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Article

A Distributed Weighted Consensus Based Cooperative Spectrum Sensing Scheme using Cyclostationary Detection

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I N F O

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A B S T R A C T

Detection of Primary Users (PUs) in the pres- ence of interference and noise and improvement of spec- trum utilization is one of the aims of Cognitive Radio (CR). In this paper, a fully distributed cooperative spectrum sens- ing scheme based on cyclostationary features techniques is proposed. The primary signal detection is realized by an OFDM fast spectrum sensing algorithm, then each Secondary User (SU) choses the information exchanging rate according to the estimated average Signal To Noise Ratio (SNR). The SUs exchange their own measurement with their local neighbors to make decision about the primary user. Simulation results show that the proposed consensus scheme can have significant lower mission detection and probability of false alarm. We also show that the proposed method performs better than the existing consensus energy detector based approach.

Keywords:

Introduction

N the previous few periods, around has been a huge upsurge of wireless communication systems. The usage of frequency bands, or spectrum, is strictly regulated by the Federal Communications Commission (FCC). The spectrum is assigned to licensed users also recognized as primary users (PU). However, various measurements of spectrum use have shown unused resources in frequency, time and space, resulting in the spectrum being underuse. Cognitive Radio (CR) aims to improve spectrum utilization by allowing the use of licensed spectrum in an uninhibited manner, by users known as Secondary Users (SU), who have no spectrum licenses.[1,2] The unused resources are referred to as spectrum holes or white spaces. There exist time intervals for which the primary system does not use the approved spectrum, these spectrum holes could be exploited for increased spectrum efficiency by cognitive radios. Spectrum sensing can be conducted either non-cooperatively, in which each secondary user conducts radio detection and makes a decision by itself, or cooperatively in which a group of secondary users perform spectrum sensing by collaboration.

The enactment of local detector damages in the occurrence of propagation belongings such as surveillance and fading produced by multipath. These channel conditions may also consequence in the problem of hidden nodes, where a secondary transceiver is outside the listening variety of a primary transmitter, but close enough to the primary receiver to make intervention. The main benefit of cooperative sensing is to improve the detecting act by manipulating the opinion diversity of spatially located SUs, then the whole group can gain benefit by collaboration.

Based on how local sensors procedure the data, cooperative detection can be modeled in two ways: central and dispersed (or distributed). In a central system, each sensor sends all of its explanations to a central decision maker or a Fusion Center (FC) who makes the final decision regarding which of the hypotheses is true using classical detection theory. In scattered obliging spectrum sensing, each sensor sends data, a summary of its pre-processed observations to the Data Fusion Center (DFC). The loss of information in summarizing the observations results in minor or no performance degradation for the decentralized system as compared to the case of centralized system.[3]

Distributed sensing attracted increased attention from researchers, because it is more useful than centralized sensing in the sense that there is no need for a backbone infrastructure and it has reduced cost. Recent work[4] obtainable a distributed approach where the authors jointly considered routing and dynamic spectrum allocation in CR ad-hoc network so that the network throughput is maximized without causing harmful interference to other licensed users. Ghasemi[5] Quantified the presentation of spectrum sensing in fading environments. Cooperation effects were studied and simulation results showed a significant act enhancement by deploying cooperation. In[6], an algorithm for pairing SUs without a centralized mechanism is proposed. The collaboration is performed between two SUs where the user closer to a primary transmitter, which has a better chance of detecting the PU transmission, cooperates with far away users. For better network performance under dynamic propagation environments, Cattivelli and Sayed[7] future a distributed spectrum sensing technique with adaptive cooperation between the SUs by making the detection problem a parameter estimation problem. They assume the information about the PU is known by every SU which cannot be correct in real life environments. Another distributed seining scheme was discussed by Ejaz et al, in [8]; their proposed scheme is based on creation of chemical fields within CR network, where the chemical field will create a gradient on each SU and lead to detection of PU. Their simulation showed effectiveness of the scheme in terms of sensing and energy consumption.

