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Optimization of Energy Detection Based Spectrum sensing in cognitive radio over $k-\mu$ Fading Channels

Parmeet Kaur , Dr. Charanjit Singh

Abstract— ***Spectrum sensing, the problem of detecting the presence of licensed user in the channel is considered in this paper. Energy detection is best suited for the spectrum sensing when prior knowledge about the primary users is unavailable. Existing works report improved versions of energy detection which primarily focuses on maximizing the detection performance. Sensing error minimization is an important aspect of spectrum sensing that needs attention. This paper focuses on the sensing error minimization of the improved energy detection algorithm in which the an optimization technique called Adaptive Ant Colony is used.***

INTRODUCTION

With the rapid growth of wireless communications, the issue of spectrum resource scarcity has been causing deep concern. Cognitive radio (CR) is considered as an efficient approach to solve this problem via opportunistic spectrum access [1, 2]. In CR systems, the secondary user (SU) is not allowed to access the licensed spectrum that is being occupied by a primary user (PU). Otherwise, if no active PU is found, the vacant spectrum can be utilized [3]. Therefore, the task to detect whether the target PU is present or not, namely spectrum sensing, is of great significance for CR.

Three classic spectrum sensing technologies are matched filter detection (MFD), cyclostationary feature detection (CFD), and energy detection (ED). MFD is viewed as the most accurate method but requires detailed prior knowledge of PU signal [4]. CFD performs reliably even with very low signal-to-noise ratio (SNR), while its computational complexity is a bottleneck [5]. Compared with them, ED does not require any prior information and consumes little calculation [6] and thereby is widely applied to detect PU. ED suffers from server performance degradation at low SNR [6]. To improve its performance, [7–9] present some ED-CFD hybrid schemes that firstly perform ED to search for PU and then reuse the observations to conduct CFD if target PU is not detected by ED. These schemes can achieve better performance under awful noise conditions, while their complexity is high because of CFD. To solve this problem, [10–12] consider performing ED twice to avoid CFD. In [10], two thresholds are preset and decisions are made directly in case that the observed energy is either large enough or small enough. Otherwise, the second ED is implemented additionally. This method can improve detection accuracy to some extent but is sensitive to noise uncertainty. An adaptive double-threshold energy detection (AED) method is proposed in [11], which adjusts its thresholds according to SNR to combat noise uncertainty. It should be pointed out that these methods are all committed to improve detection accuracy, while ignoring the importance of detection time. Reference [12] investigates the detection accuracy of AED and analyzes its detection time, indicating that the former is improved at the cost of the latter. Since long detection time impairs system throughput and agility [13], it is necessary to dig into the issue of fast ED.

ENERGY DETECTION

This method is based on the premise that the energy of a signal to be detected is always higher than the energy of the noise. It is known as blind detection scheme and its an optimal detection method when the primary user signal is unknown. It doesn't require any a prior information so it is the most widely used method for the detection of PU signal and also the

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performance depends on various factors such as the decision threshold, received SNR. simplest of all the other methods.

The binary hypothesis testing model can be described as

$$y(t) = \begin{cases} n(t), & H_0 hypothesis \\ x(t) + n(t), & H_1 hypothesis \end{cases} \qquad (1)$$

where, *y(t)* = received signal by the CR user

x(t) = transmitted signal of the primary user

n(t) = zero-mean additive white Gaussian noise (AWGN)

H_0 = null hypothesis, which indicates the absence of PU signal

H_1 = alternative hypothesis, which indicates the presence of PU signal

Performance Measures for Spectrum Sensing: Ideally any spectrum sensing algorithm should select H_0 when the primary user is absent and H_1 when it is present. Practically, spectrum sensing algorithms are prone to errors

