Paper

Performance of Hybrid Sensing Method in Environment with Noise Uncertainty

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Abstract—The paper presents a novel hybrid spectrum sensing method used in cognitive radio and presents a hybrid detector (HD) which improves the sensing performance. The proposed HD takes advantage of the energy detection (ED) principle and a method based on Covariance Absolute Value (CAV), as well as on Cyclic Autocorrelation Function (CAF). The paper shows the limitations of using ED, resulting from the uncertainty of spectral density of noise power estimation, known as the SNR wall. The paper describes a system model and presents simulation results for the OFDM signal of a WiMAX-based communications system. The simulation results refer to an ideal environment with well-known parameters, and to an environment with uncertain spectral density of noise power estimation.

Keywords—Covariance Absolute Value, Cyclic Autocorrelation Function, hybrid detector, noise uncertainty, OFDM, SNR wall, WiMAX.

1. Introduction

Cognitive radio systems [1], [2] are an effective solution to the problem of spectrum scarcity, providing dynamic spectrum access to frequencies that are temporarily not used by primary users (PU). Spectrum sensing is one of the basic tasks of cognitive radio which must be carried out to enable communications. It relies on monitoring wide-band spectrum and finding the channels not occupied by PU (licensed) users, which can be used by secondary users (SU).

There is a lot of research dealing with optimization of spectrum sensing. A common approach is to increase efficiency of hybrid architecture detectors, based on a combination of various detection methods [3], [4]. The structure of a hybrid sensing model depends on the spectrum recognition scenario used. A two-phase system which uses energy detections (ED) in the first phase could be an example of the simplest and fastest method of sensing. It enables reliable detection of strong signals, using a relatively small number of samples. In other cases, if the detected energy level does not allow for accurate ED estimation, another, more accurate method can be used.

ED is characterized by low computational complexity and simple implementation [5]. Unfortunately, it is sensitive to the uncertainty of spectral density of noise power estimation [6], [7]. Therefore, the second phase of the hybrid detector (HD) uses a method that does not require this parameter. These methods most often use distinctive features which let us distinguish noise from modulated signals. However, they are usually complex or require many samples to ensure high detection reliability. Examples of methods that can be used in the second HD phase include the following: matched filter, cyclostationary features detector, eigenvalue-based sensing detector, wavelet-based sensing detector or covariance-based detector.

The results of HD research show, inter alia, superiority of the hybrid method [8], [9]. However, these papers refer to an ideal scenario in which the uncertainty of spectral density of noise power estimation is considered. In real systems it is not possible to accurately estimate noise variance, which results in restrictions affecting the use of ED. Any measurements are characterized by finite accuracy and, thus, uncertainty. In the case of ED, this uncertainty in relation to the measurement of the spectral density of noise power is revealed as the so-called SNR wall [10].

When noise is affected by uncertainty, the existing approach turns out to be too idealistic. For this reason, the paper shows an analysis of HD efficiency in an environment with uncertainty associated with spectral density of noise power estimation.

The remaining parts of this paper present two hybrid sensing methods (HD_{CAV} and HD_{CAF}) using ED and CAV or ED and CAF, respectively. A system model for which simulations have been carried out is characterized. The results of the study for the WiMAX system are presented for two cases: the ideal case of an environment with well-known conditions, as considered in the literature so far, and for an environment with uncertainty related to spectral density of noise power estimation.

2. Hybrid Detector

A two-phase hybrid detector is proposed, combining the advantages of ED and CAV or CAF sensing approaches (Fig. 1).

For each channel, first the presence of PU is determined in the ED detection phase. Although this method is sensitive to good noise uncertainty, its undoubted advantage is the

