Performance of Collaborative Techniques for Simultaneous Sensing and Transmission in Cognitive Radio Networks

Mário Henrique Pereira Alves*, Rausley A. A. de Souza†, Adoniran Judson Braga‡ and Dayan Adionel Guimarães†
*National Institute of Telecommunications. Santa Rita do Sapucaí, MG, Brazil. Email: mario@gee.inatel.br
† National Institute of Telecommunications. Santa Rita do Sapucaí, MG, Brazil. Email: {rausley;dayan}@inatel.br
‡Universidade de Brasília. Brasília, DF, Brazil. Email: jbraga@ene.unb.br

***Abstract*—Maximizing the secondary cognitive radio network throughput under the restriction of avoiding interference to the primary network is a main concern in recent research. In the classic approach, a specific interval is devised to the task of spectrum sensing, which penalizes the secondary network throughput. Aiming at a higher throughput than in this classic approach, the continuous sensing mode can be adopted. In this mode, secondary receiving nodes sense the spectrum while other secondary users simultaneously transmit in the same frequency band. This paper compares, under the continuous sensing approach, the performances of centralized cooperative spectrum sensing techniques. The maximum eigenvalue detection and the energy detection techniques are considered. In what concerns the fusion rules, we consider the sample fusion, the decision fusion and a recently proposed eigenvalue fusion technique. It is shown that, in spite of the intrinsic interference present in the continuous mode, this approach is flexible in terms of the sensing time, eventually allowing for better sensing performance.**

I. Introduction

The use of the electromagnetic spectrum for wireless communication is growing fast nowadays: new services emerge over time, while traditional ones remain active and occupying most of the attractive bands. As a result, there is a serious spectrum scarcity to be managed by the scientific community and regulatory agencies. On the other hand, even though much of the useful radio spectrum is already allocated to conventional systems, studies have demonstrated that the assigned spectrum is significantly underutilized around the world [1]. Aiming at optimizing the space-time allocation of radio spectrum, the cognitive radio (CR) paradigm has been proposed as a solution [2]. The idea is simple: if the licensed or primary user (PU) is not transmitting for any reason, the corresponding channel can be made available for unlicensed or secondary users (SU), as long as this channel is released if the PU attempts to use it again. Therefore, the spectrum sensing task is the main functionality enabling the CR to use the best spectrum opportunities without interfering with the operation of licensed users.

The spectrum sensing can be accomplished by each CR without any help from other CR decisions or measurements, or can be cooperative (or collaborative). Non cooperative spectrum sensing suffers from channel fading and shadowing, also being very prone to the hidden terminal problem [3]. Aiming at combating such effects and achieving higher detection capabilities, the cooperative spectrum sensing has been preferably adopted. Cooperative spectrum sensing techniques can be centralized, distributed or relay-assisted [3]. In centralized cooperative sensing, data collected by each cooperating CR (e.g., samples of the received signal) is sent to a fusion center (FC) through a reporting channel. This process is called data fusion or sample fusion. After the data is processed, the FC decides upon the occupation state of the channel. Centralized cooperative spectrum sensing can also be made from the decisions about the channel occupancy state made by each cooperating CR. This operation is called decision fusion, where the final decision about the channel state is accomplished through binary operations on the CR decisions. In both centralized schemes, the final decision is informed back to the CRs through a control channel, for subsequent use by the CR network.

In order to achieve a better sensing performance, a lower probability of false alarm (P_{fa}) is desired to maximize the utilization of the available spectrum, whereas a higher probability of detection (P_{d}) is required to avoid interference to the PUs. Consequently, there is an intrinsic tradeoff between avoiding interference to the primary network and improving the throughput in the secondary network. The period during which the spectrum is sensed must be long enough so that the required P_{d} is achieved and harmful interference to the PUs is avoided. However, a channel detection time (CDT) is usually stated to limit the time during which a PU can withstand interference before the CR system detects it. During the CDT, the CRs are required to perform the sensing and transmission tasks. Thus, the longer the sensing time, the shorter the transmission time, reducing the throughput and increasing the delay for traffic in the secondary network. Such periodic transmission interruption can lead to an inefficient usage of the available spectrum, and, consequently, it can reduce the CR network capacity.

