Covariance Based Signal Detections For Cognitive Radio

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Abstract— Sensing (signal detection) is a fundamental problem in cognitive radio. The statistical covariances of signal and noise are usually different. In this paper, this property is used to differentiate signal from noise. The sample covariance matrix of the received signal is computed and transformed based on the receiving filter. Then two detection methods are proposed based on the transformed sample covariance matrix. One is the covariance absolute value (CAV) detection and the other is the covariance Frobenius norm (CFN) detection. Theoretical analysis and threshold setting for the algorithms are discussed. Both methods do not need any information of the signal, the channel and noise power as a priori. Simulations based on captured ATSC DTV signals are presented to verify the methods.

Key words: Signal detection, Sensing, Sensing algorithm, Cognitive radio, WRAN, 802.22

I. Introduction

A "cognitive Radio" is a radio which is able to sense the spectral environment over a wide frequency band and exploit this information to opportunistically provide wireless links that best meet the user communications requirements [1], [2], [3], [4]. Unique to cognitive radio operation is the requirement that the radio is able to sense the environment over huge swath of spectrum and adapt to it. That is, it is necessary to dynamically detect the existence of signals of primary users. In December 2003, the FCC issued a Notice of Proposed Rule Making that identifies cognitive radio as the candidate for implementing negotiated/opportunistic spectrum sharing [5]. In response to this, from 2004, the IEEE has formed the 802.22 Working Group to develop a standard for wireless regional area networks (WRAN) based on cognitive radio technology [6], [7], [8]. WRAN systems will operate on the VHF/UHF bands that are currently allocated for TV broadcasting services and other services such as wireless microphone. In particular, a WRAN system will be able to sense the spectrum, identify unused TV channels, and utilize these channels to provide broadband services for fixed wireless subscribers.

As discussed above, sensing is a fundamental component of cognitive radio. There are several factors which make the sensing difficult. First, the signal-noise-ratio (SNR) may be very low. For example, in the TV band, some Part 74 devices (such as wireless microphone) only transmits signal of about 50mW power in 200 kHz bandwidth. If the sensor is several hundred meters away from the devices, the received SNR may be well below -20dB. Secondly, fading and multipath in wireless signal complicate the problem. Fading will cause the signal power fluctuates dramatically (can be 10dB or even higher), while unknown multipath will cause coherent detection methods unreliable. Thirdly, noise/interference level changes with time (noise uncertainty). There are two types of noise uncertainty: receiver device noise uncertainty and environment noise uncertainty. There are several sources of receiver device noise uncertainty [9], [10], [11], [12]: (a) non-linearity of components; (b) thermal noise in components (non-uniform, time-varying). The environment noise uncertainty may be caused by transmissions of other users (unintentional (close-by) or intentional (far-away)). Due to noise uncertainty, in practice, it is very difficult to obtain the accurate noise power. Fourthly, sensing time is limited and the complexity of the sensing scheme should be low. When a cognitive user is using a spectral band and a primary user is turned on, the cognitive user must detect the primary user's signal and vacant the channel in a very short time (to avoid interference to the primary user). To save power and reduce costs, we want the sensing algorithm to have low complexity.

There have been some sensing algorithms including the energy detection [13], [9], the matched filtering (MF) [9], [8] and cyclostationary detection [14], [15], [16]. These algorithms have different requirements and advantages/disadvantages. Energy detection is a major and basic method. Unlike other methods, energy detection does not need any information of the signal to be detected and is robust to unknown multipath fading. However, energy detection is vulnerable to the noise uncertainty [9], [10], [11], [12], because the method relies on the knowledge of accurate noise power. In practice, it is very difficult to obtain the accurate noise power. To overcome this shortage, we propose new methods based on the statistical covariance or auto-correlations of the received signal. The statistical covariance matrices or auto-correlations of signal and noise are generally different. The statistical covariance matrix of noise is determined by the receiving filter. Therefore its structure is known to the receiver. Based on this structure, we can turn the covariance matrix of the received signal into another matrix. When there is no signal, the off-diagonal elements of the resultant matrix are zeros. However, when there are signals, some of the off-diagonal elements of the resultant matrix are not zeros. Based on this property, we can compare the off-diagonal elements with the diagonal elements of the transformed covariance matrix to detect signal existence. Two detection methods are proposed. One is the covariance absolute value (CAV) detection and the other is the covariance Frobenius norm (CFN) detection. The thresholds and the probability of false alarm are also found. The method can be used for various signal detection applications without knowledge of the signal, the channel and noise power. Simulations based on captured digital television (DTV) signals are done to verify the methods.

