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Machine Learning-Based Cooperative Spectrum Sensing in A Generalized α-κ-μ Fading Channel

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An improvement in spectrum usage is possible with the help of a cognitive radio network, which allows secondary users' access to the unused licensed frequency band of a primary user. Thus, spectrum sensing is a fundamental concept in cognitive radio networks. In recent years, Cooperative spectrum sensing using machine learning has garnered a great deal of attention as a technique of enhancing sensing capability. In this study, K-means clustering is taken into consideration for the purpose of analyzing the effectiveness of cooperative spectrum sensing in a generalized α-κ-μ fading channel. The proposed approach is examined using receiver operating characteristic curves to determine its performance. The effectiveness of the proposed strategy is contrasted with that of the existing detection techniques such as Cooperating spectrum sensing based on energy detection and OR-fusion-based cooperative spectrum sensing for fading channels κ-μ, α-κ-μ. As demonstrated by results, the proposed method outshines an existing method in terms of comparison parameters, as determined by simulation results in the MATLAB version.

Keywords: Cooperative spectrum sensing, Classification, k-means clustering, α-κ-μ channel

Introduction

Since its introduction, Cognitive Radio (CR) has gained widespread recognition for its innovative approach toward solving the issue sacristy of radio spectrum by utilizing the available spectrum in Primary User (PU) bands safely and without interfering with the licensed users. A CR system's efficiency is contingent upon its ability to accurately locate spectrum opportunities. An Energy Detection (ED) approach for spectrum sensing is a common non-coherent detection strategy in the literature. Yet, it operates poorly in circumstances with low SNR, especially in multipath and shadowed conditions. Incorporating the spatial diversity of several spectrum sensors, this problem can be solved with Cooperative Spectrum Sensing (CSS).[1]

The performance of CSS detection has been described for Rayleigh and Rician-lognormal fading channels for both decision fusion and data fusion procedures,[2,3] but the OR-fusion rule outperforms all other hard combining procedures in multipath fading scenarios when perfect reporting channels are used. Soft combining strategies for cooperative spectrum sensing related to energy detection were investigated by Ma *et al.*[4] Machine Learning (ML) techniques are commonly employed to classify patterns. The pattern is classified by the classifier using a feature vector derived from training data. Spectrum sensing could be viewed as a classification issue with two binary classes. In CSS, the estimated energy level for each Secondary User (SU) is referred as "feature vector," and the classifier classifies feature vector as "channel available class" or "channel unavailable class". The classifier must be trained before it can begin the online classification process. Supervised and unsupervised learning techniques are extensively utilized in ML.[5] Unsupervised learning is carried out with unlabeled data, whereas supervised learning uses labelled data.[6,7]

In wireless communication, multipath and shadowing affect radio propagation, hence appropriate fading expressions are required to characterize fading statistical patterns. To accurately characterize radio propagation, specialized fading channels κ-μ, η-μ are proposed.[8,9] However, further work is required to accurately describe channels under complex scenarios. The α-κ-μ channel model with more fading parameters gives an accurate description of small-scale nonlinear Line of Sight (LOS) propagation, it approaches α-μ channel if $k = 0$ and κ-μ when $\alpha = 2$. The α-κ-μ channel remains more

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precise than other fading models, including κ-μ, α-μ distributions.[10] K-means clustering was used in this study to improve spectrum efficiency in a α-k-μ channel. Receiver Operating Characteristic (ROC) curves are used to model and compare impact of various system parameters on performance.

System Model

In this study, a CR network with M SUs and a PU is investigated. It was hypothesized that the PU alternates between active and inactive modes with probability P_{on} and $P_{off} = (1-P_{on})$, Let Y be a variable that represents the state of PU activity, the inactive state of PU is represented by the value Y = 0, and the active state is represented by the value Y = 1. Based on this the availability of channels (Ac) is as follows

$$A_c = \begin{cases} 1, & Y = 0 \\ -1, & Y = 1 \end{cases} \qquad \ldots (1)$$

The value of Ac indicates whether the channel is available (positive value of Ac) or not (Negative value of Ac).