In the sensing stage, energy detection is widely applied because it requires lower design complexity and no previous information or primary users compared to other techniques. However, they are very unreliable in low SNR regimes.[9,10] A matched filter sensing method is theoretically optimal, but it needs a priori knowledge of the primary system, which means higher complexity and cost. Cyclostationary (CS) features detection exploits the properties of digital modulated signals. It has the ability to reliably detecting very weak signals (very low Signal-To-Noise Ratio (SNR) environments) and its performance substantially surpasses the performance of the energy detector.[11]

In this paper, we recommend a weighted measurement combining scheme without the centralized fusion center. In the sensing stage, we deploy the OFDM spectrum sensing practice.[12] After measurements, the SUs exchange their decision statistics with their local neighbors and then weight the information exchanging rate according to their own estimated average SNR values.[13, 14] It is worth noting that the proposed scheme presented in this paper has five distinct features:

1. It is a non-centralized fully distributed scheme, where secondary users establish a neighborhood with users having the desired channel character- istics without the need for a common receiver to perform data fusion.
2. Cyclostationary detectors reliably detect the presence of PUs in low SNR regimes, instead of energy detectors that are easily affected by noise power and cannot differentiate between PUS and unknown signal source (interference).[10,15]
3. Unlike other CS detection models that are rebut to random noise at the cost of high computational complexity and long sensing times, the OFDM fast spectrum sensing algorithm focuses on the sensing of OFDM signals by exploiting only the stationary part of the periodic autocorrelation function, which meaningfully simplifies the detector design.
4. Each SUs channel condition is taken into consider- ation. Finding the weight directly from the average SNR accounts for the Rayleigh fading effects.[16,13,17]
5. Once a consensus is reached, each SU holds the global decision statistics from the weighted combining throughout the network.

The rest of the paper is organized as follows. In Section 2, we present the OFDM fast spectrum sensing algorithm and the consensus related SU network model. In Section 3, we recommend our weighted consensus based spectrum sensing scheme. Extensive simulation results and comparison with existing approach are demonstrated in Section 4. The conclusion along with a summary of the main results are presented in Section 5.

Spectrum Sensing and Secondary Users Network Modeling

There are two stages in the planned CR weighted consensus scheme. In the first stage, secondary users perform primary user detection by OFDM fast spectrum sensing model. In the second stage SUs establish communication links with their own neighbors to exchange information and then calculate the weighted data to make a local decision.

Sensing and Measurement Stage

In the first stage, secondary users make dimensions about the existence of primary users at the beginning of each time slot. Various conventional detectors have been adapted for the application of spectrum sensing for CR, including: energy detectors, waveform or matched filter based detectors and cyclostationary based detectors.[18] Each of these detectors have their advantages and disadvantages with varying detection performance, im- plementation complexity, detection time (sensing time), assumptions, and requirements on the PU signal, etc.[18] Energy detection algorithms do not make any assumption on the PU signal, while matched filter detection algorithms make explicit assumptions on the known pilot waveform or the preamble to design the detectors. Feature detectors lie in middle of these two extremes and only make certain assumptions on the structural or statistical properties of the PU signal in the design of the detectors. For example, almost all man-made signals exhibit distinct cyclostationary features which can be used to detect the signals.

The primary signal is modeled using OFDM based system with N_d subcarriers. The sum of subcarriers Representing the OFDM signal are modulated using quadrature amplitude modulation (QAM).[19] Then, one OFDM symbol of N_d duration is obtained by applying Inverse Discrete Fourier transform (IDFT) to the g N_d complex symbols d_i, i = 0, . . . , N_{d-1}.[20,21] Furthermore, to eliminate the effect of Inter Symbol Interference (ISI) almost completely, a guard time of length N_c is introduced in each OFDM symbol. The guard time is chosen larger than the maximum delay spread such that multiplicity components from ne symbol cannot interfere with the next symbol. The new sequence of duration $N_s = N_c + N_d$ samples is expressed as:

$$s = [s(-N_c)s(-N_c+1)\cdots s(0)s(1)\cdots s(N_d-1)]^T \quad (1)$$

where T denotes transpose. Usually an OFDM frame contains several such blocks. The entire endless serial stream is transmitted over the wireless channel to the receiver. Let θ be the time offset, i.e. the delay after which the SU receiver receives the first OFDM symbol. If we consider that the received signal contains K OFDM symbols, we use an observation window of length N samples $N = K(N_d + N_c) + Nd$ as illustrated in Fig. 1 In an additive white Gaussian noise (AWGN) channel, the secondary user signal can be written as:

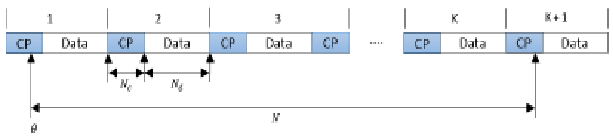

Figure 1.OFDM Signal Structure

The fundamental problem of spectrum sensing is to reliably detect the presence of absence of the primary signal, then decide about spectrum availability [22] [23]. The formulated binary hypothesis test is as follows [24]:

$$\begin{cases} H_1 : y(k) = s(n) + n(k) \\ H_0 : y(k) = n(k), \; k = 0, 1, \cdots, K(N_d + N_c) + N_d - 1 \end{cases} \quad (3)$$

where H1 and H0 correspond to the presence and absence of an OFDM signal, respectively. The number of samples during a sensing period is denoted as $L = K(N_d + N_c) + Nd$ and n(k) is the additive white Gaussian.[25] The measure of correlation between two OFDM symbols is described as

$$\hat{R}_i = \frac{1}{K}\sum_{k=0}^{K-1} \hat{r}_{i+k(N_d+N_c)}, \; i = 0, \ldots, N_d + N_c - 1 \quad (4)$$

The OFDM detector algorithm starts by the hypothesis testing. Under H_0, the received signal $\hat{R}_i$ consists of noise only without CP, while under H_1, the values of $\hat{R}_i$ will have high correlation due to the repeated data caused by the insertion of the CP with length N_c. The output of the correlator are sent serially into a shift register of length $N_c + N_d$, then classified in an ascending order according to their magnitude. After that, the upper bound of $\hat{R}_k$ is formed with a test statistic and the desired false alarm probability P_{fa} is calculated by multiplying the lower bound values of $\hat{R}_k$ and a constant η called the threshold multiplier. Finally, a sufficient statistic $\Lambda_g(\hat{R}_k)$, is used to make a decision about the presence or absence of an OFDM signal [26] as shown in Fig. 2.

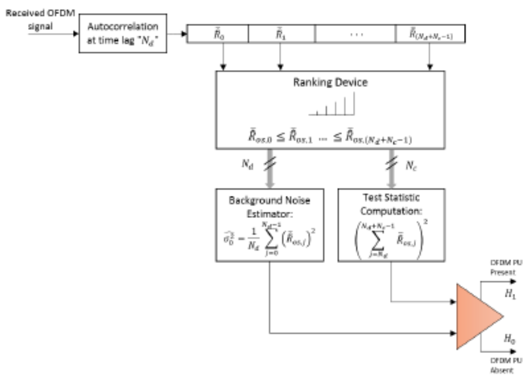

Figure 2.Block diagram of OFDM detector

The test statistic $\Lambda_g(\bar{\hat{R}})$ is derived as

$$\Lambda_g(\bar{\hat{R}}) = \left(\sum_{j=N_d}^{N_d+N_c-1} \bar{\hat{R}}_o s, j\right) \underset{H_0}{\overset{H_1}{\gtrless}} \eta\, \hat{\sigma}_0^2 \quad (5)$$

Using maximum-likelihood (ML) estimates to exploit the cyclostationarity property of the OFDM signals we get

$$\Lambda_g \sim \begin{cases} \chi_{2m}^2, & H_0 \\ \chi_{2m}'^2 + Y_e, & H_1 \end{cases}$$