The rest of the paper is organized as follows. The detection algorithms are presented in Section 2. Section 3 gives theoretical analysis and finds thresholds for the algorithms. Simulations results by using captured DTV signals are given in Section 4. Finally, conclusions are drawn in Section 5.

Some notations are used in the following: superscripts T and $\dagger$ stand for transpose and Hermitian (transconjugate), respectively. $\mathbf{I}_q$ is the identity matrix of order q.

II. Covariance based detections

Let $x(t) = s(t) + \eta(t)$ be the received signal, where $s(t)$ is the possible primary user's signal and $\eta(t)$ is the white noise. Assume that we are interested in the frequency band with central frequency f_c and bandwidth W. We sample the received signal at a sampling rate f_s, where $f_s \geq W$. Let $T_s = 1/f_s$ be the sampling period. For notation simplicity, we define $x(n) = x(nT_s)$, $s(n) = s(nT_s)$ and $\eta(n) = \eta(nT_s)$. There are two hypothesizes: $\mathbb{H}_0$, signal not exists; and $\mathbb{H}_1$, signal exists. The received signal samples under the two hypothesizes are therefore respectively as follows:

$$\mathbb{H}_0: \quad x(n) = \eta(n) \tag{1}$$
$$\mathbb{H}_1: \quad x(n) = s(n) + \eta(n), \tag{2}$$

where $s(n)$ is the transmitted signal samples passed through a wireless channel (including fading and multipath effects) and $\eta(n)$ is the white Gaussian noise samples. Note that $s(n)$ can be the superposition of multiple signals. The received signal is generally passed through a bandpass filter. Let $f(k)$, $k = 0, 1, \cdots, K$, be the normalized bandpass filter with $\sum_{k=0}^{K} |f(k)|^2 = 1$. After filtering, the received signal is turned to

$$\tilde{x}(n) = \sum_{k=0}^{K} f(k)x(n-k), \ n = 0, 1, \cdots. \tag{3}$$

(4)

Let

$$\tilde{s}(n) = \sum_{k=0}^{K} f(k)s(n-k), \tag{5}$$
$$\tilde{\eta}(n) = \sum_{k=0}^{K} f(k)\eta(n-k). \tag{6}$$

Then

$$\mathbb{H}_0: \quad \tilde{x}(n) = \tilde{\eta}(n) \tag{7}$$
$$\mathbb{H}_1: \quad \tilde{x}(n) = \tilde{s}(n) + \tilde{\eta}(n). \tag{8}$$

Let us consider L (called smoothing factor in the following) consecutive samples and define

$$\mathbf{x}(n) = \begin{bmatrix} \tilde{x}(n) & \tilde{x}(n-1) & \cdots & \tilde{x}(n-L+1) \end{bmatrix}^T, \tag{9}$$
$$\mathbf{s}(n) = \begin{bmatrix} \tilde{s}(n) & \tilde{s}(n-1) & \cdots & \tilde{s}(n-L+1) \end{bmatrix}^T, \tag{10}$$
$$\eta(n) = \begin{bmatrix} \tilde{\eta}(n) & \tilde{\eta}(n-1) & \cdots & \tilde{\eta}(n-L+1) \end{bmatrix}^T. \tag{11}$$

Define a $L \times (L+K)$ matrix as

$$\mathbf{H} = \begin{bmatrix} f(0) & f(1) & \cdots & f(K) & 0 & \cdots & 0 \\ 0 & f(0) & \cdots & f(K-1) & f(K) & \cdots & 0 \\ & & \ddots & & & \ddots & \\ 0 & 0 & \cdots & f(0) & f(1) & \cdots & f(K) \end{bmatrix}. \tag{12}$$

