Spectrum Sensing for Wireless Communication Networks

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Abstract: Spectrum sensing techniques are envisaged to solve the problems in wireless networks resulting from the limited available spectrum and the inefficiency in the spectrum usage. In this paper various Spectrum Sensing Techniques like Energy Detection, Matched Filter, Cyclo-stationary Detection, Wavelet Detection are compared. The best one is evaluated for its performance. Then Cooperative Spectrum Sensing has been discussed and evaluated for its performance.

1. INTRODUCTION

Spectrum is like real estate these days. It is a commodity which is fixed but the demand for it is increasing exponentially each day. Research these days is trying to keep pace with this demand to come up with new and innovative techniques for optimizing bandwidth utilization. It is envisaged to solve the problems in wireless networks resulting from the limited available spectrum and the inefficiency in the spectrum usage by exploiting the existing wireless spectrum using different spectrum sensing techniques.

2. SPECTRUM SENSING

2.1 Spectrum Sensing Techniques

To enhance the detection probability, many signal detection techniques can be used in spectrum sensing. In the following, we give an overview of some well-known spectrum sensing techniques.

2.1.1 Energy Detection

The energy detection method is optimal for detecting any unknown zero-mean constellation signals [1]. In the energy detection approach, the radio frequency energy in the channel or the received signal strength indicator (RSSI) is measured to determine whether the channel is occupied or not. The energy detection implementation for spectrum sensing is shown in Fig. 2.1a. The received signals $x(t)$ sampled in a time window are first passed through an FFT device to get the spectrum $X(f)$. The peak of the spectrum is then located. After windowing the peak in the spectrum of $x(t)$, we get $Y(f)$. The signal energy is then collected

$$\begin{cases} H_1, \text{ if } \sum |Y(f)|^2 \geq \lambda \\ H_0, \quad \text{otherwise.} \end{cases}$$

in the frequency domain. Finally, the following binary decision is made,

Although the energy detection approach can be implemented without any prior knowledge of the primary user signal, it still has some drawbacks. The first problem is that it can only detect the signal of the primary user if the detected energy is above a threshold. Another challenging issue is that the energy approach cannot distinguish between other secondary users sharing the same channel and the primary user [2].

The threshold selection for energy detection is also problematic since it is highly susceptible to the changing background noise and interference level.

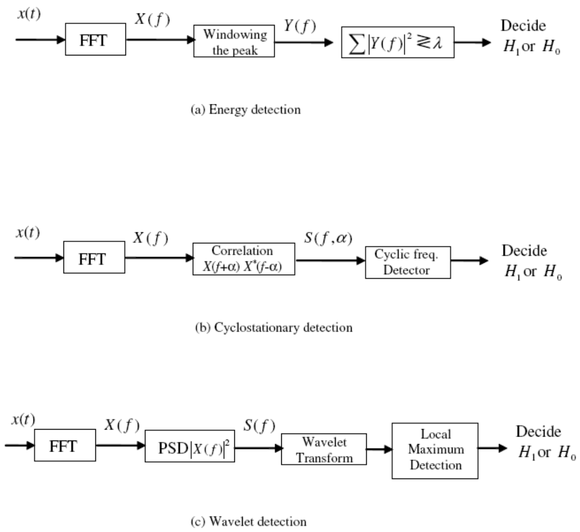


Fig. 2. 1. Implementation of various detection approaches for spectrum sensing.

2.1.2 Matched Filter

A matched filter is an optimal detection method as it maximizes the signal-to noise ratio (SNR) of the received signal in the presence of additive Gaussian noise. A matched filter is obtained by correlating a known signal, or template, with an unknown signal to detect the presence of the template in the unknown signal. This is equivalent to convolving the unknown signal with a time-reversed version of the template. Matched filters are commonly used in radar transmission. In the wireless channel selection scenario, however, the use of the matched filter can be severely limited since the information of the primary user signal is hardly available at the channel selections.

If partial information of primary user signal such as pilots or preambles is known, the use of matched filter is still possible for coherent detection. For example, in order to detect the presence of a digital television (DTV) signal, we may detect its pilot tone by passing the DTV signal through a delay-multiply circuit. If the squared magnitude of the output signal is larger than a threshold, the presence of the DTV signal can be detected. The detailed matched filter implementation for spectrum sensing is
shown in Fig. 2.1b.

