Machine Learning and an Eigenvalue-Based Technique to Improve Cooperative Spectrum Sensing in Generalized α-κ-μ Fading Channel

Srinivas Samala*, Subhashree Mishra, and Sudhansu Sekhar Singh

School of Electronics Engineering, KIIT Deemed to be University, Bhubaneswar, Odisha, India
Email: srinu486@gmail.com (S.S.); subhashree.mishrafet@kiit.ac.in (S.M.); ssinghfet @kiit.ac.in (S.S.S.)
*Corresponding author

***Abstract*—As the demand for radio spectrum continues to rise, one possible approach to addressing the problem with limited spectrum is cognitive radio. The most important aspect of effective cognitive radio implementation is spectrum sensing. In this context, we propose and examine the effectiveness of a K-means and eigenvalue-based learning method for Cooperative spectrum sensing in an α-κ-μ generalized fading channel. To measure how well the proposed method is working, we utilize receiver operating characteristic curves. In addition, a comparative analysis is performed with existing detection techniques like cooperative spectrum sensing using K-means-based energy detection specifically designed for κ-μ and α-κ-μ fading channels. Based on the findings of the MATLAB version of the simulation, the proposed approach is superior to an existing one in terms of comparison parameters.**

***Keywords*—cooperative spectrum sensing, eigenvalues, K-means, detection probability**

I. Introduction

The deficiencies of the existing approach to frequency spectrum allocation have become apparent through empirical findings, as it depends on a centralized command and control framework. The aforementioned observations have revealed that a significant proportion of the designated spectral bands frequently go unutilized [1]. To overcome this inefficiency and make better use of the scarce resources of the spectrum, Cognitive Radio (CR) technology has emerged. During times when the Primary Users (PUs) are not actively using licensed spectrum bands, CR technology permits Secondary Users (SUs) to make efficient use of these bands. However, to accommodate the occasional need for spectrum access by Primary Users (PUs), it is imperative for unlicensed users to consistently monitor the operations of PUs and swiftly vacate the frequency band when PUs begin re-transmission. The Detection of Primary Users (PUs), whether they are present or not, is an essential aspect in the efficient implementation of Cognitive Radio (CR) systems, often referred to as spectrum sensing. The primary objective of this unique approach is to enhance the efficiency of spectrum utilization while concurrently assuring fair and equal access for users with and without licenses [2].

In α-k-μ fading channels, this work provides a novel method for cooperative spectrum sensing. The suggested approach uses K-means clustering and eigenvalue-based approaches to increase the accuracy and reliability of spectrum sensing. To gain insight into the underlying channel conditions, we can use eigenvalue-based approaches that make use of the statistical features of the covariance matrix of the received signal. The widely utilized unsupervised learning method known as K-means clustering is employed for splitting the gathered data into separate clusters, enabling informed decision-making on spectrum occupancy [3, 4].

The primary goal of this work is to provide a cooperative spectrum sensing method that is adaptable to the dynamic and challenging α-k-μ fading channel conditions. This approach combines eigenvalue analysis and K-means clustering to reduce the impact of fading and noise on detection performance. The findings of this work are anticipated to aid in the development of cognitive radio systems that are more reliable and effective, enabling greater spectrum utilization in varying wireless situations.

The article is structured in the following way: Introduction to relevant literature in Section II, the implementation of the proposed approach is described in Section III, and finally, results and discussion are presented in Section IV.

II. Literature Review

Over the past decade, researchers have worked hard to develop spectrum sensing systems that maximize the usage of unused frequency bands while minimizing interference to Primary Users (PUs). Traditional spectrum sensing technologies possess several limitations. Energy detection is straightforward, but it is susceptible to noise, especially when the Signal-to-Noise Ratio (SNR) is low [5]. The utilization of matched filtering is considered to be best; however, it necessitates accurate knowledge regarding both the primary user signal and channel. Prior knowledge of Primary User (PU) signal characteristics is

Manuscript received December 11, 2023; revised February 4, 2024; accepted February 18, 2024; published May 8, 2024.

required for cyclostationary detectors. These methods perform poorly in multipath and shadowed environments. These challenges can be conquered by employing cooperative Spectrum Sensing (CSS), which makes use of several sensors to leverage spatial diversity [6].

