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MIMO-enhanced distributed spectrum sensing with diffusion based algorithms for cognitive radio systems

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ABSTRACT

Spectrum sensing (SS) is a fundamental function in cognitive radio (CR) networks, enabling efficient spectrum utilization by identifying available channels. However, existing SS methods face challenges such as low accuracy in dynamic and low signal-to-noise ratio (SNR) environments, as well as high computational complexity. To address these issues, this paper presents a distributed SS technique that combines multiple-input multiple-output (MIMO) technology with a diffusion-based (DB) cooperative algorithm. MIMO enhances spatial diversity to improve detection performance, while the DB algorithm enables efficient collaboration among secondary users, reducing both sensing time (ST) and computational time (CT). Simulations over Rayleigh (RL) and Rician (RC) fading channels evaluated metrics such as probability of detection and false alarm. Results demonstrate that the proposed MIMO-DB method outperforms existing approaches, including honey badger remora optimization (HBRO)-AlexNet, by reducing ST by 18 seconds and CT by 45 seconds at 5 dB SNR, while achieving higher detection accuracy across varying SNR levels. These findings highlight the method's robustness and efficiency, making it a promising solution for dynamic spectrum management in 5G, internet of thing (IoT) and other next-generation wireless systems.

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1. INTRODUCTION

Cognitive radio (CR) networks have been developed to enhance spectrum efficiency by allowing secondary users (SUs) to access licensed spectrum when primary users (PUs) are not actively utilizing it. A critical function in CR networks is spectrum sensing (SS), which enables accurate identification of available spectrum resources. Traditional SS techniques, such as energy detection (ED), are simple to implement but often perform poorly in low signal-to-noise ratio (SNR) environments [1]. CR technology is expected to significantly influence wireless communications by optimizing spectrum utilization. However, SS remains a considerable challenge. Various techniques have been explored to improve sensing accuracy ranging from matched filtering (MF) and cyclostationary detection (CD) to eigenvalue-based methods. Cooperative SS, which aggregates observations from multiple receivers, has also been investigated, particularly for its ability to operate effectively with minimal prior knowledge of signal or channel characteristics. Additionally, practical issues such as noise uncertainty have been addressed with solutions proposed to improve threshold determination and test statistic distributions [2], [3].

Current wireless networks face spectrum inefficiency due to static allocation policies, resulting in highly variable usage rates depending on time and location. This inefficiency has led to the emergence of next generation (xG) networks or dynamic spectrum access (DSA) systems, which promote opportunistic spectrum use. CR networks are foundational element of xG networks, with their architecture designed to dynamically adapt to available spectrum [4]. ED remains one of the most widely used SS techniques in CR networks because of its simplicity and low computational overhead. However, in orthogonal frequency division multiplexing (OFDM)-based systems, a key modulation scheme in modern wireless communication, environmental factors such as SNR levels and channel fading significantly affect detection accuracy. Analyzing detection thresholds have highlighted the need to balance the probability of detection (Pd) and probability of false alarm (Pfa) to optimize SS in dynamic environments [5], [6].

Recent research has also focused on improving energy efficiency in CR networks using multiple-input multiple-output (MIMO) technology. The dynamic nature of cognitive radio networks (CRNs), where SUs continuously sense and access the spectrum, presents unique energy consumption challenges. By optimizing MIMO configurations and SS techniques, researchers have demonstrated reductions in energy demands while maintaining reliable performance [7]. Further advancements involve the integration of communication and sensing in wireless systems through hybrid beamforming architectures. These systems employ MIMO technology and optimized OFDM waveforms to simultaneously perform data transmission and environmental sensing. This hybrid approach ensures efficient spectrum utilization while minimizing power consumption [8]–[10]. Additionally, SS and resource allocation strategies for 5G communication systems have been developed. These strategies emphasize efficient spectrum use to meet the high data rate and low latency requirements of 5G networks [11], [12]. Hybrid cooperative SS algorithms have also been developed to address noise uncertainty and fading effects, enhancing the accuracy of spectrum resource detection in dynamic environments [13], [14]. The current literature on distributed sensing in CR networks using MIMO-based SS with a diffusion-based (DB) and cooperative (CO) algorithm are surveyed along with their advantages and limitations.

Dewangan *et al.* [15] introduced a hybrid approach that integrates the honey badger remora optimization (HBRO) technique with AlexNet, a deep learning model, to improve cooperative SS in CR networks. This method combines the strengths of both the honey badger algorithm (HBA) and the remora optimization algorithm (ROA) to optimize the training of AlexNet, utilizing key signal parameters like signal energy and eigenvalue statistics. However, the focus on the RC channel model restricts its application in more varied wireless environments, such as Rayleigh (RL) or Nakagami fading channels. Additionally, the method faces challenges related to processing time and computational complexity. Relying on a single deep learning model like AlexNet may also limit its adaptability to dynamic network conditions.