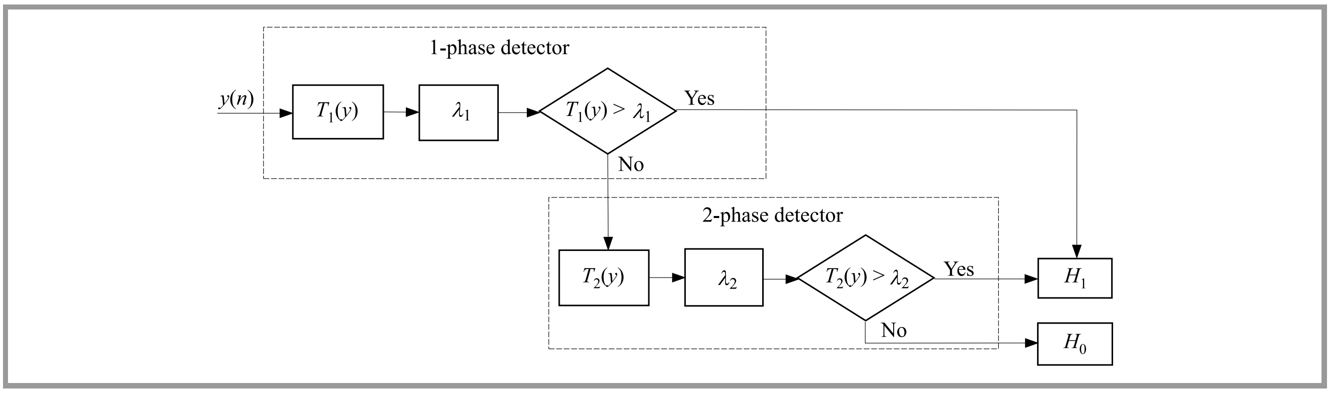

Fig. 1. Hybrid detector block diagram.

high speed of detection and accuracy at high SNR values. The decision about PU signal presence H_1 is taken only when the energy of the received signal ($T_1 = T_{ED}$) is higher than the first phase detection threshold ($\lambda_1 = \lambda_{ED}$) calculated for the assumed probability of a false alarm (P_{fa}).

If the decision cannot be made using ED, CAV or CAF, the second phase of hybrid detection is used as a more accurate approach. The decision about PU signal presence is taken when decision statistic T_2 is greater than the second phase threshold λ_2. Otherwise, a decision about PU signal absence H_2 is made. Depending on the detector used in the second phase (CAV or CAF), here $T_2 = T_{CAV}$ and $\lambda_2 = \lambda_{CAV}$, or $T_2 = T_{CAF}$ and $\lambda_2 = \lambda_{CAF}$.

2.1. ED Method

The decision rule for the energy detector can be expressed by [5], [11]:

$$T_{ED} = \frac{1}{N_S} \sum_{n=0}^{N_S-1} |y(n)|^2 , \tag{1}$$

where: $y(n)$ is the received signal, N_S is the number of signal samples.

The detection threshold for the assumed P_{fa} value is expressed as:

$$\lambda_{ED} = \sigma_\eta^2 \left(Q^{-1}(P_{fa}) \sqrt{2N_S} + N_S \right) , \tag{2}$$

where: σ_η^2 is noise variance, $Q(t)$ is the Q function given by:

$$Q(t) = \frac{1}{\sqrt{2\pi}} \int_t^{+\infty} \mathrm{e}^{-\frac{u^2}{2}} \mathrm{d}u . \tag{3}$$

Equation 2 can be used in an ideal environment, for which it is possible to estimate the noise variance with a high level of accuracy. Under real conditions, the uncertainty of measurement needs to be taken into consideration [10], assuming that the actual variance of noise is within the uncertainty interval such as:

$$\sigma^2 = \left\langle \left(\frac{1}{\rho} \right) \sigma_\eta^2 ; \rho \sigma_\eta^2 \right\rangle , \qquad \rho > 1 , \tag{4}$$

where ρ is parameter that quantifies the uncertainty degree. Considering the uncertainty associated with spectral density of noise power measurements, the detection threshold is:

$$\lambda_{ED} = \rho \sigma_\eta^2 \left(Q^{-1}(P_{fa}) \sqrt{2N_S} + N_S \right) . \tag{5}$$

The time (represented by number of samples N_S) required to the channel state corresponds to the probability values assumed and is expressed as [10]:

$$N \approx \frac{2\left(Q^{-1}(P_{fa}) - Q^{-1}(P_d) \right)^2}{\left(SNR - \left(\rho - \frac{1}{\rho} \right) \right)^2} . \tag{6}$$

Equation 6 shows that the required number of samples reaches infinity when the decreasing SNR reaches a value comparable to the area of approximated spectral density of noise power uncertainty. Figure 2 shows the number of samples needed to obtain the assumed probabilities in the SNR function [10]. Depending on the accuracy of the spectral density of noise power estimation expressed as uncertainty ($x = 10 \log \rho$), the SNR wall level is achieved at lower SNRs, but as the limit approaches, the number of samples necessary to maintain the required credibility increases rapidly.