χ^2_{2m} and χ^2_{2m} denote the central and non-central chisquare distributions. Y_e has an exponential distribution with parameter $2(\bar{\gamma}+1), \bar{\gamma}$ represents the average SNR of the fading channel.[27] In the consensus based scenario, we assume that n SUs cooperate with each other. The i[th] secondary user detects the signal and obtains the measurement y. The derivation from[27] shows that $E[\Lambda_g \mid H_0]$ and $E[\Lambda_g \mid H_1]$ and 2m + η respectively; each secondary user can estimate the average SNR from recent measurement as [28]:

$$\bar{\gamma}_i = \frac{1}{2l} \sum_{j=k-l}^{nk} (Y_{i,j} - 2m) \tag{7}$$

Where $Y_{i,j}$ is the j^{th} measurement of the ith SU and l is the estimation window.

Network Model and Consensus Notions

In the second stage, SUs establish communication links with their neighbors to locally exchange information among them and adopt the consensus iteration to obtain the global measurement statistics. The network formed by secondary users can be described by a standard graph model $\mathcal{G} = (\varepsilon, \mathcal{V})$ consisting of a set of nodes $\mathcal{J}$ = {1,2..... n} for the SU network formed by n SUs [13]. Denote each edge as an unordered pair *(i,j)*. Thus, if two secondary users are connected by an edge, it means that they can mutually exchange information. We define an edge set $\varepsilon = \{e_{ij} = (v_i, v_j) \mid i, j \in \mathcal{J}\}$.The set of neighbors of node *i* are denoted as $N_i = \{j \mid e_{ij} \in \varepsilon\}$. The number of elements in *Ni* is denoted by |*Ni* |and called the degree of node *i*. A path in *G* consists of a sequence of nodes $v_1, v_2, \ldots, v_l, l \geq 2$ such that $(e_m, e_{m+1}) \in \varepsilon$ for all 1 ≤ m ≤ *l* - 1. The graph G is connected if any two distinct nodes in G are connected by a path. For convenience of exposition, we use node and SU alternatively. We refer to v_i, v_j as the tail and head of the directed edge $e_{ij} = (v_i, v_j)$, which represents the unidirectional communication link between two neighboring SUs. A digraph is considered strongly connected if it is possible to reach any node starting on any other node following the edge directions.[14]

Let $\mathcal{G}_i = (\varepsilon_i, \mathcal{V}), i = 1, \ldots, r,$ denote a finite collection of graphs with common vertex set $\mathcal{V}$. Their union is a graph with common vertex set and an edge set that is the union of the $\varepsilon_i S$, ie., $\mathcal{G} = U^r_{i=1}\mathcal{G}_i = (U^r_{i=1}\varepsilon_i, \mathcal{V})$. The set of undirected graphs $\{\mathcal{G}_1, \ldots, \mathcal{G}_r\}$ is called jointly connected if their union is a connected digraph. In the consensus based spectrum sensing context, for the *n* SUs modelled by the graph $\mathcal{G}$, the i[th] secondary user is assigned a state variable $x_i, i \in \mathcal{J}$. Each xi will be called a consensus variable, it is used by node i for its measurement statistics of the OFDM scheme. The system reaches consensus when the individual state xi asymptotically converges to a common value x*, i.e.,

$$x_i(k) \longrightarrow x^* \text{ as } k \longrightarrow \infty, \forall\, i \in \mathcal{J}$$

where, k is the discrete time step, k = 0,1, 2;..., and $x_i(k)$ is updated based on the previous state of node i and its neighbors.[13]