In recent times, several approaches centered around eigenvalues have been put forth to detect primary users in spectrum sensing applications. Giri and Majumder [7] introduced a novel approach to cooperative spectrum sensing by employing Eigenvalues and Kernel Fuzzy C-means. The proposed model is trained and evaluated using test vectors constructed from eigenvectors extracted from the secondary user signal. Three different eigenvalue detection methods are used in cooperative spectrum sensing: energy with Minimal Eigenvalue (EME) detection, maximum Eigenvalue Detection (MED), and Maximum-Minimum Eigenvalue Detection (MMED). The superior performance of the proposed method in detecting available channels was established through a comparative analysis with existing eigenvalue methods.

Yelalwar and Ravinder [8] trained a fusion center utilizing eigenvalue-based test statistics derived from the covariance matrix of incoming signals through the use of machine learning techniques in cooperative spectrum sensing. With a self-learning threshold, the system efficiently separates Primary User (PU) signals from noise signals in low SNR environments. Classifiers such as Naive Bayes, Extra tree, Gradient boosting machine, and SVM were used to evaluate if PUs were present in the band. Simulation experiments evaluating performance in various SNR conditions show that the suggested method outperforms traditional spectrum sensing techniques. A unique technique for spectrum sensing was presented in Ref. [9], specifically designed for receivers with multiple antennas. The method relies on knowledge of the signal's cyclic frequency under consideration to detect the Primary User's (PU) presence or absence. The received signals' cyclic covariance matrices are examined for eigenvalue correlations to arrive at this conclusion. Guo *et al.* [10] presented a novel methodology to discover the threshold eigenvalue to detect the existence of multiple Primary Users (PU) broadcasting simultaneously in a spectrum sensing circumstance. This approach presents a solution to the issue of spectrum sensing by eliminating the need for any prior information regarding the Primary User (PU), thereby effectively tackling the obstacle of blind detection.

As a more realistic model of fading channels, the α-k-μ model has been proposed, because of the adaptability it provides for describing the wide range of channel conditions that can arise in practice. Within this framework, cooperative spectrum sensing has received a considerable amount of interest [11]. Cooperative sensing entails the collective detection of primary users by multiple secondary users, resulting in higher detection performance, increased resilience to fading, and improved utilization of the spectrum.

III. Proposed Method

Utilizing cooperative spectrum sensing that is based on eigenvalues in cognitive radio systems is one method for improving spectrum sensing's accuracy. This method takes advantage of the eigenvalues of the signals to ascertain whether or not the primary users are present in a fading channel. K-means clustering is used to classify the incoming signals based on their eigenvalues, which further improves the detection performance.

Consider a system model with M SUs and PU, the channel between Primary Users (PUs) and Secondary Users (SUs) is assumed to exhibit α-κ-μ fading, which is a generalization of the Rayleigh and Nakagami-m fading models. Spectrum sensing is formulated as a Neyman-Pearson and Bayes-based binary hypothesis testing problem as:

$$s_i(n) = \begin{cases} G_i(n), & H_0 \\ x_i(n) + G_i(n), & H_1 \end{cases} \qquad n = 1, 2, .., N \tag{1}$$

In the above equation existence of the *PU* signal is implied by H_1, whereas its absence is shown by H_0. The PU signal is denoted by $x_i(n)$, while white Gaussian noise is denoted by $G_i(n)$ and N is the number of samples considered. Moreover, there is a hypothesis suggesting that the *PU* alternates between periods of activity and inactivity, allowing the channel's availability (Ac) to be stated as

$$A_c = \begin{cases} \;\; 1, & S = 1 \\ - \;\; 1, & S = 0 \end{cases} \tag{2}$$

In the preceding equation, S specifies the PU's status, with S=1 representing the active state, the channel is unavailable, and S=0 showing the inactive state, the channel is available. According to Eq. (2), the probabilities of detection and false alarms can be formulated as:

$$P_d = \left[A_c^* = 1 \middle| A_c = 1 \right], P_{fa} = \left[A_c^* = 1 \middle| A_c = 0 \right] \tag{3}$$

A_c^* denoted the predicted channel availability in the preceding equation.

