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Optimizing Spectrum Sensing using Average Slope Detection and Machine Learning Techniques

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ABSTRACT
The cognitive radio network represents a pivotal advancement for 5G applications, countering the limitations posed by spectrum scarcity. Spectrum sensing is vital for identifying vacant spectrum bands in a network framework that comprises of Primary User (PU) and Secondary Users (SU's). The traditional spectrum sensing scheme like Energy detection is highly sensitive to uncertainties in noise with limited sensing accuracy. To overcome this limitation a novel method, Average Slope Detection (ASD) with Cooperative Spectrum Sensing is proposed. The Cooperative Spectrum Sensing network is simulated in MATLAB The classification of noise and PU is done be integrating Machine Learning algorithm, K-Nearest Neighbor which shows an improved accuracy by 18.34% over existing methods for a SNR -20dB.

KEYWORDS
Cognitive Radio (CR); Average Slope Detection (ASD); Spectrum scarcity; Cooperative Spectrum Sensing (CSS); MATLAB; K-Nearest Neighbor

1. INTRODUCTION

The escalating demand for wireless devices, particularly in the realm of Internet of Things (IoT) devices and wireless sensor networks, is projected to soar, potentially exceeding 29 billion IoT connections by 2027 as in [1]. This surge intensifies concerns regarding spectrum scarcity and underutilization as discussed in [2]-[4]. Remarkably, reports from the Federal Communications Commission (FCC) indicate that licensed spectrum remains underutilized by approximately 90% as given in [5].

Within this landscape, the emergence of cognitive radio networks stands as a transformative solution within 5G applications. It specifically focuses on issues related to spectrum shortage. Cognitive Radio (CR), originally introduced by Joseph Mitola in 1995, is an outstanding approach for 5G applications. It facilitates Secondary Users (SU) without a license to make use of unoccupied spectrum bands, commonly known as "spectrum holes." It accomplishes this in what is known as the "interweave paradigm" [6] without interfering with licensed Primary Users (PU).

When considering TV channel usage, cognitive radio technology is an innovative technique for maximizing the radio's electromagnetic spectrum usage. Implementing a cognitive radio using IEEE 802.22 devices requires responsible spectrum usage and is in accordance with the Cognitive Wireless RAN Medium Access Control (MAC) and Physical Layer (PHY) Specifications in [7]. It involves keeping a close watch on wireless microphone transmissions, TV broadcasts, signals, necessary medical telemetry devices, and signals from protective devices like the IEEE 802.22.1 wireless beacon. Cognitive radio, which operates under TV channels, greatly improves spectrum utilization while respecting regulations as well as decreasing interference in areas that are designated. Sensing the availability of spectrum holes for such applications is called spectrum is discussed in the following section.

At the core of CR networks lies spectrum sensing, and as discussed in [8] a pivotal process involving the periodic monitoring of specific frequency bands to identify PU is present or absent. These bands are categorized as white space, characterized by complete emptiness except for noise as shown in Fig. 1. Using the interweave paradigm, secondary users exploit spectrum holes by operating orthogonally to primary user signals in any of space, time, and frequency dimensions [6].

Noise	Partially Occupied by Interfacing signals	Communication signals, interfacing signals and noise
White Space	Grey Space	Black Space

Fig.1 Spectrum Sensing Classification

A The organization of this work is in the following manner: Section I. gives the Introduction to Cognitive Radio and the pivotal role of spectrum sensing, Section II. discusses the different methodologies that are being employed in order to carry out spectrum sensing, Section III. describes the system model of the proposed algorithm in detail, Section IV. discusses the Implementation Results in detail followed by Section V. that provides a Conclusion for the work and also briefs the Scope for Future Work

2. RELATED WORK

In the evolution of cognitive radio, several spectrum sensing schemes have been proposed and researched extensively.

One if the traditional spectrum sensing schemes has been Energy detection which is a non-coherent detection method.

It doesn't require prior knowledge of primary users. Further, it doesn't require any intricate receiver designs [9]. Even though the computational complexity of energy detection is simple, the performance of this scheme is greatly affected in low SNR cases [10].

