

Spectrum Sensing for Half and Full-Duplex Cognitive Radio

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Introduction

According to the Federal Communications Commission (FCC) [1–3], the typical radio channel occupancy is less than 15 %. The Dynamic Spectral Access has been proposed as a solution to increase the spectrum usage, and to solve the problem of the scarcity in the frequency resources due to the increasing in the demand on the wireless technologies. The Cognitive Radio (CR) technology is presented as a good candidate for applying the Dynamic Spectral Access. According to FCC, CR is an aware system, that can detect its own electromagnetic environment, so it can intelligently detect which communication channels are occupied and which are in use, and instantly move into vacant channels while avoiding occupied ones. This optimizes the use of available radio-frequency (RF) spectrum while minimizing interference. The CR idea is based on the sharing of the spectrum between users: licensed users are called Primary Users (PU) and unlicensed users are called Secondary Users (SU). SU can use the channel only when PU is idle. Generally, this activity is done in a non-cooperative context. In other words, PU is not obligated to notify SU on its activity.

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In such non-cooperative situation, SU must monitor the PU activities by sensing continuously the channel. When SU wants to transmit, he must sense the channel to check the PU status. If PU is active, then SU cannot access the channel and he should remain idle, or search for another available bands.

The spectrum monitoring is allocated to the Spectrum Sensing part in CR. Spectrum Sensing has to provide the CR with the PU status, in order to protect PU against the interference and in the other hand, to ensure an efficient use of vacant bands. Any error in the decision about the PU status can lead to either, harmful interference to PU or inefficient use of the spectrum.

Many methods have been proposed in order to perform the Spectrum Sensing [2]. Those methods can be categorized into blind, such as Energy Detector (ED) [4] and Autocorrelation Detector (ACD) [5] and non-blind, such as Cyclostationary Detector (CSD) [6] and Waveform Detector (WFD) [7]. WFD requires a perfect knowledge on the PU's signal [2, 7, 8]. Therefore it cannot be implemented in real non-cooperative scenarios, since CR deals with a great variety of signals. The classification into blind and non-blind is done according to the pre-information about the PU signal required to establish the Spectrum Sensing.

Energy Detector (ED) is the most used one in the blind category due to its low complexity. The main idea of ED is to compare the energy of the received signal to a predefined threshold depending on the noise variance which should be estimated before performing the Spectrum Sensing. Therefore, ED becomes vulnerable to the Noise Uncertainty (NU) problem incapable to diagnose the real PU status independently of detection time [9].

ACD requires an oversampling of the baseband received signal (i.e. number of samples per symbols: $N_s \geq 2$). The autocorrelation of a non-zero lag vanishes for a white noise. Otherwise, the autocorrelation will have a non zero value and indicates the presence of a communication signal (The PU's signal). The corresponding test statistic combines linearly the autocorrelation measures for different non-zero lags before making the decision on the PU status. The performance of this algorithm increases with N_s .

CSD measures the cyclostationary features of the received signal. The majority of telecommunication signals are cyclostationary thanks to the modulation process, the carrier frequency, the periodic pilot, *etc.* This fact makes CSD a good candidate for distinguishing between PU's signal and noise since the noise does not have cyclostationary features. In order to be applied, CSD needs to know (or estimate) in advance the cyclic frequency of the PU's signal. CSD tests the cyclostationary at a given cyclic frequency in order to examine the channel status.

Throughout this chapter, T_X denotes the test statistic corresponding to the detector X evaluated to make a decision on the channel status.

Performance Analysis

The Spectrum Sensing consists of making a decision on the presence of PU in the bandwidth of interest (BoI). The problem formulation on the presence/absence of the PU can be presented in a classic Bayesian detection problem: Under H_0 , the PU is absent, whereas under H_1 PU exists.

$$\begin{cases} H_0 : y(n) = w(n) \\ H_1 : y(n) = hs(n) + w(n) \end{cases} \quad (1)$$

where h is the complex channel gain. $w(n) = w_r(n) + iw_i(n)$, is assumed to be an i.i.d zero mean circular symmetric complex Gaussian noise, i.e. $E[w(n)] = E[w^2(n)] = 0$, where $E[.]$ stands for the mathematical expectation. The real part, $w_r(n)$, and the imaginary part, $w_i(n)$, of $w(n)$ are independent and have equal variance.

$$E[w_r^2(n)] = E[w_i^2(n)] = \frac{\sigma_w^2}{2} = \sigma_w^2 = E[|w(n)|^2] \quad (2)$$

Without loss of generality, we can assume that $s(n)$ is normalized. In this case, the Signal to Noise Ratio (SNR), γ , is defined as follows:

$$\gamma = \frac{|h|^2}{\sigma_w^2} \quad (3)$$

A wrong decision about the channel status can affect either the PU transmission or the efficient use of the channel. In fact, a missed detection can cause a harmful interference which is caused by the transmission of the SU in the same band of the PU. A false alarm, however, decreases the profit of the channel. Therefore, the probability of detection (p_d) should be increased as much as possible, by keeping the probability of false alarm (p_{fa}) low. This can be considered as a Neyman-Person's detection method.

Energy Detector

ED consists in evaluating T_{ED} on N received samples, and compares it to a predefined threshold λ [4, 10, 11].

$$T_{ED} = \frac{1}{N} \sum_{n=1}^N |y(n)|^2 \quad (4)$$

The distribution of T_{ED} under H_0 tends toward a central χ^2 distribution with $2N$ degree of freedom. When N becomes large, the distribution of T_{ED} tends toward a Normal Distribution according to Central Limit Theorem. Since we are interested by low SNR, where a very large number of samples must be used during the detection process. In this case, the distribution of T_{ED} can be considered as a Gaussian with a

mean μ_0^{ED} and a variance V_0^{ED} : $\mathcal{N}(\mu_0^{ED}, V_0^{ED})$.

$$T_{ED} \stackrel{H_0}{\sim} \mathcal{N}(\mu_0^{ED}, V_0^{ED}) \quad (5)$$

where $\stackrel{H_i}{\sim}$ stands for the tendance of distribution under H_i , $i \in \{0, 1\}$, and $\mathcal{N}(a, b)$ represents a Normal distribution of mean a and variance b .

Under H_1 , the distribution of T_{ED} depends on that of $s(n)$ and $w(n)$. Some researchers suggest to use the Gaussian distribution as generic model when $s(n)$'s distribution is totally unknown [10]. Such case leads to obtain a Normal Distribution of T_{ED} under H_1 for a large number of samples according to Central Limit Theorem.

$$T_{ED} \stackrel{H_1}{\sim} \mathcal{N}(\mu_1^{ED}, V_1^{ED}) \quad (6)$$

PU's signal is assumed in some cases to be deterministic with unknown value, in order to derive the analytic distribution of the test statistic [10, 12, 13]. When no assumption is taken on the distribution of the PU signal, the distribution of the test statistic becomes non-derivable [10].

The probability of False Alarm and Detection of ED for a large N can be derived as follows [10]:

$$p_{fa}^{ED} = Q\left(\frac{\lambda - \sigma_w^2}{\frac{1}{\sqrt{N}}\sigma_w^2}\right) \quad (7)$$

$$p_d^{ED} = Q\left(\frac{\lambda - (\sigma_w^2 + \sigma_s^2)}{\frac{1}{\sqrt{N}}(\sigma_w^2 + \sigma_s^2)}\right) \quad (8)$$

where $Q(x) = \frac{1}{\sqrt{2\pi}} \int_x^{+\infty} \exp(-\frac{t^2}{2}) dt$ is the Q-function

Autocorrelation Detector

For ACD, the PU signal is assumed to be oversampled. The test statistic to be derived, T_{ACD} , is presented as follows [5]:

$$T_{ACD} = \frac{1}{\hat{r}_{yy}(0)} \sum_{m=1}^{N_s-1} Re\{\hat{r}_{yy}(m)\} \quad (9)$$

where $\hat{r}_{yy}(m) = \frac{1}{N} \sum_{n=1}^N y(n)y^*(n-m)$ is an estimator of the autocorrelation function $r_{yy}(m) = E[y(n)y^*(n-m)]$, and N_s is the number of samples per symbols.

The division operation by $\hat{r}_{yy}(0)$ avoids the vulnerability of ACD to the noise uncertainty, since ACD becomes independent of the noise variance. This operation makes ACD a Constant False Alarm Rate (CFAR) detector, so that the threshold of comparison is only depending to the number on samples used in the detection process.

According to [5], the False Alarm and Detection probabilities of ACD are expressed as follows:

$$p_{fa}^{ACD} = Q\left(\lambda \sqrt{\frac{N}{\lambda^2 + \Sigma}}\right) \quad (10)$$

$$p_d^{ACD} = Q\left(\frac{\lambda - \frac{\beta\gamma}{\gamma+1}}{\sqrt{V_{ACD}}}\right) \quad (11)$$

where $\Sigma = \frac{1}{2} \sum_{l=1}^{N_s-1} e_l^2$, $\beta = \sum_{l=1}^{N_s-1} e_l \frac{r_{ss}(l)}{r_{ss}(0)}$, $V_{ACD} = \frac{(1+\gamma)\lambda^2 - 4\beta\gamma\lambda + \Sigma + \eta\gamma}{N(\gamma+1)^2}$ and $\eta = \sum_{l=1}^{N_s-1} \sum_{k=1; l \neq k}^{N_s-1} e_l e_k \frac{r_{ss}(l-k) + r_{ss}(l+k)}{r_{ss}(0)}$, With $\{e_l\}_{l=1}^{N_s-1}$ is a set of weighting coefficients.

