

Advanced Sensing Techniques of Energy Detection in Cognitive Radios

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(Invited Paper)

Abstract: Recently, spectrum sensing has been intensively studied as a key technology in realizing the cognitive radio. There have been advances in the performance of spectrum sensing through both multi-antenna and cooperative sensing schemes. In this paper, the performances and complicated scenarios of the latest spectrum sensing schemes are analytically compared and arranged into a technical tree while considering practical concerns. This paper will give a macroscopic view of spectrum sensing and will also provide insight into future spectrum sensing works.

Index Terms: Cognitive radio, cooperative sensing, multi-antenna sensing, spectrum sensing.

I. INTRODUCTION

Research has been performed on efficient spectrum usage since it was reported that considerable licensed spectra exclusively allocated to conventional wireless communication systems have been under-utilized [1]. For efficient spectrum utilization, the cognitive radio will mostly likely be the most promising technology due to its inherent spectrum sensing capability and frequency-agile radio functions [2]. Spectrum sensing has the especially important missions of finding the white space of licensed spectra and protecting the primary licensed users from interference caused by cognitive radio communications. Accordingly, spectrum sensing has been widely researched as a key technology for allowing cognitive radio communication within the real world.

Spectrum sensing can be performed by various detection techniques using a matched-filter [3], [4], a statistical feature of the primary signal [5], [6], called feature detection, and a simple energy measurement [7]–[34]. Although the first two detection techniques outperform the energy detection technique, they require prior information about the primary signals, and have a primary system-dependent performance. Heterogeneous wireless communication systems licensed to different primary spectra may overlap within a geographical region. In such circumstances, matched-filter detection or feature detection are too costly for sensing multiple primary spectra, while energy detec-

tion can operate with no prior information about primary signals. Accordingly, only the energy detection technique corresponds to the general purpose of spectrum sensing for heterogeneous wireless communication systems. That is why energy detection is the most intensively investigated sensing technique and is also the focus of this paper.

In general, for the purpose of protecting primary users from the interference caused by secondary communication, cognitive radios are operated in a geographical far distant from the primary system. Hence, the primary signal is received by the secondary sensing node in a low signal-to-noise-ratio (SNR) region below zero decibel where energy detection is very poor [14], [18]. A failure in spectrum sensing means a missed opportunity for secondary users to utilize the white space of the spectrum or harmful interference to the primary users. Therefore, sensing performance enhancement should be required for both increasing the throughput of the secondary users and also for protecting the primary users from unintended interference.

The sensing performance enhancement of energy detection can be achieved by using multi-antennas at the sensing node [14]–[17] or by cooperation between sensing nodes [18], [19]. Advances in multi-antenna and cooperative sensing are reviewed and in this paper. The aim of this study was to provide a macroscopic view of spectrum sensing, especially with energy detection, in the cognitive radio. In order to do so, a generalized sensing performance evaluation is given first, which allows for greater understanding of the multi-antenna and the cooperative sensing performances. For multi-antenna sensing techniques, the performances were analyzed and compared in consideration to practical problems. For cooperative sensing, complicated scenarios and practical considerations were arranged into a technical tree in order to describe the technique in general. The relationship between branches is also discussed in detail. Finally, a summary describes the overall structure of the research performed on the performance enhancement of energy detection. Also, technical challenges for spectrum sensing are discussed for future consideration.

The rest of this paper is organized as follows: Section II defines common terminologies and introduces scenarios within general spectrum sharing; Section III provides a general performance evaluation of energy detection, Section IV analyzes and compares the first methodology, or multi-antenna sensing techniques, that is used for enhancing the energy detection's sensing performance, Section V provides a technical tree expressing various cooperative sensing techniques, and, lastly, Section VI summarizes the study.

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II. PRELIMINARY OF SPECTRUM SHARING

Before we investigate the advances in spectrum sensing, spectrum sharing environments are categorized into several groups, and the terminology used for each scenario is summarized. The aim of this section is to give a general overview of spectrum sharing environments.

A. Open Spectrum Sharing

The spectrum sharing environment is classified first due to the existence of access priorities among heterogeneous systems within a spectrum. If every system has the same priority for accessing the spectrum resource, it is referred to open spectrum sharing (OSS) [35]–[37].

In OSS, heterogeneous systems with different channel bandwidth sizes co-exist in a common spectrum without any centralized coordinations. Hence, a distributed coordination used in managing the interference and fair access opportunities is required and is called spectrum access etiquette in OSS [38].

For example, if a system with a large bandwidth channel too frequently accesses the open spectrum or occupies it for a long time, it is difficult for other systems to get an opportunity to communicate in the spectrum. For fair spectrum sharing, the traffic arrival rates of systems with different channel bandwidths should be differentiated [35], [36]. For the same purpose, the spectrum sensing threshold control is proposed in [37]. In OSS, a system should check the spectrum availability through spectrum sensing before it starts to transmit a signal. In this literature, the sensing threshold value to detect the vacancy of a frequency channel is set at higher value for a system with a wider channel bandwidth. Therefore, the access opportunities between systems with different channel bandwidths are balanced.

Open spectrum sharing scenarios have been developed primarily for the industrial, scientific and medical (ISM) radio bands [35]–[37]. Recently, the OSS-operated radio frequency has been extended to include licensed spectra for the purpose of utilizing multi-mode terminals and inter-operability between legacy wireless communication systems [39]. In such circumstances, frequency resources belonging to various systems compose a spectrum pool. An end-user terminal can dynamically access the spectrum pool with different radio resource units depending on its application QoS and traffic condition of each system. Accordingly, the term ‘dynamic spectrum access’ is used for this category of spectrum sharing.

B. Hierarchical Spectrum Sharing

The most differentiated feature of hierarchical spectrum sharing from OSS is that there is an access priority between the primary and secondary systems. What we call the primary system is a legacy system operating in a licensed spectrum and its end-user terminals. Although the licensed spectrum is exclusively allocated to a primary system, secondary systems are allowed to use the spectrum because of the considerable amount of unused licensed spectra within time and space [1].