The matched filter (MF) technique proves to be an optimal approach for detecting spectrum availability by maximizing Signal to Noise Ratio (SNR), even during presence of Additive White Gaussian Noise (AWGN). This capability is achieved through the inherent correlation process of the method.

Prior information of the PU is needed in the form of a pilot sequence. The pilot signal refers to a known and predetermined signal that is transmitted by the PU in a communication system. The primary purpose of the pilot signal is to assist in the spectrum sensing process carried out by a secondary user (SU) in a cognitive radio network. However, effective implementation of this detector necessitates a thorough understanding of the primary user (PU) signal, and a dedicated receiver must be allocated for each PU signal [11].

Another widely recognized approach is the Cyclostationary method. This method leverages the periodicity present in the received signal and effectively distinguishes PU and noise. Unlike energy detection, it requires prior information about the PU. Another drawback of this method is reduced performance when frequency mismatch occurs as discussed in [12].

The eigenvalue-based method compares the eigenvalues of the signal's covariance matrix to find primary users in different spectrums. The changes in eigenvalues are calculated based on the statistical characteristics and doesn't require any prior knowledge of the PU. The problem rises in dynamic and noisy environments, and the dependence on the accuracy of the estimated covariance matrix [13].

Based on the above discussion, the proposed algorithm must be able handle frequency mismatch, uncertainties in noise and maintain computational simplicity. Moreover, it should also have resilience against fluctuations in the channel in order to achieve accuracy in classification. To achieve these goals, a signal processing perspective is adopted. In doing so, a balance between performance and practical implementation, ensuring the viability of the proposed scheme in real-world scenarios is achieved.

This approach boasts low cost and enhanced accuracy, enabling the accurate classification of PU signal and noise. The work is subsequently implemented using MATLAB, and the obtained results are thoroughly analyzed and compared with methodologies employed in prior studies.

3. METHODOLOGY

The Average Slope Detection methodology focuses on the statistical properties of the signal that is robust under the uncertainties caused by noise and frequency mismatches.

The work is further optimized by utilizing Cooperative Spectrum Sensing (CSS) which involves leveraging observations or data from multiple CR users to enhance sensing performance. A Cooperative Spectrum Sensing network is shown in Fig. 2.

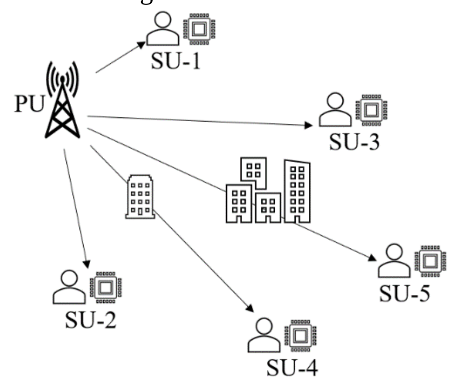

Fig. 2 Cooperative Spectrum Sensing

This approach includes multiple users aimed at reducing false alarms, minimizing missed detections, and achieving a quicker detection time. The integration of multiple sensors not only enhances detector performance but also introduces built-in redundancy, thereby enhancing reliability and robustness. However, a trade-off exists, as an increase in the number of cooperating sensing nodes leads to higher overhead traffic and greater system resource requirements for fusing the sensing results [14]. Keeping this in consideration a limited number of SU's are only considered.

In this framework, the Probability Density (PD) is very crucial. From the PD, its distribution (PDD) is calculated that is independent of noise uncertainties. The favourable characteristics of PD provide a promising avenue for robust spectrum sensing [15].