The energy value of the PU signal is measured by each SU receiver and compared to a threshold value (υ) in CSS-based ED, If the measured energy values exceed or fall below the threshold, SU passes the data (Y* = 0/1) to the Fusion Center (FC), Predicted channel availability (Ac*) is decided by FC using a hard-combining rule.[11,12] The Fig. 1 depicts the CSS-based ED model. In the case of the K-means clustering approach,[13] Each SU receiver measures the PU signal's energy value and transmits this information to the classifier. Based on this information, the availability of a channel is determined by the classifier. CSS based on k-means clustering is illustrated in Fig. 2 .

The detection, false alarm probabilities are formulated as

$$P_D = P({A_c}^* = -1 | A_c = -1)$$

$$P_{FA} = P({A_c}^* = -1 | A_c = +1) \qquad \ldots (2)$$

System Analysis

The i[th] sample of SU is expressed as

$$Z_i(n) = (Y \times h_i(n) \times W(n)) + w_i(n) \qquad \ldots (3)$$

where, Y gives PU state activity, $h_i(n)$ is the n^{th} channel coefficient sample at i^{th} SU, W(n) is PU signal, $w_i(n)$ is n^{th} sample of Additive White Gaussian Noise (AWGN). The normalized value of energy measured at i^{th} SU can be computed as

$$X_i = \left({}^{1}\!/_{N}\right) \sum_{n=1}^{N} [|Z_i(n)|]^2 \qquad \ldots (4)$$

Here, N is samples available in the window.

CSS based on Energy Detection

When used for energy detection, the test vectors can be assumed to be Gaussian distributed if the sample size is adequately large (N >> 1). For the AWGN channel, the following formulas can be used to estimate detection and false alarm probabilities

$$P_{FA}^{ED} = Q\left(\frac{\upsilon - 1}{\sqrt{{}^{2}\!/_{N}}}\right)$$

$$P_{D}^{ED} = Q\left(\frac{\upsilon - (1+\gamma)}{\sqrt{\left({}^{2}\!/_{N}\right)(1+\gamma)^2}}\right) \qquad \ldots (5)$$

N is the number of samples that were taken, υ indicate threshold value, and $\gamma = {\sigma_s}^2 / {\sigma_n}^2$ is average signal to noise power ratio (S/N). Since $h_i(n)$ in a

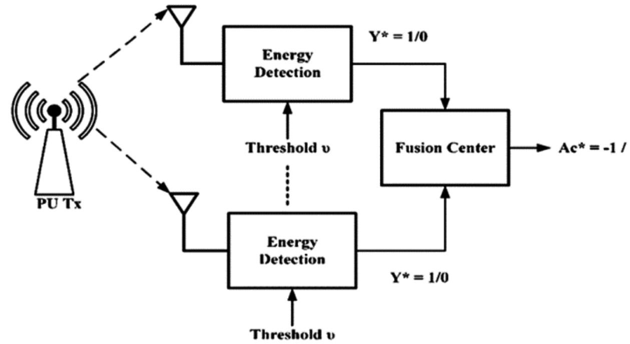

Fig. 1 — CSS using an Energy detection method

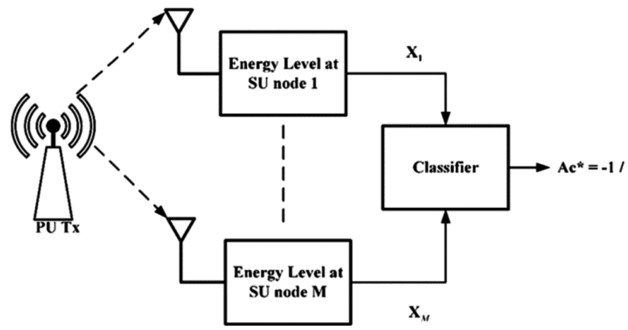

Fig. 2 — CSS using K-mean algorithm

fading channel change continuously, the detection probability for a fading channel is evaluated by averaging the P_D value over the pdf of the channel's S/N.

$$P_{DF}^{ED} = \int_0^\infty P_D^{ED} F(\gamma)\, d\gamma \quad \dots (6)$$

Given that there are M SUs, each of which sends one bit of data to the FC, the detection probability in OR logic can be calculated as

$$P_{DF}^{OR} = 1 - (1 - P_{DF}^{ED})^M \quad \dots (7)$$

CSS using K-mean Clustering

The K-mean clustering applied to CSS is illustrated in Fig. 2, in which each SU communicates the computed energy value to the classifier,[14] which constructs the energy vector based on this information.

$$X = \left[X_1, X_2, X_3, \dots \dots X_M\right]^T \quad \dots (8)$$

where, X is a column vector with M SUs, this energy vector resembles a machine learning feature vector, therefore classifier connects it with channel availability Ac.