In order to share the primary spectrum, a secondary system should not impart any harmful interference upon the primary communication. According to how the harmful interference is

defined, hierarchical spectrum sharing is divided into two categories: Underlay and overlay spectrum sharing.

B.1 Underlay Spectrum Sharing

In underlay spectrum sharing, if the interference caused by the secondary communication is received by the primary receiver under a predetermined threshold, the interference is treated as harmless. Therefore, while the harmless interference condition is maintained, a secondary transmitter is permitted to transmit its signal even if the primary link is communicating. This category is interestingly termed ‘spectrum sharing.’

In order to satisfy the interference constraint condition, the secondary transmitter must possess information about the interference channel gain between the secondary transmitter and the primary receiver [40]. Hence, channel estimation using a known signal and a feedback process between a primary receiver and a secondary transmitter should be required with an extremely high accuracy for the interference channel measurement¹. In order to realize this, the secondary user should equip a dual-mode system as follows: one is for the secondary communication and the other for the interference measurement and feedback between the secondary transmitter and the primary receiver.

Although indirect interference channel measurement schemes are presented in [41] and [42], they cannot provide an accurate interference channel measurement for fading environments. Therefore, developing effective schemes for interference channel measurement and feedback may be a bottle neck for the practical implementation of the underlay spectrum sharing scenario.

B.2 Overlay Spectrum Sharing

Different from the underlay spectrum sharing scenario, the secondary transmitter may send a signal to a secondary receiver only for a time period called the idle period, when the primary communication is inactive. In order to detect the idle period of a primary spectrum, spectrum sensing is the most important functionality in realizing overlay spectrum sharing. According to the amount of required prior information about the primary systems, spectrum sensing techniques are divided into three types, as depicted in Fig. 2.

Matched filter detection: It is widely known that the detector using a matched filter is able to achieve the optimum performance when a secondary sensing node can perform a coherent detection of the primary signal [3], [4]. However, in order to use the matched filter within spectrum sensing, the secondary sensing node must be synchronized to the primary system and must even be able to demodulate the primary signal. Accordingly, the secondary sensing node has to have prior information about the primary system such as the preamble signaling for synchronization, pilot patterns for channel estimation, and even modulation orders of the transmitted signal, et cetera.

Nowadays, heterogeneous wireless communication systems licensed to different primary spectra may overlay one another in a geographical region. In such circumstances, idle periods may

¹Under-estimated channel gain value increases the secondary transmission power, resulting in harmful interference to a primary receiver. An over-estimated channel gain value decreases the secondary transmitter power, which satisfies the interference constraint condition, but decreases the secondary link throughput.

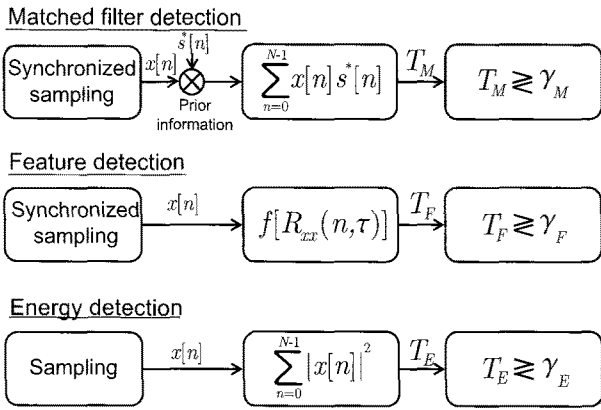


Fig. 1. Three types of spectrum sensing techniques: Only energy detection requires no prior information about the primary signal.

dynamically occur in multiple primary spectra. Therefore, in order to sense the multiple primary spectra, it is necessary to require that the secondary primary spectra, it is necessary to require that the secondary sensing node have receiver functions for use in multiple primary systems and to be prepared to suffer from demodulation complexity. Because of this, the matched-filter sensing solution is too costly for sensing multiple primary spectra.

Feature detection: The feature detection technique exploits the statistical feature built into a primary signal. Generally, the background noise and interference do not correlate to time or frequency domains. Hence, if the secondary user has statistical information about the correlation feature of the primary signal, it can increase sensing accuracy [5], [6]. For instance, the Gaussian minimum shift keying (GMSK) used in the Global System for Mobile Communications (GSM) network has inherent cyclostationarity, so that the secondary user can effectively detect the GSM signal by using it. However, this feature detection can only be applicable for few primary signals with such characteristics and requires an increase in cost and complexity for the time shift correlation process and frequency-domain transformation, respectively [44].

Energy detection: While the matched filter and feature detection capabilities require prior information about primary signals, no primary signal information is required for the energy detection technique. As depicted in Fig. 2, the only process required for the energy detector is that the primary signal energy is able to be measured within a specified duration. Next, the detector simply determines whether or not the measured signal energy is over the predetermined threshold level. When considering the general purpose of spectrum sensing with low complexity, the energy detection technique is decidedly the most feasible spectrum sensing scheme for detecting the white space of multiple primary spectra licensed to heterogeneous wireless communication systems. This explains why this paper focuses on spectrum sensing using energy detection. However, because energy detection has poor performance in comparison to matched filter and feature detections, research conducted on enhancing the performance of energy detection has been the most intensively studied research topic in the spectrum overlay scenario. In order to enhance the performance of energy detection, a number of spectrum sensing schemes using multi-antenna and coopera-

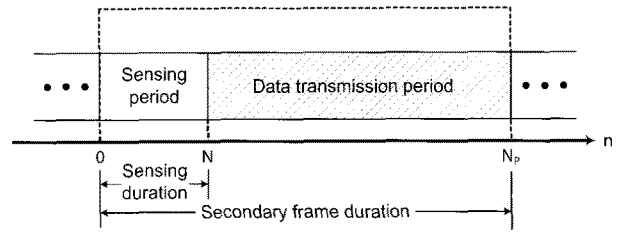


Fig. 2. Sensing and transmission structure for energy detector.

tion between secondary sensing nodes have been developed [7]–[34], and it is challenging to provide a macroscopic view of the conventional works.