Solid studies have been carried out to minimize the sensing

978-1-4799-7162-6/14/$31.00

time and maximize the CR throughput for a given interference constraint. However, these studies are based on the assumption that the CRs are required to stop transmitting to perform the spectrum sensing. The dynamic frequency hopping (DFH) method [4] changed the paradigm that the CR users are not able to perform sensing and transmission at the same time. In DFH, during the CR transmissions in a given channel, sensing is performed in parallel in other channels. After the CDT period the CR switches the operation to the best channel just sensed, and the band previously used is vacated. Hence, interruption is no longer required for sensing. Even though the DFH method has demonstrated an important advantage of this parallel sensing approach over the traditional one, the problem that the channel being sensed cannot be used for data transmission by the CR still remains.

Generally speaking, channels being sensed cannot be used for data transmission because the spectrum sensing has been treated as a conventional signal detection problem. Thus, signal detection techniques have been rarely used with adaptations regarding the CR objectives. As a counterexample, the authors in [5] have proposed a spectrum monitoring technique at the receiver based on error statistics to be performed prior to the spectrum sensing. The increase of the error rate may be caused by the presence of the PU signal and then a spectrum sensing is trigged. This considerably reduces the sensing rate, increasing the throughput in the SU network. The spectrum monitoring technique achieves a good performance if the secondary-to-primary power ratio (SPPR) is not too high. In high SPPR scenarios, the presence of the PU signal may be hardly detected or mistaken with fading of the SU signal.

The work [6] came up with a continuous sensing method based on energy detection, where sensing is performed at a receiving node of the SU network. Thus, the transmitting node of the SU network can keep transmitting while the primary user is idle, achieving a higher throughput in the SU system and continuity in sending data. However, since the SU is allowed to transmit while the spectrum is sensed, its signal becomes an intrinsic interferer in the task of sensing the PU. Capitalizing the results in [6], the authors in [7] applied the continuous sensing method in a cooperative spectrum sensing scheme using sample fusion with eigenvalue-based techniques.

Here we investigate the performance of two centralized cooperative sensing schemes using the MIMO (multiple input, multiple output) channel model adapted to the continuous sensing approach. We assess the performance of an altered version of the maximum eigenvalue detection, which we call AMED, and the performance of an altered version of the well-known energy detection, which we call AED. It is in order to remember that the ED is not a detection technique based exclusively on eigenvalues, but it can be implemented using eigenvalue information, which is the case considered here.

II. General Eigenvalue Spectrum Sensing Model

We consider a baseband linear discrete-time MIMO fading channel model, for which there is an antenna array with a sensors in a CR, or a single-sensor (single-antenna) CRs, each one collecting b samples of the received signal from p primary transmitters and q secondary transmitters during the sensing period, with $p + q < a$. Consider that these samples are arranged in a matrix $\mathbf{Y} \in \mathbb{C}^{a\times b}$. Similarly, consider that the transmitted signal samples from the primary and secondary transmitters are arranged in a matrix $\mathbf{X} \in \mathbb{C}^{p\times b}$ and in a matrix $\mathbf{S} \in \mathbb{C}^{q\times b}$, respectively. The PU and SU signals are i.i.d. (independent and identically distributed) random processes, and independent of each other. Let $\mathbf{H_x} \in \mathbb{C}^{a\times p}$ be the channel matrix with elements $\{h^{\mathrm{x}}_{ij}\}$, $i = 1, 2, \ldots, a$ and $j = 1, 2, \ldots, p$, representing the channel gain between the j-th primary transmitter and the i-th antenna sensor or i-th single-antenna CR, and let $\mathbf{H_s} \in \mathbb{C}^{a\times q}$ be the channel matrix with elements $\{h^{\mathrm{s}}_{ij}\}$, $i = 1, 2, \ldots, a$ and $j = 1, 2, \ldots, q$, representing the channel gain between the j-th secondary transmitter and the i-th antenna sensor or i-th single-antenna CR. Finally, let $\mathbf{V} \in \mathbb{C}^{a\times b}$ be the matrix containing thermal noise samples that corrupt the received signal. The matrix of collected samples is then