k−μ fading model

The *k-μ* fading model has been shown to represent effectively the small-scale variations of a fading signal in LOS communications. Physically, this fading model considers a signal composed of clusters of multipath waves propagating in a non homogeneous environment. Within any cluster, the phases of the scattered waves are random and have similar delay times with delay-time spreads of different clusters being relatively large. The clusters of multipath waves are assumed to have scattered waves with identical power values, and each cluster consists of a dominant component with arbitrary power. To this effect, parameters μ and k correspond to the number of multipath clusters, and the ratio between the total power of the dominant components and the total power of the scattered waves, respectively. These two parameters render this fading model remarkably flexible as its capturing range is particularly broad. This is also evident by the fact that the widely known Rician and Nakagami-*m* fading models are included as special cases for μ = 1 and k = 0, respectively. Therefore, this model can provide a meaningful insight on how fading affects the performance of an energy detector, which ultimately leads to a significant improvement on the design of cognitive radio systems in terms of energy efficiency and cost.

Relationship between *k-μ* can be written as

$$\mu = \frac{E^2(R^2)}{Var\,(R^2)}\frac{1+2k}{(1+k)^2} \qquad (2)$$

where Var(.) denotes mathematical variance

E(.) denotes statistical expectation

As the energy detector is largely considered by a predefined threshold value λ and th overall performance is evaluated by considering 2 parameters that is probability of false alarm P_f and probability of detection. Further the probability of missed detection is derived from it.

$$P_f = \frac{\Gamma(u,\frac{\lambda}{2})}{\Gamma(u)} \qquad (3)$$

$$P_d = Q_u(\sqrt{2\Upsilon}, \sqrt{\lambda}) \qquad (4)$$

Where u= TW(product of time and bandwidth),Υ= SNR value and λ=Threshold value

$Q_m(a,b)$ represents the Marcum q function

Generally the average probability of detection is obtained by averaging P_d over the corresponding SNR fading statistics

$$\overline{P_d} = \int_0^\infty Q_u\left(\sqrt{2\Upsilon}, \sqrt{\lambda}\right) p_\Upsilon(\Upsilon)\mathrm{d}\Upsilon \qquad (5)$$

$$p_\Upsilon(\Upsilon) = \frac{\mu(k+1)^{\frac{\mu+1}{2}} e^{-\mu k}}{k^{\frac{\mu-1}{2}} e^{\mu(1+k)\frac{\Upsilon}{\overline{\Upsilon}}}} \frac{\Upsilon^{\frac{\mu-1}{2}}}{\overline{\Upsilon}^{\frac{\mu+1}{2}}} \mathrm{I}_{\mu-1}\left(2\mu\sqrt{k\frac{\Upsilon}{\overline{\Upsilon}}(k+1)}\right)$$

By substituting the value of equation (6) into equation (5)

$$\overline{P_d} = \int_0^\infty \frac{\mu Q_u\left(\sqrt{2\Upsilon}, \sqrt{\lambda}\right)\mathrm{I}_{\mu-1}\left(2\mu\sqrt{k\frac{\Upsilon}{\overline{\Upsilon}}(k+1)}\right)}{k^{\frac{\mu-1}{2}} e^{\mu k}\,\overline{\Upsilon}^{\frac{1-\mu}{2}}\,\Upsilon^{\frac{1-\mu}{2}}(k+1)^{-\frac{\mu+1}{2}} e^{\mu(1+k)\frac{\Upsilon}{\overline{\Upsilon}}}}$$

Finally the infinite series representation can be expressed by comparing the above equations with Whittaker hypergeometric function.

In square law selection diversity scheme, each diversity branch has a square law device, and the branch with the maximum statistic is selected. Thus the test statistic of SLS is

$\Lambda_{SLS} = \max\{\Lambda_1, \ldots\ldots\ldots\ldots\ldots\ldots\ldots, \Lambda_L\}$

The false alarm probability P_f can be derived as

$$P_{f,SLS} = 1-(1-P_f)^L \qquad (8)$$

Further the probability of detection can be obtained as

$$P_{d,SLS} = 1-\prod_{l=1}^{L}(1-P_f) \qquad (9)$$

Where L refers to the no of branches used
When this SLS is combined with k-μ fading channel the P_f can be obtained as following

$$P_f^{SLS}=1-[1-\frac{\Gamma(u,\frac{\lambda}{2})}{\Gamma(u)}] \quad (10)$$

Therefore, this model can provide a meaningful insight on how fading affects the performance of an energy detector, which ultimately leads to a significant improvement on the design of cognitive radio systems in terms of energy efficiency and cost.