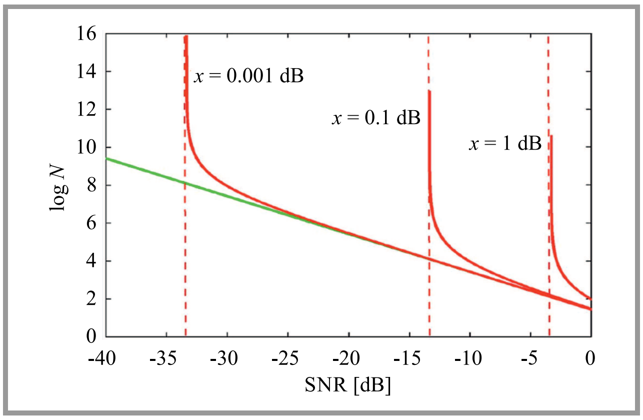

Fig. 2. Number of samples as a function of SNR, depending on the uncertainty of spectral density of noise power estimation.

The detector cannot provide a reliable decision if the signal power level is lower than the uncertainty associated with the spectral density of noise power measurement. SNR wall as function of uncertainty is expressed by Eq. 7 and shown in Fig. 3:

$$SNR_{Wall} = \frac{\rho^2 - 1}{\rho}. \quad (7)$$

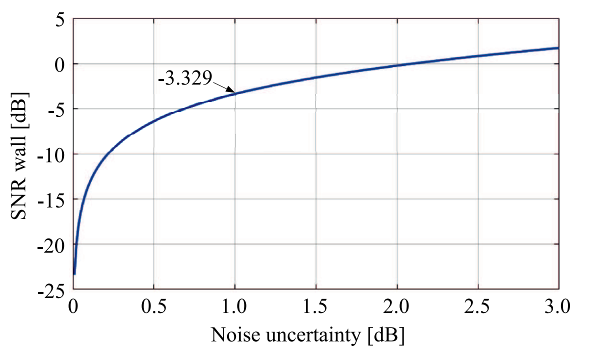

Fig. 3. SNR wall as a function of noise uncertainty.

2.2. CAV Method

CAV is based on differences between noise and signal autocorrelation. The autocorrelation of received signal is [12]:

$$\phi(l) = \frac{1}{N_S}\sum_{n=0}^{N_S-1} y(n)\cdot y(n-l), \quad l = 0,1,\ldots,L-1, \quad (8)$$

where N_S is number of signal samples, L is the smoothing factor.

Statistical covariance matrices R_x of the entire signal and noise can be estimated using an $\hat{R}_x$ matrix symmetric and Toeplitz formed for L consecutive signal samples:

$$\hat{R}_x(N_S) = \begin{bmatrix} \phi(0) & \phi(1) & \ldots & \phi(L-1) \\ \phi(1) & \phi(1) & \ldots & \phi(L-2) \\ \vdots & \vdots & \ddots & \vdots \\ \phi(L-1) & \phi(L-2) & \ldots & \phi(0) \end{bmatrix}. \quad (9)$$

Based on the symmetric property of the autocorrelation matrix, T_1 and T_2 ratios are expressed as follows:

$$T_1 = \frac{1}{L}\sum_{n=1}^{L}\sum_{m=1}^{L} |r_{nm}|, \quad (10)$$

$$T_2 = \frac{1}{L}\sum_{n=1}^{L} |r_{nn}|, \quad (11)$$

where r_{nm} and r_{nn} are $\hat{R}_x$ matrix elements.