2.1.3 Cyclostationary Detection

If the signal of the primary user exhibits strong cyclostationary properties, it can be detected at very low SNR values. A signal is said to be cyclostationary (in the wide sense) if its autocorrelation is a periodic function of time *t* with some period. The cyclostationary detection can be performed as follows [3]. Firstly, one can calculate the cyclic autocorrelation function (CAF) of the observed signal $x(t)$, $Rx(\tau)$, as

$Rx(\tau) = E[x(t+\tau)x^*(t-\tau)e^{-j2\pi\alpha t}]$

where $E[\cdot]$ denotes the statistical expectation operation and α is called *cyclic frequency*.

The discrete Fourier transformation of the CAF can then be computed to obtain the spectral correlation function (SCF), $S(f,\alpha)$, also called cyclic spectrum, which is a two-dimensional function in terms of frequency and cyclic frequency.

Finally, the detection is completed by searching for the *unique cyclic frequency* corresponding to the peak in the SCF plane. The detailed cyclostationary detection implementation for spectrum sensing is shown in Fig. 2.1c. This detection approach is
robust to random noise and interference from other modulated signals, because the noise has only a peak of SCF at the zero cyclic frequency and the different modulated signals have different unique cyclic frequencies.

2.1.4 Wavelet Detection

For signal detection over wideband channels, the wavelet approach offers advantages in terms of both implementation cost and flexibility in adapting to the dynamic spectrum as opposed to conventional use of multiple narrowband bandpass filters (BPF) [4]. In order to identify the locations of vacant frequency bands, the entire wideband is modeled as a train of consecutive frequency sub-bands where the power spectral characteristic is smooth within each sub-band but changes abruptly on the border of two neighboring sub-bands. By employing a wavelet transform of the power spectral density (PSD) of the observed signal $x(t)$, the singularities of the PSD $S(f)$ can be located and thus the vacant frequency bands can be found. The detailed wavelet detection implementation for spectrum sensing is shown in Fig.

Spectrum sensing approach	Advantages	Disadvantages
Energy detection	Does not need any prior information low computational cost	Cannot work in low SNR cannot distinguish users sharing the same channel
Matched filter	Optimal detection performance low computational cost	Requires a prior knowledge of the primary user
Cyclostationary detection	Robust in low SNR robust to interference	Requires partial information of the primary user high computational cost
Wavelet detection	Effective for wideband signal	Does not work for spread spectrum signals; high computational cost

2.1d.

Table 2.1. Advantages and Disadvantages of Spectrum Sensing Techniques.

One critical challenge of implementing the wavelet approach in practice is the high sampling rates for characterizing the large bandwidth. The advantages and disadvantages of the aforementioned spectrum sensing techniques are summarized and compared in Table 2.1.

2.2 Performance of Spectrum Sensing

It has been found that the optimal detector for detecting a weak unknown signal from a known zero-mean constellation is the energy detector, even though there are some fundamental limits when SNR is below a certain threshold [1]. The energy detection is performed by measuring the energy of the received signal in a fixed bandwidth *W* over an observation time window *T*. The performance analysis of the energy detector has been studied for AWGN channels in [5,6,7] and for Rayleigh fading channels in [8,9,10]. In the following, we briefly present the main results that describe the performance of the energy detector over Rayleigh fading channels. The details of the proof are omitted here and can be found in [8,9].

We assume that each channel selection performs local spectrum sensing independently. For simplicity, we consider the *i*th channel selection ($1 \le i \le K$) only

$$x_i(t) = \begin{cases} n_i(t), & H_0 \\ h_i s(t) + n_i(t), & H_1 \end{cases}$$

to see how the energy detector works. The local spectrum sensing is to decide between the following two hypotheses,

where $x(t)$ is the observed signal at the *i*th channel selection and $s(t)$ is the signal transmitted from the primary user, $n_i(t)$ is the additive white Gaussian noise (AWGN) and h_i is the complex channel gain of the sensing channel between the primary user and
the *i*th channel selection. As shown in Fig. 2.1a, the energy collected in the frequency domain is

$$D_i \sim \begin{cases} \chi^2_{2u}, & H_0 \\ \chi^2_{2u}(2\gamma_i), & H_1 \end{cases}$$

which serves as a decision statistic with the following distribution

where $\chi^2_{2u}(2\gamma_i)$ denotes a central chi-square distribution with 2*u* degrees of freedom and χ^2_{2u} denotes a non-central chi-square distribution with 2*u* degrees of freedom and a non-centrality parameter 2*γi*, respectively. *γi* is the instantaneous SNR of the received signal at the *i*th channel selection and *u* = *TW*.