III. GENERALIZED PERFORMANCE OF ENERGY DETECTOR

This section firstly provides a generalized system model for spectrum sensing as well as evaluating the energy detector's performance in terms of detection and false alarm probabilities. The generalized energy detection performance dealt with in this section is the basis for the technical comprehension of the advanced energy detection techniques such as multi-antenna spectrum sensing and cooperative sensing as discussed in Sections IV and V, respectively.

A. System Model for Spectrum Sensing

According to the basic concept of overlay spectrum sharing, the secondary user should sense the existence of the primary signal within the licensed spectrum prior to the secondary transmission. Based on this principle, each secondary transmission frame duration is divided into a sensing period and a data transmission period, as shown in Fig. 2. Sensing duration N is defined as the length of the sensing period in which the secondary user ceases transmission and then senses the primary spectrum. If any primary user signal is detected during the sensing period, the secondary user stops the transmission until the primary user signal is again undetectable. Otherwise, if no primary user signal is detected, the secondary user continues transmission during the data transmission period.

Apparently, longer and frequent sensing periods improve sensing performance but shorten the data transmission period. Conversely, shorter and more sporadic sensing periods degrade sensing performance but lengthen the data transmission period. Hence, there is a tradeoff between sensing performance and secondary user throughput. Using this tradeoff, throughput optimization of sensing duration [7] or secondary frame duration [8] has been attempted. However, this study concentrates on the ways of improve sensing performance under the assumption of a fixed sensing duration and period by introducing a variety of traditional and newly developed detection techniques.

B. Sensing Performance

Two hypotheses are related to the detection of primary user signals: The null hypothesis \mathcal{H}_0 and the alternative hypothesis \mathcal{H}_1 . \mathcal{H}_0 describes a situation in which a primary user signal does not exist in the primary spectrum, and \mathcal{H}_1 expresses the case

in which a primary signal does exist. The objective of energy detection is to estimate which hypothesis is more credible and to decide whether \mathcal{H}_0 or \mathcal{H}_1 is correct by measuring the energy.

The sensing performance of the energy detector can be evaluated via two general performance metrics: The false alarm probability P_{FA} and the detection probability P_D . A false alarm event occurs when the energy detector decides upon \mathcal{H}_1 when the correct decision is \mathcal{H}_0 , the probability of which is defined as the false alarm probability. When a false alarm happens, the secondary user does not exploit the spectrum which is actually empty, and loses an opportunity to transmit its data. Hence, the lower the false alarm probability, the higher is the throughput of the secondary user. On the other hand, the detection probability is defined as the probability of the energy detector making a correct decision for \mathcal{H}_1 . If the detection fails, or a “miss detection” occurs, the secondary user starts an undesirable transmission in the primary spectrum where the primary user is also transmitting, and, therefore causes a strong interference with the primary user signal. This degrades the signal quality of the primary communication and violates the fundamental doctrine of overlay spectrum sharing. Therefore, when the detection probability is higher, it is then possible to provide enhanced protection for the primary user.

However, there is a tradeoff relationship between the spectrum usage efficiency (i.e., the false alarm probability) and the sensing performance (i.e., the detection probability). As illustrated in Fig. 3, although the proportion between the false alarm probability and the detection probability can be adjusted via threshold control, it is not possible to simultaneously attain a low false alarm probability and a high detection probability or a low miss detection probability, as long as the probabilistic characteristics of the received signal are fixed. In order to enhance the sensing performance, the probability density function (PDF) of each hypothesis should be steepened or the distance between two PDFs needs to be lengthened. This can be accomplished via two methods as follows: 1) Intensifying the received SNR of the primary user measured at the secondary user or 2) increasing the *dimension* or *degree-of-freedom* of the received signal space.

Intensifying the received SNR is very challenging within a practical situation, due to noise uncertainty, shadowing, and multi-path fading, whose effects are neither predictable nor able to be compensated for [9]. Thus, we focus upon increasing the degree-of-freedom of the received signal space. If the secondary user receives an increased number of observation samples, they are combined into an aggregated observation and the final decision can be made with more reliability. The sources for degree-of-freedom are mainly time and space. If the secondary user sums N samples of received energy within a sensing period, as depicted in Fig. 2, we obtain N degree-of-freedom in the time domain. However, as N increases, the time fraction that the secondary user can effectively use for data transmission decreases and, hence, restricts the increased use of the degree-of-freedom within the time domain.

Therefore, the degree-of-freedom of the sensing signal space should be expanded into the spatial domain. For practical situations, if the secondary user is equipped with M antennas or M secondary users are engaged in cooperative sensing, we have an opportunity for exploiting M degree-of-freedom within the

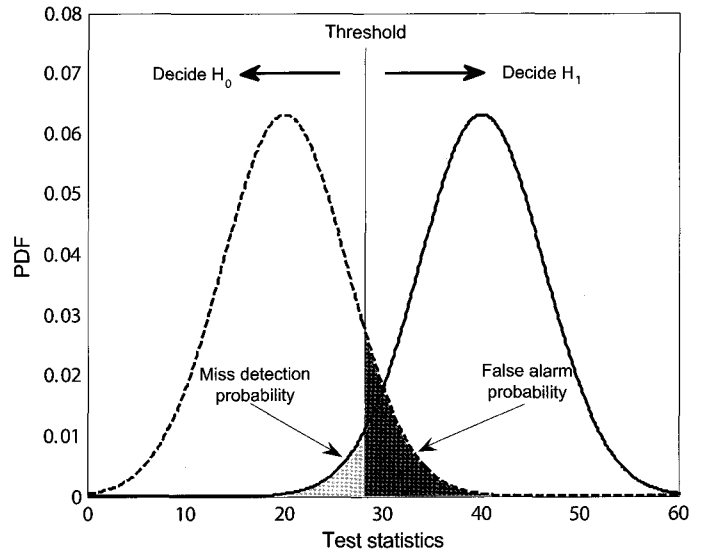


Fig. 3. PDF of test statistics. Miss detection and false alarm cannot be reduced simultaneously.

spatial domain. As a simple and basic sensing scenario, it is assumed that M nodes are located at spatially independent positions, so M degree-of-freedom can be fully exploited during the energy detection process, which will provide a performance basis to compare with the sensing performance in the correlated channel between antennas or adjacent sensing nodes in multi-antenna sensing and cooperative sensing, respectively.