Usman *et al.* [16] developed an additive white gaussian noise (AWGN) model, demonstrating that integrating ED with electromagnetic (EM) enhances performance in low-SNR conditions. Their findings, validated through simulation plots based Pfa and Pd accuracy, confirm the effectiveness of this approach. Future studies could expand upon this by exploring other channel models, like RL and Rician (RC) fading channels, and investigating cognitive officers (CO) detection methods to improve SS accuracy further. In addition various optimization algorithms have been paired with deep learning methods to boost SS performance. This approach leverages critical signal features such as energy and eigenvalue statistics to enhance SS capabilities.

Xu *et al.* [17] developed a cooperative spectrum sensing (CSS) technique utilizing a multifeatures combination network that incorporates convolutional neural networks (CNNs) to extract spatial features and gate recurrent unit (GRU) models to capture temporal information. This approach enables the network to integrate local features from multiple nodes, thereby enhancing detection performance. Despite its advantages, the multifeatures combination network encounters challenges in terms of computational complexity.

Algriree *et al.* [18] proposed a SS technique specifically designed for 5G-MIMO systems, enhancing spectrum availability and signal clarity through the use of an ED algorithm paired with a cosine law to filter traffic signals. The process then incorporates partitioning using the welch algorithm and windowing via the Hann algorithm, aiming to reduce excessive power delivery to the MIMO system. This SS technique is applied in both CO and non CO setups to efficiently manage multiple waveforms. However, while it focuses on SS performance across varying SNR conditions, it does not thoroughly address other important factors such as resource allocation, throughput optimization, or the computational complexity.

Cai *et al.* [19] introduced an innovative SS approach utilizing a spectrogram-aware convolutional neural network (S-CNN), where the CNN receives the spectrogram of signal samples- created using short-time Fourier transform (STFT)-as input. This technique aims to extract both temporal and frequency characteristics from the spectrogram. However, the method mainly concentrates on enhancing detection performance in offline environments, while significant challenges such as computational complexity and scalability remain unaddressed.

Jothiraj *et al.* [20] proposed an adaptive threshold-based dragonfly optimization algorithm for CSS in CR networks. This approach aims to enhance detection accuracy and spectrum efficiency by dynamically adjusting the sensing threshold, allowing more efficient identification of spectrum holes. The dragonfly optimization algorithm strikes a balance between exploration and exploitation to optimize SS performance. However, the model mainly focuses on static or semi-dynamic environments, and does not fully investigate the algorithms robustness or adaptability in highly dynamic conditions, such as fluctuating SNR, rapidly changing user activity or unpredictable interference patterns.

Gomaa *et al.* [21] introduced a hybrid detection method for CSS, integrating additive wavelet transform (AWT) and Haar discrete wavelet transform (HDWT) with homomorphic decomposition to reduce noise prior to the decision making process. Their study examines the effectiveness of various fusion rules (OR, AND, and majority) for CO sensing, utilizing fixed-time sensing intervals. However, the research does not fully investigate how the models perform in different fading environments such as RL and Nakagami channels or in rapidly changing wireless conditions. Additionally, the trade-off between detection accuracy and energy consumption remains a key aspect that has not been thoroughly addressed.

Bani and Kulkarni [22] proposed that hybrid SS methods, which integrate ED and matched detector (MD) are highly effective in boosting performance, especially in low-SNR and heterogeneous environments. CSS further improves detection accuracy by utilizing collaboration among multiple CR users. Future advancements could aim at lowering the computational complexity of these methods and investigating the incorporation of additional detectors such as CD, to better manage situations where only partial information about PUs is available.

Kumar *et al.* [23] suggested hybrid SS models that combine various detection methods to improve the performance of 5G and 6G waveforms. These models including hybrid matched filter (HMF) algorithms, show better performance compared to conventional techniques like MF especially in RL and RC channels under noisy conditions. However, these advanced methods typically demand higher computational resources and real-time channel estimation, which lead to system complexity. With the growing need for spectrum in 5G and 6G, future research should prioritize balancing performance gains with system efficiency and manageable computational requirements.