Cyclostationary Detector

In [6], the authors propose the Generalized Likelihood Ratio Test (GLRT) detector based on the cyclostationary features of the PU signal:

$$T_{CSD} = N \hat{r}_y \mathbf{K} \hat{r}_y^T \quad (12)$$

where the upper script T stands for the transpose of a matrix, and r_y is defined as follows:

$$r_y = \begin{bmatrix} \text{Re}\{\hat{r}_{yy}(\tau_1, \alpha)\}, \text{Re}\{\hat{r}_{yy}(\tau_2, \alpha)\} \dots, \text{Re}\{\hat{r}_{yy}(\tau_M, \alpha)\}, \\ \text{Im}\{\hat{r}_{yy}(\tau_1, \alpha)\}, \text{Im}\{\hat{r}_{yy}(\tau_2, \alpha)\} \dots, \text{Im}\{\hat{r}_{yy}(\tau_M, \alpha)\} \end{bmatrix} \quad (13)$$

$\hat{r}_{yy}(\tau_i, \alpha)$ is the estimated cyclic autocorrelation function (CAF) at a cyclic frequency α and a time lag τ_i , and M is the number of the time lags used in the detection process:

$$\hat{r}_{yy}(\tau_i, \alpha) = \sum_{n=1}^N y(n)y^*(n - \tau_i)e^{-j2\pi\alpha n} \quad (14)$$

$\mathbf{K}$ stands for the covariance:

$$\mathbf{K} = \frac{1}{2} \begin{bmatrix} \text{Re}\{\mathbf{P} + \mathbf{Q}\} & \text{Im}\{\mathbf{Q} - \mathbf{P}\} \\ \text{Im}\{\mathbf{P} + \mathbf{Q}\} & \text{Re}\{\mathbf{P} - \mathbf{Q}\} \end{bmatrix} \quad (15)$$

where $\mathbf{P} = \begin{pmatrix} P_{pq} \end{pmatrix}$ and $\mathbf{Q} = \begin{pmatrix} Q_{pq} \end{pmatrix}$ are found as follows:

$$\begin{aligned} P_{p,q} &= \sum_{m=\frac{1-L}{2}}^{\frac{L-1}{2}} f(m)\hat{r}_{yy}\left(\tau_p, \alpha + \frac{2\pi m}{N}\right)\hat{r}_{yy}^*\left(\tau_q, \alpha + \frac{2\pi m}{N}\right) \\ P_{p,q} &= \sum_{m=\frac{1-L}{2}}^{\frac{L-1}{2}} f(m)\hat{r}_{yy}\left(\tau_p, \alpha + \frac{2\pi m}{N}\right)\hat{r}_{yy}\left(\tau_q, \alpha - \frac{2\pi m}{N}\right) \end{aligned} \quad (16)$$

$f(m)$ is a normalized window, so that $\sum_{m=1}^L f(m) = 1$. The distribution of T_{CSD} is provided [6] under H_0 by a central χ^2 of $2M$ degrees of freedom, and H_1 by a non-central χ^2 distribution with $2M$ degree of freedom and a non-centrality parameter of $N\hat{r}_x\mathbf{K}\hat{r}_x^T$.

$$\begin{cases} T_{CSD} \stackrel{H_0}{\sim} \chi_{2M}^2 \\ T_{CSD} \stackrel{H_1}{\sim} \chi_{2M}^2 \left(N\hat{r}_x\mathbf{K}\hat{r}_x^T \right) \end{cases} \quad (17)$$

The probability of false alarm and detection are given based on the distributions under H_0 and H_1 respectively:

$$p_{fa}^{CSD} = \gamma(\lambda/2, M) \quad (18)$$

$$p_d^{CSD} = Q_M\left(\sqrt{\lambda}, \sqrt{N\hat{r}_x\mathbf{K}\hat{r}_x^T}\right) \quad (19)$$

where $\gamma(a, b)$ is the upper incomplete gamma function and $Q_M(a, b)$ is the generalized Marcum Q-function.

Half and Full Duplex Cognitive Radio

Recently, the Full-Duplex transmission has gained a lot of attention thanks to recent advancements in the Self-Interference Cancellation (SIC), which makes the appli-

cation of FD communication possible. FD has been proposed in order to double the channel efficiency, where the same bandwidth is used simultaneously for both transmission and reception. However, FD transceiver should be able to eliminate the self interference. Due to many imperfections, a perfect elimination of the self-interference cannot be reached in real world applications [14, 15]. In wireless systems, the FD is considered as achieved if the Residual Self Interference (RSI) power becomes lower than the noise level. For that, an important SIC gain is required (around 110 dB for a typical WiFi system [14]). This gain can be achieved using the passive suppression and the active cancellation. The passive suppression is related to many factors that reduce the Self Interference (SI) such as the transmission direction, the absorption of the metals and the distance between the transmitting antenna, T_x , and the receiver, R_x . The active cancellation reduces the Self-Interference (SI) by using a copy of the transmitted signal at T_x . This copy is used in addition to the estimated channel between T_x and R_x to eliminate the self interference. The estimation of channel coefficients becomes an essential factor in the active cancellation process. Any error in the channel estimation leads to decreasing the SIC gain.

In the context of CR, FD means that SU is able to transmit and sense the channel as the same time. The SU makes a decision on the PU status using a Test Statistic depending on the PU signal and the noise. Any residual interference from the SU can affect the test statistic norm and leads to a wrong decision on the presence of PU.

Traditionally, Spectrum Sensing algorithms are deigned to deal with a Half-Duplex (HD). HD-CR divides the active period into two successive slots: the sensing slot and the transmission slot. During the sensing slot, SU must stop transmission in order to do not affect the decision reliability.

In FD-CR, SU remains active during the Sensing slot. This can be done without affecting the channel decision reliability by doing the SIC on the SU signal. After performing SIC, SU applies a Spectrum Sensing techniques to examine the PU status.

IN HD-CR, the detection problem to diagnose between H_0 and H_1 can be presented as in (17), whereas under FD-CR, the detection problem becomes as follows:

$$\begin{cases} H_0 : y(n) = gz(n) + w(n) \\ H_1 : y(n) = hs(n) + gz(n) + w(n) \end{cases} \quad (20)$$

where $z(n)$ is the SU signal and g represents the channel effect between T_x and R_x . By applying SIC, CR can eliminate the reflected SU signal from the received mixed signal. In ideal situation, where $gz(n)$ is totally eliminated, Eq. (20) refers to that of HD hypothesis (17).

Figure 1 shows the sensing-transmitting period of CR under FD and HD modes. It is clear that under HD, SU must stop the transmission each time the spectrum sensing is established. This issue leads to decrease the Data-Rate of SU. This problem is solved with FD-CR, but with a cost of degradation of Spectrum Sensing performance if the SIC is not efficient enough. For the two modes, SU can continue using the same bandwidth only if the Spectrum Sensing decides that PU is absent.

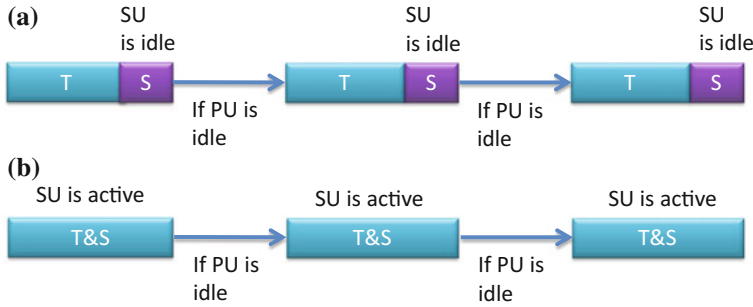


Fig. 1 CR Activity Structure for FD and HD transmission. Under HD, the activity period is divided into two slots: transmission slot and sensing slots, whereas under FD, CR performs the sensing while it is transmitting. **a** Half-Duplex Cognitive Radio activity. **b** Full-Duplex Cognitive Radio activity

Work Objectives

In our work, we are aiming at developing a new detector under HD. This detector should be blind that is make the sensing process more flexible. In addition, this fact avoid any pre-requisite information required by the non-blind detectors such as CSD. Moreover, the developed detector takes into account the problems that are frequently existing with the blind detectors. For example, ED suffers a performance degradation due to the noise uncertainty problem. Over more, ACD requires a high oversampling rate in order to present an efficient performance, so that at the limiting case, when the number of samples per symbol is two, ACD is poor comparing to ED. Also, this limitation will be avoided by our developed detectors. Besides that, to overcoming the problems of the state of the art detectors, the developed detectors present an efficient performance, require a short observation time and have a moderate complexity.

For FD mode, our main goal is to eliminate the distortion of the low noise amplifier (LNA), which is a main limiting factor that prevent the FD to be established. The residual power of this distortion affects the test statistic examining the channel status. To ensure a reliable evaluated test statistic, we are aiming at eliminating the LNA's distortion by using a simple and efficient algorithm. The proposed algorithm shows its superiority relatively to another state of the art one recently proposed.

Approaches Based on Cumulative Power Spectral Density

In this section, we present our new Spectrum Sensing algorithms based on the cumulative sum of the Power Spectral Density [16]. First, the baseband PU signal, $s(n)$, that might exist in the BoI can be modeled as follows:

$$s(n) = \sum_k b_k g(n - kN_s) = s_p(n) + js_q(n) \quad (21)$$

b_k are the symbols to be modulated, $g(n)$ is the shaping window, N_s stands for the number of samples per symbol (sa/sy), and satisfies the Nyquist criterion, $N_s = \frac{F_s}{B} \geq 2$, where F_s is the sampling frequency and $s_r(n)$ and $s_i(n)$ are the real and imaginary parts of $s(n)$ respectively. $s(n)$ has a bandwidth B and a real and even autocorrelation function. The same model of $s(n)$ has been used in [12] and [13], where $s(n)$, is assumed to be complex-valued zero mean unknown deterministic signal. $s_r(n)$ and $s_i(n)$ are assumed to be independent and have the same autocorrelation function.

Our new proposed Spectrum Sensing detectors are mainly based on the cumulative sum of the Power Spectral Density (PSD) of the received signal. When assuming the whiteness of the noise samples, the noise's PSD becomes flat. This aspect does not exist for the PU signal, which is assumed to be oversampled. Therefore its PSD is no longer flat. If the PU is absent, the cumulative sum of the received signal PSD has a close shape to a straight line. Whereas a curved shape is obtained when PU exists.

To enhance the robustness of our contribution, hard and soft cooperative schemes are introduced. In those two schemes, the spectrum is divided into two parts. The first part corresponds to the negative frequency points, while the second part deals with the positive frequency points. Hence, two test statistics are calculated, based on the Cumulative PSD of each of those two parts, and they are then combined according to the considered scheme.

The performance of our detectors is better than ones of the ED, ACD, and CSD under Gaussian and Rayleigh fading channels. Besides that, our detectors are less sensitive to the Noise Uncertainty than ED and they can be made independent from the noise variance.

Introduction to the Power Spectral Density

The power spectral density (PSD), $P_x(\nu)$, of a signal $x(n)$ can be estimated as the Fourier Transform of $\hat{r}_{xx}(m)$ as follows [17]:

$$P_x(\nu) = \lim_{N \rightarrow +\infty} \sum_{m=N/2-1}^{N/2} \hat{r}_{xx}(m) \exp \{-j2\pi\nu \frac{m}{N}\} \quad (22)$$

Since $w(n)$ is i.i.d., its autocorrelation becomes a dirac function:

$$r_{ww}(m) = \sigma_w^2 \delta(m) \quad (23)$$

In this case, $P_w(\nu)$ becomes flat on the band $[-B, B]$. On the other hand, $P_w(\nu)$ is real and even since $\hat{r}_{ww}(m)$ is real and even. It is obvious to deduce that the cumulative sum of the PSD becomes a straight line, with a slope σ_w^2 . The over-sampling aspect of $s(n)$ makes it non i.i.d., then its PSD, $P_s(\nu)$, becomes not constant on $[-B; B]$.