For a given degree-of-freedom obtained from M nodes and a sensing duration of N samples, suppose $x_m(n)$ is the received signal at the m -th sensing node and $s(n)$ is the common primary user signal that we wish to detect. The signal $s(n)$ is transmitted over a fading channel whose gain is $h_m(n)$ and then corrupted by the noise $w_m(n)$. In this case, the detection problem is formulated as:

$$\begin{aligned} \mathcal{H}_0 : x_m(n) &= w_m(n) \\ \mathcal{H}_1 : x_m(n) &= h_m(n)s(n) + w_m(n) \end{aligned} \quad (1)$$

for $m = 1, 2, \dots, M$ and $n = 1, 2, \dots, N$. The signal $s(n)$ is assumed to be phase-shift keying (PSK) modulated with the received signal power P . The channel gain $h_m(n)$ follows an independent and identically distributed (i.i.d.) Rayleigh fading channel, i.e., $h_m(n) \sim \mathcal{CN}(0, \sigma_h^2)$. The noise $w_m(n)$ is an i.i.d. zero-mean, complex-valued additive white Gaussian noise (AWGN), i.e., $w_m(n) \sim \mathcal{CN}(0, \sigma_w^2)$.

As mentioned before, we employed an energy detector, which combines the measured energy during the sensing duration along the sensing nodes. Assuming each node and each sample is independent, the energy is combined with equal gain. The decision rule can be written as:

$$T = \sum_{n=1}^N \sum_{m=1}^M |x_m(n)|^2 \underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\gtrless}} \eta \quad (2)$$

where T is the test statistic for the binary hypothesis test and η is the threshold [10]. In order to derive the false alarm and detection probabilities, the probabilistic characteristics such as

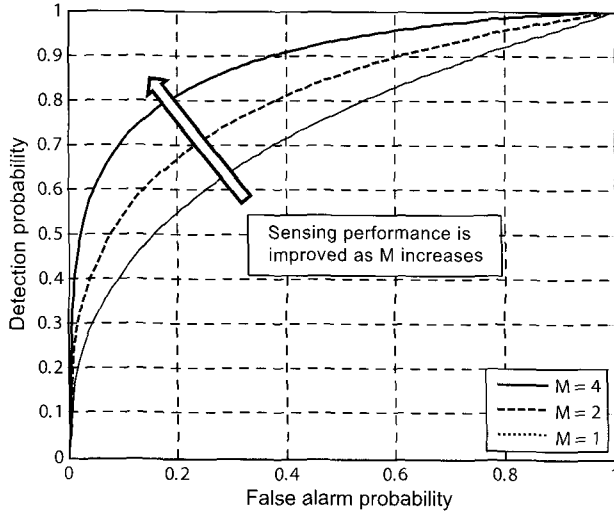


Fig. 4. Relation between detection probability and false alarm probability ($\gamma = -5$ dB, $N = 10$).

the PDF of the test statistic are first developed for both \mathcal{H}_0 and \mathcal{H}_1 . T is the sum of the squared Gaussian random variables and follows a Chi-squared distribution with a degree of freedom of $2MN$. When assuming sufficiently high degree of freedom, the Chi-squared distribution approaches the Gaussian distribution by the central limit theorem (CLT) [11]. According to the CLT, the detection problem (1) can be rewritten as:

$$\begin{aligned} \mathcal{H}_0 : T &\sim \mathcal{N}(MN\sigma_w^2, MN\sigma_w^4) \\ \mathcal{H}_1 : T &\sim \mathcal{N}(MN(P\sigma_h^2 + \sigma_w^2), MN(P\sigma_h^2 + \sigma_w^2)^2). \end{aligned} \quad (3)$$

Using the probabilistic model in (3), we can obtain detection probability P_D and the false alarm probability P_{FA} . P_D and P_{FA} have the following relationships [12], [13]:

$$\begin{aligned} P_D(M) &= Q\left(\frac{1}{1+\gamma}(Q^{-1}(P_{FA}) - \sqrt{MN}\gamma)\right) \\ P_{FA}(M) &= Q(\sqrt{MN}\gamma + (1+\gamma)Q^{-1}(P_D)) \end{aligned} \quad (4)$$

where $Q(\cdot)$ is the tail probability of the Gaussian distribution and $\gamma = P\sigma_h^2/\sigma_w^2$ is the SNR of the primary user measured at the secondary sensing node.

The above relationship between the detection and false alarm probabilities is depicted in Fig. 4. We assume a very low SNR for the primary user: $\gamma = -5$ dB, which is necessary in order to detect the primary user even when the signal experiences deep fade. The sensing duration is fixed to $N = 10$ samples. Due to the intrinsic tradeoff between the two performance metrics, it was already shown that achieving higher detection probability and low false alarm probability is difficult. If the detection probability increases, then the false alarm probability also increases.

The sensing performance curve is shifted in the direction of improving both performance metrics only when the additional degree of freedom is achieved. In Fig. 4, as the degree of freedom M increases, the detection probability increases while the false alarm probability decreases without sacrificing any other metrics such as secondary user throughput. With this in mind, we investigate how to achieve an additional degree of freedom

in spectrum sensing, accomplished by equipping multiple antennas with a secondary user or cooperating with neighboring nodes by exchanging sensing information.

IV. SENSING WITH MULTI-ANTENNA

Spectrum sensing schemes exploiting multi-antenna setups are investigated in [13], [14]–[16]. Ideally, it can be assumed that the channels for each antenna are faded independently, and the performance of the multi-antenna-aided spectrum sensing is largely identical to the result in (4).

Taking advantage of different fading channels for multiple antennas, the maximum-ratio-combining (MRC) or antenna selection increases the spectrum sensing performance [14]. However, the secondary user utilizing energy detection cannot coherently receive the primary signal due to unavailability of the primary signal information, including the modulation technique, pilot signaling and so on. Hence, unfortunately, any schemes requiring the channel measurements cannot be practically implemented with the energy detector scheme.