If analog filter is used, the matrix $\mathbf{H}$ should be defined based on the analog filter property. Considering the statistical covariance matrices of the signals and noise defined as

$$\mathbf{R}_x = \mathrm{E}(\mathbf{x}(n)\mathbf{x}^\dagger(n)), \tag{13}$$
$$\mathbf{R}_s = \mathrm{E}(\mathbf{s}(n)\mathbf{s}^\dagger(n)), \tag{14}$$
$$\mathbf{R}_\eta = \mathrm{E}(\eta(n)\eta^\dagger(n)), \tag{15}$$

we have

$$\mathbf{R}_x = \mathbf{R}_s + \mathbf{R}_\eta. \tag{16}$$

From (6), we can verify that

$$\mathbf{R}_\eta = \sigma_\eta^2 \mathbf{G}, \tag{17}$$

where σ_η^2 is the white noise variance and $\mathbf{G} = \mathbf{H}\mathbf{H}^\dagger$. Note that $\mathbf{G}$ is a positive definite Hermitian matrix. It can be decomposed to

$$\mathbf{G} = \mathbf{Q}^2, \tag{18}$$

where $\mathbf{Q}$ is also a positive definite Hermitian matrix. Define

$$\tilde{\mathbf{R}}_x = \mathbf{Q}^{-1}\mathbf{R}_x\mathbf{Q}^{-1}, \tag{19}$$
$$\tilde{\mathbf{R}}_s = \mathbf{Q}^{-1}\mathbf{R}_s\mathbf{Q}^{-1}. \tag{20}$$

Then

$$\tilde{\mathbf{R}}_x = \tilde{\mathbf{R}}_s + \sigma_\eta^2 \mathbf{I}_L. \tag{21}$$

If there is no signal, then $\tilde{\mathbf{R}}_s = 0$. Hence the off-diagonal elements of $\tilde{\mathbf{R}}_x$ are all zeros. If there is signal and the signal samples are correlated, $\tilde{\mathbf{R}}_s$ is not a diagonal matrix.

Hence, some of the off-diagonal elements of $\tilde{\mathbf{R}}_x$ should not be zeros. Let r_{nm} be the elements of matrix $\tilde{\mathbf{R}}_x$. Let

$$T_1 = \frac{1}{L}\sum_{n=1}^{L}\sum_{m=1}^{L}|r_{nm}|, \tag{22}$$

$$T_2 = \frac{1}{L}\sum_{n=1}^{L}|r_{nn}|, \tag{23}$$

$$T_3 = \frac{1}{L}\sum_{n=1}^{L}\sum_{m=1}^{L}|r_{nm}|^2, \tag{24}$$

$$T_4 = \frac{1}{L}\sum_{n=1}^{L}|r_{nn}|^2. \tag{25}$$

Then, if there is no signal, $T_1 = T_2$ and $T_3 = T_4$. If there is signal, $T_1 > T_2$ and $T_3 > T_4$. Hence, we can detect the signal presence by comparing T_1 with T_2 or T_3 with T_4.

In practice, we can only approximate the statistical covariance matrix using limited signal samples. Define the sample auto-correlations of the received signal as

$$\lambda(l) = \frac{1}{N_s}\sum_{m=0}^{N_s-1}\tilde{x}(m)\tilde{x}^*(m-l),\ l = 0, 1, \cdots, L-1. \tag{26}$$

The statistical covariance matrix $\mathbf{R}_x$ can be approximated by the sample covariance matrix defined as

$$\mathbf{R}_x(N_s) = \begin{bmatrix} \lambda(0) & \lambda(1) & \cdots & \lambda(L-1) \\ \lambda^*(1) & \lambda(0) & \cdots & \lambda(L-2) \\ \vdots & \vdots & \vdots & \vdots \\ \lambda^*(L-1) & \lambda^*(L-2) & \cdots & \lambda(0) \end{bmatrix}. \tag{27}$$

Note that the sample covariance matrix is Hermitian and Toeplitz. Based on the sample covariance matrix, we obtain two detection methods as follows.

Algorithm 1: The covariance absolute value (CAV) detection

Step 1. Sample and filter the received signal as described above.

Step 2. Choose a smoothing factor L and a threshold γ_1, where γ_1 should be chosen to meet the requirement for the probability of false alarm. This will be discussed in the next section.

Step 3. Compute the auto-correlations of the received signal $\lambda(l)$, $l = 0, 1, \cdots, L-1$, and form the sample covariance matrix.