Consequently, $P_y(\nu)$, becomes real and even, since $w(n)$ and $s(n)$ are assumed to be independent. $P_y(\nu)$ is flat under H_0 , whereas it is non flat under H_1 .

Based on this fact, the differentiation between the two hypotheses: H_0 and H_1 can be realized using the shape of the cumulative sum of PSD of random signals.

The PSD of a random signal $y(n)$ can be estimated as follows [17]:

$$\hat{P}_x(\nu) = \frac{1}{N} |Y(\nu)|^2 \quad (24)$$

where $Y(\nu)$ is the Discrete Fourier Transform (DFT) of the signal $y(n)$ with N samples:

$$Y(\nu) = \sum_{m=N/2-1}^{N/2} y(n) \exp \{-j2\pi\nu \frac{m}{N}\} \quad (25)$$

Cumulative Power Spectral Density-Based Detector

To diagnose the channel status, the test statistic to be estimated in should take into account the relative position of the obtained CPSD shape with respect to the reference straight line, which stands for the noise-only case (H_0). This test statistic is then compared to a threshold, λ , to obtain a decision on the presence of the PU signal. The value of λ must be set according to a target probability of false alarm, p_{fa} .

Let us define the CPSD, $C_y(\nu)$, of the received signal $y(n)$, over a discrete frequency interval $I = [k; l]$:

$$C_y(\nu) = \sum_{u=k}^{\nu} \hat{P}_y(u); \quad k \leq \nu \leq l, \quad (26)$$

where $\hat{P}_y(\nu)$ is the estimated PSD of $y(n)$ and can be found similarly to Eq. (24). In this manuscript, the test statistic is related to the Normalized CPSD, $\Gamma(\nu)$, of $y(n)$. $\Gamma(\nu)$ is defined as follows:

$$\Gamma(\nu) = \frac{C_y(\nu)}{(l - k + 1)\sigma_w^2} \quad (27)$$

The term $(l - k + 1)\sigma_w^2$ corresponds to the mean value of the last term of $C_w(\nu)$: $C_w(l)$. $C_w(\nu)$ stands for the CPSD of $w(n)$.

$$\begin{aligned} E[C_w(l)] &= \frac{1}{N} \sum_{\nu=k}^l E[|W(\nu)|^2] \\ &= (l - k + 1)\sigma_w^2 \end{aligned} \quad (28)$$

Thanks to the flat PSD of $w(n)$, the shape of $C_y(\nu)$ is closed to the straight line $R(\nu; k, l)$ under H_0 .

$$R(\nu; k, l) = \frac{\nu - k + 1}{l - k + 1} \quad (29)$$

Under H_1 this property is not satisfied, since the PSD of $s(n)$ is not constant, and $\Gamma(\nu)$ has higher values than the ones obtained under H_0 due to the power of $s(n)$.

Figure 2 shows $\Gamma(\nu)$ under H_0 and H_1 with a SNR of 0 dB, $N = 10,000$ samples and $N_s = 2$ sa/sy. The $\Gamma(\nu)$ shape presented in this figure, can be considered as a detection criterion, if this shape is closed to $R(\nu; k, l)$, then H_0 is selected by the detector, else, H_1 is decided.

Motivated by the discussion above, the test statistic T can be obtained as the difference between $\Gamma(\nu)$ and the reference straight line $R(\nu; k, l)$. Accordingly, we introduce the two following detectors:

1. T_p : The normalized CPSD of $y(n)$ over the positive frequency points: $1 \leq \nu \leq N/2$, $\Gamma_p(\nu)$, can be defined as follows:

$$\begin{aligned} \Gamma_p(\nu) &= \frac{1}{M\sigma_w^2} \sum_{u=1}^{\nu} P_y(u) \\ &= \frac{2}{N^2\sigma_w^2} \sum_{u=1}^{\nu} |Y(u)|^2 \end{aligned} \quad (30)$$

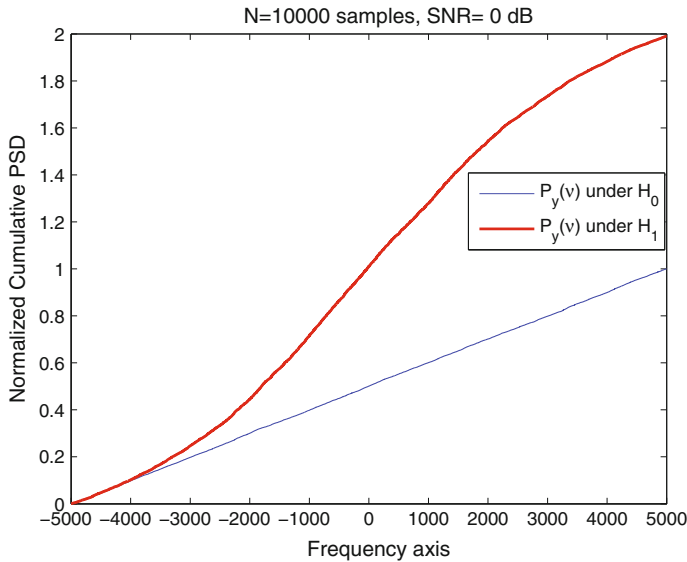


Fig. 2 Normalized Cumulative PSD of the received signal under H_0 and H_1

The T_p detector stands for the difference between $\Gamma_p(\nu)$ and $R(\nu; 1, M) = \frac{\nu}{M}$ [16]

$$\begin{aligned}
 T_p &= \sum_{\nu=1}^M \left(\Gamma_p(\nu) - \frac{\nu}{M} \right) \\
 &= \sum_{\nu=1}^M \Gamma_p(\nu) - \frac{M+1}{2} \\
 &= \frac{2}{N^2 \sigma_w^2} \sum_{\mu=1}^M (M - \nu + 1) |Y(\nu)|^2 - \frac{N/2 + 1}{2} \quad (31)
 \end{aligned}$$

2. T_a : The detection process based on the CPSD of all frequencies of $y(n)$ (i.e. $-M + 1 \leq \nu \leq M$), T_a , can be defined similarly to (31) as follows:

$$\begin{aligned}
 T_a &= \sum_{\nu=-M+1}^M \left(\Gamma_a(\nu) - \frac{\nu+M}{N} \right) \\
 &= \sum_{\nu=-M+1}^M \Gamma_a(\nu) - \frac{N+1}{2} \quad (32)
 \end{aligned}$$

T_a is an extended version of T_p to cover the positive and negative frequencies.

Proposed Cooperative Detectors

In order to exploit the even parity of the PSD of the PU signal, and the i.i.d property of $W(\nu)$ [16], two cooperative detectors are proposed. The first proposed detector, T_{or} , aims to exploit all the bandwidth of the signal $y(n)$, by applying two test statistics: T_p tests the shape of the CPSD of $\hat{P}_y^p(\nu)$ (which is T_p) and T_n tests the CPSD shape of $\hat{P}_y^n(\nu)$ defined by:

$$\hat{P}_y^n(\nu) = \hat{P}_y(-\nu + 1), \quad 1 \leq \nu \leq M \quad (33)$$

$\hat{P}_y^n(\nu)$ corresponds to the negative frequency points. The detector, T_{or} , takes a final decision by performing a logical OR operation on the decisions of T_p and T_n .

The cooperative detector, T_{av} , performs the average between $\hat{P}_y^p(\nu)$ and $\hat{P}_y^n(\nu)$, before the computation of the CPSD. The averaging process makes the PSD more smooth.

OR Detector

T_{or} acts as hard cooperative detector of T_p and T_n by using an OR-rule.

$$T_{or} = OR(D_{T_p}, D_{C_n}) \quad (34)$$

where D_{T_p} and D_{C_n} are the detection results of T_p and C_n respectively.

Averaging Detector

T_{av} is introduced by averaging $\hat{P}_y^p(\nu)$ and $\hat{P}_y^n(-\nu + 1)$, $1 \leq \nu \leq \frac{N}{2}$, to obtain $P_y^{av}(\nu)$. The average operation leads to evaluate a more accurate test statistic since the estimator $P_s(\nu)$ is deterministic and even while $\hat{P}_w(\nu)$ is i.i.d.

$$\begin{aligned} P_{av}(\nu) &= \frac{\hat{P}_y^p(\nu) + \hat{P}_y^n(\nu)}{2} \\ &= \frac{\hat{P}_y(\nu) + \hat{P}_y(-\nu + 1)}{2}; \quad 1 \leq \nu \leq \frac{N}{2} \end{aligned} \quad (35)$$

T_{av} , can be considered as a soft combining detectors of T_p and T_n .

$$\begin{aligned} T_{av} &= \sum_{\nu=1}^M \left(\Gamma_{av}(\nu) - \frac{\nu}{M} \right) \\ &= \sum_{\nu=1}^M \Gamma_{av}(\nu) - \frac{M+1}{2} \end{aligned} \quad (36)$$

where Γ_{av} is the normalized CPSD corresponding to $P_{av}(\nu)$ (see Eq. (30)), and it is defined similarly to (30). The average PSD, $P_{y,av}(\nu)$, can illustrate a more smooth PSD of the received signal, especially for the noise component. This smoothing can help the detector to well distinguish between the two hypotheses, H_0 and H_1 (Fig. 3).

Performance Evaluation

In this section, we compare the performance of our detectors with that of ED [4], ACD [5] and CSD [6], under Gaussian and Rayleigh channels. A 16-QAM baseband modulated PU signal is considered with a rectangular shaping window.