$$\mathbf{Y} = \mathbf{H_x X} + \mathbf{H_s S} + \mathbf{V}. \tag{1}$$

In eigenvalue-based spectrum sensing technique, idle channels are detected using test statistics based on the eigenvalues $\{\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_a\}$ of the sample covariance matrix of the received signal, which is given by

$$\mathbf{R} = \frac{1}{b}\mathbf{Y}\mathbf{Y}^\dagger, \tag{2}$$

where $\dagger$ means complex conjugate and transpose. The decision is made by comparing the desired test statistic against a threshold which is normally set according to a target constant false alarm rate. The decision process is then a binary hypothesis test for which $\mathcal{H}_0$ means that PU signals are absent, and $\mathcal{H}_1$ means that PU signals are present.

A. Collaborative Eigenvalue Spectrum Sensing with Sample Fusion

We assume that each of the m cooperating CRs collect n samples of the received signal coming from a single primary transmitter and a single secondary transmitter ($p = q = 1$). In the general eigenvalue spectrum sensing model previously described we have $a = m$ and $b = n$. The matrix $\mathbf{Y} \in \mathbb{C}^{m\times n}$ is made available to the FC, from which the sample covariance matrix $\mathbf{R} \in \mathbb{R}^{m\times m}$ is computed, and then the eigenvalues $\{\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_m\}$. The test statistics for the AMED and AED with sample fusion (sf) are computed according to:

$$T^{\mathrm{sf}}_{\mathrm{AMED}} = \frac{\lambda_1 + \lambda_2}{2P_{\mathcal{H}_0}}, \tag{3}$$

$$T^{\mathrm{sf}}_{\mathrm{AED}} = \frac{\|\mathbf{Y}\|_F^2}{mnP_{\mathcal{H}_0}} = \frac{\sum_{i=1}^{m}\lambda_i}{mP_{\mathcal{H}_0}}, \tag{4}$$

where $\|\cdot\|_F$ is the Frobenius norm of the underlying matrix, and $P_{\mathcal{H}_0}$ is the SU (transmitting node) signal power plus the noise power. In AMED we are interested in the ratio between the average of the two largest eigenvalues and $P_{\mathcal{H}_0}$, whereas in the AED we are interested in the ratio between the average of all eigenvalues and $P_{\mathcal{H}_0}$. The thermal noise power σ^2 is assumed to be known and the same in each CR input, with uncorrelated samples, and the SU signal power is assumed to be correctly estimated using, for example, a pilot channel.

Conventionally, all the eigenvalue-based methods rely on the fact that, in the limiting (asymptotic) regime of m, $n \to \infty$, m/n constant, the population covariance matrix in the presence of white noise only is a diagonal matrix with its nonzero elements equal to the thermal noise power σ^2, which means that the set of eigenvalues will have just the value σ^2 with multiplicity m. When the PU signals are present, the set of eigenvalues will have p larger values, and these methods try to assign the $\mathcal{H}_1$ channel state using this contrast between the p larger eigenvalues and the remaining $m-p$ smaller ones. When the same asymptotic analysis is applied to the continuous sensing approach, the eigenvalues will not have multiplicity m even prior to the arrival of the PU signals, since some SUs are transmitting at the same time. Consequently, the assignment of the test statistic to one of the hypotheses will become more difficult, worsening the decision performance for all methods. In principle, this fact may discourage the continuous sensing approach since it is worse when compared in equal conditions to the classic approach. However, this approach is flexible in terms of the sensing time, eventually allowing for better sensing performance.