Problem Formulation

In the fading channels it is be useful to investigate the case where secondaries will not always notice the arrival of the primary users and also the case where only the secondary will leave when collisions occur. Additionally, the state equations should be generalized to larger number of channels and the effects of timing offset between primary user arrival and secondary user sensing period could be studied. The second issue that how to do joint access control and resource allocation to maximize the total system capacity and minimize the interference to PUs when there are sensing errors in the secondary network may also be considered. In the current research various drawbacks of the existing schemes are to be improved like probability of missed detection and average detection in case of noisy channels also.

Proposed Work

In the proposed model the above defined drawbacks are considered to improve the existing fading channel. Using the proposed approach the missed detection and the efficiency in case of noisy channel is also improved. In this research an optimization scheme called AACO (Adaptive Ant Colony Optimization) is used which is defined as follows:

It is an efficient ant colony optimization algorithm with uniform mutation operator using self-adaptive approach has been proposed. Here mutation operator is used for enhancing the algorithm escape from local optima. The algorithm converges to the optimal final solution, by gathering the most effective sub-solutions.

In Self-Adaptive Approach, the parameters are encoded into pheromones and undergo mutation and recombination. The idea is that better parameters leads to better pheromones for finding shortest path or largest path, according to combinational problem. A self-adaptive approach, a single mutation rate is used. With this mutation rate p [0, 1], a new mutation rate p' [0, 1] is found using following equation. In this equation, γ is the learning rate which controls the adaption speed and it is taken as 0.22. The mutation rate is not allowed to go below 1/L.

$$p'=(1+\frac{1-p}{p}exp(-\Upsilon,N(0,1)))^{-1} \quad (11)$$

Ant colony optimization algorithm with uniform mutation operator using self-adaptive approach is used. Here mutation operator is used for enhancing the algorithm escape from local optima. In this method, an additional operator, mutation operator, is used and the new mutation rate is generated by the self-adaptive approach using above equation. Here ACO algorithm generates the current solution (w) by using mutation operator, random position is changed by new mutation rate in current solution(w). After changing random position, new solution (w') is generated. Then the cost of this new solution (w') is compared by the current solution(w), if the cost of new solution is less than (or greater than) current solution, according to combinational problem, then new solution is replaced by current solution. This process is repeated until maximum iteration is not reached. In the current research cognitive radio spectrum sensing network is implemented using the κ-μ fading channel investigates the performance of an energy detector over generalized $\kappa-\mu$ and $\kappa-\mu$ *extreme* fading channels, which have been shown to provide remarkably accurate fading characterization. Physically, this fading model considers a signal composed of clusters of multipath waves propagating in a non-homogeneous environment. Within any cluster, the phases of the scattered waves are random and have similar delay times with delay-time spreads of different clusters being relatively large. The clusters of multipath waves are assumed to have scattered waves with identical power values, and each cluster consists of a dominant component with arbitrary power. To this effect, parameters μ

and κ correspond to the number of multipath clusters, and the ratio between the total power of the dominant components and the total power of the scattered waves, respectively. To optimize the basic fading an optimized scheme is implemented in it called AACO on 25 number of nodes.

Result and Discussion

In this part the analysis of the results generated is to be done so that a comparative study may be done in order to check efficiency of the proposed model.