The decision statistic for CAV is:

$$T_{CAV} = \frac{T_1}{T_2}, \quad (12)$$

and detection threshold λ_{CAV} is calculated as:

$$\lambda_{CAV} = \left(1 + (L-1)\sqrt{\frac{2}{N_S\pi}}\right)\left(1 - \frac{P_{fa}}{Q}\sqrt{\frac{2}{N_S}}\right)^{-1}. \quad (13)$$

2.3. CAF Method

According to [13], the complex $x(t)$ process with the average zero value is cyclostationary in a wide sense, if its autocorrelation function (varying in time domain) is periodic with the repetition period T_f and can be represented as a Fourier series:

$$R_{xx}(t,\tau) = \sum_{\alpha} R_{xx}^{\alpha}(\tau)e^{j2\pi\alpha t}, \quad (14)$$

where values are added by integral multiples of the basic frequency $\alpha = \frac{k}{T_f}$, $k = 1, 2, 3\ldots$. The Fourier series coefficients depending on the time lag have the following form:

$$R_{xx}^{\alpha}(\tau) = \lim_{T\to\infty}\frac{1}{T}\int_{-\frac{T}{2}}^{\frac{T}{2}} R_{xx}(\tau)e^{-j2\pi\alpha t}dt \quad (15)$$

The $R_{xx}^{\alpha}(\tau)$ function is called the cyclic autocorrelation function (CAF) [14], and the CAF Fourier transform:

$$S_{xx}^{\alpha}(f) = \int_{-\infty}^{\infty} R_{xx}^{\alpha}(\tau)e^{-j2\pi f\tau}dt \quad (16)$$

is called the spectral correlation density function.

One can see that CAF is discrete in terms of frequency and continuous in terms of time lag.

For non-cyclostationary CAFs processes, $R_{xx}^{\alpha}(\tau) = 0$, $\forall\alpha \neq 0$. Each non-zero value of the α parameter, where $R_{xx}^{\alpha}(\tau) = 0$, is called the cyclic frequency.

CAF for the OFDM signal has the following form [15]:

$$R_{xx}^{\alpha} = \frac{A}{T_S}\frac{\sin(\pi N_S\Delta f\tau)}{\sin(\pi\Delta f\tau)}e^{j2\pi\left(f_0+\Delta f\frac{N_S-1}{2}\right)}\times$$
$$\times\int_{-\infty}^{\infty} e^{-j2\pi(\alpha_n-f)}G(f)G(\alpha_n-f)df, \quad (17)$$

where $G(f)$ is the Fourier transform of a rectangular pulse shape, A is the variance of symbol sequence, $T_s = T_u + T_g$ is the symbol duration, $T_u = \frac{1}{\Delta f}$ is the useful symbol duration, Δf is the subcarrier spacing, and T_g is the guard interval duration. The detection threshold λ_{CAF} is:

$$\lambda_{CAF} = tg\cdot\frac{1}{2}\pi\left(1 - P_{fa\_CAF}\right). \quad (18)$$

3. System Model

In cognitive radio, the sensing of the primary user's signals is directly connected with the cognitive system scenario. In this paper the WiMAX (IEEE 802.16-2004 [16]) was assumed as the licensed system with its parameters specified in Table 1. The following detection parameters were also assumed:

- probability of a detection $P_d = 0.9$,
- probability of a false alarm $P_{fa} = 0.1$,
- uncertainty associated with spectral density of noise power estimation $x = \pm 1$ dB.

For the HD second phase using the CAF, detection of a single CAF peak is used ($\alpha = 0$ and $\tau = T_u$). This case is similar to [17], and the difference lies in other decision statistics.

Table 1
Parameters of the licensed system used

Parameter	Value
Bandwidth	3.5 MHz
OFDM symbol duration	80 μs
OFDM useful symbol duration	64 μs
Cyclic prefix ratio	1/4
FFT size	256

The decision statistics for proposed CAF is:

$$T_{CAF} = \left| \frac{R_x^\alpha}{R_y^\alpha} \right|, \tag{19}$$

where: R_x^α is the empirical CAF of the OFDM signal, R_y^α is the empirical noise CAF. T_{CAF} test is a simple ratio test between R_x^α and R_y^α evaluated for $\alpha = 0$ and $\tau = T_u$. The test compares characteristic points of CAF for OFDM signals and noise.

The question that remains open is how to acquire noise samples for the test. One of the solutions proposed in literature is to take data from a rarely used channel. American channel 37 reserved for radio astronomy is a good example here. Another proposal is to use samples from the tested channel, provided that a previous decision has been made that there is no emission in the PU channel.

4. Simulation Results

The aim of the simulations was to check the efficiency of HD_{CAV} and HD_{CAF} methods in comparison to other available techniques, i.e. ED, CAV, CAF. Three metrics were used to evaluate the sensing efficiency:

- sensitivity of the sensing P_d,
- reliability of the sensing P_{fa},
- sensing time.

