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Application of K-means for spectrum sensing in cognitive radio networks under fading

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Abstract: Machine learning techniques for cooperative spectrum sensing are achieving greater heights than the classical methods for spectrum sensing. Among all the unsupervised techniques, K-means gives promising results as found from literature study. Hence, in our paper we have executed the spectrum sensing using K-means as the machine learning technique. In this paper, we have shown performance of K-means classifier in cases without fading in the channel and also in cases including multipath fading in the channel. Before classification, the classifier needs to be trained. The energy levels received at the cognitive users are used as training vectors for classification of channel into either of the two classes : channel available class or channel unavailable class. The classifier then determines which class the test vector belongs to. Simulation has been done extensively to observe the misclassification rate for different values of the threshold parameter.
Keywords: Cognitive radio, cooperative spectrum sensing, k-means, fading, unsupervised, wireless communication, threshold parameter, energy level, misclassification rate

I. INTRODUCTION

The immense growth in the use of smart devices hosting convoluted application has led to an increase in traffic in wireless network technology. According to CISCO Visual Networking Index(VNI), due to tremendous increasing of wireless applications and data rates, the data traffic is expected to increase eightfold by 2020. However, the spectrum scarcity problem cannot be solved due to current fixed spectrum allocation policy used by the government. Recent advancement in wireless technology is creating a spectrum shortage problem on a daily basis. Cognitive radio, a novel technology, attempts to solve these problems by dynamically using the free spectrum in wireless communication. Basically, Cognitive Radio is an intelligent wireless communication device that can change its operating parameters dynamically based on interaction with the environment in which it operates. The experiments by FCC show that at any given time and location, much (between 80% and 90%) of the licensed spectrum is underutilized. Such temporarily unused spectrum slots are called spectrum holes, resulting in spectral inefficiency. Thus not only is spectrum usage low in some licensed bands, but also true scarcity of radio spectrum compounds the problem [7]. Consequently, the growth of wireless applications may be hindered. Key features of a cognitive radio transceiver thus include radio environment awareness and spectrum intelligence. The latter refers to an ability to learn the spectrum environment and adapt transmission parameters. For instance, two types of cognitive radio networks are distinguished based on the spectrum bands:

1) On unlicensed bands: These include ISM (industrial, scientific and medical) bands such as 902–928 MHz, 2.4–2.5 GHz, and 5.725–5.875GHz. ISM bands are also shared with non-ISM applications, e.g., Bluetooth, IEEE 802.11/WiFi. These bands can be utilized by cognitive radio.
2) On licensed bands: The spectrum is licensed into different applications, e.g., aeronautical and maritime communications, AM radio etc. But there is significant under-utilization of licensed spectrum which can be overcome with the help of cognitive radio[18][19]. For instance, the wireless regional area network (WRAN) standard operates in unused television (TV) channels in 698–806 MHz.

The cognitive radio (CR) requires four main functions spectrum sensing, spectrum management, spectrum sharing, and spectrum mobility to dynamically access both licensed and unlicensed spectrum bands [6]. IEEE 802.22 standard is known as CR standard because of cognitive features it contains. The standard is still in development stage. One of the most distinctive features of IEEE 802.22 standard is it’s spectrum sensing requirement. Energy detection is a anticipating low-complexity and low-cost spectrum sensing technique. This measures the received signal energy within the pre-defined bandwidth and time period. The measured energy is then compared with a threshold to determine the status (presence/absence) of the transmitted signal. Not requiring channel gains and other parameter estimates, the energy detector has low implementation cost. The detection of spectrum holes is a difficult signal processing problem. This problem is made much more difficult due to signal fading that manifests itself in 2 ways: multipath fading(Rayleigh fading) and shadowing(large scale fading).

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In [10] authors have proposed novel CSS schemes based on machine learning techniques. Machine learning algorithms have been widely used for the pattern classification problems, where the feature vector extracted from the training data is fed into the classifier to categorize the pattern into a certain class. Spectrum sensing can be thought of as a binary-class classification problem. For CSS, we consider an "energy vector", each component of which is the energy level determined at individual secondary node, as a *feature vector*. The classifier categorizes this feature vector either into the "channel available class" or the "channel unavailable class". The classifier has to undergo through a training (learning) phase before the online classification starts. In general, two types of learning algorithms exist, namely the "supervised" and the "unsupervised". In case of the supervised learning, the training feature vectors are fed to the classifier with their actual labels; while in case of the unsupervised learning, the same are fed without any label. In [11], K-means classifier has been implemented extensively under generalized κ-µ fading channels by quantifying performance in terms of ROC, probability of detection, probability of false alarm etc. In this paper, we propose to use unsupervised learning approach such as the K-means clustering for CSS. The K-means clustering algorithm partitions the features into *K* clusters. Each cluster is mapped to either the channel available class or the channel unavailable class. Here, we aim towards quantifying performance of the classifier in terms of misclassification rate against different values of threshold parameter.