A. Realization of Eigenvalues

The ability of eigenvalue-based detection to exploit the statistical properties of incoming signals makes it more efficient in cooperative spectrum sensing within cognitive radio networks. This approach effectively encapsulates the intrinsic structure and patterns present in the observed data, thereby increasing the ability to identify primary users. The eigenvalue-based detector offers a computationally effective way to optimize energy consumption during cooperative sensing, which makes it perfect for low-resource cognitive radio systems [12].

In this context, s(n) denotes the signal received at SU, it is expressed as:

$$s(n) = \sqrt{\beta_s} h(n) x(n) + \sum_{i=1}^{m} \sqrt{\beta_i} d(n) y(n) + G(n) \quad (4)$$

In the given equation, the variable β_s denotes the fading gain between PU and SU, and $h(n)$ represents the fading coefficient that follows the α-κ-μ fading distribution. The PU's sent signal is denoted by $x(n)$, between interfering sources the SU β_i represents the fading gain, and $d(n)$ the fading coefficient is determined by the distribution *α-κ-μ* fading. The signal transmitted by the interfering sources is represented as $y(n)$, whereas $G(n)$ denotes the presence of additive white Gaussian noise (AWGN) characterized by a zero mean and a variance of σ^2. Assume that there exists a set of Q transmitting primary users (PUs), denoted as PUq, and each PUq is associated with a channel order P concerning every secondary user (SU). Assuming that the transmitted PU signal is also examined in N consecutive samples, the signal and noise vectors corresponding to these samples can be defined as [13]:

$$s_N(n) \triangleq \left(s^T(n), s^T(n-1), s^T(n-2), ..., s^T(n-N+1)\right)^T \quad (5)$$

$$x_N(n) \triangleq \left(x_1^T(n), x_2^T(n), ..., x_Q^T(n)\right)^T \quad (6)$$

$$G_N(n) \triangleq \left(G^T(n), G^T(n-1), G^T(n-2), ..., G^T(n-N+1)\right)^T \quad (7)$$

The system of equations can be represented in matrix form as:

$$s_N(n) = Hx_N(n) + G(n) \quad (8)$$

The above expression uses the MN×(Q+NQ) order matrix H, which is defined as:

$$H \triangleq \left[H_1, H_2, H_3, ..., H_Q\right] \quad (9)$$

Since H_Q is an MN×(Q+N)-order matrix in the above statement, it may be written as:

$$H_q \triangleq \begin{bmatrix} h_q(0) & \cdots & \cdots & h_q(Q_q) & \cdots & 0 \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ 0 & \cdots & h_q(0) & \cdots & \cdots & h_q(Q_q) \end{bmatrix} \quad (10)$$

The received signals' statistical covariance matrices can then be expressed as:

$$R_s = HR_x H^H + \sigma_n^2 I_{MN} \quad (11)$$

In the aforementioned equation, an identity matrix with dimensions MN is denoted by the symbol I_{MN}. The notation $(.)^H$ signifies the Hermitian transpose operation, and $R_s = E[X_N(n) X_N^H(n)]$.

The covariance matrix R_s eigenvalue decomposition can be written as follows:

$$R_s = VDV^H \quad (12)$$

The eigenvectors of R_s are represented by the unitary matrix V, and their corresponding eigenvalues are represented by the diagonal elements of the diagonal matrix D in the above equation. We can use D's diagonal elements to find its eigenvalues.

$$\lambda_i = D(i, i) \quad (13)$$

Here, λi denotes the *ith* eigenvalue. Let Ls = [λ_{min}, λ_1, $\lambda_2 \ldots$, $\lambda_{max}]^T$ be the signal feature vector.