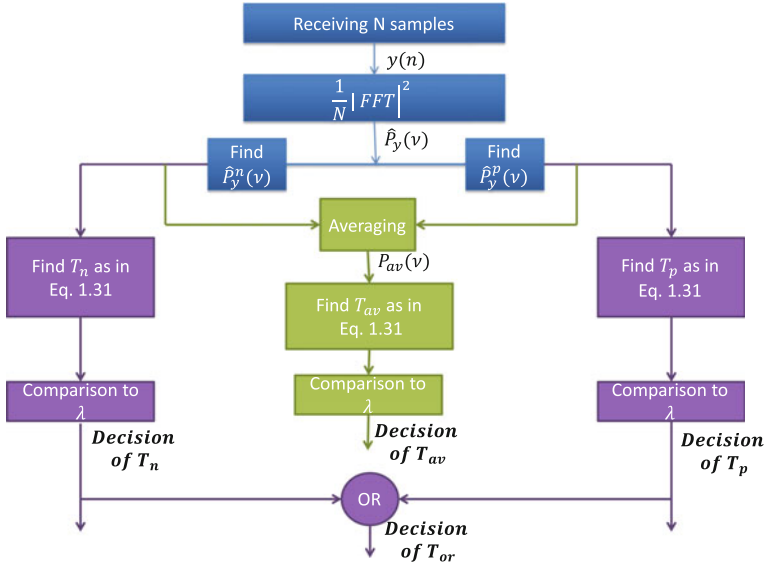


Fig. 3 The architecture of the proposed detectors

Gaussian Channel

First, Let us present the analytic False Alarm and Detection Probabilities of our proposed detectors, derived under Gaussian channel [16].¹

1. The False Alarm probability of T_p , $p_{fa,p}$, is found as follows:

$$p_{fa,p} = Q\left(\frac{\lambda}{\sqrt{V_0}}\right) \quad (37)$$

where V_0 is the variance of T_p under H_0 , and it is defined as follows:

$$\begin{aligned} V_0 &= E[T_p^2] - E^2[T_p] \\ &= \frac{N}{6} + \frac{1}{2} + \frac{1}{12N} \end{aligned} \quad (38)$$

On the other hand, the probability of detection of T_p , $p_{d,p}$, is:

$$p_{d,p} = Q\left(\frac{\lambda - \mu_1}{\sqrt{V_1}}\right) \quad (39)$$

¹The analytic study of the false alarm alarm and probabilities of the proposed detectors is presented in details in [16].

where μ_1 and V_1 are the mean and the variance of T_p under H_1 respectively:

$$\mu_1 = \frac{2|h|^2}{N^2\sigma_w^2} \sum_{v=1}^M (M - v + 1) |S(v)|^2 \quad (40)$$

$$\begin{aligned} V_1 &= E[T_p^2] - E^2[T_p] \\ &= V_0 + \frac{8\gamma}{N^3} \sum_{v=1}^M (M - 1 + v)^2 |S(v)|^2 \end{aligned} \quad (41)$$

T_a is an extension of T_p , which covers all the N frequency point instead of only the positive frequency points ($N/2$ points). In order to obtain the corresponding False Alarm, $p_{fa,a}$, and detection, $p_{d,a}$ probabilities, we can simply replace $M = N/2$ by N in the expressions of $p_{fa,p}$ and $p_{d,p}$ respectively.

2. T_{or} :

As T_p and T_n are independent and have the same statistics and T_{or} applies the OR-rule, the probability of false alarm $p_{fa,or}$, and the probability of detection $p_{d,or}$, of T_{or} can be found as follows [18]:

$$p_{fa,or} = 1 - (1 - p_{fa,p})^2 \quad (42)$$

$$p_{d,or} = 1 - (1 - p_{d,p})^2 \quad (43)$$

3. T_{av} :

The probability of false alarm, $p_{fa,av}$, and detection, $p_{d,av}$, of T_{av} are expressed as follows:

$$p_{fa,av} = Q\left(\frac{\lambda - \mu_0^{av}}{\sqrt{V_0^{av}}}\right) \quad (44)$$

$$p_{d,av} = Q\left(\frac{\lambda - \mu_1^{av}}{\sqrt{V_1^{av}}}\right) \quad (45)$$

where: $\mu_0^{av} = 0$ and $V_0^{av} = \frac{V_0}{2}$ are the mean value and the variance of T_{av} under H_0 respectively, and $\mu_1^{av} = \mu_1$ and $V_1^{av} = \frac{V_1}{2}$ are the mean value and the variance under H_1 respectively.

The analytic and the simulated ROC curves of proposed detectors, are with good agreement as shown in Fig. 4. The simulation was done under the following conditions: 16-AM modulation, $\gamma = -12$ dB, $N = 1000$ samples and $N_s = 3$ sa/sy.

As shown in the same figure, T_{av} is the most efficient. T_{av} and T_{or} outperform significantly T_a and T_p . For that reason, we will only compare T_{av} and T_{or} to other known detectors.

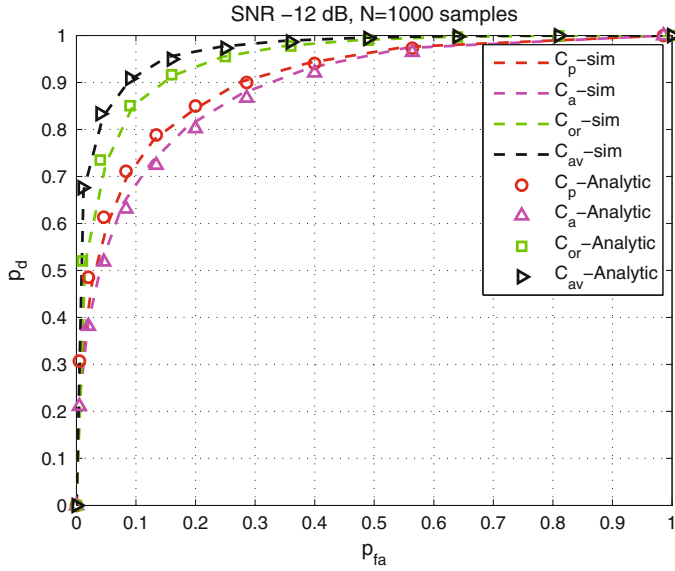


Fig. 4 Analytic results versus Simulation results for the proposed detectors under Gaussian channel.

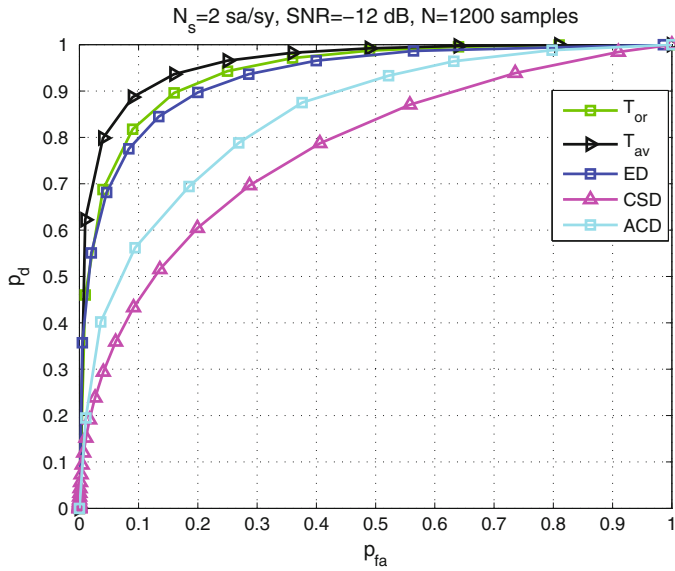


Fig. 5 ROC curves of our proposed detectors with T_{ed} and T_{ac} for $N_s = 2$ sa/sy

Figure 5 presents the ROC curves under Gaussian channel of various detectors for $N_s = 2$. The simulation is done under $N = 1200$ samples and $\gamma = -12$ dB. CSD and ACD shows a poor performance relatively to T_{av} , T_{or} and ED, while T_{av} outperforms

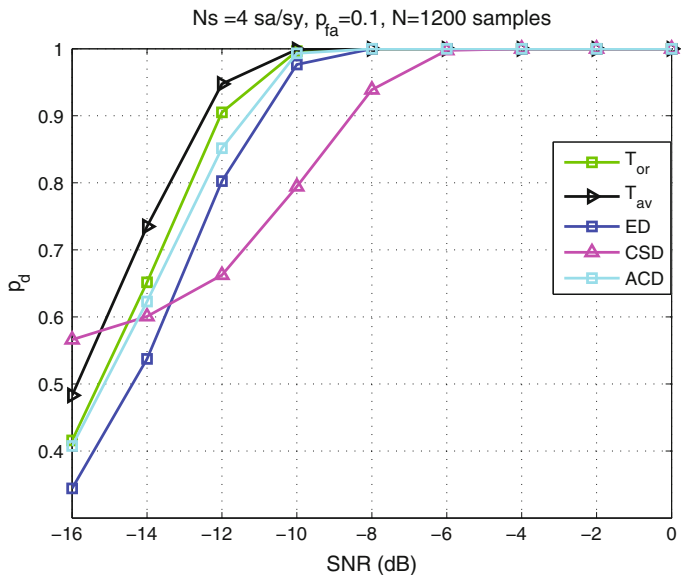


Fig. 6 Performance of our proposed detectors with ED and CSD for $p_{fa} = 0.1$ and $N_s = 4 \text{ sa/sy}$

all other detectors. Figure 6 shows the variation of the probability of detection in terms of SNR for a $p_{fa} = 0.1$, $N = 1200$ samples and $N_s = 4 \text{ sa/sy}$. Our detectors, T_{av} and T_{or} reach a higher probability of detection than the other detectors N_s . As shown in this figure, ACD outperforms ED for $N_s = 4 \text{ sa/sym}$, this is because ACD's performance increases with N_s .

Sensing Time

According to IEEE 802.2 regulation [19], the time sensing should be no longer than 2 s, with a maximal $p_{fa} = 0.1$ and a minimal $p_d = 0.9$. For that reason, the observation time required to ensure a reliable sensing process becomes a challenge for any Spectrum Sensing algorithm. In this section, we compare the sensing time of proposed algorithm to these of ED, ACD and CSD by evaluating the required number of samples to reach $(p_{fa}; p_d = 0.1; 0.9)$ under different SNR.

The simulation is performed under $N_s = 3 \text{ sa/sy}$. Figure 7 shows that when SNR decreases the number of samples increases, this is because a high number of samples can make the detection process more reliable. As shown in this figure, T_{av} and T_{or} can reach this target at a given SNR with lower number of samples than ED, ACD and

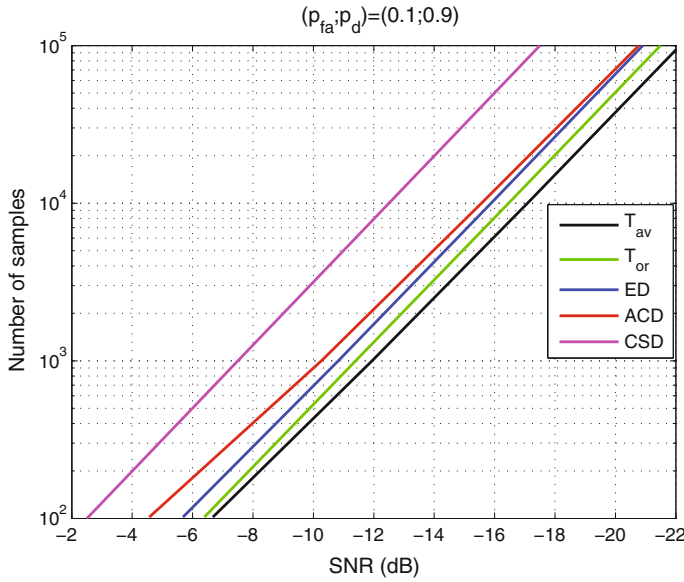


Fig. 7 The number of samples required to reach $(p_{fa}; p_d) = (0.1; 0.9)$ in terms of SNR

CSD. For example, with SNR of -10 dB, T_{av} and T_{or} reach this target with $N \simeq 400$ and $N \simeq 500$ samples respectively, whereas ED, ACD and CSD need $N \simeq 700$, 900 and $N \simeq 3500$ respectively to reach $(p_{fa}; p_d) = (0.1; 0.9)$.