Mabrook *et al.* [24] proposes an adaptive neuro-fuzzy inference system (ANFIS) for optimizing cooperative SS in CR networks. The ANFIS model is trained using identity numbers, repetition parameters and channel power levels to accurately detect free spectrum channels. It integrates adaptive methods to improve sensing performance under varying SNR levels. Simulations demonstrate the method’s efficiency in overcoming fading and shadowing challenges, outperforming traditional detection methods. However, the study assumes relatively static network conditions and a limited number of users, which may hinder scalability. Additionally, the computational demands of the ANFIS model could face challenges for real-time deployment in large-scale or dynamic networks.

In Lorincz *et al.* [25] introduced square-law combining techniques in MIMO-OFDM CR networks, showing that multi-antenna configurations enhance detection performance. However, the use of OFDM showing synchronization complexity and increases computational demands, making it less suitable for lightweight distributed sensing environments.

Budati and Valiveti [26] proposed a CR sensing method that utilizes the generalized likelihood ratio test (GLRT) and Neyman Pearson (NP) detection rules to improve user sensing detection. While their approach increases accuracy under known signal models, it requires prior information and produces higher computational overhead, which may limit flexibility in dynamic spectrum environments.

Many current SS techniques encounter difficulties when dealing with complex fading environments such as RL and RC channels, often struggling in low-SNR scenarios. In this study, to address the inefficiency of traditional SS methods in dynamic and low-SNR environments. While methods such as HBRO-AlexNet [15] and ED with entropy [16] have made significant contributions, to face limitations, including high computational complexity, scalability issues and poor performance in low-SNR conditions. To overcome these challenges, to propose a novel MIMO-DB SS technique. The approach leverages MIMO for enhanced spatial diversity and DB algorithm to enable efficient collaboration among SUs. This approach that reduces sensing time (ST) and computational time (CT) while maintaining high detection accuracy.

The key findings of this research are as follows:

- The proposed DB algorithms facilitates efficient collaboration among SUs. By iteratively refining local energy estimates through cooperative process, it reduces the Pfa while maintaining a high Pd.
- The system achieves reduced ST and CT by optimizing detection performance through iterative cooperation, making it well-suited for large-scale CR networks. The inclusion of MIMO technology

enables quicker local SS and the DB algorithm ensures faster convergence compared to traditional consensus-based methods, improving both detection accuracy and computational efficiency.
– The proposed system is highly scalable, capable of handling numerous SUs without the need for centralized control, and it performs effectively in both static and dynamic spectrum conditions.

The rest of this paper is structured as follows: section 2 presents the methodology, section 3 discusses the results, and section 4 concludes with the implications and future directions.

2. PROPOSED METHOD

This research presents a novel approach that combines MIMO-Based SS with a DB cooperative algorithm for distributed sensing in CR networks. Figure 1 illustrates the block diagram of the proposed distributed MIMO and DB SS system.

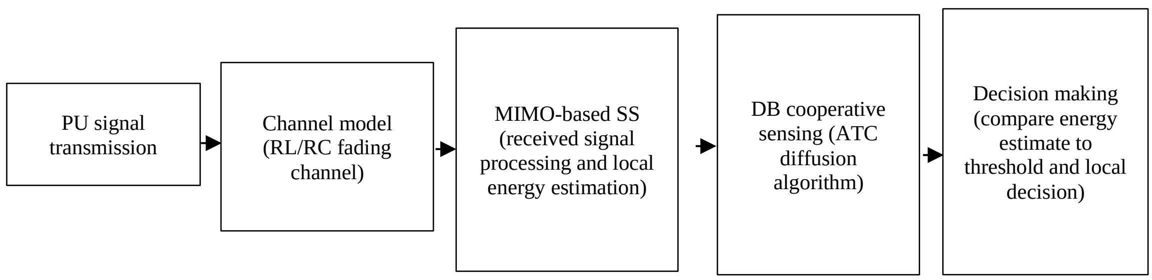


Figure 1. Block diagram of distributed MIMO and DB SS

The MIMO-DB SS technique was implemented in MATLAB using the configurations outlined in Table 1. Simulations were performed with 10–50 SUs, a range of SNR values and specified iteration settings. To model real-world scenarios, both RL and RC fading channels were included to assess robustness under dynamic wireless conditions. MIMO technology was selected for its capability to provide spatial diversity and enhance detection performance in fading environments. The DB algorithm followed an adapt-then-combine (ATC) approach, iteratively refining local energy estimates. This approach is recognized for its efficiency in distributed sensing, its ability to coverage under dynamic conditions and its enhanced detection accuracy.