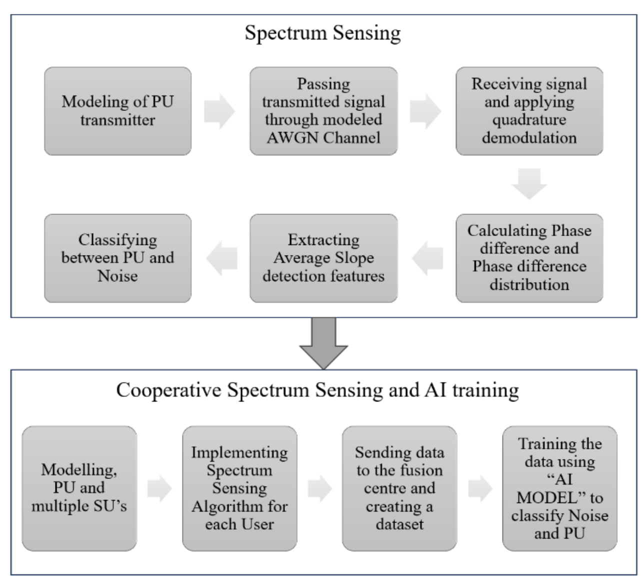

Fig. 3 Methodology Proposed – Average Slope Detection

To extract essential signal features, the ASD approach is actively employed. These extracted features form fundamental inputs for Machine Learning (ML) models that classify PU signals from noise.

The reasoning for integrating machine learning algorithms in this context stems from the extensive repository of past wireless data. This data holds significant features and fluctuation trends within the radio environment. This information is leveraged for tasks such as parameter configuration and performance enhancement. This integrated approach aims to heighten the accuracy of PU classification, enhances the spectrum sensing framework [16].

The block diagram in Fig. 3 briefs the methodology proposed by this work.

3.1 System Model

The system model for spectrum sensing [17] is introduced by the following binary hypothesis shown in Equation (1) and Equation (2),

$$H_0 : y_i(n) = u_n \quad (1)$$

$$H_1: y_i(n) = g_{PU\,i}(n) \times \exp\left[j\left(\frac{2\pi f_c}{f_s}n + \emptyset_i(n)\right)\right] + u(n) \quad (2)$$

The state H_0 occurs when the SU receives only noise and the PU is not utilizing the spectrum. The state H_1 occurs when the PU is actively utilizing the spectrum. The carrier frequency and sampling frequency is denoted by f_c and f_s respectively. The Additive White Gaussian noise (AWGN) given by u(n) is the noise in the received signal when the spectrum is unutilized. The received signals of each SU are denoted by $y_i(n)$, with $n = 1,2,3, \dots N$, where N represents the total number of samples and i denotes the user. The instantaneous amplitude and phase of the PU as received by ith user is denoted by $g_{PU\,i}(n)$ and $\emptyset_i(n)$ respectively.

3.2 Average Slope Detection

The concept of Phase Difference Distribution and the derivation of the approximate PD distribution within an AWGN channel is discussed. Subsequently, the Average Slope Detection (ASD) technique is derived.

a. Phase Difference Distribution Calculation

The employed methodology is based on extracting features from the PD distribution. The ASD algorithm is applied to unveil patterns based on the shape features of the PD distribution. These algorithms provide a comprehensive analysis of the intricate information in phase differences, emphasizing both shape and algebraic attributes helping in the classification of received signals according to the hypothesis.

Phase Difference of the signal [18] is defined as Equation (3) and Equation (4) as shown below.

$$\varphi_n = \arctan\frac{Im\big(y(n)\big)}{Re\big(y(n)\big)} \quad (3)$$

$$\theta_n = (\varphi_{n+1} - \varphi_n)\ mod\ 2\pi \quad (4)$$

The imaginary and real parts of $y(n)$ are denoted by $Im\big(y(n)\big)$ and $Re\big(y(n)\big)$. The phase of the received signal is denoted by φ_n [19].

$$f_{noi}(\theta_n) = \frac{1}{2\pi} \quad (5)$$

$$f_{siga}(\theta_n) = \frac{1}{2\pi} + \left(\frac{\gamma}{4} - \frac{\gamma^2}{8}\right) \quad (6)$$

The PDF of the gaussian noise PD distribution is given by Equation (5) and the and that of the modulated signal under AWGN is given by Equation (6) with $\eta = \theta_0 - \theta_n$.

Here, $\gamma = \frac{P}{\delta_n^2}$ is the instantaneous SNR [19]. And $\theta_0 = \frac{2\pi f_c}{f_s}$ denotes the PD between $y(n)$ and $y(n+1)$ [15].

b. Slope Detection

The mathematical model reveals that the PD distribution of a noise signal remains constant, while for the modulated signal, it takes the form of a cosine wave that varies with the sampling frequency. Consequently, the PDF serves as a valuable tool for detecting the presence PU signals and white space. To achieve this, the ASD algorithm is implemented to calculate the average slope. This average slope then functions as a feature, aiding in the detection of the shape of the signal or noise within the channel. Fig. 4 represents the presence of PU under AWGN. Here, point M represents the maximum value of PDF, A represents the value of PDF at 0 and B represents the value of PDF at 2π.