B. Cooperative Spectrum Sensing using the K-means Algorithm

In the following section, the signal feature vector Ls will be subjected to classification using the K-means algorithm [14]. The purpose of this classification process is to determine whether there is a Primary User (PU) present and if the channel is available for usage by a Secondary User (SU). Consider the classifier's training feature vector to be $\overline{L} = [\, , L_S^2, L_S^3, \ldots\ldots, L_S^R]$, where R is the total number of feature vectors used during training and L_S^r is a vector of two-dimensional features. Let C_k represent a class containing all features vector in the k^{th} class, where $k = 1,2,3, \ldots., K$.

After fixing the centroid of cluster C_1 to the mean of L_S^r on the condition of H_0, the centroids (ϕ_k) of the other clusters C_k can be found using the formula

$$\phi_k = \frac{1}{n(C_k)} \sum_{L_s^r \in C_k} L_s^r \quad (14)$$

In the given context, $n(.)$ denotes the cardinality parameter, as a mathematical constant, the Θ (distortion) in the K-means clustering method is defined as the product of the squared distances between each cluster and its centroids, divided by the total number of clusters. The value of K is defined as

$$\theta(C_1, C_2, C_3, ...C_K, \phi_1, \phi_2, \phi_3, ..., \phi_K) = \sum_{k=1}^{K} \sum_{L_s^r \in C_k} \left\| L_s^r - \phi_K \right\|^2 \quad (15)$$

Let $\|.\|$ denote the p^2-norm. The utilization of clustering techniques in this work aims to mitigate distortion. Therefore, the definition of an optimal objective function is:

$$\min_{\substack{\phi_1,\phi_2,\phi_3,...,\phi_K \\ C_1,C_2,C_3,...C_K}} \theta\left(C_1, C_2, C_3, ...C_K, \phi_1, \phi_2, \phi_3, ..., \phi_K\right) \quad (16)$$

After training using the K-means clustering approach, we can check the channel's availability with Eq. (17)

$$\frac{\left\|\hat{L} - \phi_1\right\|}{\min_{k=1,2,3..,K}\left\|\hat{L} - \phi_k\right\|} \geq \delta \quad (17)$$

where δ is a classification threshold and $\hat{L}$ is the set of test feature vectors. If the above equation is true for $\hat{L}$, then the channel is unavailable; otherwise, it may be available.

C. The α-k-μ Fading Channel

Signal strength fluctuations across a wireless link are described by α-k-μ fading channel, a sophisticated mathematical model. The comprehension of statistical characteristics of the wireless channel is particularly advantageous in situations such as spectrum sensing. This knowledge can greatly assist in the development and implementation of cognitive radio applications and dynamic spectrum access. This fading model's non-linear characteristics of small-scale Line of sight can be accurately reflected in a variety of contexts. It can also be utilized to study spectrum sensing's short-range and real-time properties in the presence of severe fading. The expression of an envelope pdf for the α-k-μ model is given by [15]:

$$h^{\alpha-k-\mu}(\rho) = \frac{\alpha\rho^{\frac{(\mu+1)\alpha}{2}-1}\mu\left(1+k\right)^{\frac{1+\mu}{2}}}{\exp\left(\mu k\right)k^{\frac{1}{2}(\mu-1)}} \times$$
$$I_{\mu-1}\left(\sqrt{(1+k)k}\rho^{\alpha/2}2\mu\right) \times \exp\left(-\mu\rho^{\alpha}\left(1+k\right)\right) \quad (18)$$