Table 1. Simulation parameters of the proposed method

Parameters	Values
Number of transmit antennas M_t (MIMO configuration)	2,4
Number of receive antennas M_r (MIMO configuration)	2,4
N number of samples for ED	500 to 1000
Number of iterations for diffusion	50 to 100
Number neighbors N_i for diffusion	3 to 5
Number of SUs	10 to 50
RL fading coefficient	Mean 0, variance 1
RC K factor K	0 to 10
Pfa and Pd range	[0 to1]
SNR range (dB)	-20 to 10

2.1. System model

Consider a CR network comprising multiple SUs, each equipped with MIMO antennas. The SUs perform distributed SS to detect the presence of a PU. Each SU operates locally and enhances detection accuracy by collaborating with neighboring SUs through a DB algorithm. The system leverages MIMO for spatial diversity, which improves detection performance in fading environments. Both RL and RC fading channels are used to model various wireless propagation conditions.

2.2. Channel modeling

The PU signal travels through either RL or RC fading channels, depending on the surrounding environments. The RL channel represents a non-line-of-sight (NLOS) scenario with multiple scattered paths, commonly found in urban or indoor settings.

$$H_{Rayleigh}(t) = \sqrt{\frac{1}{2}}(G_1 + jG_2) \quad (1)$$

Where G_1 and G_2 represent independent Gaussian random variables and j is the imaginary unit. The RC channel models a line-of-sight (LOS) scenario, characterized by both a discrete signal path and scattered components. The RC K-factor determines the balance between the LOS and NLOS elements.

$$H_{Rician}(t) = \sqrt{\frac{K}{K+1}}H_{LOS} + \sqrt{\frac{1}{K+1}}H_{NLOS} \quad (2)$$

Here, H_{LOS} denotes the deterministic LOS component, while H_{NLOS} represents the RL fading component. The RC factor K reflects the power ratio between the direct path and the scattered paths.

2.3. Multiple-input multiple-output-based spectrum sensing

Each SU utilizes its MIMO antenna array to conduct local SS in order to detect the presence of the PU. The detection method employed is ED, which assesses the energy of the received signal.

2.3.1. Received signal model

The received signal $y_i(t)$ at SU i at time t over the MIMO channel is:

$$y_i(t) = H_i(t)s(t) + n_i(t) \quad (3)$$

where, $H_i(t)$ is $M_R \times M_T$ channel matrix (RL or RC), s(t) is the transmitted signal from the PU, $n_i(t)$ is the AWGN vector with variance σ_n^2.

2.3.2. Energy detection

Each SU calculates the energy of the incoming signal within a specific time frame, denoted as T, to ascertain whether the PU is active. The energy estimates E_i for the i-th SU can be expressed as (4):

$$E_i = \frac{1}{2}\sum_{t=1}^{T} \|y_i(t)\|^2 \quad (4)$$

Where $\|y_i(t)\|^2$ represents the Euclidean norm (energy) of the received signal at time t. The MIMO advantage improves the detection performance by increasing the effective SNR, which can be modeled as:

$$SNR_{MIMO} = \frac{M_R M_T P_S}{\sigma_n^2} \quad (5)$$

where P_s is the power of the PU signal.

2.3.3. Detection decision

The SU makes a local decision, based on the energy estimate E_i. This is done by comparing E_i to a predefined detection threshold λ.

$$\text{Decision: } E_i \begin{cases} > \lambda \text{ PU is present } (H_1) \\ \leq \lambda \text{ PU is absent } (H_0) \end{cases} \quad (6)$$

The threshold λ can be determined based on the desired Pfa and noise variance:

$$\lambda = \sigma_n^2\left(1 + \sqrt{\frac{2SNR}{M_R}}\right) \quad (7)$$

2.4. Cooperative sensing via diffusion algorithm

After each SU completes its local sensing, to collaborate using a DB algorithm to boost detection precision and robustness. A significant benefit of the diffusion method is its capacity to manage communication failures and offer greater reliability component to conventional consensus-based algorithms.

2.4.1. Adapt-then-combine diffusion algorithm

In the ATC diffusion algorithm, each SU refines its individual energy estimates by integrating its own observations with the estimates shared by neighboring SUs.

a. Adaptation step: each SU adjusts its local energy $E_i(k)$ at time k as (8):

$$\hat{E}_i(k+1) = \hat{E}_i(k) + \mu_i \left(E_i(k) - \hat{E}_i(k)\right) \tag{8}$$

where, μ_i is the step-size parameter that controls the rate of adaptation. $E_i(k)$ is the local energy estimate of SU i at time k. $\hat{E}_i(k)$ is the current estimate of SU i.

b. Combination step: after adaptation, each SU combines its updated energy estimate with the estimates from its neighboring nodes.