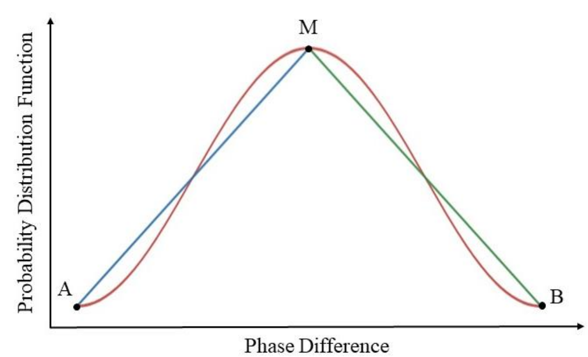

Fig. 4 PDF vs Phase Difference

The following Equations (7 - 9) are used to calculate the ASD for PDF which is used as a feature to classify the presence of PU and white space.

$$T^s = \frac{|tan_{AM}^s| + |tan_{BM}^s|}{2} \quad (7)$$

$$tan_{AM}^s = \frac{f_{sig}(x_M) - f_{sig}(0)}{x_M} \quad (8)$$

$$tan_{BM}^{s} = \frac{f_{sig}(x_M) - f_{sig}(2\pi)}{x_M - 2\pi} \quad (9)$$

T^s represents average slope of the PD distribution. From Equation (8) and Equation (9), the slope of line AM and BM, in Fig. 5, is calculated.

3.3 Cooperative Spectrum Sensing

In a cooperative spectrum sensing network, multiple users concurrently sense the spectrum [20]. Each SU individually performs spectrum sensing using the ASD algorithm. The resulting PDD from each user is transmitted to the fusion center, where the data are aggregated and recorded, forming a dataset. Subsequently, a suitable Machine Learning algorithm is chosen and trained using this dataset. When real-time data is received, the fusion center applies the trained ML algorithm to classify signals as either noise or PU signals.

3.4 Machine Learning Algorithm

In the context of Machine Learning Algorithm the KNN – classification is applied. A set of k nearest neighbours for a given point x is given as S_x [21]. The set of points is considered as a subset of the, $S_x \subseteq D$. It was already stated there will k neighbors therefore, the cardinality of S_x will be k, $|S_x| = k$. Further only the points in D will be considered and not those in S_x. This ensures that the selected neighbors are distinct from the point S_x itself.

$$dist\ (x, x') \geq \underset{(x'', y'')}{max} dist(x, x'') \quad (10)$$

For any point outside the set of k-nearest neighbours S_x, the distance from that point to the given point S_x is at least as large as the distance from S_x to the furthest point within S_x. This ensures that the k-nearest neighbours are indeed the closest points to S_x in the dataset, maintaining a clear and consistent definition of proximity for classification between noise and PU signal.

4. IMPLEMENTATION RESULTS

This section highlights the outcomes of simulations and approximations concerning PD distributions of PU signal and noise, as seen in Fig. 5 and Fig. 6 respectively. The alignment between simulation results and approximations validates the accuracy of our derivations. Notably, these distributions exhibit distinct shapes: $f_{sigr}(\theta)$ resembles a cosine wave, varying with sampling frequency while $f_{noi}(\theta_n)$ maintains a consistent straight-line shape.

Even in scenarios with low SNRs, these shape differences persist, indicating distinguishable characteristics between $f_{sigr}(\theta)$ and $f_{noi}(\theta_n)$. This highlights how identifying the Phase Difference Distributions' forms will remain essential for identifying the Primary User's (PU) signal. Consequently, spectrum sensing becomes a classification problem where a straight line and a cosine curve are differentiated.