In order to evaluate the practical performance of multi-antenna-aided spectrum sensing, one more thing that we should discuss is the correlation between antennas. As intuitively expected, the sensing performance becomes degraded as the correlation between antennas increases. In IEEE 802.22 wireless rural area network (WRAN), the secondary WRAN system should be located outside of the keep-out region which is set for protecting the primary users. The radius of the keep-out region is generally assumed to be over one hundred kilometers. Accordingly, such a large distance between the primary transmitter and the secondary user generates a small received-channel angular spread value, which results in a highly correlated channel between antennas at the secondary receiver [17].

A. Simple Energy Detection with Multi-Antenna

The performance of a simple energy detection that considers the correlated antennas is investigated in [13]. The detection problem (2) that considers the antenna correlation can be written as:

$$\begin{aligned} \mathcal{H}_0 : T &\sim \mathcal{N}(MN\sigma_w^2, MN\sigma_w^4) \\ \mathcal{H}_1 : T &\sim \mathcal{N}\left(MN(P\sigma_h^2 + \sigma_w^2), N \sum_{m=1}^M (P\sigma_h^2\lambda_m + \sigma_w^2)^2\right) \end{aligned} \quad (5)$$

where $\lambda_m, m \in 1, 2, \dots, M$ are the eigen-values of the following correlation matrix:

$$R_{ij} = \begin{cases} \rho^{i-j}, & i \leq j \\ R_{ji}^*, & i > j \end{cases}$$

$i, j = 1, 2, \dots, M$, and ρ ($0 \leq \rho \leq 1$) is the correlation between adjacent antennas.

From the detection problem in (5), we can calculate the detection and false alarm probabilities as follows:

$$P_{De}(M) = Q\left[\frac{(\eta_e - MN(\gamma + 1))}{\sqrt{N \sum_{m=1}^M (\gamma\lambda_m + 1)^2}}\right]$$

$$\begin{aligned}
P_{Do}(M) &= Q \left[\left(\eta_o - N \sum_{m=1}^M \gamma \lambda_m \right) / \sqrt{N \sum_{m=1}^M (\gamma \lambda_m)^2} \right] \\
P_{Fo}(M) &= Q \left[\left(\eta_o - N \sum_{m=1}^M \frac{\gamma \lambda_m}{\gamma \lambda_m + 1} \right) / \sqrt{N \sum_{m=1}^M \left(\frac{\gamma \lambda_m}{\gamma \lambda_m + 1} \right)^2} \right]
\end{aligned} \quad (9)$$

$$P_{Fe}(M) = Q \left[Q^{-1}(P_D) \sqrt{\frac{1}{M} \sum_{m=1}^M (\gamma \lambda_m + 1)^2 + \gamma \sqrt{MN}} \right] \quad (6)$$

where the decision threshold is determined as:

$$\eta_e = Q^{-1}(P_{De}) \sqrt{N \sum_{m=1}^M (\gamma \lambda_m + 1)^2 + MN(\gamma + 1)}. \quad (7)$$

B. Optimum Energy Detection with Multi-Antennas

In Section IV-A, the sensing performance of the simple energy detection was shown in a correlated channel. However, in a correlated channel, the optimum sensing performance can be achieved by the likelihood ratio test (LRT) [10]. In this case, the decision rule can be expressed as:

$$T = \sum_{n=1}^N \sum_{m=1}^M Y_m^H(n) Y_m(n) \underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\gtrless}} \eta_M^* \quad (8)$$

where $Y_m(n) = \frac{1}{\sigma_w} \sqrt{\frac{\gamma \lambda_m}{\gamma \lambda_m + 1}} u_m X(n)$, $m \in \{1, 2, \dots, M\}$ when $X(n) = [x_1(n), x_2(n), \dots, x_M(n)]$, and λ_m and u_m are the m -th eigenvalue and eigenvector of the antenna correlation matrix, respectively.

Applying the CLT to (8) for the same reason as in (3), the detection and false alarm probabilities can be calculated in (9) where the decision threshold is given as

$$\eta_o = Q^{-1}(P_{Do}) \sqrt{N \sum_{m=1}^M (\gamma \lambda_m)^2 + N \sum_{m=1}^M \gamma \lambda_m}.$$

C. Performance Comparison of Multi-Antenna Sensing Schemes

The sensing performances of the energy detection in (6) and the optimum detection in (9) are compared with that of single antenna case ($M=1$) in (4). For any values of M and γ , the following relationship can be determined:

$$\begin{aligned}
\lim_{\rho \rightarrow 1} P_{Do}(M) &> \lim_{\rho \rightarrow 1} P_{De}(M) > P_D(1) \\
\lim_{\rho \rightarrow 1} P_{Fo}(M) &< \lim_{\rho \rightarrow 1} P_{Fe}(M) < P_F(1)
\end{aligned} \quad (10)$$

where the number of antennas M is larger than one.

The first observation of (10) is that sensing with multiple antennas always outperforms sensing with a single antenna even if

channels between the antennas are highly correlated. There is another observation of (10) in that the optimum LRT detection outperforms simple energy detection in both the detection and false alarm probabilities in the correlated antenna case. The performance difference between them comes from the differently weighted matrices. In the optimum LRT detection, the weighted matrix is determined based on the antenna correlation while all spatial channels are equally weighted for the simple energy detection. However, additional complexity is required in order to calculate the weighted matrix in (8) via the optimum LRT detection.

For the case of $\rho = 0$, another relationship among the sensing performances in (4), (6), and (9) can be made as follows:

$$\begin{aligned}
\lim_{\rho \rightarrow 0} P_{Do}(M) &= \lim_{\rho \rightarrow 0} P_{De}(M) = P_D(M) \\
\lim_{\rho \rightarrow 0} P_{Fo}(M) &= \lim_{\rho \rightarrow 0} P_{Fe}(M) = P_F(M).
\end{aligned} \quad (11)$$

This result shows that if the correlation is very low, the sensing performance of the energy detection and the optimum LRT detection closely approaches the generalized sensing performance in (4). Therefore, in such a case, the energy detection is nearly the optimum. And, its sensing performance can be improved upon continuously as the number of antennas is increased.