$$\hat{E}_i(k+1) = \hat{E}_i(k) + \sum_{j\epsilon N_i} \omega_{ij}\, \mu_i \left(E_i(k) - \hat{E}_i(k)\right) \tag{9}$$

where N_i is the set of neighboring SUs for SU i. ω_{ij} is the weight assigned to the neighbor j based on link quality. This diffusion process continues iteratively until the energy estimates of all SUs. Coverage, leading to more accurate global decisions.

c. Convergence: the diffusion process iterates until the energy estimates converge to stable values. Each SU then uses its final energy estimate to make a decision about the presence of the PU.
d. Pd: the probability that the system correctly detects the presence of the PU given by (10).

$$P_d = P(\hat{E}_i > \lambda \mid H_1) \tag{10}$$

e. Pfa: the probability that the system falsely detects the presence of the PU when no PU is present.

$$P_{fa} = P(\hat{E}_i > \lambda \mid H_0) \tag{11}$$

f. ST: ST T_S refers to the time each SU spends on performing local SS, including signal collection and ED. It depends on the number of samples N, the sampling period Δt, and the complexity of the MIMO system.

$$T_s = N \times \Delta t \tag{12}$$

g. CT: the CT T_C is the total time taken for the DB algorithm to converge. It is influenced by the number of iterations K, the step size μi, and the number of neighbors involved in the information exchange.

$$T_c = K \times I \times T_{update} \tag{13}$$

where I is the number of information exchanges in each iteration and T_{update} is the time required for each update step.

3. RESULTS AND DISCUSSION

This section outlines the experimental analysis conducted to evaluate the proposed approach under different scenarios. The method was implemented using MATLAB software, with the system configuration consisting of an Intel i7 processor, Windows 11 operating system and 8 GB RAM. The simulation parameters for the proposed approach are detailed in Table 1.

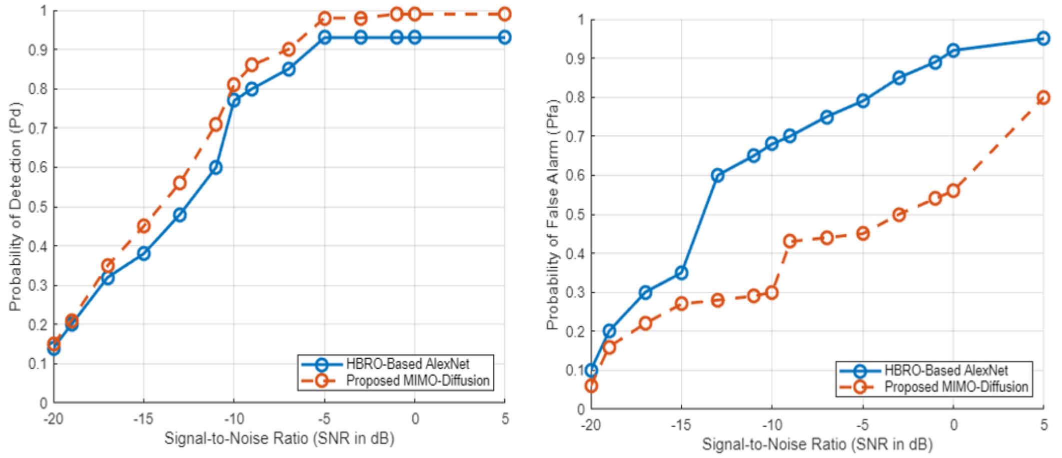
3.1. Testing scenarios

Performance is evaluated under both RL and RC fading conditions and results are measured using Pd, Pfa, ST, and CT. Comparative benchmarks include HBRO-AlexNet and ED with EM methods. No external datasets are used, all signal and noise samples are synthetically generated using MATLAB based on standard SS models, including MIMO ED with fading channels.

3.2. Performance analysis

In this section, the proposed method effectiveness is assessed using various parameters outlined in Table 1. Figures 2(a) and (b) illustrates the performance analysis over a RL fading channel, showing the relationship between the Pd and the Pfa. To evaluate the proposed approach, its performance is compared against an existing SS technique based on HBRO-AlexNet [15] model. Figure 2(a) presents the Pd at various SNR levels. In the existing technique SNR values ranged from -20 dB to 5 dB and corresponding Pd values were recorded. At lower SNRs especially below -10 dB, the detection performance was suboptimal. For instance at -20 dB the detection probability was 0.14, gradually improving to 0.93 at 0 dB. In contrast, the proposed MIMO-DB algorithm demonstrates significantly better detection performance at all SNR levels. Even at low SNRs such as -20 dB, the proposed method achieves a Pd of 0.15, slightly outperforming the existing technique. As the SNR increases, the Pd steadily improves, reaching 0.99 at 0 dB and maintaining consistency at higher SNR levels.