For the *i*th channel selection with the energy detector, the average probability of false alarm, the average probability of detection, and the average probability of miss over Rayleigh fading channels are given by, respectively,

$$
\begin{aligned}
P_{\mathrm{f},i} &= \mathbf{E}_{\gamma_i}\left[\mathrm{Prob}\{D_i > \lambda | H_0\}\right] \\
&= \frac{\Gamma(u, \frac{\lambda_i}{2})}{\Gamma(u)}, \\
P_{\mathrm{d},i} &= \mathbf{E}_{\gamma_i}\left[\mathrm{Prob}\{D_i > \lambda | H_1\}\right] \\
&= \mathrm{e}^{-\frac{\lambda}{2}} \sum_{n=0}^{u-2} \frac{1}{n!}\left(\frac{\lambda_i}{2}\right)^n + \left(\frac{1+\bar{\gamma}_i}{\bar{\gamma}_i}\right)^{u-1} \\
&\quad \times \left[\mathrm{e}^{-\frac{\lambda_i}{2(1+\bar{\gamma}_i)}} - \mathrm{e}^{-\frac{\lambda_i}{2}} \sum_{n=0}^{u-2} \frac{1}{n!}\left(\frac{\lambda_i \bar{\gamma}_i}{2(1+\bar{\gamma}_i)}\right)^n\right]
\end{aligned}
$$

$$P_{\mathrm{m},i} = 1 - P_{\mathrm{d},i}$$

Fig. 3.1, shows that the energy detection performance of one channel selection becomes worse when SNR decreases.

3 Cooperative Spectrum Sensing

One of the most critical issues of spectrum sensing is the hidden terminal problem, which happens when the channel selection is shadowed. In Fig. 3.3, channel selection 1 is shown to be shadowed by a high building over the sensing channel. In this case, the channel selection cannot reliably sense the presence of the primary user due to the very low SNR of the received signal. Then, this channel selection assumes that the observed channel is vacant and begins to access this channel while the primary user is still in operation.

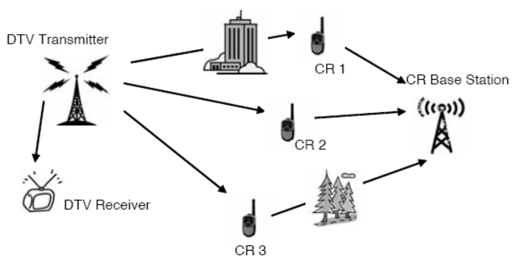
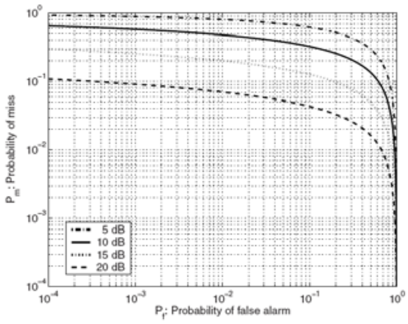


Fig. 3.1 Complementary ROC curves in a Rayleigh fading channel

To address this issue, multiple channel selections can be coordinated to performance spectrum sensing cooperatively. It has been shown that cooperative spectrum sensing can increase the probability of



detection in fading channels [9]. In general, cooperative spectrum sensing is performed as follows:

Fig. 3.2 Cooperative spectrum sensing in channel selection networks; CR 1 is shadowed over the sensing channel and CR 3 is shadowed over the reporting channel.

· *Step 1*: Every channel selection performs local spectrum measurements independently and then makes a binary decision.

· *Step 2*: All the channel selections forward their binary decisions to a common receiver which is an access point (AP) in a wireless LAN or a base station (BS) in a cellular network.

· *Step 3*: The common receiver combines those binary decisions and makes a final decision to infer the absence or presence of the primary user in the observed band.