The remainder of the paper is organized as follows. In section II, the system model is discussed and analysed to the minutest level possible. The subsections in section II describe one by one the Primary user and secondary user model followed by a brief on energy detection model. The other subsections in section II discuss about the K-means clustering, classification in preence and absence of fading and performance evaluation against some specific values of parameters. This s followed by results in section III. Section IV finally concludes the paper.

II. SYSTEM MODEL AND ANALYSIS

A. Primary and Secondary Users Model

We consider a cognitive radio (CR) network sharing frequency channel with two primary users (PUs). The network consists of two secondary users (SUs). The location of the SUs and the PUs considering a two-dimensional space is shown in Fig. 1.

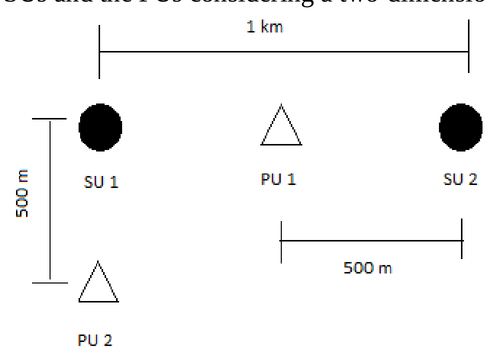

Fig. 1 Arrangement of PUs and SUs in two-dimensional space

The PUs can be either active or inactive at a particular time. Let s1 and s2 denote the states of PU 1 and PU 2 resp. The value of state corresponds to 0 for inactive PU and 1 for active PU. We also assume a specific probability of the PUs to be in active and inactive states denoted by v(s1,s2). The values of v(s1,s2) for all the four combinations of s1 and s2 are assumed to be

$$v(s1,s2)=\begin{cases}0.36, s1=0, s2=0\\ 0.24, s1=0, s2=1\\ 0.24, s1=1, s2=0\\ 0.16, s1=1, s2=1\end{cases} \quad (1)$$

B. Energy Detection Model

Each SU performs energy detection for a duration of τ. The total number of samples that will be received by each SU from each PU in this time duration is ωτ where ω indicates the bandwidth. Incorporating noise in this, the i th signal sample received by the nth SU from the two PUs can be stated as

$$Z_n(i)=\sum_m s_m h_{m,n} X_m(i)+N_n(i) \quad \text{where } m=1,2 \quad (2)$$

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where subscript m denotes the m^{th} PU, X(i) is the signal transmitted by m^{th} PU, $N_n(i)$ is the thermal noise at n^{th} SU and $h_{m,n}$ refers to the channel gain between m^{th} PU and n^{th} SU. The energy level estimated by n^{th} SU from all the samples normalized by noise spectral density η is given by

$$Y_n = \frac{2}{\eta}\sum_{i=1}^{\omega\tau}\left|Z_n(i)\right|^2 \tag{3}$$

The energy vector that will be generated due to the energy levels of the two SUs is given as

$$Y = (Y_1, Y_2)^T \tag{4}$$

For large number of samples, the energy level of Y_n can be considered to be Gaussian distribution for a given S with mean μ and variance σ^2 such that

$$\mu_{Y_n} = 2\omega\tau + \frac{2\tau}{\eta}\sum_m s_m g_{m,n}\rho_m \quad \text{where } m = 1,2 \tag{5}$$

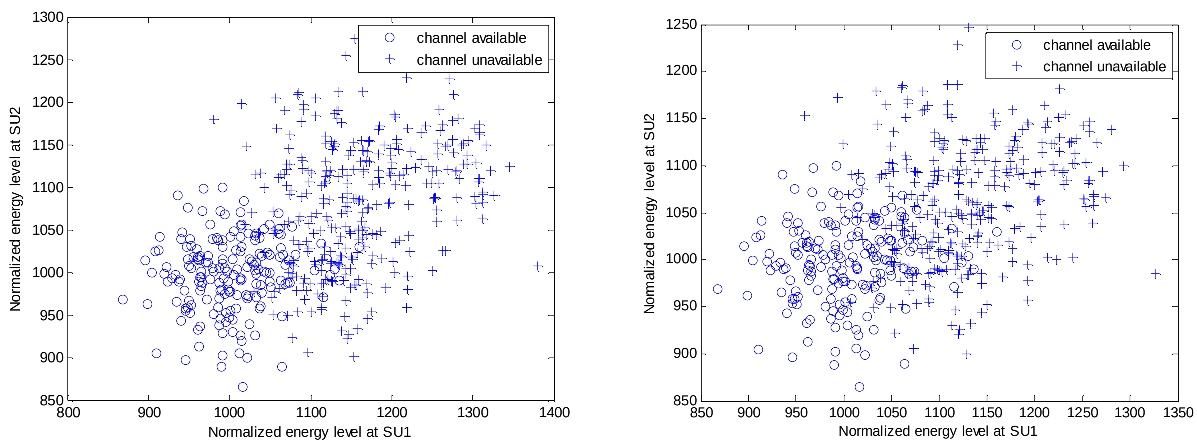
$$\sigma^2_{Y_n} = 4\omega\tau + \frac{8\tau}{\eta}\sum_m s_m g_{m,n}\rho_m \quad \text{where } m = 1,2 \tag{6}$$