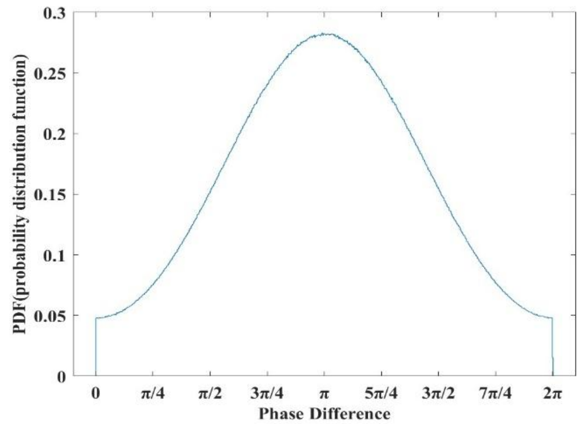

Fig. 5 PD distribution of PU under AWGN channel with SNR = 0 dB

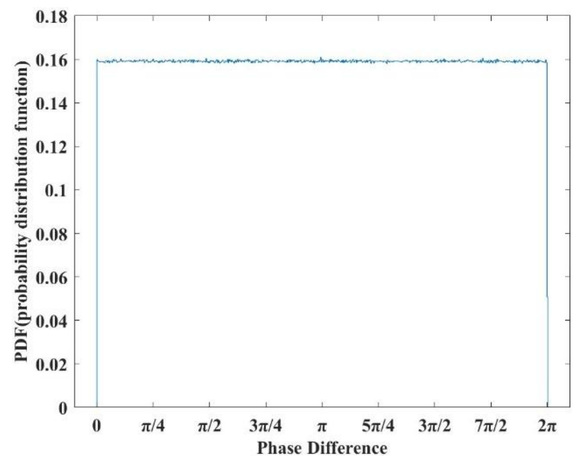

Fig. 6 PD distribution of AWGN channel

The Probability of Detection (Pd) versus Signal-to-Noise Ratio (SNR) graph, utilized to assess the algorithm's performance across different SNR conditions is shown in Fig. 7. In comparison to the traditional Energy Detection algorithm, which is known for its computational simplicity, ASD algorithm demonstrates superior accuracy despite its higher computational complexity. This indicates that while the ASD algorithm may be more computationally intensive, it offers enhanced performance, as evidenced by the higher Pd values across various SNR levels.

The Cooperative Spectrum Sensing network is simulated in MATLAB by assuming 5 SU's which are at different distances from the PU. There will be different energy levels recorded by each user but the total noise floor of the network will be constant making the SNR of each user different. The location of the of the PU and SU's are assumed to be fixed with a noise floor of -20 dB. The ASD algorithm is applied at each SU and their PDD value is sent to the fusion centre. The accuracy of the KNN algorithm is observed to be 85.8% essentially out performing the SVM algorithm by 18.34%.

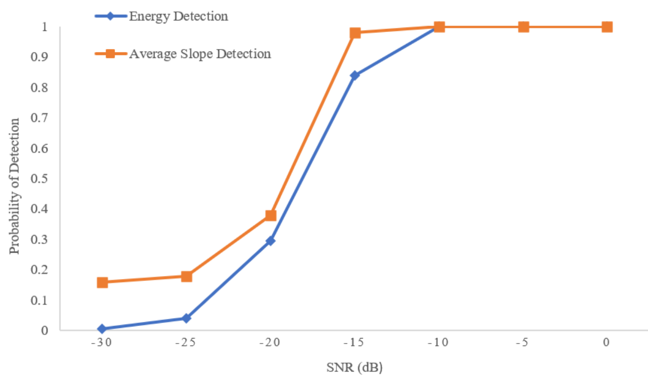

Fig. 7 Performance Analysis of ASD algorithm (Pd vs SNR)

The Pd vs Pf curves in Fig. 8 illustrate that under conditions of noise uncertainty and carrier frequency mismatch, KNN algorithm exhibits better performance when compared to SVM algorithm, as evidenced by its ROC curve. This suggests that SVM struggles to effectively discern the presence or absence of the Primary User's signal.