Step 4. Transform the sample covariance matrix to obtain

$$\tilde{\mathbf{R}}_x(N_s) = \mathbf{Q}^{-1}\mathbf{R}_x(N_s)\mathbf{Q}^{-1}, \tag{28}$$

Step 5. Compute

$$T_1(N_s) = \frac{1}{L}\sum_{n=1}^{L}\sum_{m=1}^{L}|r_{nm}(N_s)|, \tag{29}$$

$$T_2(N_s) = \frac{1}{L}\sum_{n=1}^{L}|r_{nn}(N_s)|, \tag{30}$$

where $r_{nm}(N_s)$ are the elements of the transformed sample covariance matrix $\tilde{\mathbf{R}}_x(N_s)$.

Step 6. Determine the presence of the signal based on $T_1(N_s)$, $T_2(N_s)$ and the threshold: if $T_1(N_s) > \gamma_1 T_2(N_s)$, signal exists; otherwise, signal not exists.

Algorithm 2: The covariance Frobenius norm (CFN) detection

Step 1. Sample and filter the received signal as described above.

Step 2. Choose a smoothing factor L and a threshold γ_2, where γ_2 should be chosen to meet the requirement for the probability of false alarm. This will be discussed in the next section.

Step 3. Same as Algorithm 1.

Step 4. Same as Algorithm 1.

Step 5. Compute

$$T_3(N_s) = \frac{1}{L}\sum_{n=1}^{L}\sum_{m=1}^{L}|r_{nm}(N_s)|^2, \tag{31}$$

$$T_4(N_s) = \frac{1}{L}\sum_{n=1}^{L}|r_{nn}(N_s)|^2. \tag{32}$$

Step 6. Determine the presence of the signal based on $T_3(N_s)$, $T_4(N_s)$ and the threshold: if $T_3(N_s) > \gamma_2 T_4(N_s)$, signal exists; otherwise, signal not exists.

III. Theoretic analysis and the thresholds

The validity of the algorithms relies on the assumption that the signal samples are correlated, that is, $\tilde{\mathbf{R}}_s$ is not a diagonal matrix (some of the off-diagonal elements of $\tilde{\mathbf{R}}_s$ should not be zeros). Define

$$\bar{\mathbf{s}}(n) = \begin{bmatrix} s(n) & s(n-1) & \cdots & s(n-L-K+1) \end{bmatrix}^T, \tag{33}$$

and the statistical covariance matrix of the transmitted signal as

$$\bar{\mathbf{R}}_s = \mathrm{E}(\bar{\mathbf{s}}(n)\bar{\mathbf{s}}^\dagger(n)). \tag{34}$$

Then $\mathbf{s}(n) = \mathbf{H}\bar{\mathbf{s}}(n)$ and

$$\mathbf{R}_s = \mathbf{H}\bar{\mathbf{R}}_s\mathbf{H}^\dagger, \tag{35}$$

$$\tilde{\mathbf{R}}_s = \mathbf{Q}^{-1}\mathbf{H}\bar{\mathbf{R}}_s\mathbf{H}^\dagger\mathbf{Q}^{-1}. \tag{36}$$

Obviously, if the signal samples $s(n)$ are statistically independent and identically distributed (i.i.d), then $\bar{\mathbf{R}}_s = \mathbf{I}_{L+K}$, and therefore $\tilde{\mathbf{R}}_s = \mathbf{I}_{L+K}$. At this case, the assumption is invalid and the algorithms cannot detect the signal.

However, usually the signal samples should be correlated due to the following reasons.

(1) The signal is oversampled. Let $T_0 = 1/W$ to be the Nyquist sampling period. Let $s(nT_0)$ to be the sampled signal based on the Nyquist sampling rate. Based on the sampling theorem, the signal $s(t)$ can be expressed as

$$s(t) = \sum_{n=-\infty}^{\infty} s(nT_0)g(t - nT_0), \tag{37}$$

where $g(t)$ is an interpolation function. Hence, the signal samples $s(n) = s(nT_s)$ are only related to $s(nT_0)$. If the sampling rate at the receiver $f_s > W$, that is, $T_s < T_0$, then $s(n) = s(nT_s)$ must be correlated.