The power attenuation $g_{m,n}$ is given as

$$g_{m,n} = PL(\left\|c_m^{PU} - c_n^{SU}\right\|).\psi_{m.,n}.\upsilon_{m,n} \tag{7}$$

where $\psi_{m,n}$ is the shadowing component, $\upsilon_{m,n}$ denotes the multipath fading component, PL(d) = d^(-α) where α is the path loss exponent. c_m^{PU} denotes coordinate of m^{th} PU and c_n^{SU} denotes the coordinate of the n^{th} SU. ρ_m refers to the power transmitted by the m^{th} PU.

The scatter plots for energy vectors is shown in figure 2 for both the cases with fading and without fading when the PU transmit power is 80 mW. The energy levels received at the SUs are in mW.



(a) When there is no fading (b) When there is fading

Fig.2 Scatter plots of energy vectors when PU transmit power is 80 mW.

C. K-Means Clustering based CSS

K-means is one of the simplest unsupervised learning algorithms that solve the well known clustering problem. Clustering based on k-means is closely related to a number of other clustering and location problems. These include the Euclidean k-medians (or the multisource Weber problem) [2], [3] in which the objective is to minimize the sum of distances to the nearest center and the geometric k-center problem [1] in which the objective is to minimize the maximum distance from every point to its closest center. K-means performs division of objects into clusters which are similar between them and are dissimilar to the objects belonging to another cluster. The procedure follows a simple and easy way to classify a given data set through a certain number of clusters

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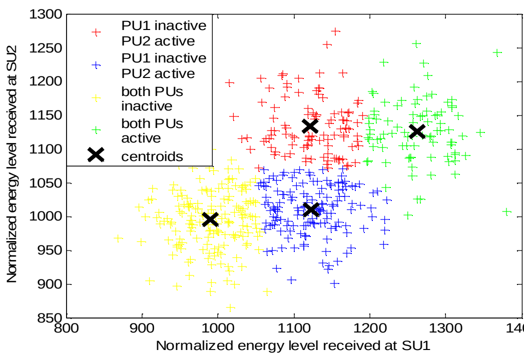
(assume k clusters) fixed apriori. The main idea is to define k centers, one for each cluster. These centers should be placed in a cunning way because of different location causes different result. So, the better choice is to place them as much as possible far away from each other. The next step is to take each point belonging to a given data set and associate it to the nearest center. When no point is pending, the first step is completed and an early group age is done. At this point we need to re-calculate k new centroids as barycenter of the clusters resulting from the previous step. After we have these k new centroids, a new binding has to be done between the same data set points and the nearest new center[4]. A loop has been generated. As a result of this loop we may notice that the k centers change their location step by step until no more changes are done or in other words centers do not move any more. Finally, this algorithm aims at minimizing an objective function known as squared error function.

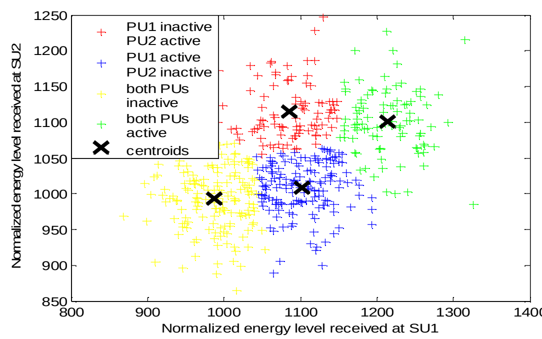
We first train the classifier with a set of Gaussian distributed energy level dataset already generated as mentioned in section II. We classify the sample sin the dataset into four clusters depending on which of the PUs are active and which are inactive. After the training is over, we test the model with the same set of values. The classification is done as describe in the next section.

D. Classification without fading and in presence of fading

The energy vectors are grouped into four clusters. One of the clusters yellow in colour denotes the energy vectors received when both the Pus are inactive i.e, the channel is available for use by the cognitive users. The green cluster denotes that both the PUs are active. The rest of the two clusters denote one of the PUs is active. That is, other than the yellow cluster, the samples in the other three clusters belong to channel unavailable class. 36% of the total 500 vectors were considered to be belonging to this cluster for training. After classification using K-means classifier, the statistics got changed due to which we find a misclassification rate which is elaborated in results section.