The following phases are required to construct the classifier:

Phase 1: To begin, acquire a sufficient amount of training energy vectors

$$\bar{X} = \{X^1, X^2, X^3, \dots \dots . X^p\} \quad \dots (9)$$

where, $X^p \in R^{M\times 1}$, $p = 1,2,3 \dots . P$ are the training energy vectors.

Phase 2: Now, this classifier is being trained to find the centroids of various clusters using k-mean strategy.

Phase 3: once classifier is trained successfully, a test energy vector is applied to it to determine predicted channel availability Ac*.

Phase 4: To calculate P_{FA} and P_D values, it is necessary to compare the values of Ac and Ac*.

Unsupervised techniques like K-means split the set of unlabeled extracted features into K distinct clusters. Here the clusters are represented as $\varphi_s, s = 1,2,3, \dots , K$ and further assumed that cluster φ_s as a centroid of C_s. The centroid C_1 is set as per the Eq. (10), Because cluster will simply include noise, therefore centroid can be computed offline, Cluster 1's centroid adjusted to a mean of X, with Y assigned to a value of 0.

$$C_1 = E[X^p / Y = 0] \quad \dots (10)$$

The expectation is represented by the letter E, the centroids of the remaining clusters can be calculated by taking the arithmetic average of the training vectors φ_s as

$$C_s = \frac{1}{n(\varphi_s)} \sum_{X^p \in \varphi_s} X^p \quad \dots (11)$$

where, $n(.)$ indicate cardinality parameter, the ψ (distortion) is defined for K-mean clustering technique in terms of total squared distances between clusters, from their associated centroids added over the number of clusters K, expressed as

$$\psi(\varphi_1, \varphi_2, \varphi_3, \dots . \varphi_K, C_1, C_2, \dots \dots C_K) = \sum_{s=1}^{K} \sum_{X^p \in \varphi_s} \|X^p - C_s\|^2 \quad \dots (12)$$

where, $\|.\|$is the p[2]-norm. Clustering is used in this study to attempt to decrease distortion; thus, optimization can be defined as

$$\min_{\substack{\varphi_1,\varphi_2, \dots\dots \varphi_K \\ C_1, C_2, \dots\dots C_K}} \psi(\varphi_1, \varphi_2, \varphi_3, \dots . \varphi_K, C_1, C_2, C_3, \dots . C_K) \quad \dots (13)$$

Algorithm: for CSS K-Means Clustering

Input: K Total clusters

$C_1 = E[X^p / Y = 0]$

C_s: Initialized randomly, where $s = 2,3, \dots , K$

Vectors used for training are $\bar{X} = \{X^1, X^2, X^3, \dots , X^p\}$

Output: C_s,where $s = 2,3, \dots , K$

1. Repeat
2. Every data point is assigned to the nearest centroid to diminish $\psi(\varphi_1, \varphi_2, \varphi_3, \dots . \varphi_K, C_1, C_2, C_3, \dots . C_K)$
3. Calculate the mean of allocated points to update centroids.

$$C_s = \frac{1}{n(\varphi_s)} \sum_{X^p \in \varphi_s} X^p$$

4. Until Convergence

After completing the training phase, we now know the centroids of each cluster. The classification step begins by determining which class the test energy vector belongs to. For this, we employ a threshold value $\delta (\delta > 0)$ to classify test energy vectors as specified in Eq. (14).

$$\frac{\|\hat{X}-C_1\|}{\min_{s=1,2,3,..,K}\|\hat{X}-C_s\|} \geq \delta \qquad \dots (14)$$

If the preceding equation is satisfied, the test vector $\hat{X}$ is categorized as channel unavailable class; otherwise, it is categorized as channel accessible class.[15] The threshold value δ is used to control the P_{FA} and miss detection; in this case, the threshold value is used to control the P_{FA}.