(2) The propagation channel has multipath. If the channel has multipath, the actually signal component at the receiver is

$$s(t) = \int_{-\infty}^{\infty} h(\tau)s_0(t-\tau)\mathrm{d}\tau, \tag{38}$$

where $s_0(t)$ is the original transmitted signal and $h(t)$ is the multipath channel response. Since the sampling period T_s is usually very small, the integration (38) can be approximated as

$$s(t) \approx T_s \sum_{k=-\infty}^{\infty} h(kT_s)s_0(t-kT_s). \tag{39}$$

Hence,

$$s(nT_s) \approx T_s \sum_{k=K_0}^{K_1} h(kT_s)s_0((n-k)T_s), \tag{40}$$

where $[K_0T_s, K_1T_s]$ is the support of the channel response $h(t)$, that is, $h(t) = 0, t \notin [K_0T_s, K_1T_s]$. If $K_1 > K_0$ (multipath channel), obviously the signal samples $s(nT_s)$ are correlated even if the original signal samples $s_0(nT_s)$ are i.i.d..

(3) The original signal is correlated. In most cases, the practical physical signal samples are correlated.

Let P_d be the probability of detection, that is, at hypothesis $\mathbb{H}_1$, the probability of the algorithm having detected the signal. Let P_{fa} be the probability of false alarm, that is, at $\mathbb{H}_0$, the probability of the algorithm having detected the signal. Obviously, for a good detection algorithm, P_d should be high and P_{fa} should be low. The requirements of the P_d and P_{fa} depend on applications.

The choice of the threshold γ is a compromise between the P_d and P_{fa}. Since we have no information on the signal (actually we even do not know if there is signal or not), it is difficult to set the threshold based on the P_d. Hence, usually we choose the threshold based on the P_{fa}. First we set a limit for P_{fa}, that is, $P_{fa} \leqslant P_0$. Then we find a threshold γ_0 such that $P_{fa} = P_0$. Therefore, we can only choose the threshold satisfying $\gamma \geq \gamma_0$. To find the threshold based on the required P_{fa}, we can use either theoretical derivation or simulation. If simulation is used to find the threshold, we can generate white Gaussian noises as the input (no signal) and adjust the threshold such that $P_{fa} \leqslant P_0$. Note that the threshold here is related to the number of samples used for computing the sample auto-correlations and the smoothing factor L, but not related to the noise power. If theoretical derivation is used, we need to find the statistical distributions of $T_j(N_s),\ j = 1,2,3,4$. In general, it is difficult to find the statistical distributions of $T_j(N_s)$. Here we discuss the special case when $\mathbf{Q} = \mathbf{I}_L$.

When $\mathbf{Q} = \mathbf{I}_L$, $T_j(N_s)$ becomes

$$T_1(N_s) = \lambda(0) + \sum_{l=1}^{L-1} \frac{2(L-l)}{L}|\lambda(l)|, \tag{41}$$

$$T_2(N_s) = \lambda(0), \tag{42}$$

$$T_3(N_s) = \lambda^2(0) + \sum_{l=1}^{L-1} \frac{2(L-l)}{L}|\lambda(l)|^2, \tag{43}$$

$$T_4(N_s) = \lambda^2(0). \tag{44}$$

Now we analyze the P_{fa} at hypothesis $\mathbb{H}_0$. It can be verified that, for real noise,

$$\mathrm{E}(T_1(N_s)) = \left(1 + (L-1)\sqrt{\frac{2}{N_s\pi}}\right)\sigma_\eta^2, \tag{45}$$

$$\mathrm{E}(T_2(N_s)) = \sigma_\eta^2, \tag{46}$$

$$\mathrm{Var}(T_2(N_s)) = \frac{2}{N_s}\sigma_\eta^4, \tag{47}$$

$$\mathrm{E}(T_3(N_s)) = \frac{L+N_s+1}{N_s}\sigma_\eta^4, \tag{48}$$

$$\mathrm{E}(T_4(N_s)) = \frac{N_s+2}{N_s}\sigma_\eta^4, \tag{49}$$

$$\mathrm{Var}(T_4(N_s)) = \left(\frac{8}{N_s} + \frac{40}{N_s^2} + \frac{48}{N_s^3}\right)\sigma_\eta^8. \tag{50}$$

It is more tough to obtain the variance of $T_1(N_s)$.