HD sensing should significantly increase efficiency. However, insertion of the uncertainty of noise variance into the scenario may significantly worsen the results. For this reason, the proposed hybrid detectors were first tested for the ideal case, i.e. in an environment that did not take into account the uncertainty of spectral density of noise power estimation. Then, the tests were repeated for an environment with such uncertainty.

To determine the dependence of P_d on SNR with the assumed number of samples, the probability of a false alarm was set at 10% ($P_{fa} = 0.1$).

Figure 4 shows a comparison of HD_{CAV} performance with ED and CAV sensing techniques for N OFDM signal symbols versus SNR for the ideal case. For 10 OFDM symbols, HD_{CAV} reaches $P_d = 90\%$ for SNR lower by at least 0.8 dB, and for 50 symbols, it is 2 dB referring to the best of of the two single methods (ED). The hybrid detection scheme considered achieves better results than detectors based on exclusively on ED or CAV.

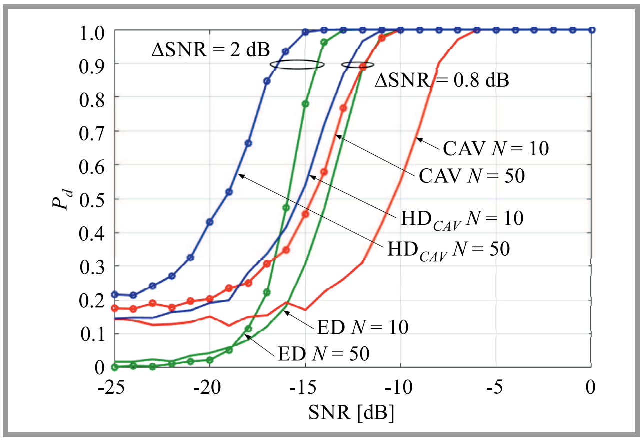

Fig. 4. Probability of detection vs. SNR for HD_{CAV} without the influence of uncertainty of spectral density of noise power estimation.

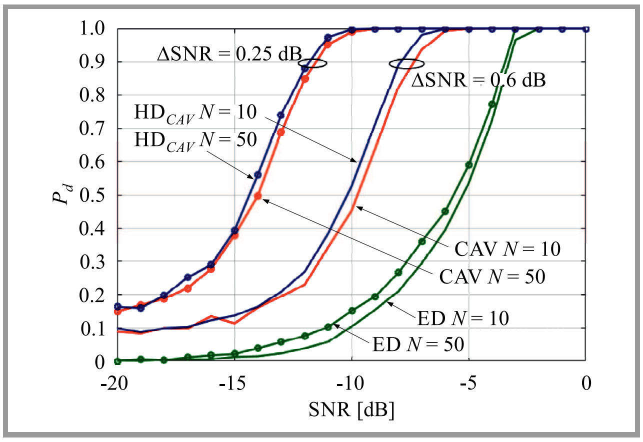

Fig. 5. Probability of detection vs. SNR for HD_{CAV} with the influence of uncertainty of spectral density of noise power estimation.

Figure 5 shows the same comparison as presented in Fig. 4, but with the uncertainty of noise variance. In this situation the results are considerably worse. For 10 OFDM symbols, HD_{CAV} reaches $P_d = 90\%$ for SNR lower by almost 0.6 dB, and for 50 symbols, it is 0.25 dB referring to the best of the two single methods (CAV). The uncertainty of noise variance leads to significant deterioration of the HD detection performance. One can see that the biggest gain from the use of HD is achieved for short signals. So, the longer the signal, the more dependent HD performance becomes on the method used in the second phase of detection.