In the above equation non-linear characteristics of the propagation medium are represented by parameter α, the symbol k represents the relative strengths of the scattering and dominating waves, whereas the value μ represents multipath fading components, and the first-order Bessel function of interference by symbol I. The pdf SNR for α-k-μ channel can be calculated as:

$$f^{\alpha-k-\mu}(\rho) = \frac{\gamma^{\frac{(\mu+1)\alpha}{4}-1}}{\bar{\gamma}^{\frac{-\alpha}{4}(1+\mu)}} \times I_{\mu-1}\left(\sqrt{(1+k)k}2\mu\frac{\gamma^{\alpha/4}}{\bar{\gamma}^{\alpha/4}}\right)$$
$$\times \exp\left(-\frac{\gamma^{\alpha/2}}{\bar{\gamma}^{\alpha/2}} \times (1+k)\mu\right) \times \frac{\left[\alpha\mu k^{\frac{1-\mu}{2}}\left(1+k\right)^{\frac{1+\mu}{2}}\right]}{2\exp\left(k\mu\right)} \quad (19)$$

The symbols γ and $\bar{\gamma}$ in the preceding equation represent SNR and Average SNR, respectively. The Nakagami-m fading channel, the Rician fading channel, and the Rayleigh fading channel are all special examples of the more generic α-k-μ channel, whose parameter ranges are tabulated in Table I.

TABLE I. NAKAGAMI-M, RICIAN, AND RAYLEIGH FADING CHARACTERISTICS

Type of Channel	α-k-μ Channel Parameters		
	α	***k***	***μ***
Rayleigh	2	k→0	1
Rician	2	3	1
Nakagami-m	2	k→0	3
k-μ	2	k ≥ 0	μ > 0

IV. RESULT AND DISCUSSION

By employing K-means clustering, the system can categorize and group diverse data effectively, allowing for a more dynamic and flexible spectrum sensing technique. Cooperative sensing based on eigenvalues simultaneously enhances the accuracy and reliability of spectrum occupancy detection. These methodologies provide adaptable utility throughout a wide range of geographical spectrums, guaranteeing resilient operation in diverse environmental circumstances and radio frequency environments. The integration of eigenvalue-based sensing and K-means clustering not only enhances the efficient use of spectrum but also enables smooth adjustment, rendering it a valuable resolution for forthcoming wireless communication systems functioning in dynamic real-world environments.

To carry out the simulation study, we utilized a total of 1000 samples, with 500 samples allocated for testing and the remaining 500 samples for training. For the primary user transmission, we employed BPSK modulation with a power level of unity, and the α-k-μ channel for PU-to-SU communication. The classifier is trained using the feature vectors, which are eigenvalue estimations, obtained from the SU node. The feature vector is generated using a set of M = 2 and N = 500 samples in total, having a −10 dB expected average Signal-to-Noise Ratio (SNR).

As illustrated in Fig. 1, the evaluation of Cooperative Spectrum Sensing (CSS) using the K-means algorithm operates in an α-k-μ channel environment involving PUs and SUs. Eigenvalues and energy estimates are utilized as feature vectors in this analysis. The simulation parameters are set as follows: N = 500, K = 2, μ = 3, α = 1.2, k close to 0, and an average Signal-to-Noise Ratio (SNR) of −10dB. The detection probability in K-means-based CSS rapidly rises with an increase in the false alarm probability, as seen in Fig. 1. This measure ensures that the second user is provided with precise and reliable data regarding the availability of channels. The performance of estimating methods based on eigenvalues and energy values demonstrates a high degree of comparability. However, the estimation based on eigenvalues tends to provide marginally better performance in comparison to energy values [16]. Based on the simulation findings, it is shown that when the false alarm probability is set at 0.4, the eigenvalue detection technique demonstrates a probability of detection of 0.977. Conversely, the energy detection approach exhibits a little lower probability of detection at 0.932.