Rayleigh Channel

In this section, we evaluate the performance of our proposed detectors under Rayleigh fading channel. The analytic probability of false alarm remains the same since it is independent of the channel gain h , which is assumed to be a circular symmetric Gaussian variable, but it keeps a constant value during a spectrum sensing period. On the contrary, the probability of detection depends on h , therefore it will have a new form depending on the distribution of the SNR, $\gamma, f_\gamma(\gamma)$, in the Rayleigh channel.

$$f_\gamma(\gamma) = \frac{1}{\bar{\gamma}} \exp\left(-\frac{\gamma}{\bar{\gamma}}\right) \quad (46)$$

where $\bar{\gamma}$ is the average SNR.

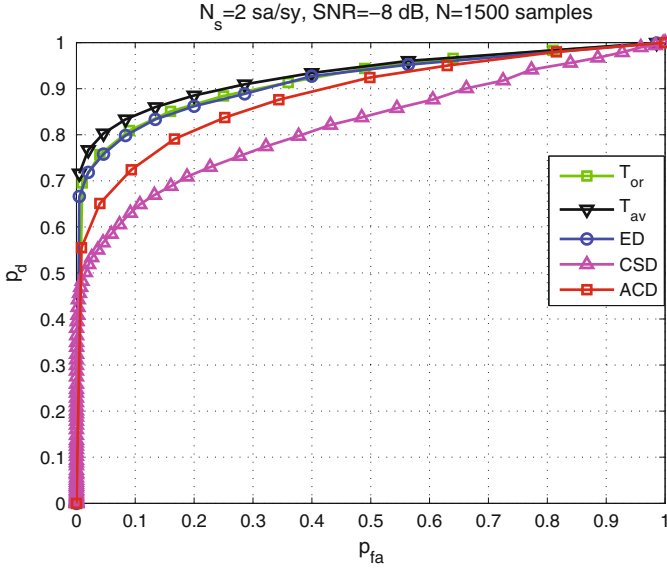


Fig. 8 ROC curve under Rayleigh fading channel for $N_s = 2$ sa/sy

To find the probability of detection, P_{dray} , under Rayleigh channel, the probability of detection, P_{dgauss} under Gaussian channel should be averaged with respect to $f_\gamma(\gamma)$.²

$$P_{dray} = \int_0^{+\infty} P_{dgauss} f_\gamma(\gamma) d\gamma \quad (47)$$

Figure 8 shows the ROC curves under Rayleigh Fading channel for $N_s = 2$ sa/sy with $N = 1500$ samples and average SNR of -8 dB.

Under Rayleigh fading channel, T_{av} and T_{or} are still outperforming ED, ACD and CSD. The impact of the same fading affected by $P_y^p(\nu)$ and $P_y^n(\nu)$ on the cooperation established by T_{av} and T_{or} can be shown in Fig. 8, where the gap of performance between our detectors on the one side and ED, ACD, and CSD on the other becomes smaller when comparing it to that under Gaussian channel.

Complexity Analysis

Our simulations show that our proposed detectors outperforms the Energy, the Auto-correlation and the Cyclostationary detectors. Here, we will compare the complexity of our detectors to the complexity to the other detectors. According to Eq. (31), the

²A detailed derivation of the probability of detection of the proposed detectors is presented in [16].

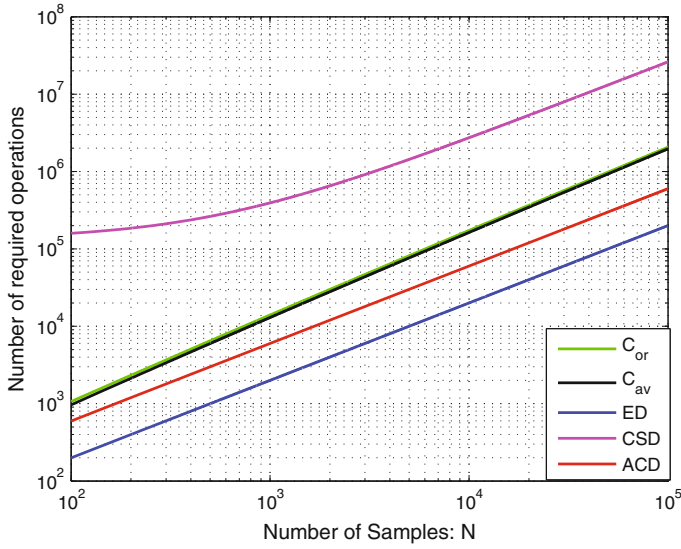


Fig. 9 The complexity of our proposed detector comparing to ED and CSD

Table 1 Comparison of different Spectrum Sensing Algorithms

Algorithm	PU signal requirement	Limitations	Complexity
ED	Blind	Sensitive to noise uncertainty	Low
ACD	Blind	Poor performance for low oversampling rate	Low
CSD	Cyclic frequency	Long sensing time	High
T_{or}	Blind	Applicable on oversampled signals	Moderate
T_{av}	Blind	Applicable on oversampled signals	Moderate

complexity of our proposed detector can be found. The complexity, Q , is linearly proportional to the number samples used in the detection process:

$$Q = L_q N \quad (48)$$

where $L_q > 2$ depends on the used detectors.³

Figure 9 shows that T_{av} is of less complexity than T_{or} . Our proposed detectors are slightly more complicated than ED and ACD. On the other hand, T_{av} and T_{or} have

³The derivation of the complexity of the proposed detectors can be found in [16].

less complexity and CSD. Consequently, our proposed detectors are of moderate complexity relative to CSD and ED.

Table 1 shows a briefed comparison among the proposed detectors and the state of the art detectors. This comparison is done with respect to the pre-requirement, the limitation and the complexity.

Robustness of Our Proposed Detectors Under Noise Uncertainty

In this section, we analyze the effect of the noise uncertainty (NU) on our proposed detectors. Due to the normalization (see Eq. (27)), the noise variance should be pre-estimated. That means, the performance of our proposed detectors is sensitive to the estimation of the noise variance. In this section, the impact of the NU on the robustness of our proposed detectors is evaluated.

The estimated noise variance $\hat{\sigma}_w^2$ can be modeled as follows:

$$\hat{\sigma}_w^2 \in \left[\frac{1}{r} \sigma_w^2, r \sigma_w^2 \right] \quad (49)$$

σ_w^2 is the nominal value of the noise variance and r stands for the noise uncertainty factor with $r \geq 1$. In this manuscript, the distribution of $\hat{\sigma}_w^2, f_{\hat{\sigma}_w^2}(\hat{\sigma}_w^2)$, is assumed to be uniform in logarithmic scale.

$$f_{\hat{s}}(\hat{s}) = \begin{cases} \frac{1}{2\rho}, & s - \rho \leq \hat{s} \leq s + \rho \\ 0, & \text{elsewhere} \end{cases} \quad (50)$$

where $s = 10 \log_{10}(\sigma_w^2)$, $\hat{s} = 10 \log_{10}(\hat{\sigma}_w^2)$ and $\rho = 10 \log_{10}(r)$.

The performance of the proposed detectors is numerically found, based on the model of Eq. (50). Figure 10 shows that the ROC curves of our proposed detectors and ED under an uncertainty factors $\rho = 0.6$ dB. It can be shown that T_{av} , T_{or} and T_p outperform significantly ED that has a similar performance to T_a . In addition, the performance of T_{av} and T_{or} tends toward that of T_p , then the NU affects the gain of the cooperation established by T_{av} and T_{or} to enhance the performance.

Figure 11 presents the performance loss of our detectors and ED for $p_{fa} = 0.1$, this figure shows $\Delta p_d = p_d(0) - p_d(\rho)$, where $p_d(0)$ and $p_d(\rho)$ stand for the probability of detection for the case where there is no NU and where NU is equal to ρ dB respectively. Figure 11 shows that our detectors are less sensitive to the noise uncertainty than the energy detector for $p_{fa} = 0.1$.

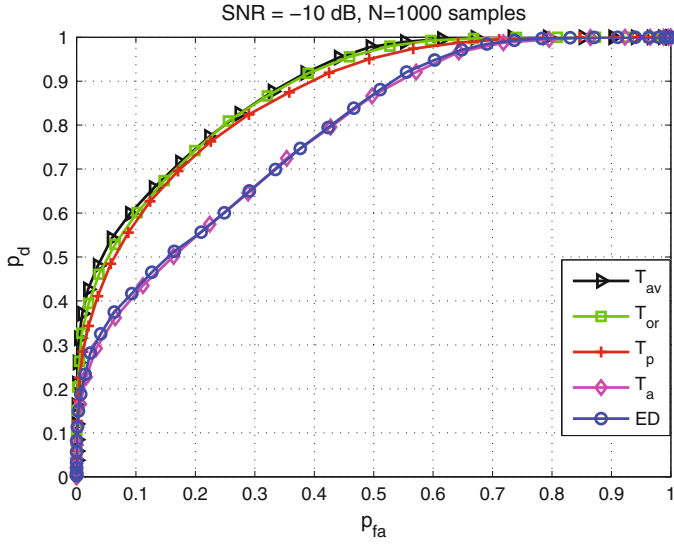


Fig. 10 ROC curves of the proposed schemes under noise uncertainty (NU)

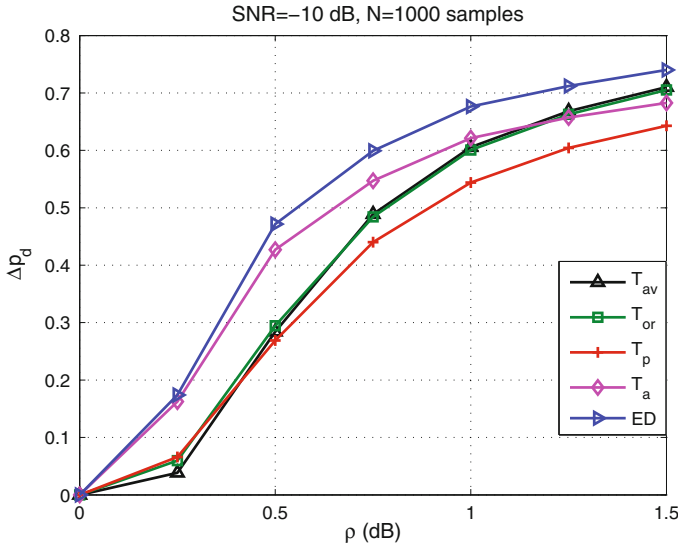


Fig. 11 Performance loss of p_d in terms of noise uncertainty for $p_{fa} = 0.1$

Spectrum Sensing Based on Self Normalized CPSD

According to Eq. (27), the CPSD should be normalized by a factor containing the noise variance, that necessitates a pre-estimation of the noise variance. This fact leads to a possible noise uncertainty. In this section, we introduce a new model for the proposed detectors, which is based on a self normalization of the CPSD. Instead of normalizing by the mean value of the last term of $CP_w(\nu)$, the CPSD will be normalized using its last term. The self normalized CPSD of the received signal is defined as follows:

$$sc_y(\nu) = \frac{CP_y(\nu)}{CP_y(l)}; \quad k \leq \nu \leq l \quad (51)$$

For $[k; l] = [-M+1; M]$, $CP_y(M)$ is the estimated energy of the received signal. Using Parseval's theorem, $CP_y(M)$ becomes:

$$\begin{aligned} CP_y(M) &= \frac{1}{N} \sum_{\nu=-M+1}^M |Y(\nu)|^2 \\ &= \sum_{n=1}^N |y(n)|^2 \end{aligned} \quad (52)$$

For $[k; l] = [1; M]$, $CP_y(M)$ is the half of the energy of the received signal, this is because of the symmetric property of $P_w(\nu)$ and $P_s(\nu)$.