(a) When there is no fading



(b) When there is fading

Fig. 3 Labelled data after training and classification

E. Performance Evaluation

The pdf of k-u channel is given from [9] as :

$$h(\rho) = \frac{2\mu(1+\kappa)^{\frac{1+\mu}{2}}}{\kappa^{\frac{\mu-1}{2}}\exp(\mu\kappa)}\rho^{\mu}\exp[-\mu(1+\kappa)\rho^{2}]I_{\mu-1}[2\mu\sqrt{\kappa(1+\kappa)}\rho] \tag{8}$$

For Rayleigh distribution of multipath fading, value of μ should be taken as 1 and value of κ should be taken almost equal to 0. By putting the corresponding values of μ and κ in the equation above, we find the pdf to be

$$h(\rho) = 2\rho\exp(-\rho^{2}) \tag{9}$$

which is a Rayleigh distribution pdf with the value of shape parameter as 0.7 the square of which gives the variance of the Rayleigh distribution.

After the training process as mentioned in the previous subsection, suppose a vector y is used as a test vector for classification. y is classified as channel unavailable class if the following condition is satisfied.

$$\frac{\|y-\alpha_1\|}{\min_{1,2,\ldots,k}\|y-\alpha_k\|} \geq \beta \tag{10}$$

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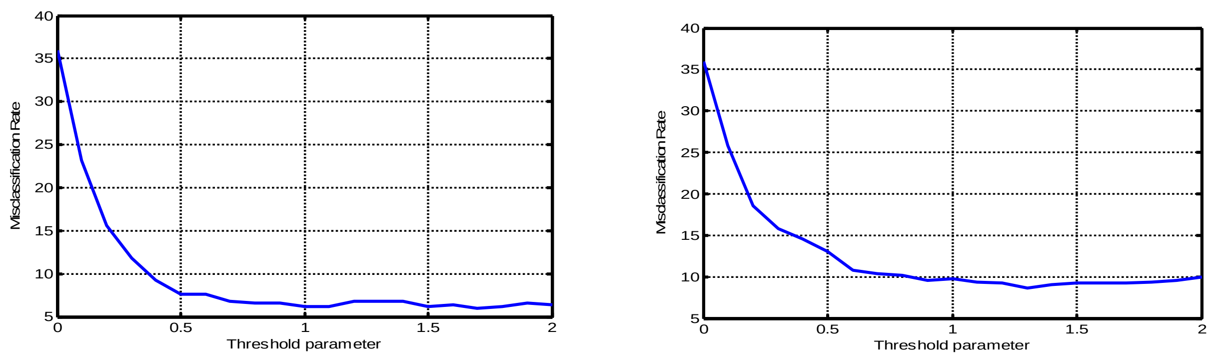
Or else the vector y is classified as channel available class. The parameter ß acts as a threshold to control the misclassification rate. A total of 500 energy vectors have been used for training purpose. The same set of 500 vectors are used for testing purpose. The misclassification rate obtained for various cases are described in the next section. The values of several parameters that have been used for simulation in MATLAB are : Bandwidth ω is 5MHz, sensing duration τ is 100µs, path-loss component α is 4 and noise spectral density η is -174dB. Shadowing component $\psi_{m,n}$ is assumed to be 1and $\upsilon_{m,n}$ is taken to be 0.81.

III.RESULTS AND DISCUSSION

The misclassification rate is plotted against different values of threshold parameter ß under fading and without fading. For the case when there is no fading, the least misclassification rate is observed to have a value of 6% at a threshold value of 1.7 and for the case with Rayleigh distribution of multipath fading having shaping parameter as 0.7, the minimum misclassification rate is observed to be 8.6% at a threshold value of 1.3. The plots for misclassification rate vs threshold parameter are shown in figures 4(a) and 4(b). The results reveal that the misclassification rate is more in case with fading. This can be because of the fact that due to fading, the energy levels received at the cognitive users are changed to some level. This change depends on the amount of fading. More the fading, more is the change in the received values and more is the misclassification rate.



(a) When there is no fading (b) When there is fading

Fig. 4 Plot of misclassification rate vs threshold parameter

IV.CONCLUSION

K-means clustering based classification has been used as an unsupervised technique for cooperative spectrum sensing. It is a promising approach for cooperative spectrum sensing in cognitive radio networks. We quantify the performance of the classifier in terms of misclassification rate against different values of threshold parameter. The results confirm the fact that the classifier can classify the energy vectors more accurately when there is no fading. It implies the misclassification rate increases with increase in fading in the channel. The classifier can further be improved by using the energy vectors as features for classification one by one.

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