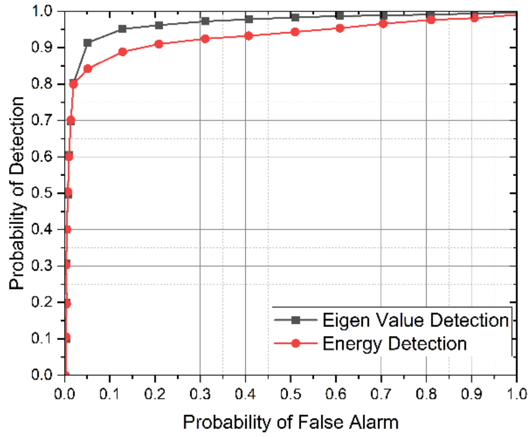

Fig. 1. Analyzing ROC performance for CSS in the fading channel *α-k-μ* using Eigenvalue and Energy detection feature vectors with M = 2.

The effectiveness of CSS utilizing k-means algorithm based on eigenvalue and Energy detection methods is evaluated in Fig. 2. This evaluation is conducted in three different fading scenarios, namely Nakagami-m (with α = 2, k approximately equal to 0, and μ = 3), Rayleigh (with α = 2, k tending to 0, and μ = 1), and Rician (with α = 2, k equal to 3, and μ = 1). The simulations were performed using an average signal-to-noise ratio (SNR) of -10dB, a sample size (N) of 500, and a parameter (K) set to 3. The results of the simulations indicate that the Rician channel demonstrates a greater probability of detection in comparison to other channels. The following detection probabilities are obtained from the three fading channels for a given false alarm probability (0.2): Rician channels have detection probabilities of 0.98 for eigenvalues and 0.97 for energy detection respectively. In a similar vein, it can be shown that the Rayleigh channel exhibits a probability of detection of 0.94 for eigenvalue detection and 0.93 for energy detection. Conversely, the Nakagami-m channel demonstrates a detection probability of 0.922 for eigenvalue detection and 0.89 for energy detection. It is worth noting that the performance of eigenvalue-based estimates and energy value-based estimation exhibits a high degree of similarity. However, in terms of performance, the eigenvalue-based estimate demonstrates a modest advantage over energy values in all three channel cases.

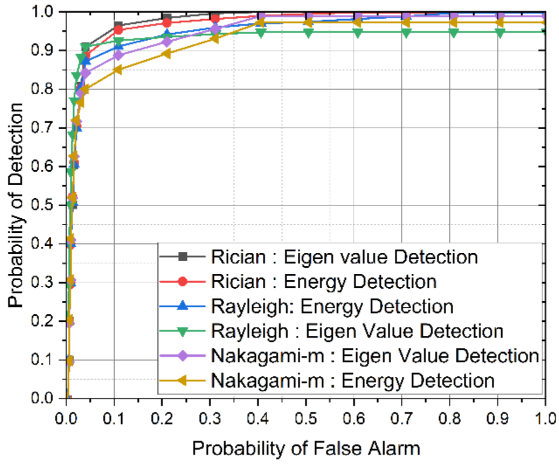

Fig. 2. Performance comparison in α-k-μ fading channels with different fading circumstances for K-means Cooperative Spectrum Sensing (CSS) using energy detection and eigenvalues, with M = 2.

The effectiveness of k-means-based CSS with eigenvalue and energy detection techniques is evaluated in α-k-μ (with α = 1.2, k about 0, and μ = 3) and k-μ (with k approximately 0 and μ = 3) channels are being considered at a SNR of -10dB. The number of samples (N) is 500, and the number of channels (K) is 2. Fig. 3 presents a graphical representation that effectively demonstrates the relationship between false alarm probability and the probability of successful detection. The comparison is made within the context of the α-k-μ fading model. Regarding detection probability, the outcomes obtained using the CSS method that relies on k-means clustering surpass those of the k-μ fading channel. This conclusion holds for both eigenvalue and energy detection methods. Furthermore, the eigenvalue technique consistently produces improved results in both channel scenarios. The graphical representation demonstrates that the performance of eigenvalue detection in the presence of a k-μ fading channel is comparable to that of the energy detection approach in the presence of an α-k-μ channel.