V. COOPERATIVE SENSING

The energy detector is generally operated in a very low SNR region. Hence, if a signal from the primary transmitter is severely shadowed as well as faded, a secondary sensing node should experience difficulty in deciding whether the primary spectrum is unused or occupied by the primary system. From the small scale point of view, a spatially faded primary signal can be effectively sensed by using a multi-antenna. However, it cannot be the solution to the secondary sensing node which is located in a deeply shadowed geographical region from the primary transmitter, which can be overcome by cooperative sensing techniques.

Cooperative sensing takes advantage of geographical varieties of secondary sensing nodes which experience different channel conditions. As depicted in Fig. 5, spatially distributed sensing nodes measure the signal from the primary transmitter, and report the measurement results to the fusion center. The fusion center makes the final decision about the primary spectrum availability based on the collected measurement results. Therefore, even if some of the sensing nodes are shadowed from the primary transmitter, the sensing performance can be improved upon via the primary signal measurements of other unshadowed sensing nodes.

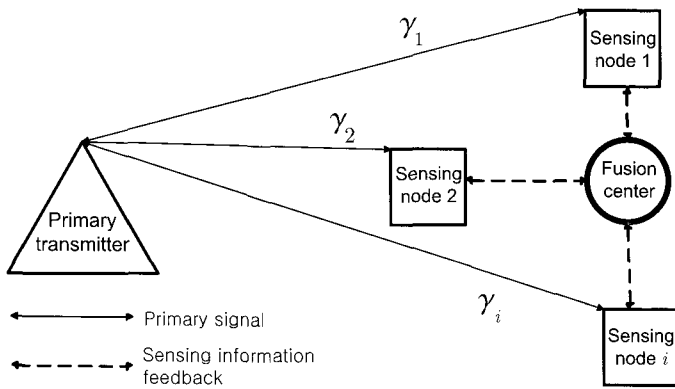


Fig. 5. Cooperative sensing.

Due to the simple system model of multi-antenna sensing, the performances of the multi-antenna sensing schemes can be clearly analyzed and compared using definite mathematical expressions from the previous section. However, for cooperative sensing, system models cannot be unified because there are too many variations in sensing scenarios. Correspondingly, a direct performance comparison between different schemes is usually unavailable since one cooperative sensing scheme solves a problem, but still requires additional problems to be solved by other proposed schemes.

In this situation, it is effective to attain insights within a technical area by arranging the conventional works as a technical tree, as is shown in Fig. 6. In this technical tree, cooperative sensing is categorized into two main branches: Cooperative sensing using soft-information and cooperative sensing using hard information. Each issue branches into performance evaluations and has its own practical problems and solutions.

A. Soft-Information Decision Fusion

In cooperative sensing techniques using soft-information, each sensing node reports its raw primary signal measurement in (1) to the fusion center. In this case, the index m in (1) denotes a secondary sensing node. If the local sensing information of M secondary users is perfectly delivered to the fusion center, the spectrum sensing performance of the secondary network is also exactly identical to the result shown in (4). However, there are a number of techniques that can enhance the cooperative sensing performance, as well as issues that should be considered for a practical implementation of the cooperative spectrum sensing in the real world.

A.1 Performance in a Correlated Channel

Similarly to the multi-antenna sensing performance with a correlated channel, the performance of cooperative sensing is degraded by secondary sensing nodes experiencing correlated shadowing [19]. For instance, if the distance between two adjacent secondary sensing nodes is between 40 and 80 meters, the correlation value between the two nodes is over 0.5 at 1.9 Ghz [45]. If cognitive radios intend to involve a small coverage network, cooperative sensing should be designed to reflect the correlation.

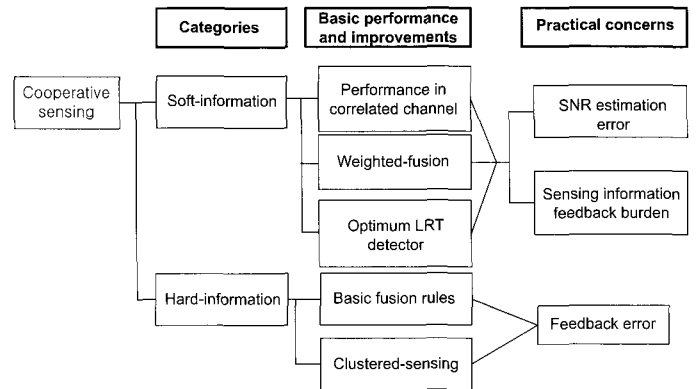


Fig. 6. Technical tree in performance enhancement of energy detector.

A.2 Weighted-Fusion

Sensing nodes should be located in geographically independent positions in order to avoid correlated channels. When considering such a case, the distance between the primary transmitter and each sensing node is different. Hence, as depicted in Fig. 5, the average SNR values γ_i of the measured primary signal at each sensing node are different. Intuitively, sensing information reported by a sensing node with a higher SNR from that of the primary transmitter provides more credits in determining the existence of the primary signal. Accordingly, in order to enhance the cooperative sensing performance, the sensing information from different sensing nodes are properly weighted and fused based on the SNR values of the received primary signal [20]–[22].

In [20], the performance of the optimum LRT detector is proposed in the same manner as the optimum LRT detector for the multi-antenna in the previous section, and evaluated. Using the LRT detector, the fusion center can reflect the different detection probabilities of sensing nodes with different average SNR values, and fuse the sensing information from a sensing node with a higher SNR, thus indicating more importance.

In [21], the average performance of cooperative sensing is evaluated with respect to location probability for uniformly distributed secondary sensing nodes. The LRT-based cooperative sensing performance should be evaluated differently according to channel model because the LRT detector directly uses the PDFs of the received primary signal at the sensing nodes. While the Chi-square distribution is assumed in [20] and [21], the case considering the log-normal fading model is dealt with in [22].

