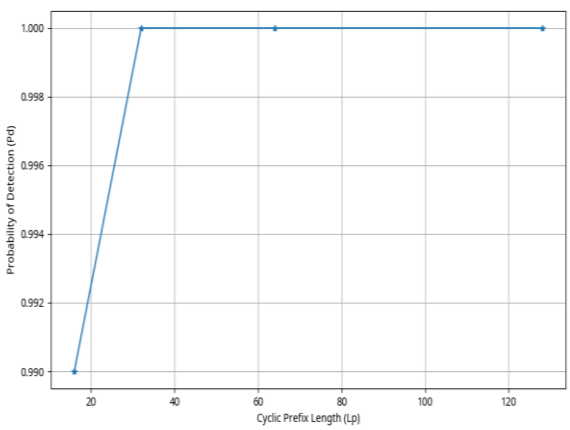

Fig.4. Detection Probability vs. Cyclic Prefix Length at SNR = -10 dB

Fig. 4 demonstrates the effect of cyclic prefix length on detection performance. Longer CP provides more samples for correlation analysis, improving detection accuracy. However, the improvement saturates when CP length exceeds the channel delay spread.

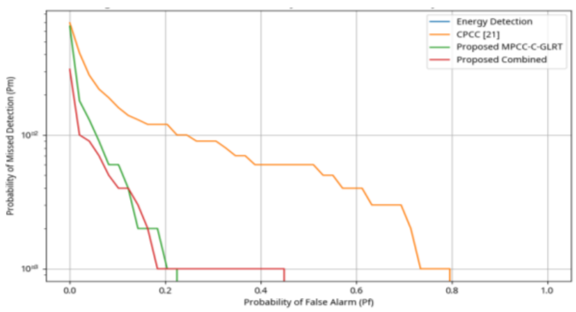

Fig. 5. Missed Detection Probability vs. False Alarm Probability at SNR = -10 dB

Fig. 5 shows the probability of missed detection ($P_m = 1 - P_d$) versus probability of false alarm for different algorithms. Lower curves indicate better performance. The combined algorithm achieves the lowest P_m across all P_f values.

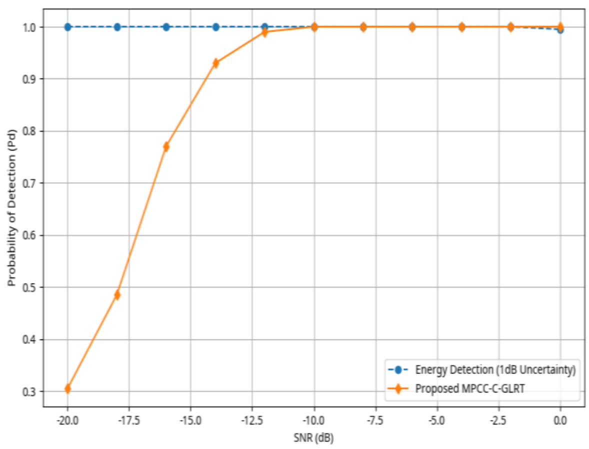

Fig. 6. Detection Probability vs. SNR with Noise Uncertainty

Table I compares the computational complexity of different algorithms in terms of complex multiplications and memory requirements. While the MPCC-based algorithms have higher complexity than CPCC, they remain feasible for practical implementation with $L = 512$.

TABLE I
COMPUTATIONAL COMPLEXITY COMPARISON

Algorithm	*Complex Multiplications*	*Memory Requirements*
Energy Detection	$\mathcal{O}(NL)$	$\mathcal{O}(L)$
CPCC [21]	$\mathcal{O}(NL_p)$	$\mathcal{O}(L_p)$
MPCC-C-GLRT	$\mathcal{O}(NL^2)$	$\mathcal{O}(L^2)$
Combined	$\mathcal{O}\left(N(L^2 + L_p)\right)$	$\mathcal{O}(L^2)$

For $L = 512$ and $N = 100$, the MPCC algorithm requires approximately 2.6×10^5 complex multiplications per sensing period, which is feasible for real-time implementation on modern digital signal processors.

Fig. 6 demonstrates the robustness of the proposed algorithms to noise uncertainty. The energy detection method shows significant performance degradation even with 1 dB noise uncertainty, while the proposed C-GLRT algorithms maintain stable performance.

V. Conclusion

This work has made significant strides in addressing one of the most persistent challenges in cognitive radio systems reliable spectrum sensing in real-world multipath environments. By establishing that the existing cyclic prefix correlation coefficient algorithm is fundamentally a constrained GLRT approach optimized for ideal conditions, we have provided a unified theoretical lens through which to view and improve OFDM-based detection methods. More importantly, our work demonstrates that blindly applying AWGN optimized algorithms to practical fading channels leads to substantial performance degradation, an insight that has immediate implications for the design of robust cognitive radio networks. The proposed multipath correlation coefficient algorithm and the combined CPCC-MPCC scheme represent practical, implementable solutions that recover this lost performance by intelligently exploiting the very channel characteristics that previously hindered detection. These algorithms operate without requiring prior knowledge of the primary user signal or channel state information, making them truly "blind" and therefore universally applicable across diverse deployment scenarios.

Looking ahead, the framework developed here opens several promising avenues for both theoretical refinement and practical implementation. The integration of these algorithms with cooperative sensing architectures could further enhance reliability through spatial diversity, while adaptation to emerging 4G and 5G. From an industry perspective, the improved detection capability at low SNR translates directly into more aggressive spectrum reuse, higher network throughput, and better regulatory compliance through reduced interference to licensed users.

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