Using eigenvalue and energy detection, Fig. 4 shows how well k-means-based CSS performs for a range of cluster values in the α-k-μ and k-μ channels. The graph exhibits a noticeable rise in the probability of detection as the values of K increase in both scenarios. Moreover, it is evident that the α-k-μ channel continuously outperforms the k-μ channel. Furthermore, it can be observed that the eigenvalue detection method demonstrates enhanced performance in comparison to energy value detection in both scenarios, particularly when the number of clusters is increased.

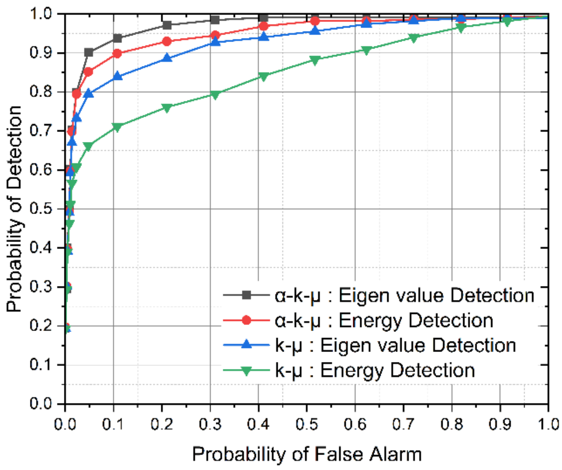

Fig. 3. Comparison of CSS performance conducted in α-k-μ and k-μ channels, considering M = 2, and employing K-means based on eigenvalues and energy detection.

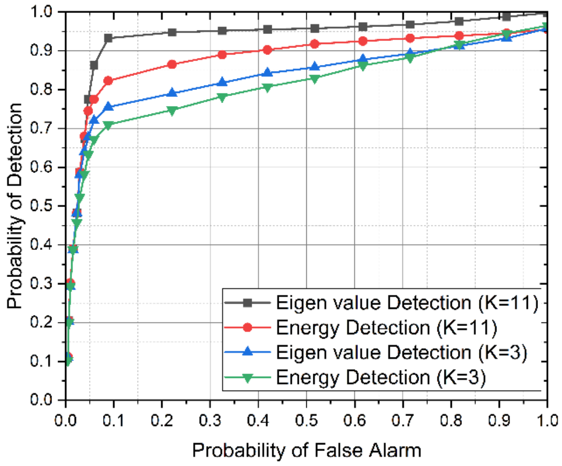

Fig. 4. Comparing the effectiveness of eigenvalue and energy detection approaches with K-means-based CSS in k-μ and α-k-μ fading channels (M = 2, average SNR = –10 dB), with different cluster values (K = 3 and 11).

V. Conclusion

In conclusion, the proposed method which combines K-means with eigenvalue-based learning, the *α-κ-μ* fading model has demonstrated promising outcomes for cooperative spectrum sensing. The ROC (receiver operating characteristic) curves are employed as a criterion to assess the effectiveness of our suggested strategy through in-depth simulations and analysis. The comparison showed that the proposed method has significant benefits over the existing cooperative spectrum sensing approach that uses k-means-based energy detection for various fading channels. According to the simulated results, our method achieves a false alarm probability of less than 5% together with a detection probability of more than 90% with a –10dB SNR. The results emphasize the efficiency of our suggested approach in improving the reliability of cooperative spectrum sensing, which is essential for dealing with the increasing need for radio spectrum in the presence of limited availability.

Conflict of Interest

The authors declare no conflicts of interest.

Author Contributions

While working with Subhashree Mishra and Sudhansu Sekar Singh, Srinivas Samala researched and wrote a paper on cooperative spectrum sensing's performance utilizing machine learning techniques. Finally, the version was approved by all authors.

Acknowledgment

KIIT deemed to be University has provided us with invaluable assistance and direction throughout the course of our investigation; for this, we are extremely grateful. Their contributions to this paper have substantially improved its quality.