Similarly, Figure 2(b) illustrates the Pfa, which remains significantly lower across all tested SNR levels. The proposed MIMO-DB algorithm with a RL fading channel exhibits a lower Pfa at all SNR levels when compared to the HBRO-AlexNet [15] method.

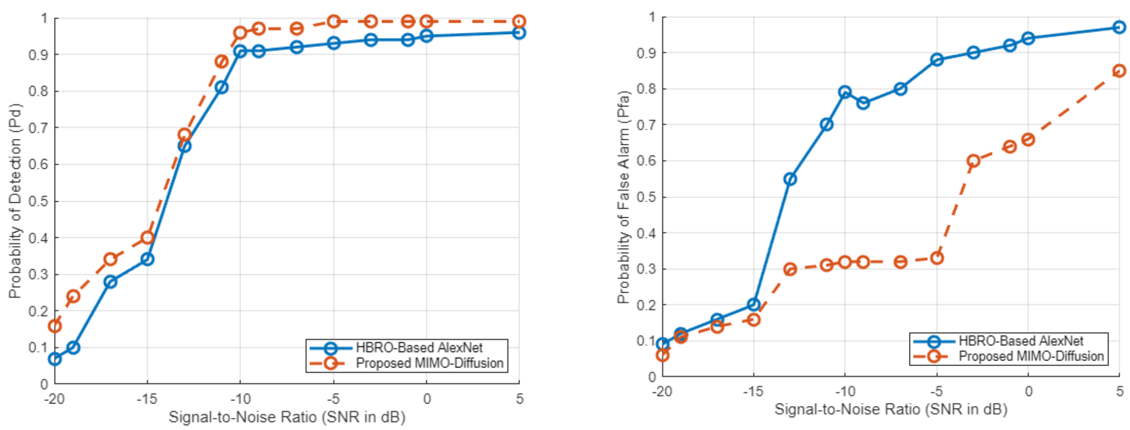


(a) (b)

Figure 2. Performance analysis with RL channel: (a) Pd and (b) Pfa

For example, at an SNR of -20 dB, the Pfa was reduced to 0.06, in contrast to the 0.10 Pfa observed with the HBRO-AlexNet [15] technique. Even though this method Pfa reached 0.80 at 5 dB, it still remained below that of the HBRO-AlexNet [15] approach.

Figures 3(a) and (b) presents the performance analysis with a RC channel in terms of Pd and Pfa. The detection performance of the MIMO-DB algorithm with the RC channel was assessed and compared to the HBRO-AlexNet [15] based method. Figure 3(a) illustrates the primary metric for comparison was the Pd across various SNR levels. The results indicate consistent improvements with the offered method, which shows significant gains in detection performance at all SNR levels. Notably, the presented approach achieves a Pd of 0.99, outperforming the 0.95 achieved by HBRO-AlexNet [15]. Figure 3(b) depicts the Pfa, indicating a lower rate across varying SNR levels. These results validate the robustness of the proposed approach in both low and high SNR conditions.

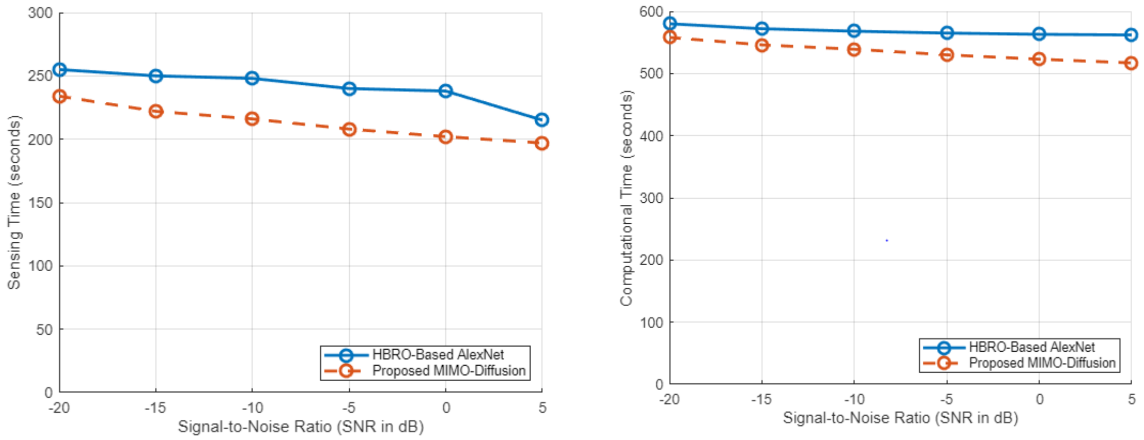


(a) (b)