This normalization is equivalent to a scaling and does not change the shape form of the CPSD.

Without taking into account the relative position of $sc_y(\nu)$ with respect to the reference straight line, the decision about the presence of the PU signal is made by comparing the $sc_y(\nu)$ shape to the reference line. Figure 12 shows $sc_y(\nu)$ under H_0 and H_1 for a SNR $ss = 0$ dB. We have a straight line under H_0 and a curved shape under H_1 .

Similarly to the detectors T_p , T_a , T_{or} and T_{av} , we define the test statistics of the Self-Normalized detectors: T_p^s , C_a^s , T_{or}^s and T_{av}^s as follows respectively:

$$T_p^s = \sum_{\nu=1}^M |sc_y(\nu) - d(\nu)| \quad (53)$$

$$T_a^s = \sum_{\nu=-M+1}^M |sc_y(\nu) - D(\nu)| \quad (54)$$

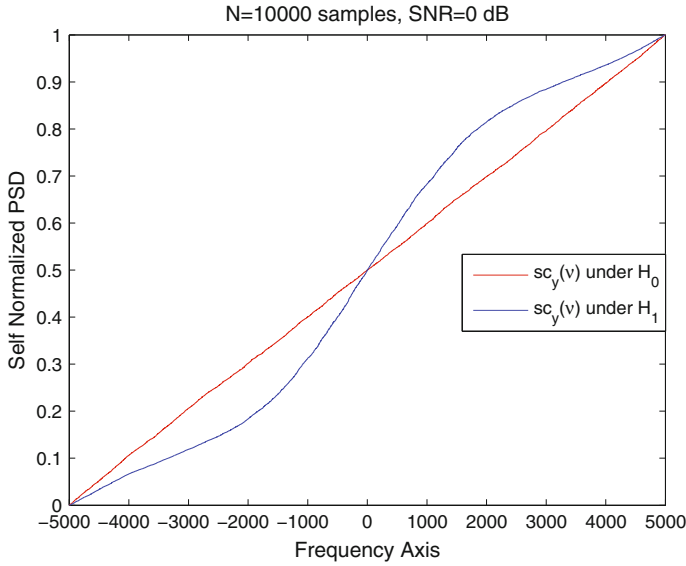


Fig. 12 Self normalized CPSD under H_0 and H_1

$$T_{or}^s = OR(D_{T_p^s}, D_{T_n^s}) \quad (55)$$

$$T_{av}^s = \sum_{v=1}^M |sc_y^{av}(v) - d(v)| \quad (56)$$

where $D_{T_p^s}$ and $D_{T_n^s}$ are the made decisions based on T_p^s and T_n^s respectively. T_n^s is defined similar to T_p^s , but it corresponds to the negative frequency points, and $sc_y^{av}(v)$ is given by:

$$sc_y^{av}(v) = \frac{\sum_{u=1}^v P_y^{av}(u)}{\sum_{u=1}^M P_y^{av}(u)} \quad (57)$$

Figure 13 shows the performance of those proposed detectors under NU of 0 and 0.5 dB with $N_s = 3 sa/sy$. For NU = 0 dB, T_{av} , T_{or} , T_{or} and T_a outperform T_{av}^s , T_t^s , T_{or}^s and T_a^s respectively. When the NU 0.5 dB, the performance of T_{av}^s , T_t^s , T_{or}^s and T_a^s was not affected, whereas the detectors T_{av} , T_{or} , T_{or} and T_a suffer a performance degradation and become less robust than the self normalization detectors, as shown in Fig. 13a, b.

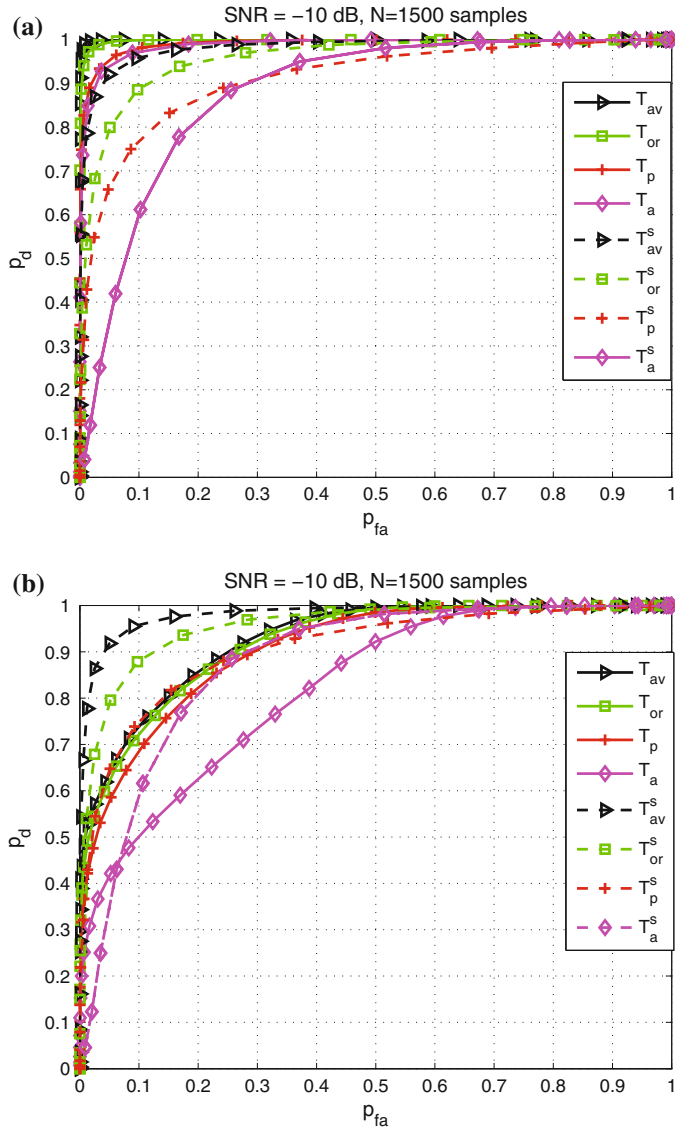


Fig. 13 ROC curves of the proposed schemes under NU = 0 and 0.5 dB. **a** $\rho = 0$ dB. **b** $\rho = 0.5$ dB

Spectrum Sensing for Full-Duplex Cognitive Radio

Applying FD in CR requires efficient techniques to achieve an important SIC, in order to eliminate the SU signal existing in the received mixture and avoid any impact on the decision of the Spectrum Sensing process.

SIC should consider the receiver impairments such as the non-linearity of amplifiers and the oscillator noise. In fact, experimental results show the effect of the hardware imperfections that considered as the main limiting performance factors [14, 20–22]. These imperfections can affect the SIC process by preventing a good estimation of the channel between T_x and R_x and introducing residual power to the received mixture.

The authors of [14] modify their method previously proposed in [23] to estimate the channel and the Non-Linearity Distortion (NLD) of the receiver Low-Noise Amplifier (LNA). Their method requires two training symbol periods. During the first period, the channel coefficients are estimated in the presence of the NLD. The non-linearity of the amplifier is estimated in the second period using the already estimated channel coefficients. It is worth mentioned that the estimation of the NLD parameters in the second phase depends on the one of the channel coefficients done in the first phase. However the estimation of the channel coefficients in the first phase can be depending on unknown NLD parameters. To solve the previous dilemma, we propose hereinafter an estimation method of the NLD in such way that the estimation of the channel cannot be affected by the NLD.

Many works have deal with the application of FD in CR [11, 24–27], In [24–27], the RSI is modeled as a linear combination of the SU signal without considering hardware imperfections. In [11, 25] the Energy Detection (ED) is studied in FD mode and the probability of detection and false alarm are found analytically. According to our best knowledge, there was no analytic relationship between the RSI, p_d and p_{fa} for both HD and FD mode.

This work deals with the Spectrum Sensing in real world applications. At first we analytically address the impact of the RSI power on the detection process. For that objective, we derive a relation between the RSI power, the probabilities of detection and false alarm under HD and FD modes. Secondly, we analyze the NLD impact on the channel estimation and the Spectrum Sensing performance. Hereinafter, a novel method is proposed to suppress the NLD of LNA without affecting the channel estimation process. Further, our proposed method outperforms significantly the method proposed in [14]. In addition, using our method, the receiver requires only one training symbol period to perform the estimation of the channel and the NLD estimation.

System Model

To deal with a real scenario, we admit, in our work, the signal waveform of [28], where we assume that PU signal and SU signals are wideband OFDM signal. Throughout the following, uppercase letters represent frequency-domain signals and

lower-case letters represent signals in time-domain. In this work, we are interesting to the additive receiver distortion which is dominated by the NLD of the LNA [14], the received signal can be modeled as follows:

$$Y_a(m) = GZ(m) + W(m) + D(m) + \eta HS(m) \quad (58)$$

G is the channel between the SU transmitter antenna T_x and the SU receive antenna R_x , $Z(m)$ is the SU signal, $W(m)$ is an Additive White Gaussian Noise (AWGN), $D(m)$ represents the NLD of the LNA, $S(m)$ is image of the the PU signal on R_x and $\eta \in \{0, 1\}$ is the PU indicator ($\eta = 1$ under H_1 and $\eta = 0$ under H_0).

After applying the SIC and the receiver imperfections mitigation, the obtained signal, $\hat{Y}(m)$ becomes as follows;

$$\hat{Y}(m) = \xi(m) + W(m) + \eta HS(m) \quad (59)$$

where $\xi(m)$ is the RSI and is defined as:

$$\xi(m) = (G - \hat{G})Z(m) + D(m) - \hat{D}(m) \quad (60)$$

$\hat{G}$ and $\hat{D}(m)$ are the estimated channel and the NLD respectively. Ideally $\hat{G} = G$ and $\hat{D}(m) = D(m)$, therefore Eq. (59) becomes: $\hat{Y}(m) = W(m) + \eta HS(m)$, which corresponds to a HD mode. Any mistake in the cancellation process may lead to a wrong decision about the PU presence.