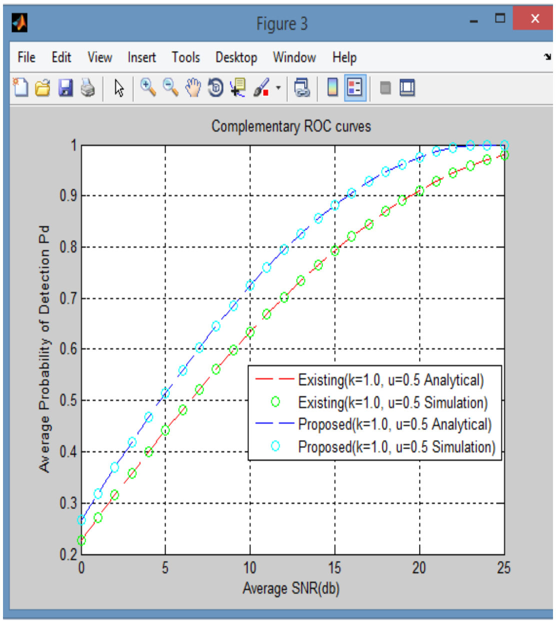

Fig 2 Graph between average probability of detection and average SNR

In this graph the existing and proposed values are compared. P_d is very low at lower SNR values while its value increases with the increase in the value of SNR.

In this graph the existing and proposed values are compared. P_d that refers to probability of detection is very low at lower SNR values while its value increases with the increase in the value of SNR. Here both simulation and analytical are compared.The proposed method gives better result comparatively even at lower SNR values. From the above defined graph it is very clear that the proposed optimized model is performing far better than that of existing one in case of noise also. In this graphs are generated using the values of k and μ and using both the simulink and analytical case in both existing and purposed method. As the AACO technique finds the best path so the average probability of detection is better by using this method.

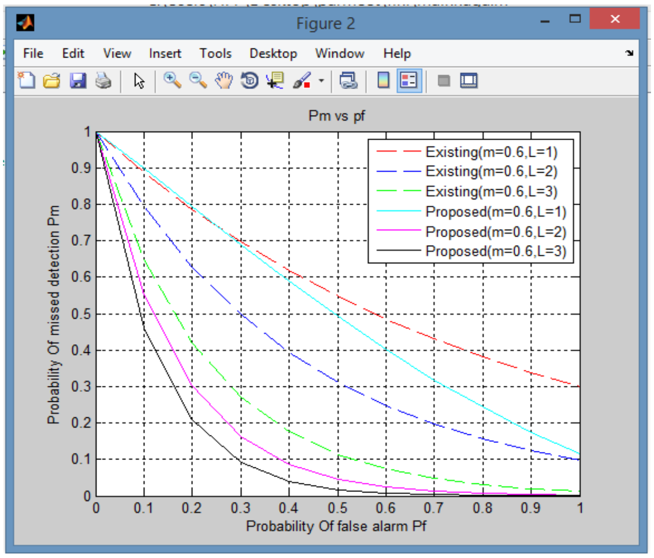

Fig 3: Graph between probability of missed detection and probability of false alarm

As we fix the value of false alarm for a graph it can be clearly concluded that the probability of missed detection is less in case of proposed technique.

CONCLUSION

This research analyzed the performance of ED in optimized $\kappa-\mu$ fading channels. Novel analytic expressions were derived for the average probability of detection for both cases. The overall performance of the detector is optimized by the value of the corresponding fading parameters since it is very sensitive even at small variations, particularly as the average SNR increases. It was also demonstrated that a significant performance improvement is achieved in both severe and moderate fading conditions as the number of users or diversity branches increases. Furthermore, it was shown that the optimized $\kappa-\mu$ extreme fading model provides adequate fading characterization of the fading effect in the low SNR regime and thus improves the performance of the energy detector. In the existing technique the optimization is

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done.through the Adaptive Ant Colony Optimization. Using the proposed approach the results are improved to great extent. The average missed detection is improved and in case of noise in the network its efficiency is not dropped. As a result, the offered results are useful in quantifying the effect of fading in ED spectrum sensing, which can ultimately lead to improved and/or more energy-efficient CR based communication systems. In the future scope the average missed detection may be improved using any other optimization technique. Apart from the scalability issue the security of the network may also be improved.

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