In [20], it is shown that the LRT-based cooperative detector outperforms the equal-gain-combining (EGC) detector in (1). However, there is a practical implementation difficulty of the cooperative sensing techniques using the LRT. In order to perform the LRT, the fusion center must have information about the channel model and the average SNR values between sensing nodes and the primary transmitter. Therefore, if the SNR values are not accurately estimated or the statistical characteristics of channel models are different from the actual values, the performance of the LRT-based cooperative sensing will be degraded. Accordingly, the performance of the LRT-based cooperative sensing needs to address the SNR-estimation errors.

A.3 Consideration of SNR-Estimation Errors

SNR-estimation errors can be generated by two main causes: The inherent estimator error and the inaccurate source samples for the estimator. When considering both causes, the performance degradation of cooperative sensing due to the SNR-estimation errors is analyzed in [23] assuming the finest SNR estimator with the Cramer-Rao-lower-bound performance, which shows that the required number of sensing nodes to satisfy a pre-determined sensing accuracy should be large depending on the SNR-estimation errors.

However, from a practical implementation point of view, most of the conventional SNR estimators might not be applicable to secondary sensing nodes performing the energy detection because they need some prior information about the primary signals such as coherent received signal sampling, the PDFs of the primary signals, or the Doppler shift of the primary signal's spectrum [46], [47]. As we know, the most favorable characteristic of the energy detector is that it requires no prior information about primary signals. Therefore, investigations on SNR estimators taking advantage of the statistical characteristics of the background noise floor² should become a key for practical implementations of cooperative sensing.

As an example for overcoming the SNR-estimation errors in cooperative sensing, a cooperative sensing scheme utilizing random matrix theory is proposed in [24]. In this approach, only the maximum and minimum eigenvalues of the covariance matrix, composed by collecting sensing information, are used to determine the existence of the primary signal. Therefore, the SNR-estimation process is not needed. Although this scheme requires additional computational complexity for calculating the eigenvalues, its performance is better than that of the EGC detector.

A.4 Sensing Information Feedback Problem

Since the sensing information from the sensing nodes is reported to the fusion center, additional radio resource consumed for reporting should be considered. Although the performance is generally improved upon as the number of cooperative sensing nodes increases, the amount of the sensing information feedback burden is proportional to the number of cooperative sensing nodes [25]. Therefore, the tradeoff between the overhead reduction for the sensing information reporting and the cooperative sensing performance needs to be an important design consideration.

In [25], the performance optimization in consideration of the tradeoff is analyzed. However, the objective function defined by a linear combination of the sensing performance and the sensing information feedback burden generates an ambiguous quantity³, hence it is difficult to apply when evaluating the performance of the cooperative sensing scheme. Accordingly, a more general framework is required in evaluating this tradeoff frame.

Alternatively, feedback information reduction schemes are investigated in [26] and [27]. In those papers, the soft information

of a secondary sensing node is quantized into two bits. In (1), the original detection problem results in binary states. However, in [26], the presence of the primary signal is expressed via four states as follows: Strong empty, weak empty, weak presence and strong presence. Because thresholds for the four states are given heuristically, this work shows that cooperative sensing with two-bit-quantized soft information can almost achieve sensing performance using perfect soft information. A more advanced soft information quantization scheme is proposed in [27]. This scheme also uses two bits for the soft information quantization. Different from [26], thresholds to divide the primary signal information into four states are analytically proposed considering probability distribution of the fading channel between the primary transmitter and the secondary receiver. Results of this work confirm that the sensing performance from the perfect soft information fusion can almost be achieved by only a two-bit-quantized primary signal strength level.

Another concern to the feedback problem is how to deliver the sensing information to the fusion center. So far there have been few scenarios for realizing the feedback information delivery. In [28], wireless local area network (WLAN) delivers the sensing information to the fusion center. However, WLAN has a very small coverage area with a radius of less than 15 meters. If cooperative sensing is operated in this small area, the sensing information between sensing nodes will experience a highly correlated shadow fading. Accordingly, in this case, it is difficult for the cooperative sensing to experience the gain of sensing performance from the geographical diversity of the secondary sensing nodes. In addition, the feedback can be transmitted using a spread spectrum transmission methodology without harmful interference to the primary system [29]. This kind of secondary transmission is known as underlay spectrum sharing, as classified in Section II. Above all, although the cognitive radio identifies and utilizes an empty spectrum for the secondary usage, it seems to be a paradox that we are able to tell that the legacy licensed systems needs to be used for sensing information reporting.

B. Hard-Information Decision Fusion

In cooperative sensing using hard-information decision fusion, a sensing node reports only binary state information to the fusion center. The binary state information is generated by each sensing node, which has its own local energy detector. Accordingly, the hard-information decision fusion requires minimized radio resource consumption for sensing information feedback. Generally, the performance of cooperative sensing using hard-information is worse than that using soft-information [20]. However, from a practical implementation point of view, cooperative sensing with hard-information is worth considering due to its minimized feedback burden.

B.1 Basic Fusion Rules

There are three decision fusion rules in cooperative sensing using hard-information: The AND fusion rule, the OR fusion rule and the majority fusion rule. The AND fusion rule declares the existence of the primary signal \mathcal{H}_1 if all sensing nodes report the decision state \mathcal{H}_1 . Using the OR fusion rule, \mathcal{H}_1 is true

²Statistical characteristics of the background noise floor are the only information used by the general energy detector.

³Generally, the sensing performance metrics such as detection or false-alarm probabilities can be expressed in percentile, and the amount of feedback information can be measured in bits per second. However, the linear combination of those two quantities is hard to express in a quantity unit.