Spectrum Sensing Based on Weighted Average Combining Consensus

In this section, we present a consensus-based distributed scheme to achieve the weighted combining through local interactions among SUs, instead of processing the measurements in the centralized FC. Following the notation of consensus [14], we denote the value of the i[th] agents measurement Yi as xi, and the proposed weighted average combining consensus based combining scheme is shown as

$$x_i(k+1) = x_i(k) + \frac{\epsilon}{\sigma_i} \sum_{j \in N_i} \Big(x_j(k) - x_i(k)\Big), i \in \mathcal{J} \tag{9}$$

where, ϵ is the iteration step size satisfying the maximum noise degree constraint [13] and $\sigma_i \geq 1$ is the weighting ratio. In cooperative spectrum sensing, weighted combining is a scheme to improve the detection performance.[24] The global decision statistics Y_g is from the weighted sum of the n local measurements.[28]

$$Y_g = \sum_{i=1}^{n} \omega_i Y_i, \tag{10}$$

Y^i is the non-quantized output of the detectors of the i[th] SU, and ω_i is the related weight. In shadowing and fading channel environment, some nodes will have a better location dependent SNR than others. A simple way for gaining from this diversity is setting the weight ω_i directly from the estimated average SNR as [28]:

$$\omega_i = \frac{\bar{\gamma}_i}{\sum_{i=1}^{N} \bar{\gamma}_i} \tag{11}$$

This results in a high weight for SU nodes with a high SNR and low weight for SU with low SNR. Accordingly, we chose the ratio σ_i as:

$$\sigma_i = \begin{cases} \bar{\gamma}_i, & \bar{\gamma}_i \geq 1 \\ 1, & \bar{\gamma}_i < 1 \end{cases} \tag{12}$$

$\bar{\gamma}_i$ is obtained from (7) and saturation is used to ensure σ_i 1 for all i. Then the decision value of the consensus algorithm is equal to

$$x_i(k) \longrightarrow x^* = \frac{\sum_{i=1}^{n} \bar{\gamma}_i x_i(0)}{\sum_{i=1}^{n} \bar{\gamma}_i} \tag{13}$$

Finally, by combining the decision value x* with the threshold η, every secondary user obtains the global decision.[14]

$$H = \begin{cases} 1, & x_i = x^* > \eta \\ 0, & \text{otherwise} \end{cases} \tag{14}$$

Simulation and Results

Sensing Stage

In this section, we investigate by Monte-Carlo simulation the performance of the distributed weighed consensus based cooperative spectrum sensing using OFDM. We start by simulating the OFDM spectrum sensing detector in terms of probability of detection versus SNR for different detection time.The OFDM signal is modulated with 16-QAM with Nd subcarriers and a CP length of Nc, and the wireless channel is an additive white Gaussian noise channel. We assume the length of the observation window $L = K(N_d + N_c) + N_d$ where $N_d = 32$, $N_c = N_d/4 = 8$, and different values of OFDM blocks K changed from 200 to 800. From Fig. 3. We observe that by increasing the the number of OFDM symbols and increasing the detection time we get higher probability of detection and the detector sensitivity improves. However, there is a tradeoff between sensing time and the probability of detection, since a long sensing time keeps the PU safe from interference because there will be less time for the SU to access the PU band. On the other hand, a short sensing time makes the PU more subject to interference and maximizes the probability of detection. Also, the detection time has direct impact on power consumption.

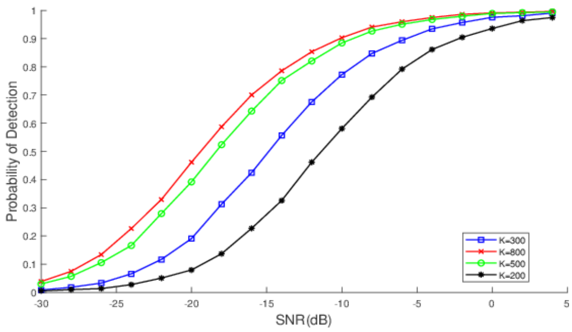

Figure 3.Probability of detection versus SNR of the proposed detector for different detection time