Figure 6 shows the comparison of HD_{CAF} performance with the ED and CAF sensing techniques for N OFDM signal symbols versus SNR for the ideal case. For 10 OFDM sym-

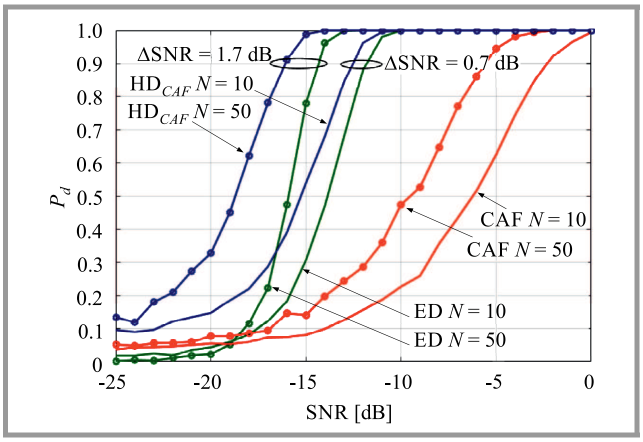

Fig. 6. Probability of detection vs. SNR for HD$_{CAF}$ (without the influence of uncertainty of spectral density of noise power estimation).

bols, HD$_{CAF}$ reaches $P_d = 90\%$ for SNR lower by 0.7 dB, and for 50 symbols, it is 1.7 dB referring to the best of the two single methods (ED). Also, in this case, HD shows better detection parameters than other methods. For HD, the assumed $P_d = 0.9$ is reached at lower SNR values than for the other methods.

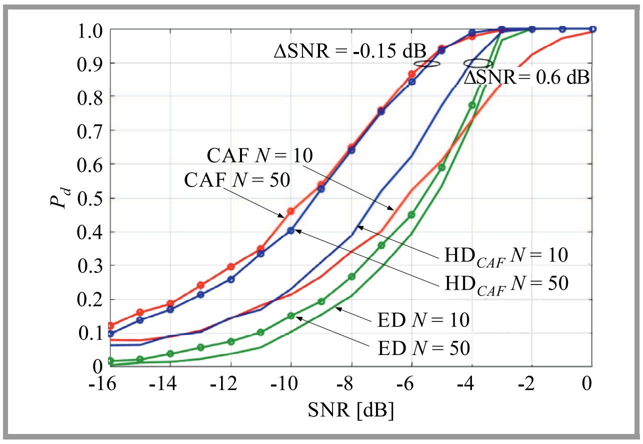

Fig. 7. Probability of detection vs. SNR for HD$_{CAF}$ with the influence of uncertainty of spectral density of noise power estimation.

Similarly, Fig. 7 shows the performance of the same detectors as in Fig. 6, with the uncertainty of noise variance. In this scenario, the results are much worse. For 10 OFDM symbols, HD$_{CAF}$ reaches $P_d = 90\%$ for SNR lower by almost 0.6 dB referring to the best of the two single methods (ED). However, for 50 symbols, HD$_{CAF}$ is worse than the best of the two single methods (CAF) by 0.15 dB. It can be seen that for the environment with the uncertainty of spectral density of noise power estimation, the gain from the use of HD$_{CAF}$ is achieved just for a short signal observation time.

In order to compare the presented detectors, the receiver operating characteristic (ROC) curves were determined (for HD$_{CAV}$ – Fig. 8, Fig. 9, and for HD$_{CAF}$ – Fig. 10, Fig. 11).

It can be noticed that for the ideal case (Fig. 8), HD$_{CAV}$ is significantly better than the other single detectors. HD$_{CAV}$ reaches $P_d = 90\%$ for P_{fa} lower than 6.5%, compared to the better of the single methods (ED). According to the theoretical assumptions, introduction of HD increases reliability sensing due to minimizing P_{fa}.

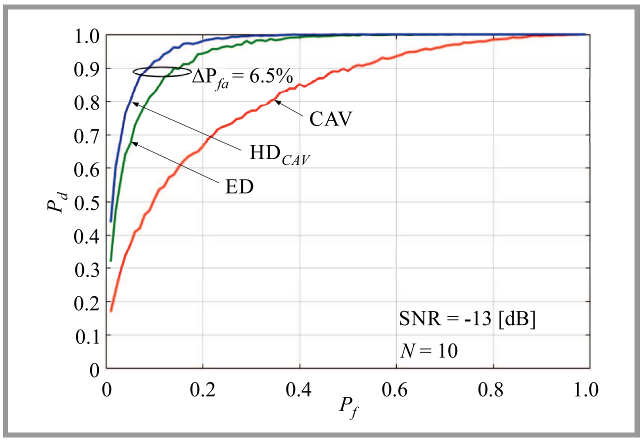

Fig. 8. ROC curves for HD$_{CAV}$ (without the influence of uncertainty of spectral density of noise power estimation).