The α-k-μ Channel

This fading model can be used in wide range of situations to accurately reflect non-linear features of small-scale LOS.[16] It may also be used to investigate the short-range and real-time sensing characteristics of spectrum sensing under extreme fading circumstances.[17] An envelope pdf of α-k-μ model is expressed as

$$h^{\alpha-k-\mu}(\rho) = \frac{\alpha\mu(1+k)^{\frac{1+\mu}{2}}\rho^{\frac{(\mu+1)\alpha}{2}-1}}{k^{\frac{1}{2}(\mu-1)}exp(\mu k)} \times exp\left(-\mu\rho^{\alpha}(1+k)\right) \times I_{\mu-1}\left(\sqrt{(1+k)k}\rho^{\alpha/2}2\mu\right) \qquad \dots (15)$$

In the preceding equation, α denotes the non-linear propagation medium features, k denotes the overall power ratios of the dominant and scattering waves, μ denotes the multipath fading components, I is modified first-order Bessel function.

The α-κ-μ channel's pdf SNR is given by the formula:

$$f^{\alpha-k-\mu}(\rho) = \frac{\left[\alpha\mu k^{\frac{1-\mu}{2}}(1+k)^{\frac{1+\mu}{2}}\right]}{2exp(k\mu)} \times \frac{\gamma^{\frac{(\mu+1)\alpha}{4}-1}}{\gamma^{\frac{-\alpha}{4}(1+\mu)}} \times exp\left(-\frac{\gamma^{\alpha/2}}{(\bar{\gamma})^{\alpha/2}} \times (1+k)\mu\right) \times I_{\mu-1}\left[\sqrt{(1+k)k}2\mu\frac{\gamma^{\alpha/4}}{(\bar{\gamma})^{\alpha/4}}\right] \qquad \dots (16)$$

In the above equation, SNR and Average SNR are denoted with γ and $(\bar{\gamma})$ respectively.

The α-k-μ channel is a generalized model; various renowned fading characteristic like Nakagami-m, k-μ & its extreme distribution, Rician, Rayleigh, α-μ and one-sided gaussian are regarded as distinct cases of this model, the ranges of α, k, and μ are shown in Table 1.[18,19]

Results and Discussion

For the simulation study, 1000 energy samples were used (half for testing and half for training), BPSK modulation is used for PU transmission with P_{on}= 0.5, the α-k-μ channel is used between PU and SUs. The feature vectors (energy estimates) from the SU node are used to train the classifier. The unlabeled feature vector that was used to train the classifier can be seen in Fig. 3. N = 500 samples and M = 2 are used to construct a feature vector with an average SNR of −12 dB. According to the results of the simulation, determining the class of the feature vector is challenging in this case. Once trained, the classifier can cluster the data according to the labels provided. As can be seen in Fig. 4, data has been grouped into two classes, one for channels that are available and one for channels that aren't.

The k-means algorithm-based CSS performs well in the α-k-μ channel with α = 1.25, k→0 & μ = 3, when SNR on an average of −12 dB, N is 500, and K is 3 illustrated in Fig. 5. Conventional detection schemes like OR[20] and energy detection[21,22] are outperformed by the k-means based CSS technique. The k-means based CSS method and traditional

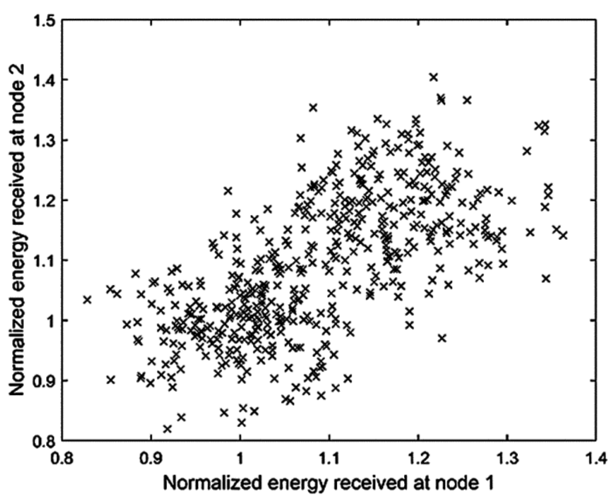

Fig. 3 — Training the classifier on unlabeled features

Table 1 — fading characteristics of Nakagami-m, Rician, Rayleigh, k-μ, k-μ extreme distributions, one-sided gaussian and α-μ

$\alpha-k-\mu$	Rician	Rayleigh	One-sided Gaussian	Nakagami-m	$\alpha-\mu$	$k-\mu$	$k-\mu$ Extreme
α	2	2	2	2	$\alpha > 0$	2	2
k	3	$k \to 0$	$k \to 0$	$k \to 0$	0	$k \geq 0$	$k \to \infty$
μ	1	1	0.5	3	$\mu > 0$	$\mu > 0$	$\mu \to 0$

detection methods have been used the same environmental parameter values. As illustrated in Fig. 5, When false alarm probability grows, the detection probability increases rapidly in k-mean based CSS, ensuring that the second user receives precise channel availability information. On the other hand, conventional detection approaches have consistently failed to deliver reliable channel information. As a result, a second user cannot access the channel.