Residual Self Interference Effect

In order to decide the existence of the PU, we use commonly used Energy Detector (ED) by comparing the energy, T , of the received signal to a predefined threshold, λ .

$$T = \frac{1}{N} \sum_{m=1}^N |\hat{Y}(m)|^2 \underset{H_0}{\overset{H_1}{\gtrless}} \lambda \quad (61)$$

By assuming the i.i.d property of $\epsilon(n)$, $w(n)$ and $s(n)$ ($\epsilon(n)$ is the time domain version of $\xi(m)$), then $\xi(m)$, $W(m)$ and $S(m)$ become i.i.d. [29]. In this case, the distribution of T should asymptotically follow a normal distribution for a large number of samples, N , according to Central Limit Theorem. Consequently, the probabilities of False Alarm, p_{fa}^F , and the Detection, p_d^F , under the FD mode can be obtained as follows [29] (Fig. 14):

$$p_{fa}^F = Q\left(\frac{\lambda - \mu_0}{\sqrt{V_0}}\right) = Q\left(\frac{\lambda - (\sigma_w^2 + \sigma_d^2)}{\frac{1}{\sqrt{N}}(\sigma_w^2 + \sigma_d^2)}\right) \quad (62)$$

$$p_d^F = Q\left(\frac{\lambda - \mu_1}{\sqrt{V_1}}\right) = Q\left(\frac{\lambda - (\sigma_w^2 + \sigma_d^2 + \sigma_s^2)}{\frac{1}{\sqrt{N}}(\sigma_w^2 + \sigma_d^2 + \sigma_s^2)}\right) \quad (63)$$

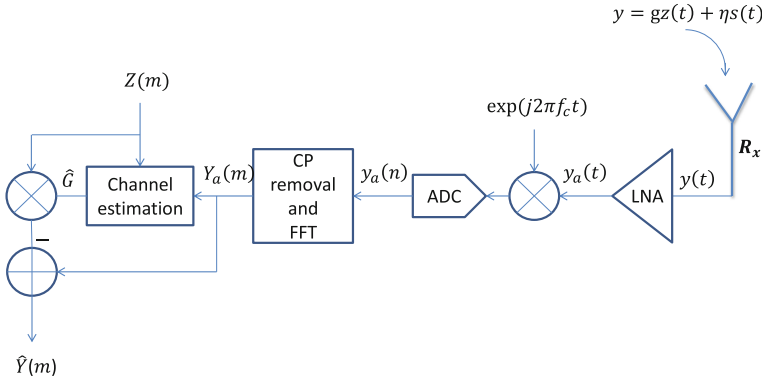


Fig. 14 Classical SIC circuit for OFDM receiver [29]

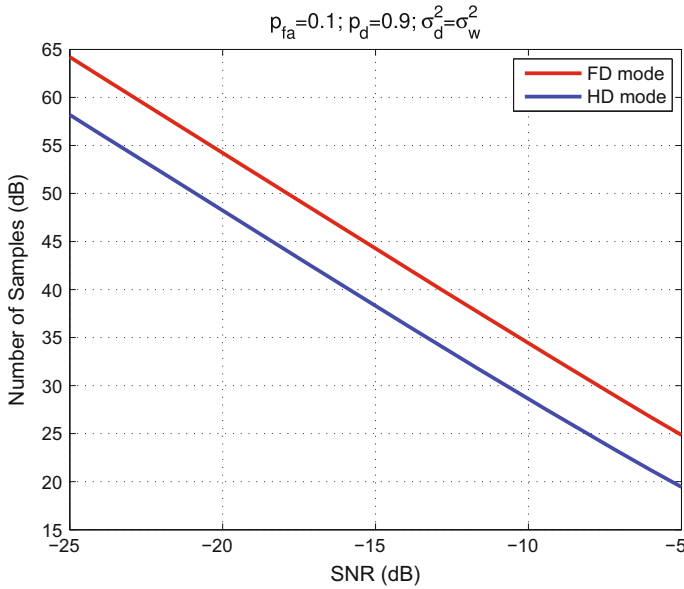


Fig. 15 The number of samples required to reach $P_d = 0.9$ and $P_{fa} = 0.1$ [29]

where μ_i and V_i are the mean and the variance of T under H_i respectively, $i \in \{0; 1\}$, $\sigma_d^2 = E[|\xi(m)|^2]$ represents the RSI power, $\sigma_w^2 = E[|W(m)|^2]$ and $\sigma_s^2 = E[|HS(m)|^2]$. The SNR, γ_s , is defined as: $\gamma_s = \frac{\sigma_s^2}{\sigma_w^2}$. If the SIC is perfectly achieved, i.e. $\sigma_d^2 = 0$, p_{fa}^F and p_d^F take their expressions under the HD mode.

Figure 15 shows the required number of samples to reach $p_d = 0.9$ and $p_{fa} = 0.1$ under the HD and FD modes with respect to the SNR. In FD mode, we set $\sigma_d^2 = \sigma_w^2$ as the target values of σ_d^2 in digital communication.

Figure 15 shows that the number of required samples slightly increases under the FD modes. For example if $\gamma_x = -5$ dB, then 85 samples are enough to reach the target ($P_d; P_{fa}$) under the HD mode while under FD mode, around 300 samples are needed. This means that in CR, the RSI power should be minimized as much as possible in order to do not affect the Spectrum Sensing performance ($\sigma_d^2 \ll \sigma_w^2$).

Let us define the Probability of Detection Ratio (PDR), δ , for the same probability of false alarm under FD and HD modes, as follows:

$$\delta = \frac{p_d^F}{p_d^H} \text{ with } p_{fa}^F = p_{fa}^H = \alpha \quad (64)$$

where p_d^H and p_{fa}^H are the probabilities of detection and false alarm under HD respectively, $0 \leq \alpha \leq 1$ and $0 \leq \delta \leq 1$. As with an excellent SIC, the probability of detection reached in FD can have mostly the same value as that in HF for the same probability of false alarm. In order to show the effect of RSI on δ , let us define the RSI to noise ratio γ_d as follows:

$$\gamma_d = \frac{\sigma_d^2}{\sigma_w^2} \quad (65)$$

Using (62) and (64), the threshold, λ , can be expressed as follows:

$$\lambda = \left(\frac{1}{\sqrt{N}} Q^{-1}(\alpha) + 1 \right) (\sigma_w^2 + \sigma_d^2) \quad (66)$$

By replacing (66) in (63), γ_d can be expressed as follows:

$$\gamma_d = \frac{(1 + \gamma_x) Q^{-1}(\delta P_d^H) - Q^{-1}(\alpha) + \sqrt{N} \gamma_s}{Q^{-1}(\alpha) - Q^{-1}(\delta P_d^H)} \quad (67)$$

If $\delta = 1$, then we can prove that γ_d becomes zero, which means that the SIC is perfectly achieved. Figure 16 shows the curves of γ_d for various values of PDR, δ , with respect to the SNR, γ_x , for $P_d^H = 0.9$ and $\alpha = 0.1$. This figure shows that as δ increases γ_d decreases. To enhance the PDR, the selected SIC technique should mitigate at most the SI. In fact, for $\gamma_x = -5$ and a permitted loss of 1 % (i.e. $\delta = 0.99$), γ_d is about -15 dB, which means the RSI power becomes 15 dB under the noise level.

Effect of the Amplifier Distortion

In real world applications, many imperfections prevents the application of the full duplex transceiver. One of the most important performance limiting factor is the NLD of LNA [14, 20–23]. According to NI 5791 datasheet [28], the NLD power is of 45 dB below the power of the linear amplified component. We present a new efficient algorithm, which shows a reliable performance comparing to that proposed in [14] and make the channel estimation performed without the influence of NLD. In addition, the Spectrum Sensing keeps a good performance under FD using this algorithm contrary to that proposed in [14].

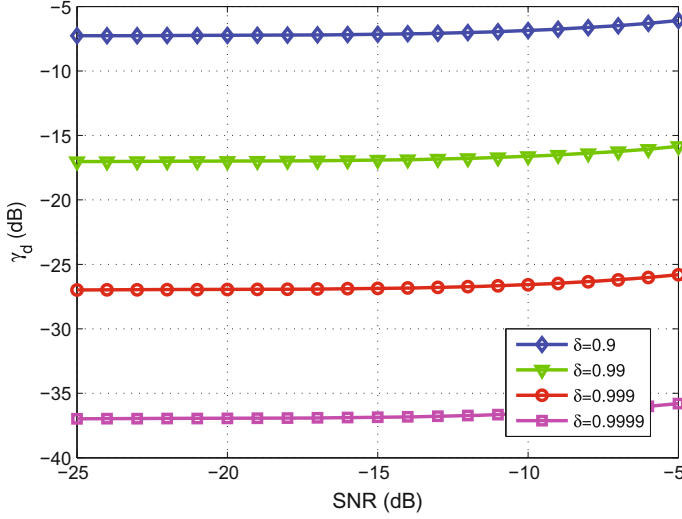


Fig. 16 Evolution of γ_d with respect to γ_x for various values of δ , $(P_{fa}^H; P_d^H) = (0.1; 0.9)$ [29]

Estimation of the Non-linearity Distortion of LNA

The NLD stands for the odd degrees greater than one [30]. By limiting to the third degree since the component of higher degrees are of neglected power [14], the NLD component can be presented as follows:

$$d(t) = \beta y^3(t) \quad (68)$$

where β is the NLD coefficient. The estimation of β can be helpful to suppress the LNA output. In this case, the channel estimation is no longer affected by the NLD. The overall output signal of the LNA, $y_a(t)$, can be expressed as follows:

$$y_a(t) = \theta y(t) + \beta y^3(t) \quad (69)$$

θ and $y(t)$ are the power gain and the input signal of the LNA respectively. To estimate θ and β , by a and b respectively, one can minimize the following cost function based on the Least Square Error:

$$\mathcal{J} = E \left[\left(y_a(t) - (ay(t) + by^3(t)) \right)^2 \right] \quad (70)$$

By deriving $\mathcal{J}$ with respect to a and b we obtain:

$$\frac{\partial \mathcal{J}}{\partial a} = 0 \Rightarrow aE[y^2(t)] + bE[y^4(t)] = E[y_a(t)y(t)] \quad (71)$$

$$\frac{\partial \mathcal{J}}{\partial b} = 0 \Rightarrow aE[y^4(t)] + bE[y^6(t)] = E[y_a(t)y^3(t)] \quad (72)$$

Using Eqs. (71) and (72), a linear system of equations can be obtained:

$$\begin{bmatrix} a \\ b \end{bmatrix} = A^{-1}B \quad (73)$$

where:

$$A = \begin{bmatrix} E[y^2(t)] & E[y^4(t)] \\ E[y^4(t)] & E[y^6(t)] \end{bmatrix}; B = \begin{bmatrix} E[y_a(t)y(t)] \\ E[y_a(t)y^3(t)] \end{bmatrix} \quad (74)$$

Once the non-linearity coefficient, β , is estimated, the non-linearity component can be subtracted from the output signal of the amplifier.