Figure 3. Performance analysis with RC channel: (a) Pd and (b) Pfa

Figures 4(a) and (b) illustrates the performance analysis in terms of ST and CT over a RC. In Figure 4(a) shows the proposed MIMO-DB SS technique was evaluated against the existing HBRO-AlexNet [15] method by examining the ST across various SNR levels. ST is a vital metric in CR networks, as it influences the systems ability to detect the PU promptly and efficiently. The proposed MIMO-DB technique showed a marked improvement in ST within the tested SNR range. At an SNR of -20 dB, the ST was reduced to 234 seconds, indicating a faster detection process compared to the HBRO-AlexNet [15] method. As the SNR improved, the ST continued to decrease, reaching 197 seconds at 5 dB. This highlights the efficiency of the introduced method, especially in low-SNR conditions, where swift SS is crucial for maintaining the systems overall responsiveness.

In Figure 4(b) shows the computational efficiency of the MIMO-DB SS technique was evaluated in comparison to the existing HBRO-AlexNet [15] method by examining the CT across different SNR levels. The MIMO-DB technique showed a notable reduction in CT over the entire SNR of 5 dB. This consistent decline in CT across all SNR levels highlights the enhanced efficiency of the proposed method.



(a) (b)

Figure 4. Performance analysis with RC channel: (a) ST and (b) CT

3.3. Comparative analysis

The comparative results presented in Table 2 clearly indicate that the developed MIMO-DB method with RL and RC fading channel outperforms the HBRO-AlexNet-based [15] approach across all SNR levels. At higher SNR values (above -5 dB), both methods converge toward high Pd, though the MIMO-DB still maintains a slight advantage, achieving a Pd of 0.99. Additionally, the proposed method demonstrates a more controlled increase in Pfa, with a maximum of 0.80 at 5 dB, compared to 0.95 in the HBRO-AlexNet [15] method.

Table 2. Evaluation of MIMO-diffusion vs HBRO based AlexNet [15]

Performance metrics	Methods	Types of channel	SNR					
			-20	-15	-10	-5	0	5
Pd	HBRO based AlexNet [15]	RL	0.14	0.38	0.77	0.93	0.93	0.93
		RC	0.07	0.34	0.91	0.93	0.95	0.96
	MIMO-diffusion	RL	0.24	0.45	0.81	0.98	0.99	0.99
		RC	0.16	0.4	0.96	0.99	0.99	0.99
Pfa	HBRO based AlexNet [15]	RL	0.1	0.35	0.68	0.79	0.92	0.95
		RC	0.09	0.2	0.79	0.88	0.94	0.97
	MIMO-diffusion	RL	0.06	0.27	0.3	0.45	0.56	0.8
		RC	0.06	0.16	0.32	0.33	0.66	0.85
ST	HBRO based AlexNet [15]	RC	255	250	248	240	238	215
	MIMO-diffusion		234	222	216	208	202	197
CT	HBRO based AlexNet [15]	RC	580	572	568	565	563	562
	MIMO-diffusion		556	546	539	530	523	517

Furthermore, the comparison shows that the developed MIMO-DB SS technique consistently reduces ST when compared to the HBRO-AlexNet [15] approach across all SNR levels. At higher SNRs, such as 5 dB, the method further reduces the ST by 18 seconds (215 s to 197 s). Additionally, the CT of the proposed framework at 5 dB is 45 seconds less than that of the HBRO-AlexNet [15] approach (from 562 s to 517 s). These reductions in CT and ST highlight the superior efficiency of the proposed method in managing the computational demands of detecting the PU, particularly in challenging low-SNR environments.

To assess the effectiveness of the introduced MIMI-DB SS technique, it was compared to the existing ED with EM method [16]. The comparison was based on the Pd at fixed Pfa of 0.1 and 0.2 across varying SNR levels. The MIMO-DB technique showed significant improvements in Pd at all SNR levels, particularly at lower SNRs. For instance, at -20 dB, the Pd reached 0.40, which is higher than the corresponding value achieved by the ED with EM method. This trend persisted throughout the SNR range with this method achieving a Pd of 0.75 at -13 dB, consistently outperforming the existing method across all SNR levels, as shown in Table 3.