The k-means based CSS and conventional detection methods performance are compared in α-k-μ (α = 1.25, k ≈ 0, μ = 3) and k-μ (k ≈ 0, μ = 3) channels, when SNR of −12 dB, N is 500, and K is 2. The Fig. 6 depiction of the plot comparing false alarm probability to the chance of a successful detection makes it abundantly evident that for α-k-μ fading model CSS technique based on k-means clustering has a higher detection probability than the k-μ fading channel does. Conventional detection methods work better when k-μ channel is used instead of α-k-μ fading model.

The performance of CSS based on k-means and conventional approaches is examined in Fig. 7 for three unique circumstances of α-k-μ fading such as: Nakagami-m (α = 2, k ≈ 0, μ = 3), Rayleigh (α = 2, k → 0, μ = 1) and Rician (α is 2, k = 3 and μ = 1), when average SNR of −12 dB, N is 500, and K is 2. In the case of k-means based CSS, the Rician channel has a

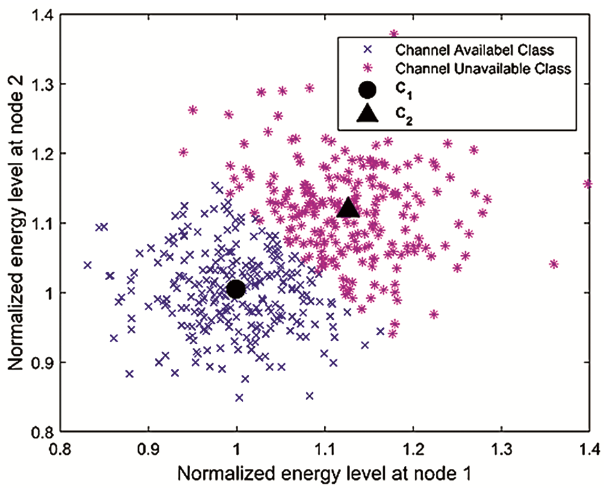

Fig. 4 — Clustered data after training the classifier

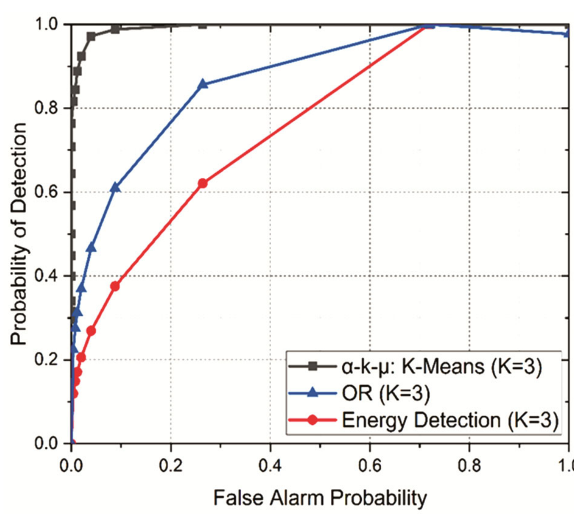

Fig. 5 — Performance evaluation of ROC in α-k-μ fading channel for CSS using K-means, Energy detection, and OR-combining for M = 2