Numerical Results

Figure 17 shows the residual power of the NLD cancellation. The NLD power is fixed to 45 dB under the linear component [28]. This power is reduced to less than -300 dB after the application of our method. The method of [14] reduces the NLD power by around 50 dB. β is estimated using various numbers of training symbols, N_e . In this simulation, OFDM modulations are used with 64 sub-carriers and a CP length equal to 16. The received power is fixed to -5 dBm and the noise power to -72 dBm [28]. As shown in Fig. 17, the residual power of NLD decreases with an increasing of N_e when the method of [14] is applied. However, the proposed method

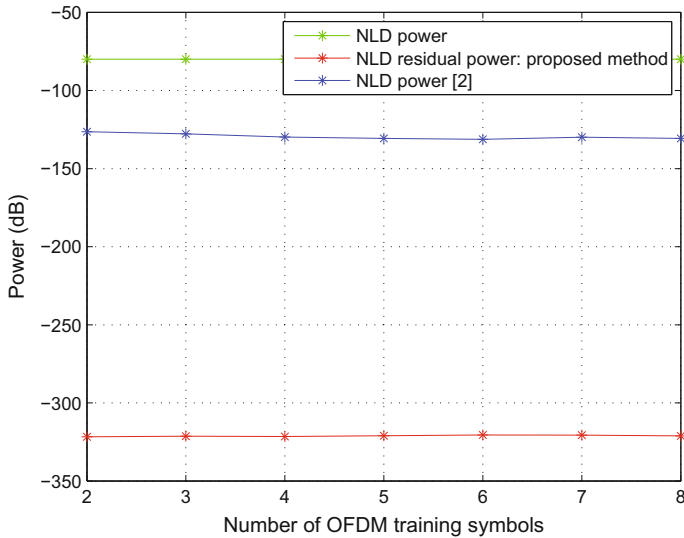


Fig. 17 The effect of the number of training symbols on the NLD residual power [29]

keeps a constant value of this power. Our technique outperforms significantly the method proposed in [14]. To show the impact of NLD on the channel estimation and the RSI power, Fig. 18 shows the power of $\hat{Y}(m)$ obtained in FD under H_0 . The channel is estimated according to the method previously proposed by [31] as follows:

$$\hat{g} = IDFT \left\{ \frac{1}{N_e} \sum_{k=0}^{N_e} \frac{Y_a^k(m)}{Y^k(m)} \right\}$$

with $\hat{G} = DFT\{\hat{g}(1, \dots, n_{tap})\}$ (75)

where $IDFT$ stands for the inverse discrete Fourier transform and n_{tap} is the channel order. The number of training symbols, N_e , is fixed to 4 symbols. To deal with a practical scenario, the number of sub-carrier is 64, the transmitted signal is of -10 dB (i.e. 20 dBm), and the noise floor is -102 dB (i.e. -72 dBm) [28]. The transceiver antenna is assumed to be omni-directional with 35 cm separation between T_x and R_x , so that a passive suppression of 25 dB is achieved [15]. According to the experimental results of [15], in a low reflection environment, 2 channel taps are enough to perform the SIC when the passive suppression is below 45 dB. Furthermore, the line of sight channel is modeled as Rician channel with K-factor about 20 dB. The non-line of sight component is modeled by a Rayleigh fading channel.

Figure 18 shows that our method leads to mitigate almost all the self interference, so that the power of $\hat{Y}(m)$ becomes very closed to the noise power. However, with the method of [14], the RSI power increases with the NLD power because the NLD power is a limiting factor of the channel estimation which leads to a bad estimation of the channel.

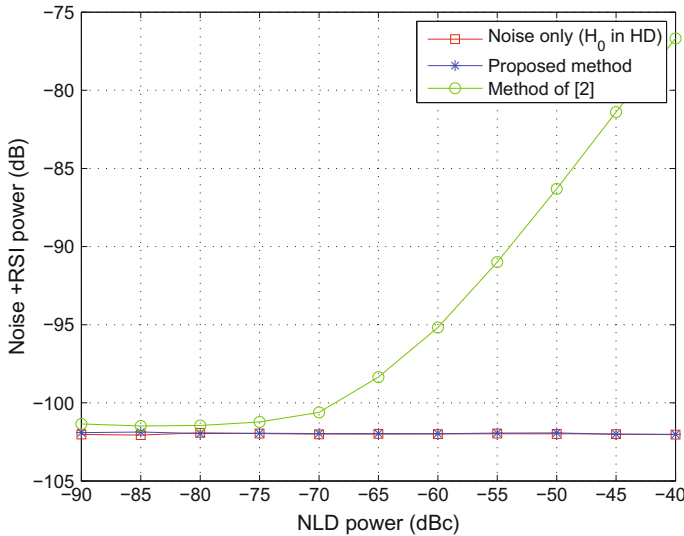


Fig. 18 The power of $\hat{Y}(m)$ under H_0 obtained after applying: (1) our proposed method, (2) the method of [14] is applied and (3) under HD mode [29]

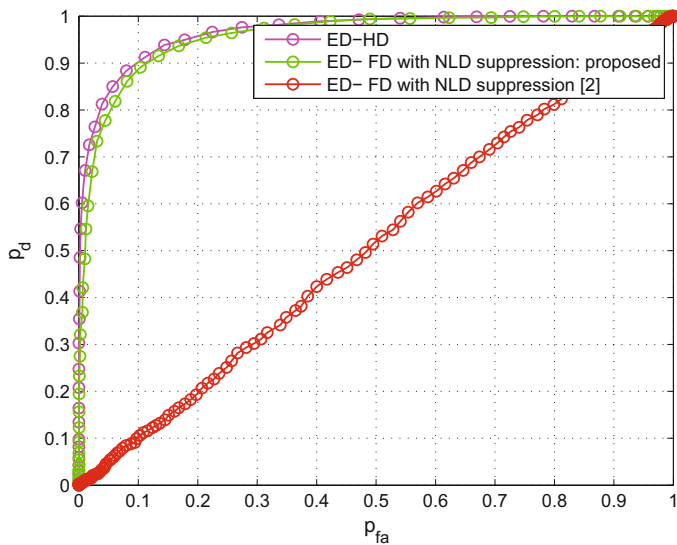


Fig. 19 The ROC curve after applying the proposed technique of NLD suppression [29]

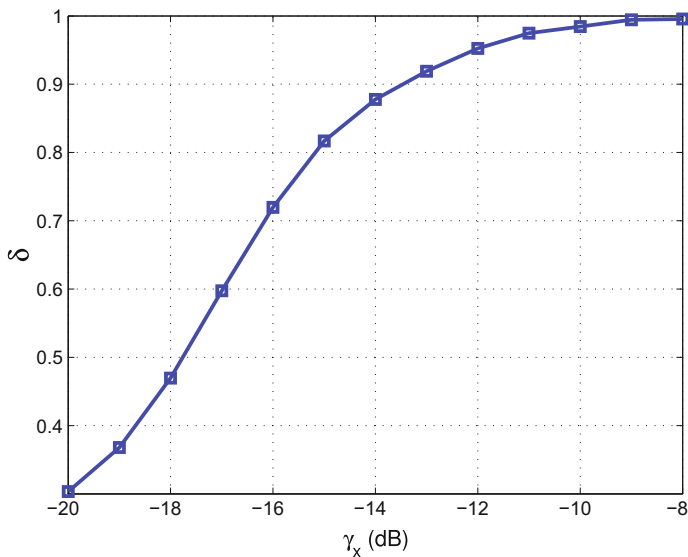


Fig. 20 The gain ratio: $\delta = \frac{p_d^F}{p_d^H}$ for different values of SNR [29]

To show the impact of the NLD on the Spectrum Sensing, Fig. 19 shows the ROC in various situations under $\gamma_x = -10$ dB. The simulations parameters in this figure are similar to those of Fig. 18, only the NLD power is 45 dB under the linear compo-

nent according to NI 5791 indications [28]. The method of [14] leads to a linear ROC, which means that no meaningful information about the PU status can be obtained. By referring to Fig. 18, the RSI power is of -82 dB for a NLD power of -45 dBc, which means that γ_d in this case is about 20 dB. This high RSI power leads to a harmful loss of performance (see Fig. 16). From the other hand, our method makes the ROC in FD mode almost colinear with that of the ROC of HD mode, which means that all SI and receiver impairments is mitigated.

Figure 20 shows the PDR for a target $\alpha = 0.1$ and $p_d^H = 0.9$. The ratio δ increases with the SNR. At a low SNR of -10 dB, δ becomes closed to 1, so that a negligible performance loss is happen. As the SNR decreases the detection process in FD mode becomes more sensitive to the RSI power.

Conclusion

In this chapter, we address the Spectrum Sensing for Half and Full-Duplex Cognitive Radio.

For Half-Duplex mode, new Spectrum Sensing detectors based on the Cumulative Power Spectral Density (CPSD) were proposed. Our proposed detectors verify the linearity of the CPSD shape of the received signal. This shape is almost linear if and only if the PU is absent.

Hard and soft decision schemes are used to combine the CPSD measures, which are derived based on the two symmetric parts of the Power Spectral Density. False alarm and detection probabilities were derived analytically under both Gaussian and Rayleigh flat fading channels. The simulation results show the performance superiority of our detectors comparing to other detectors especially the energy detector.

In addition, simulation results show that the proposed detectors are less affected by the noise uncertainty than the energy detector. However, to avoid the impact of the noise uncertainty, the measured CPSD is normalized by the estimated energy of the received signal. By doing this, we make our detectors independent from noise variance.

In a future work, we are looking to enhance the Power Spectral Density estimator, and to extend our algorithms to deal with Multiple Antennas Spectrum Sensing problem.

On the other hand, we deal with the Full-Duplex CR by addressing the impact of the Residual Self Interference on the Spectrum Sensing for Full-Duplex Cognitive Radio. An analytic relation is derived relating the residual self interference with the probabilities of detection and false alarm under Full-Duplex and Half-Duplex modes. Furthermore, a new method is proposed to mitigate an important receiver impairment, which is the Non-Linear Distortion of the Low Noise Amplifier. This method shows its efficiency, leading the Spectrum Sensing performance in Full-Duplex mode to be closed to that under Half-Duplex mode.

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