Table 3. Evaluation of MIMO-diffusion vs ED with EM [16] for different Pfa for the Pd

Pfa	Method	SNR									
		-20	-17	-15	-13	-10	-9	-7	-5	-3	0
Pfa=0.1	ED with EM [16]	0.32	0.41	0.51	0.66	0.94	0.97	0.99	1	1	1
	MIMO-diffusion	0.4	0.56	0.65	0.75	0.97	1	1	1	1	1
Pfa=0.2	ED with EM [16]	0.42	0.51	0.61	0.75	0.95	0.91	0.98	1	1	1
	MIMO-diffusion	0.48	0.6	0.74	0.85	0.96	0.98	1	1	1	1

Table 4 presents the structured comparison clearly demonstrates that proposed MIMO-DB technique offers a balanced and efficient solution compared to more complex modern methods, particularly in low SNR environments.

Table 4. Evaluation of MIMO-diffusion vs modern SS techniques

Method	Key features	Detection accuracy	Sensing/CT	Limitation
ED with EM [16]	Statistical; iterative estimation	Modern	Low to moderate	Sensitive to noise; slow at low SNR
HBRO-AlexNet [15]	Deep learning+metaheuristic optimization	High	High	High overhead, poor for real time applications
Proposed MIMO-DB	MIMO+diffusion (distributed, cooperative)	Very high	Low to moderate	Lightweight, robust, scalable

3.4. Discussion

Previous studies have primarily focused on SS techniques such as HBRO-AlexNet [15] and ED with entropy [16]. However, these approaches face challenges in dynamic environments, particularly in achieving low ST and CT without compromising detection accuracy. To study aims to address these limitations through the proposed MIMO-DB technique achieved a Pd of 0.99 at 0 dB, significantly outperforming HBRO-AlexNet [15], which achieved 0.95 under the same conditions. Additionally, ST was reduced by 18 seconds and CT decreased by 45 seconds compared to HBRO-AlexNet [15] at 5 dB, highlighting the efficiency of this approach. Results indicate that the integration of MIMO spatial diversity and DB algorithms improves detection accuracy and convergency speed. In comparison to HBRO-AlexNet [15], which relies on deep learning models with high computational demands, the MIMO-DB technique reduces overhead without sacrificing performance.

While the simulation results demonstrate the effectiveness of the proposed method, real-world testing is necessary to confirm its scalability and performance under unpredictable interference patterns. The finding suggest that MIMO-DB SS can significantly improve dynamic SS in next-generation networks. Future research could investigate integrating this approach with adaptive machine algorithms to enhance decision-making in more complex environments, explore implementation in large-scale wireless networks. It provides evidence that the proposed MIMO_DB SS technique addresses critical gaps in CR networks, offering higher detection accuracy, reduced ST and greater efficiency. These advancements contribute to the development of robust SS methods for next-generation networks.

The proposed MIMO-DB method offers high scalability through its fully distributed design, requiring each node to exchange information only with the neighbors. Unlike centralized methods with complexity, this approach keeps low communication overhead and ensures linear computational growth, even in large networks.

4. CONCLUSION

This paper presented a MIMO-DB SS framework aimed at addressing key challenges in CR networks, particularly spectrum utilization and the detection of PU activity. By integrating MIMO technology with a DB cooperative algorithm, the proposed method demonstrated superior performance compared to conventional techniques such as ED with EM and HBRO-AlexNet. It achieved higher detection accuracy across various SNR levels, with marked improvements in low- SNR conditions where traditional methods often underperform. Additionally, the approach significantly reduced both ST and CT, enhancing efficiency in dynamic and resource-constrained environments.

The methods distributed architecture ensures scalability and robustness, making it a strong candidate for real time deployment in emerging wireless systems such as 5G and IoT. Future research will focus on implementing the technique in real-world settings using software-defined radios (SDRs), evaluating its performance in high-mobility environments and extensions to multi-band and wideband SS. Integrating lightweight machine learning models may further improve responsiveness through real-time threshold adjustment in rapidly changing conditions.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Srikantha Kandhgal Mochigar	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓	
Rohitha Ujjini Matad		✓			✓		✓			✓	✓	✓		

C : **C**onceptualization	I : **I**nvestigation	Vi : **Vi**sualization
M : **M**ethodology	R : **R**esources	Su : **Su**pervision
So : **So**ftware	D : **D**ata Curation	P : **P**roject administration
Va : **Va**lidation	O : Writing - **O**riginal Draft	Fu : **Fu**nding acquisition
Fo : **Fo**rmal analysis	E : Writing - Review & **E**diting	

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper, as no new data were created or analyzed in this study.

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