Since N_s is usually very large, based on the central limit theorem, $T_2(N_s)$ can be approximated by the Gaussian distribution with mean σ_η^2 and variance $\frac{2\sigma_\eta^4}{N_s}$. Hence, the probability of false alarm for the CAV algorithm is

$$\begin{aligned}
&P_{fa} = P\left(T_1(N_s) > \gamma_1 T_2(N_s)\right) \\
&= P\left(T_2(N_s) < \frac{1}{\gamma_1}T_1(N_s)\right) \\
&\approx P\left(T_2(N_s) < \frac{1}{\gamma_1}\left(1 + (L-1)\sqrt{\frac{2}{N_s\pi}}\right)\sigma_\eta^2\right) \\
&= P\left(\frac{T_2(N_s) - \sigma_\eta^2}{\sqrt{\frac{2}{N_s}}\sigma_\eta^2} < \frac{\frac{1}{\gamma_1}\left(1 + (L-1)\sqrt{\frac{2}{N_s\pi}}\right) - 1}{\sqrt{2/N_s}}\right) \\
&\approx 1 - Q\left(\frac{\frac{1}{\gamma_1}\left(1 + (L-1)\sqrt{\frac{2}{N_s\pi}}\right) - 1}{\sqrt{2/N_s}}\right)
\end{aligned}$$

where

$$Q(t) = \frac{1}{\sqrt{2\pi}}\int_t^{+\infty} e^{-u^2/2}\mathrm{d}u. \tag{51}$$

If we want $P_{fa} \leqslant P_0$, we should choose the threshold such that

$$\frac{\frac{1}{\gamma_1}\left(1 + (L-1)\sqrt{\frac{2}{N_s\pi}}\right) - 1}{\sqrt{2/N_s}} \leqslant Q^{-1}(1-P_0). \tag{52}$$

That is,

$$\gamma_1 \geq \frac{1 + (L-1)\sqrt{\frac{2}{N_s\pi}}}{1 + Q^{-1}(1-P_0)\sqrt{\frac{2}{N_s}}}. \tag{53}$$

Similarly, $T_4(N_s)$ can be approximated by the Gaussian distribution with mean $\frac{N_s+2}{N_s}\sigma_\eta^4$ and variance $\left(\frac{8}{N_s}+\frac{40}{N_s^2}+\frac{48}{N_s^3}\right)\sigma_\eta^8$. Using the same derivation as above, we obtain the threshold for the CFN algorithm as

$$\gamma_2 \geq \frac{L+N_s+1}{N_s+2+Q^{-1}(1-P_0)\sqrt{8N_s+40+\frac{48}{N_s}}}. \tag{54}$$

The computational complexity of the two algorithms is as follows.

Filtering the received signals: $(K+1)N_s$ multiplications and additions (if N_s is large, FFT can be used to reduce the complexity);

Computing the auto-correlations of the received signal: LN_s multiplications and additions;

Transforming the sample covariance matrix: $2L^3$ multiplications and additions;

Others: at most L^2 multiplications and additions;

Total: $(K+L+1)N_s+2L^3+L^2$ multiplications and additions.

The energy detection needs about $(K+2)N_s$ multiplications and additions. Usually choosing $L \leqslant 20$ is enough, while N_s is very large. Hence, the computational complexity of the proposed methods is comparable to that of the energy detection.

IV. Simulations

In the following, we will give some simulation results using the captured DTV signals [17]. The real DTV signals (field measurements) are collected at Washington D.C., USA. The data rate of the vestigial sideband (VSB) DTV signal is 10.762 MHz. The recorded DTV signals were sampled at 21.524476M samples/sec and down converted to a low central IF frequency of 5.381119 MHz (one fourth the sampling rate). The analog-to-digital conversion of the RF signal used a 10-bit or a 12-bit A/D. Each sample was encoded into a 2-byte word (signed int16 with a two's complement format). The multipath channel and the SNR of the received signal are unknown. In order to use the signals for simulating the algorithms at very low SNR, we need to add white noises to obtain various SNR levels [11]. The captured DTV signal and the added white noise are passed through a raised cosine filter (bandwidth 6 MHz, rolling factor 1/2, 89 tapes). The number of samples used is 400000 (corresponding to 18.60 ms). The smoothing factor is chosen as $L=16$. The threshold is set based on the $P_{fa}=0.1$ and fixed for signals. The threshold is not related to noise power.

For comparison, we also simulate the energy detection (with or without noise uncertainty) for the same system. The threshold for the energy detection is given in [9]. The energy detection needs the noise power as a priori. Due to the noise uncertainty [9], [10], [11], [12], the estimated (or assumed) noise power may be different from the real noise power. Let the estimated noise power be $\hat{\sigma}_\eta^2=\alpha\sigma_\eta^2$.