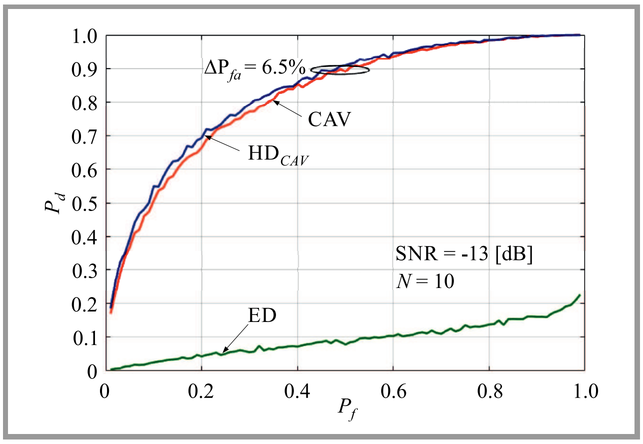

Fig. 9. ROC curves for HD$_{CAV}$ (with the influence of uncertainty of spectral density of noise power estimation).

Figure 9 shows the ROC curves taking into account the uncertainty of the noise variance effect. In this case, the results are much worse. HD$_{CAV}$ reaches $P_d = 90\%$ for P_{fa} lower by at least 2.5%, compared to the better of the single methods (CAV).

In the ideal case (Fig. 8), the detection threshold for the first phase based on ED ($\lambda_1 = \lambda_{ED}$) was calculated from Eq. 2, which did not account for the uncertainty of noise variance. That is why the results show HD superiority compare to other methods. However, by analyzing the ROC curves after taking into account the uncertainty (Fig. 9), one may notice that ED and SNR wall have a great impact on the reliability of HD.

Considering hybrid detection based on CAF in the second phase, one can see that for the ideal case (Fig. 10), HD$_{CAF}$ is also better than other single detectors. HD$_{CAF}$ reaches $P_d = 90\%$ for P_{fa} lower than 6%, compared to the better of the single methods (ED). This time, the introduction of HD (by minimizing P_{fa}) also increases the reliability of sensing.

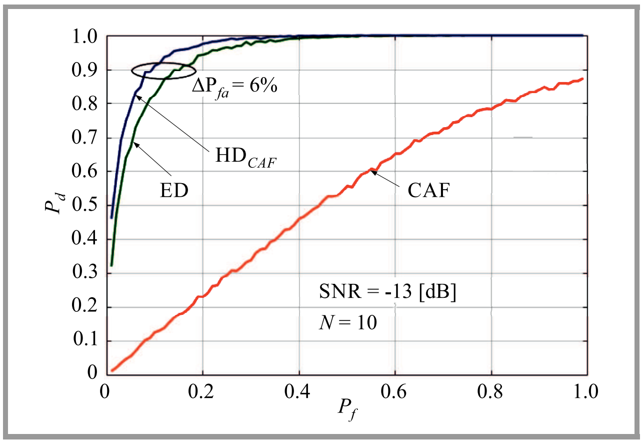

Fig. 10. ROC curves for HD_{CAF} (without the influence of uncertainty of spectral density of noise power estimation).

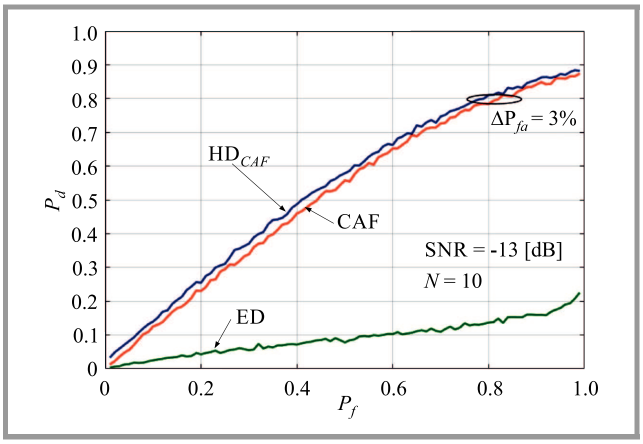

Fig. 11. ROC curves for HD_{CAF} (with the influence of uncertainty of spectral density of noise power estimation).