In the above cooperative spectrum sensing algorithm, each cooperative partner makes a binary decision based on its local observation and then forward one bit of the decision to the common receiver. At the common receiver, all one-bit decisions are fused together according to an "OR" logic. This cooperative sensing algorithm is referred to as *decision fusion*. An alternative form of cooperative spectrum sensing can be performed as follows. Instead of transmitting the one-bit decision to the common receiver in Step 2 of the above algorithm, each channel selection can just send its observation value directly to the common receiver [11]. This alternative approach can then be seen as *data fusion* for cooperative networks. Obviously, the one-bit decision needs a low bandwidth control channel. Moreover, it has been recently found that a hard decision approach can perform almost as well as that of the soft decision one in terms of detection performance [11].

3.1 Cooperative Spectrum Sensing Performance

In cooperative spectrum sensing, all channel selections measure the licensed spectrum and make the decisions independently. If the decision in one channel selection is *H*0, then a symbol *{−1}* will be transmitted to the BS. If*H*1 is true, then *{1}* is forwarded to the BS. The transmission of the decisions from all channel selections to the BS can be seen as a multiuser access protocol, which can be based on TDMA or FDMA. The BS collects all *K* decisions and makes the final decision using an OR rule. Let*Z* denote the decision statistic in the BS, then it can be described as

$$Z \sim \begin{cases} \{H_0^{\mathrm{BS},1}, \cdots, H_0^{\mathrm{BS},K}\}, & \mathcal{H}_0 \text{ (signal is absent)} \\ \text{otherwise}, & \mathcal{H}_1 \text{ (signal is present)} \end{cases}$$

where $H_0^{\mathrm{BS},i}$ denotes the decision *H*0 received from the *i*th channel selection at the BS for *i* = 1- - - *K*. This expression demonstrates that the BS decides the signal is absent only if all channel selections decide the absence of the signal. On the other hand, the BS assumes that the primary user is present if there exists at least one channel selection which assumes the presence of the primary user signal. Therefore, the false alarm probability of the cooperative spectrum sensing is given by

$$\begin{aligned} Q_{\mathrm{f}} &= \mathrm{Prob}\{\mathcal{H}_1 | H_0\} \\ &= 1 - \mathrm{Prob}\{\mathcal{H}_0 | H_0\} \\ &= 1 - \prod_{i=1}^{K} (1 - P_{\mathrm{f},i}) \end{aligned}$$

where *Pf,i* denotes the false alarm probability of the *i*th channel selection in its local spectrum sensing. The miss probability of cooperative spectrum sensing is given by

$$\begin{aligned} Q_m &= \mathrm{Prob}\{\mathcal{H}_0 | H_1\} \\ &= \prod_{i=1}^{K} P_{\mathrm{m},i} \end{aligned}$$

where *P*m,*i* denotes the miss probability of the *i*th channel selection in its local spectrum sensing.

Figure 3.3 shows that the performance curves of cooperative spectrum sensing for different number of channel selections over Rayleigh fading channels with the average SNR $\bar{\gamma}$ = 10 dB. It is obvious that the probability of miss is greatly reduced with a larger value *K* for a given probability of false alarm. As such, we may refer to *K* as the *sensing diversity gain* of the cooperative spectrum sensing. It can be seen that cooperative spectrum sensing will go through two successive channels: (1) *sensing channel* (from the primary user to channel selections); and (2) *reporting channel* (from the channel selections to the common receiver). The merit of cooperative spectrum sensing primarily lies in the achievable space diversity brought by the independent sensing channels, namely *sensing diversity gain*, provided by the multiple channel selections.

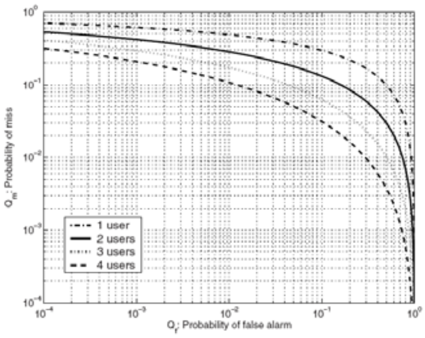


Fig. 3.3 Complementary ROC curves in Rayleigh fading channels

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