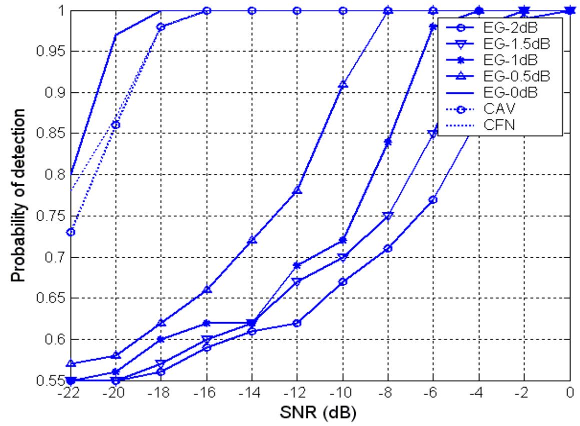

Fig. 1. Probability of detection (WAS-003/27/01)

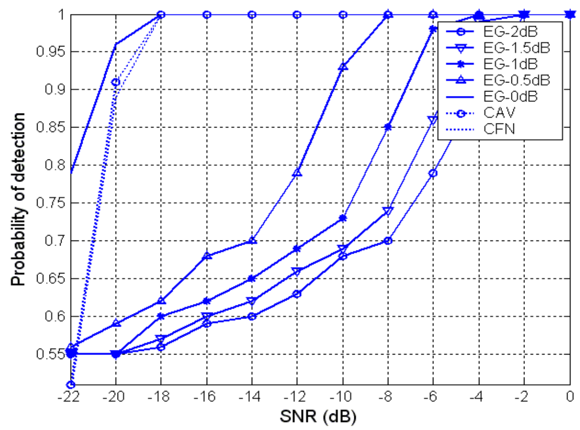

Fig. 2. Probability of detection (WAS-049/34/01)

The noise uncertainty factor (in dB) is defined as

$$B=\max\{10\log_{10}\alpha\}. \tag{55}$$

It is assumed that α (in dB) is evenly distributed in an interval $[-B,B]$ [9], [6]. In practice, the noise uncertainty factor of receiving device is normally 1 to 2 dB [9], [11]. The environment (interference) noise uncertainty can be much higher [9].

The probabilities of false alarm (P_{fa}) are shown in Table I (note that the probability of false alarm is not related to the SNR and noise power because there is no signal), where and in the following "EG-x dB" means the energy detection with x-dB noise uncertainty. The P_{fa} for the proposed methods and the energy detection without noise uncertainty meet the requirement ($P_{fa} \leqslant 0.1$), but the P_{fa} for the energy detection with noise uncertainty far exceeds the limit. This means that the energy detection is very unreliable in practical situations with noise uncertainty.

Figure 1 gives the probability of detection results based on the DTV signal file WAS-003/27/01 (the receiver is outside and 48.41 miles from the DTV station; antenna

method	EG-2 dB	EG-1.5 dB	EG-1 dB	EG-0.5 dB	EG-0dB	CAV	CFN
P_{fa}	0.499	0.497	0.495	0.487	0.102	0.103	0.104

TABLE I

Probabilities of false alarm (sensing time 18.60 ms)

height is 30 feet) [17]. Figure 2 gives the results based on the DTV signal file WAS-049/34/01 (the receiver is indoor and 20.15 miles from the DTV station; antenna height is 6 feet) [17]. If the noise variance is exactly known ($B = 0$), the energy detection is pretty good. The proposed methods are slightly worse than the energy detection with ideal noise power. However, as discussed in [9], [11], [12], noise uncertainty is always present. As shown in the figures, if there is 1 to 2 dB noise uncertainty, the detection probability of the energy detection is much worse than that of the proposed methods.

In summary, all the simulations show that the proposed methods work well without using information of the signal, the channel and noise power. The energy detection are not reliable (low probability of detection and high probability of false alarm) when there is noise uncertainty.

V. Conclusions

Methods based on the sample covariance matrix of the received signal have been proposed. Statistical theories have been used to set the thresholds and obtain the probability of false alarm. The methods can be used for various signal detection applications without knowledge of the signal, the channel and noise power. Simulations based on the captured DTV signals have been done to verify the methods.

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