References

[1] S. Lin, B. Zheng, F. Chen, and and R. Zhang, "Intelligent reflecting surface-aided spectrum sensing for cognitive radio," *IEEE Wireless Communications Letters*, vol. 11, pp. 928–932, Feb. 2022.

[2] S. Mishra, S. Sagnika, S. S. Singh, and B. S. P. Mishra, "Spectrum allocation in cognitive radio: A PSO-based approach," *Periodica Polytechnica Electrical Engineering and Computer Science*, vol. 63, pp. 23–29, Jan. 2019.

[3] W. Wu, Z. Li, S. Ma, and J. Shi, "Performance improvement for machine learning – Based cooperative spectrum sensing by feature vector selection," *IET Communications*, vol. 14, pp. 1081–1089, April 2020.

[4] B. Vivekananda, "Nakagami-m fading detection with eigenvalue spectrum algorithms," *Journal of Electronics and Informatics*, vol. 3, pp. 138–149, Jul. 2021.

[5] P. Chauhan *et al.*, "Cooperative spectrum prediction-driven sensing for energy-constrained cognitive radio networks," IEEE Access, vol. 9, pp. 26107–26118, Feb. 2021.

[6] D. Janu, K. Singh, and S. Kumar, "Machine learning for cooperative spectrum sensing and sharing: A survey," *Transactions on Emerging Telecommunications Technologies*, vol. 33, p. e4352, Jan.2022.

[7] M. K. Giri and S. Majumder, "Eigenvalue-based cooperative spectrum sensing using kernel fuzzy c-means clustering," *Digital Signal Processing*, vol. 111, pp. 1–14, April 2021.

[8] R. Yelalwar and Y. Ravinder, "Eigenvalue fusion-based machine learning approach for cooperative spectrum sensing in cognitive radio," *International Journal of Computer Aided Engineering and Technology*, vol. 17, pp. 303–317, Sep. 2022.

[9] S. Narieda and H. Naruse, "Improved MCAS based spectrum sensing with multiple antennas," *IEICE Communications Express*, vol. 10, pp. 30–35, Jan. 2021.

[10] C. Guo, M. Jin, Q. Guo, and Y. Li, "Spectrum sensing based on combined eigenvalue and eigenvector through blind learning," *IEEE Communications Letters*, vol. 22, pp. 1636–1639, Jun. 2018.

[11] D. Milic, M. Smilic, Z. Nikolic, S. Milosavljevic, and A. Toskovic, "Influence of cut-off level and α-k-μ distribution parameters on outage probability and amount of fading," in *Proc. 57th International Scientific Conference on Information, Communication and Energy Systems and Technologies*, North Macedonia, June 2022, pp. 1–4.

[12] S. I. Ojo, Z. K. Adeyemo, and F. K. Ojo, "Energy-efficient cooperative spectrum sensing for detection of licensed users in a cognitive radio network using eigenvalue detector," *International Journal of Wireless and Mobile Computing*, vol. 23, pp. 123–131, Oct. 2022.

[13] W. Zhao, S. S. Ali, M. Jin, G. Cui, N. Zhao, and S. J. Yoo, "Extreme eigenvalues-based detectors for spectrum sensing in cognitive radio networks," *IEEE Transactions on Communications*, vol. 70, pp. 538–551, Oct. 2021.

[14] R. Yelalwar and Y. Ravinder, "Unsupervised machine learning schemes for cooperative spectrum sensing in cognitive radio," *International Journal of Computer Applications in Technology*, vol.73, pp. 66–78. Oct. 2023.

[15] F. R. A Parente, F. P. Calmon, and J. C. S. S. Filho, "Asymptotic system performance over generalized fading channels with application to maximal-ratio combining," *Journal of Communication and Information Systems*, vol. 35, pp. 171–180, Jul. 2020.

[16] S. Samala, S. Mishra, and S. S. S ingh, "Machine learning-based cooperative spectrum sensing in a generalized α-κ-μ fading channel," *Journal of Scientific & Industrial Research*, vol. 82, pp. 219–225, Feb. 2023.