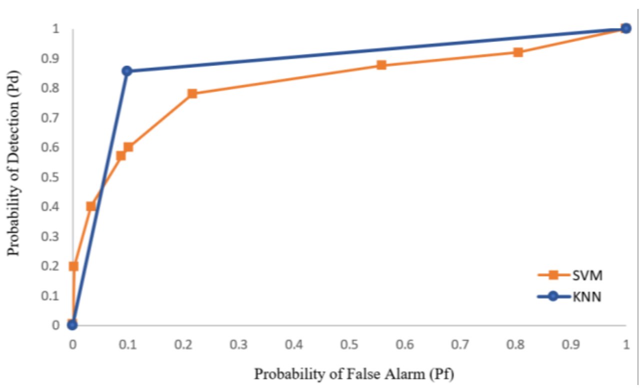

Fig. 8 Performance Analysis of ASD algorithm (Pd vs Pf)

From Table 1 we can observe that, The KNN algorithm achieves an accuracy of 85.8%, significantly outperforming the SVM algorithm by 18.34%. Other performance metrics are also compared in Table 1.

Table. 1 Comparison of ML Classification Results

Model	KNN	SVM
Accuracy (Validation)	85.8%	72.5%
Total Cost (Validation)	9561	18473
Prediction Speed	~87000 obs/sec	~41000 obs/sec
Training Time	120	2678.5 sec
Model Size (Compact)	~5 MB	~16 kB

In Section 2, a comprehensive discussion was provided on why this approach is favored over conventional spectrum sensing techniques. The proposed methodology has been evaluated against the approaches outlined in [10], [11], and [12], demonstrating notable advancements. Table 2 highlights the significant improvements in Probability of Detection at low SNR conditions achieved with the proposed method, underscoring its effectiveness compared to existing solutions.

Table. 2 Comparing Pd with existing methodologies

Spectrum Sensing Scheme	SNR	Pd
Energy Detection [10]	-10 dB	~ 0.55
Matched filter [11]	-15 dB	~ 0.5
Cyclostationary [12]	-15 dB	~ 0.6
Average Slope Detection	-15 dB	0.9788

5. CONCLUSION

The application of the ASD algorithm in Cooperative Spectrum Sensing facilitates a distinct differentiation between noise and PU signal. Unlike the commonly utilized energy-based detection technique, which exhibits subpar performance in low SNR scenarios, ASD, particularly when integrated with PDD, emerges as a superior method for spectrum sensing. Furthermore, the training of the KNN algorithm enables the effective classification of PU and noise signals.

The future scope of this paper lies in exploring the different attacks that faced by the cognitive radio and how the ASD algorithm can perform under that condition.

REFERENCES

1. S. Sinha. (2024). IoT Analytics — State of IoT 2024 https://iot-analytics.com/number-connected-iot-devices/ [Accessed Sep (2024)]
2. S. Haykin. (2005). Cognitive radio: brain-empowered wireless communications. IEEE Journal on Selected Areas in Communications, 23, (2), 201-220. https://doi.org/10.1109/JSAC.2004.839380
3. E. Hossain, D. Niyato, and Z. Han. (2009). Dynamic Spectrum Access in Cognitive Radio Networks. Cambridge University Press.
4. Ian F. Akyildiz, Won-Yeol Lee, Mehmet C. Vuran, Shantidev Mohanty. (2006) Next generation/dynamic spectrum access/cognitive radio wireless networks: A survey. Comput. Netw., 50(13), 2127-2159. https://doi.org/10.1016/j.comnet.2006.05.001
5. Spectrum Policy Task Force — Federal Communications Commission. https://www.fcc.gov/document/spectrum-policy-task-force/
6. E. Biglieri, A. J. Goldsmith, L. J. Greenstein, N. B. Mandayam and H. V. Poor. (2013). Principles of Cognitive Radio. New York, USA: Cambridge Univ. Press.
7. IEEE standard - information technology-telecommunications and information exchange between systems-wireless regional area networks-specific requirements-part 22: Cognitive wireless ran mac

and phy specifications: Policies and procedures for operation in the bands that allow spectrum sharing where the communications devices may opportunistically operate in the spectrum of primary service. IEEE Std 802.22-2019 (Revision of IEEE Std 802.22-2011). (2020). 1-1465. https://doi.org/10.1109/IEEESTD.2020.9086951