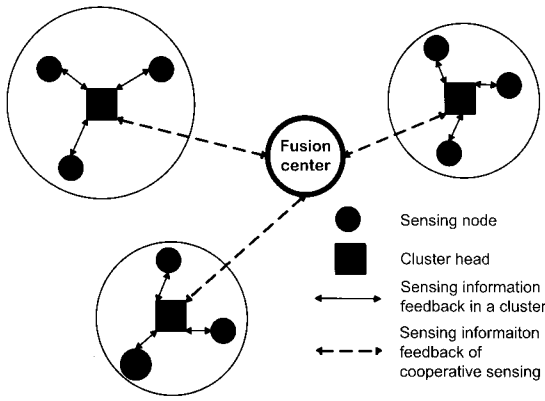


Fig. 7. Cluster-based cooperative sensing.

if \mathcal{H}_1 is reported by at least one sensing node. The fusion center adopting the majority rule decides upon \mathcal{H}_1 when the number of \mathcal{H}_1 results is larger than the number of \mathcal{H}_0 results. The majority fusion rule is considered as a simple suboptimal fusion rule [31]. The OR fusion rule performs best for detection probability, and the worst for false alarm probability. The AND fusion rule performs the worst in detection and false alarm probabilities, opposite that of the OR fusion rule.

B.2 Local Decision and Feedback Errors

In order to perform hard-decision fusion, each sensing node has a local energy detector for making its own decision. For the cooperative sensing, each sensing node has a different sensing accuracy because of the different geographical position of each sensing nodes with respect to the primary transmitter. Hence, local decision errors from sensing nodes with low SNR values from the primary transmitter degrade the sensing performance. It is pointed out in [32] that the sensing performance is not always improved upon when the number of sensing nodes increases in cooperative sensing using hard-information fusion. Therefore, only selected sensing nodes with SNR values over a predetermined threshold have to report their decisions while the unselected sensing nodes remain silent. From this fact, we can deduce that hard-information decision fusion is also not free from the SNR estimation between the primary transmitter and the sensing nodes, and the estimated SNR values should be delivered to the fusion center.

The feedback error of the sensing information may occur within cooperative sensing using hard information. In contrast to the soft information feedback error, the hard information may cause a totally opposite decision at the fusion center. Hence, the feedback error of hard-information degrades the sensing performance more severely in comparison with that of soft-information using cooperative sensing.

In hard-information decision fusion, the effect of feedback error on the sensing performance is investigated of [28]. According to the results in [28], the feedback error limits the sensing performance of hard-information decision fusion. Accordingly, it is suggested that diversity techniques, such as space time or frequency coding schemes, should be adopted for more reliable hard sensing information feedback.

B.3 Cluster-based Cooperative Sensing

Cluster-based sensing schemes have been proposed in order to utilize selection diversity in cooperative sensing using hard-information decision fusion. In cluster-based cooperative sensing, a whole sensing node is divided into several clusters. A cluster head exists in a cluster for collecting sensing information, as well as for reporting the collected information to the fusion center, as depicted in Fig. 7 [33], [34].

It is generally assumed that the cluster head and sensing nodes within a cluster are located in close proximity to each other. Hence, the wireless link between a cluster head and its sensing nodes is reliable enough for exchanging the sensing information without error. For the same reason, the radio resources consumed for exchanging sensing information within a cluster are minimized. Accordingly, the feedback burden for the sensing information delivery or the feedback error within a cluster are not research issues. However, we have to consider the same feedback error problem between the cluster head and the fusion center. Therefore, for enhanced performance of the cluster-based sensing scheme, we should be able to choose a cluster head that is able to make the most credible local decision and then report the local decision to the fusion center with the most reliable channel [33], [34].

Just as in [28], it is shown that the sensing information reporting error dominantly limits the performance of cluster-based sensing. In order to minimize the reporting error, a sensing node with the maximum SNR between the sensing node and the fusion center is elected as a cluster head. It is pointed out in [34] that a larger number of clusters or sensing nodes does not guarantee a more improved sensing performance. Based on the tradeoff between the sensing information reporting overhead and sensing accuracy, a cluster head selection scheme is proposed to enhance sensing performance. Subsequently, the optimum cluster number is analyzed in terms of the number of sensing nodes and the average SNR for them.

VI. SUMMARY AND DISCUSSION

This paper studied sensing performance enhancement techniques including multi-antenna sensing and cooperative sensing within cognitive radios. In order to clarify the overall relationship between them, a summary of this paper is given in Fig. 8. The whole spectrum sensing techniques introduced in this paper are divided into two categories: Sensing performance enhancements available in a single sensing node, and those achieved via cooperation between sensing nodes. Each category has elemental sensing techniques dealt with in detail as part of this paper.

Through reviewing a number of advanced sensing techniques, we were able to reach a conclusion that further investigations are needed for 'Intermediate Solutions' in the multiple sensing nodes cooperation category of Fig. 8. When developing more practical parameter estimation techniques, it might be possible to create a realizable sensing scheme which can closely achieve the optimum LRT performance. Based on our survey, one practical concern is raised for the practical implementation of cooperative sensing: The methodologies for sensing information exchange. Conventional scenarios for this seem unrealistic. In order to realize cooperative sensing, a multiplexing scheme and

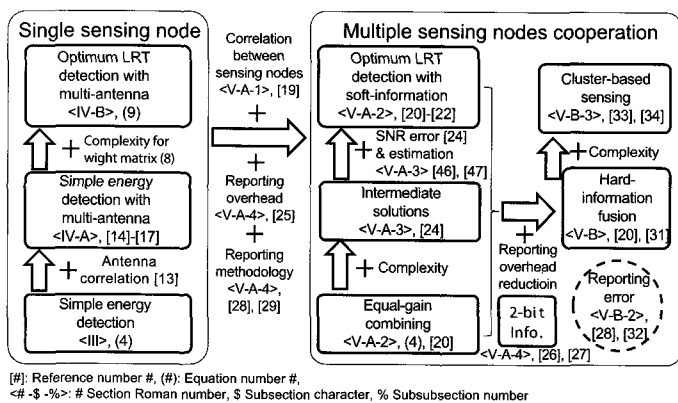


Fig. 8. Summary of spectrum sensing techniques.

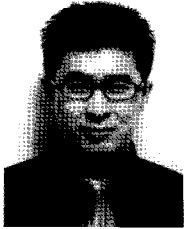
protocols for the sensing information, reporting of plural sensing nodes should be investigated as part of future works.

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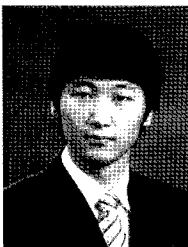
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