In Fig. 4, we show the performance limitation of energy detectors in the case of the SNR wall. A phe-nomenon which states that if the noise variance is not confined to an exact interval it is impossible for energy detectors to robustly distinguish the signal from noise when the SNR falls below a certain value, even if the sensing time tends to infinity. In the real environment, The presence of thermal noise and noise due to trans- missions by other users make the knowledge about the exact noise power impossible.[12]

Cooperative Consensus Algorithm

In the second stage, we also conduct a Monte Carlo simulation for the cooperative weighted average con-sensus algorithm and compare it to the existing model.[14] We use a 10 node network topology where the SUs cooperating with each other form a communication graph as shown

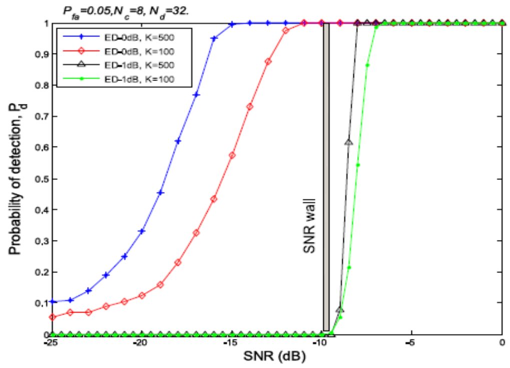

Figure 4.Probability of detection versus SNR of the energy detector with and without noise power uncertainty

in Fig. 5. We assume that all secondary users experience independent and identically distributed Raleigh fading. From the sensing stage, we get the output, Y_i, of every secondary user using the OFDM scheme. Each SU estimates the average SNR $\bar{\gamma}_i$ from (??) with m = 6 and Є = 0.19. The final decision is made after the consensus result x^* is reached.[14]

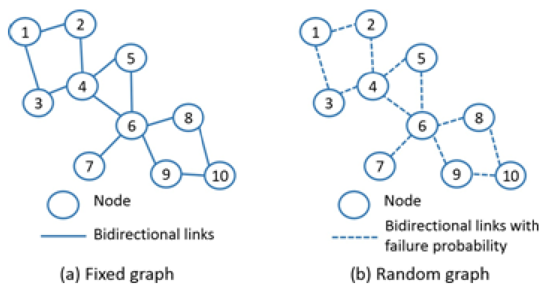

Figure 5.Network topology with ten secondary users

Fig. 6 shows the convergence of the proposed algo- rithm under fixed communication graph topology. We have found that within 10 steps the consensus has been reached on the global decision statistics. Fig. 7 shows the convergence of the proposed algorithm, under a random communication graph topology with independent link failure. We set the failure probability of each link to 0.4. We observed that within 18 steps consensus has been reached, which is slightly slower than the fixed graph case.

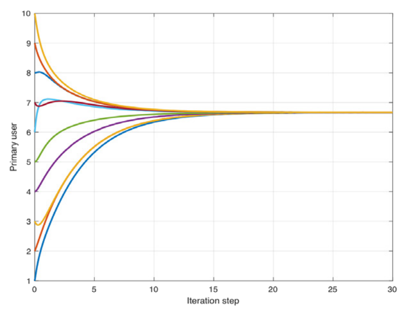

Figure 6.Convergence of the network with a 10-node fixed graph

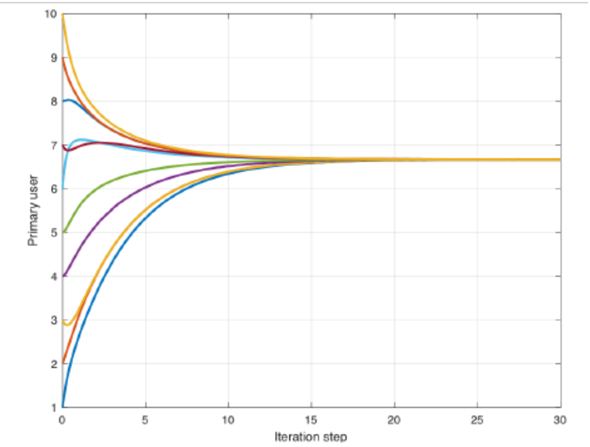

Figure 7.Convergence of the network with a 10-node fixed graph

Under the bidirectional communication link condition, for fixed topology shown in Fig. 5, we denote our results as OFDM weighted gain combining (OFDM-WGC), de- note the results in [14] weighted gain combining (WGC), and denote the results from [13] as equal gain combining (EGC).