Figure 11 shows the ROC curves taking into account the uncertainty of the noise variance effect. In this case the results are much worse. For the conditions under consideration, HD_{CAF} does not reach $P_d = 90\%$. But generally, HD_{CAF} allows for decreasing P_{fa} by 3% comparing to the better of the single methods (CAF).

This time, the weak performance of ED in an environment with the uncertainty of spectral density of noise power estimation results in the fact that HD_{CAF} is useless and the SNR wall has too big an impact on the reliability of HD.

To compare both HD solutions in terms of detection time, the results achieved were presented and compared with the number of samples.

The simulation results show P_d vs. sensing time, expressed in the number of samples for HD_{CAV} and HD_{CAF} in Figs. 12 and 13, respectively. The results have been presented just for an environment with the uncertainty of spectral density of noise power estimation, in order to show how considerable a reduction of sensing time is possible with the HD method.

Figure 12 shows that for –5 dB SNR, $P_d = 90\%$ can be achieved for a number of samples lower by at least 400, which represents a reduction of sensing time by 26%. For –10 dB SNR, $P_d = 90\%$ can be achieved 1600 signal samples faster (17% less time).

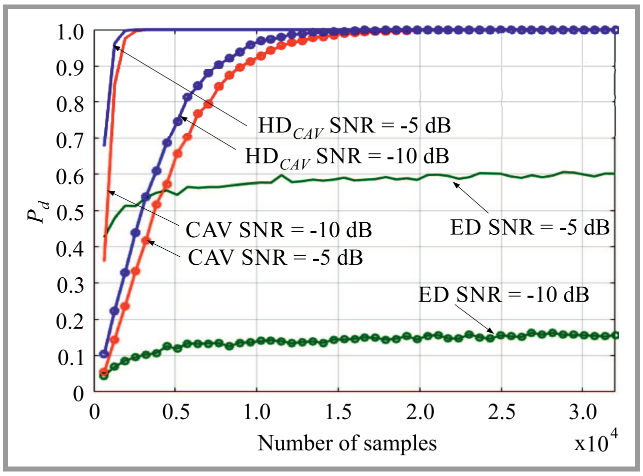

Fig. 12. Probability of detection vs. sample numbers function for HD_{CAV} (with the influence of uncertainty of spectral density of noise power estimation).

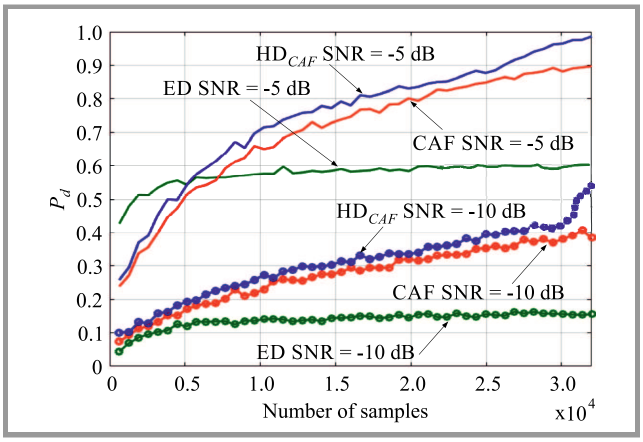

Fig. 13. Probability of detection vs. sample numbers function for HD_{CAF} (with the influence of uncertainty of spectral density of noise power estimation).

In Fig. 13, simulation results for HD_{CAF} show that for –5 dB SNR, $P_d = 90\%$ can be achieved for a number of samples lower by at least 4000 (13% reduction of sensing time). For –10 dB SNR, HD_{CAF} does not reach the required level of P_d for the taken number of samples considered in the simulations. It can be concluded that HD_{CAF} is slower than HD_{CAV} – it requires more samples.

5. Conclusions

The HD allows for the increase of sensing efficiency in cognitive radio, especially in comparison to individual methods, i.e. ED, CAV or CAF. By taking into account two extreme cases: the ideal and the worst ones (with 1 dB uncertainty of spectral density of noise power estimation), it is possible to conclude that the more accurate the estimation of SNR, the higher the HD gain. And even in the worst scenario, HD makes it possible to detect the signal quicker (even by 26%), at the same time lowering P_{fa} and increasing P_d.

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