8. Singh S., & Mohan Sharma R. (Eds.). (2019). Handbook of Research on the IoT, Cloud Computing, and Wireless Network Optimization. IGI Global.
9. Bharatula S. and Murthy B.S. (2022) A novel spectrum sensing technique for multiple network scenario. Proceedings of International Conference on Communication and Artificial Intelligence: ICCAI 2021, Springer Nature, Singapore. https://doi.org/10.1007/978-981-19-0976-4_9
10. P. Semba Yawada, An Jian Wei and M. Mbyamm Kiki. (2015). Performance evaluation of energy detection based on non-cooperative spectrum sensing in cognitive radio network. 4th International Conference on Computer Science and Network Technology (ICCSNT), Harbin, China, 1036-1040. https://doi.org/10.1109/ICCSNT.2015.7490914
11. F. Salahdine, H. E. Ghazi, N. Kaabouch and W. F. Fihri. (2015) Matched filter detection with dynamic threshold for cognitive radio networks. 2015 International Conference on Wireless Networks and Mobile Communications (WINCOM), Marrakech, Morocco, 1-6. https://doi.org/10.1109/WINCOM.2015.7381345
12. A. Serbes, H. Cukur and K. Qaraqe. (2020). Probabilities of False Alarm and Detection for the First-Order Cyclostationarity Test: Application to Modulation Classification. IEEE Communications Letters, 24(1), 57-61. https://doi.org/10.1109/LCOMM.2019.2947043
13. P. K. Verma, P. Jain and S. K. Soni. (2017). Performance analysis of blind eigen value with multiple antenna-based spectrum sensing in cognitive radio. Recent Developments in Control, Automation & Power Engineering (RDCAPE), Noida, India, 372-377. https://doi.org/10.1109/RDCAPE.2017.8358299
14. M. Golvaei and M. Fakharzadeh. (2021). A Fast Soft Decision Algorithm for Cooperative Spectrum Sensing. IEEE Transactions on Circuits and Systems II: Express Briefs, 68(1), 241-245. https://doi.org/10.1109/TCSII.2020.3010587
15. Y. Wang, W. Xu, F. Wang, X. Qin, N. Ma and M. Pan. (2023). Robust Spectrum Sensing Based on Phase Difference Distribution. IEEE Transactions on Cognitive Communications and Networking, 9(1), 28-42. https://doi.org/10.1109/JSAC.2004.839380
16. M. A. Inamdar and H. V. Kumaraswamy. (2020). Accurate primary user emulation attack (PUEA) detection in cognitive radio network using KNN and ANN classifier. Proc. 4th Int. Conf. Trends Electron. Informat. (ICOEI)(48184), Tirunelveli, India, 490–495. https://doi.org/10.1109/ICOEI48184.2020.9143015
17. J. Bala Vishnu, Saswat Kumar Ram, and N. Deepan. (2023). Energy-efficient adaptive sensing for cognitive radio sensor network in the presence of primary user emulation attack. Computers and Electrical Engineering, 106. https://doi.org/10.1016/j.compeleceng.2023.108619
18. Yang Jian, Yan Xiao, Gao Mingfei, Lian Hao, Zhang Han, Feng Zhiyong and Zhang Yifan. (2014). A novel spectrum sensing scheme based on phase difference. Proc. IEEE Wireless Commun. Netw. Conf. (WCNC), Istanbul, Turkey, 264–268. https://doi.org/10.1109/WCNC.2014.6951978
19. R. Pawula, S. Rice, and J. Roberts. (1982). Distribution of the phase angle between two vectors perturbed by Gaussian noise. IEEE Trans. Commun., 30, (8), 1828–1841. https://doi.org/10.1109/TCOM.1982.1095662
20. Parvathi. A. K., & Sakthivel. V. (2021). Low Complexity Adaptive Spectrum Sensing using Modified FRM Filter Bank. International Journal of Electronics, 1–20. https://doi.org/10.1080/00207217.2021.2001866
21. R. M and V. Ananthanarayanan. (2022) Machine Learning based Prediction Analysis in Intrusion Detection. 2022 International Conference on Electronics and Renewable Systems (ICEARS), Tuticorin, India, 1153-1159. https://doi.org/10.1109/ICEARS53579.2022.9752061

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