For comparison, we mainly consider probability of detection P_d, probability of false alarm P_f, and average SNR $\bar{\gamma}$. The tradeoff between P_d and P_f indicates that a low P_d will result in missing detection of primary users with high probability, which in turn increases the interference to primary users. On the other hand, a high P_f will result in low spectrum utilization as false alarms increase the number missed opportunities (white spaces). Also, P_f is independent of $\bar{\gamma}$ since there is no primary signal under H_0.

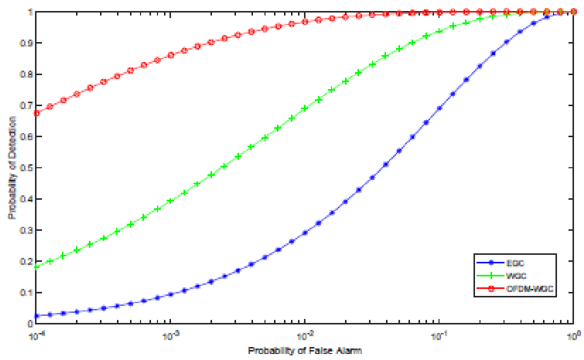

Figure 8.Receiver operating characteristic under i.i.d Rayleigh fading

Fig. 8 shows the receiver operating characteristic (ROC) of the three schemes in each secondary users measurement. We can clearly see that the performance has significantly improved by our proposed OFDM weighted gain combining (OFDM-WGC) scheme, com- pared to both WGC and EGC schemes. The proposed OFDM-WGC scheme achieves a satisfactory perfor- mance; when the false alarm is set to 10−2 the detection probability reaches 0.9, while both WGC and EGC are still below 0.5.

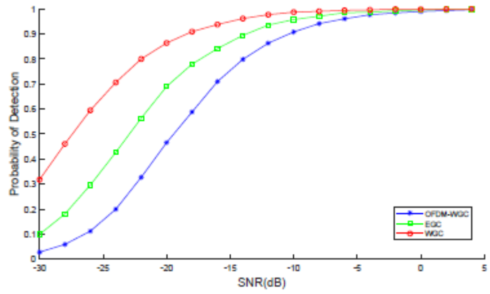

Figure 9.Detection probability with respect to average SNR under i.i.d Rayleigh fading

Fig. 9 shows the detection probability curves with respect to the average SNR when P_f is 0.005. We can see that when the average SNR is below 5 dB, our future scheme OFDM-WGC achieves much better act than the WGC and the EGC. When the average SNR is higher than 5 dB the performance of the three schemes becomes much closer together.

Conclusion

Existing cooperative spectrum algorithms use energy detection for PU sensing. Despite the wide usage of energy detection for PU sensing in cooperative spectrum algorithms, they are incapable of detecting a PU signal below a minimum SNR, regardless of the duration of detection time. In the presence of noise uncertainty, it is impossible to robustly distinguish the signal from noise at SNR values lower than the SNR wall, even if the sensing time tends to infinity. The method proposed here uses CS detection models that are robust to random noise at the cost of high computational complexity and long sensing times, the OFDM fast spectrum sensing algorithm focuses on the sensing of OFDM signals by exploiting only the stationary part of the periodic autocorrelation function, which significantly simplifies the detector design. Furthermore, implementing a de- centralized cooperative weighted system will result in a significantly lower miss detection and probability of false alarm. Simulation results have been presented to show that our approach outperforms the existing work with en- ergy detection under low SNR measurement conditions. Future work will pursue analyzing CS detection at the network level by studying the throughput performance.

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