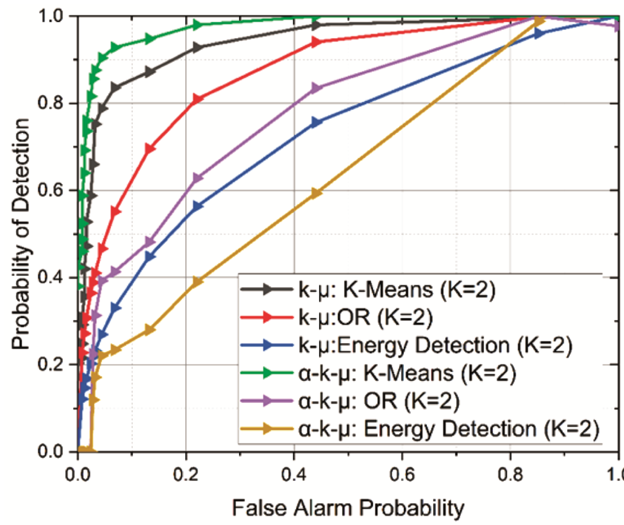

Fig. 6 — Performance comparison of CSS using K-means, Energy detection, and OR fusion in α-k-μ, k-μ channels with M = 2

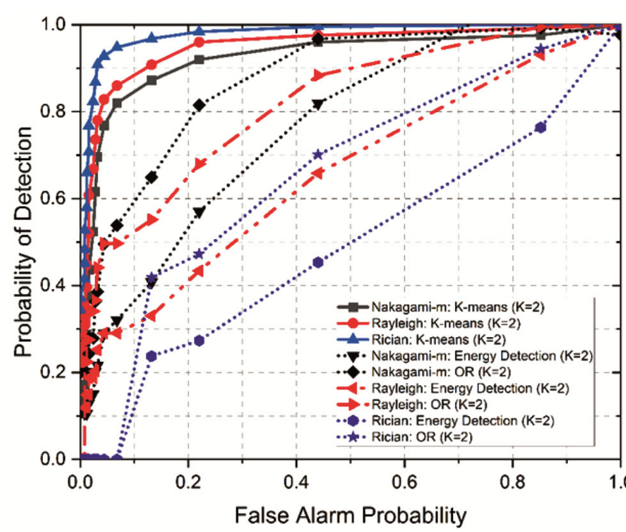

Fig. 7 — Performance comparison of K-means based CSS, Energy detection, and OR combining in an α-k-μ channel under different fading scenarios with M = 2

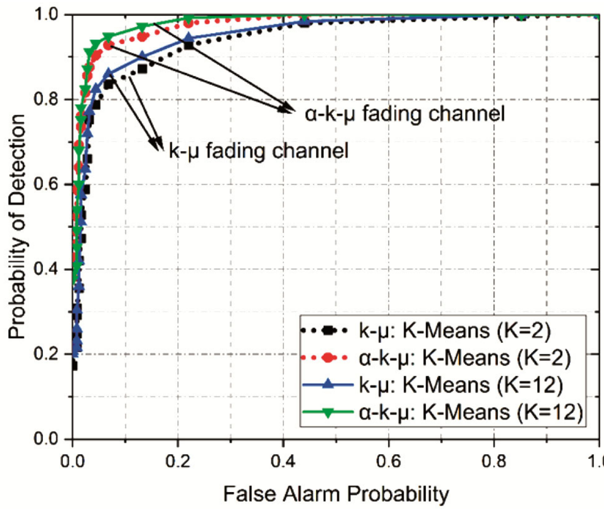

Fig. 8 — Performance comparison of k-means based CSS (with K = 2 and 12) in k-μ, α-k-μ fading channels with M = 2 and average SNR = −12 dB

higher detection probability than other channels. In conventional methods, the Nakagami-m channel outperforms other channels.

The performance k-mean based CSS for various cluster values under channels α-k-μ and k-μ is depicted in Fig. 8. From the graph it is evident that detection probability increases as the value of K increases in both situations, although the α-k-μ channel provides better results than the k-μ channel.

Conclusions

The advent of Industry 4.0 and its extensive interconnectedness places heavy demands on the available spectrum resources, leading to a shortage of spectrum. Cognitive Radio (CR) is a potential technique for enhancing spectrum use by detecting spectrum holes. The cooperative spectrum sensing performance in a generalized α-k-μ channel is analyzed using k-means clustering approach. According to simulation results, K-means-based CSS in α-k-μ fading channel significantly improves ROC performance when compared to energy detection-based CSS and OR-fusion-based CSS. The effectiveness of CSS based on k-means is also studied using the k-μ, α-k-μ fading channels for various cluster values. As the value K increases, α-k-μ fading channel performs significantly better than k-μ channel. In light of the simulation findings, it is clear that the suggested method efficiently detects spectrum holes, which is critical in the case of an Industry 4.0 application.

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