B. Collaborative Eigenvalue Spectrum Sensing with Eigenvalue Fusion

In collaborative sensing with eigenvalue fusion, each of the m cooperating CRs is responsible for computing its own sample covariance matrix, estimating its eigenvalues and transmitting these eigenvalues to the FC. Again, n is the number of samples of the signal received by each CR, but now the order of the covariance matrices is not attached to m. Then, let $J \times J$ be the desired order of the sample covariance matrix to be computed by the i-th CR, $i = 1, ..., m$. Assuming that n/J is an integer number, a matrix $\mathbf{Y}_i$ with samples from the received signal can be formed by arranging the n samples taken by the i-th CR in J rows and n/J columns, preferably with $n/J \gg J$, which implies $n \gg J$ for more accuracy of the sample covariance matrix estimation. In the general eigenvalue spectrum sensing model previously described we have $a = J$ and $b = n/J$. Notice that if each CR is equipped with an antenna array with J elements, each element collects n/J samples. The matrices $\mathbf{Y}_i \in \mathbb{C}^{J \times n/J}$ are given by

$$\mathbf{Y}_i = \begin{bmatrix} Y_i(1) & \ldots & Y_i(n/J\,) \\ \vdots & \ddots & \vdots \\ Y_i(n+1-n/J\,) & \cdots & Y_i(n) \end{bmatrix}, \tag{5}$$

where $Y_i(j)$ is the j-th sample collected by the i-th CR, and the sample covariance matrices are given by

$$\mathbf{R}_i = \frac{J}{n}\mathbf{Y}_i\mathbf{Y}_i{}^{\dagger}. \tag{6}$$

The mJ eigenvalues of these covariance matrices are computed and sent to the FC. The next part of the sensing process is to combine the eigenvalues received at the FC for the computation of the test statistic. Through some modifications in (3) and (4), the test statistics in the eigenvalue fusion (ev) scheme are given by

$$T_{\text{AMED}}^{\text{ev}} = \frac{1}{2mP_{\mathcal{H}_0}} \sum_{i=1}^{m} (\lambda_{1,i} + \lambda_{2,i}), \tag{7}$$

$$T_{\text{AED}}^{\text{ev}} = \frac{1}{JmP_{\mathcal{H}_0}} \sum_{j=1}^{J} \sum_{i=1}^{m} \lambda_{j,i}, \tag{8}$$

where $\{\lambda_{1,i} \geq \lambda_{2,i} \geq \cdots \lambda_{J,i}\}$ are the J eigenvalues associated with the i-th CR.

For the AMED, the proposed eigenvalue combining rule is the average of the two largest eigenvalues from each CR divided by $P_{\mathcal{H}_0}$. For the AED, the test statistic is computed from the average of all eigenvalues divided by $P_{\mathcal{H}_0}$. Recall that $P_{\mathcal{H}_0}$ is the SU transmitting node signal plus noise power.

Notice that the difference between the sample fusion and the eigenvalue fusion schemes goes beyond a simple shift of the eigenvalue computations from the FC to the CRs. In the sample fusion, samples collected by the CRs are sent to the FC, where one sample covariance matrix from all CR samples is formed. The eigenvalues of this matrix are computed and then the desired test statistic is formed. In the eigenvalue fusion, each CR forms one covariance matrix based solely on his samples and computes its eigenvalues. The eigenvalues from different CRs are then sent to the FC, where they are combined to form the test statistic. Notice that this eigenvalue fusion approach reduces the volume of data sent in the reporting channel (from the CRs to the FC) when compared with the sample fusion scheme.

C. Collaborative Eigenvalue-Based Spectrum Sensing with Decision Fusion

In Section I we have mentioned that the centralized cooperative spectrum sensing can be made on a decision fusion basis, in which CR decisions are combined at the FC so that the final decision is made. Commonly used decision fusion combining rules are AND, OR and majority-voting, which are collectively classified under the general term z-*out-of*-M. The FC infers the PU signal being transmitted, i.e. $\mathcal{H}_1$, when there exists *at least* z out of M CRs inferring $\mathcal{H}_1$. Otherwise, the FC decides the PU signal not being transmitted, i.e, $\mathcal{H}_0$. If $z = 1$, the 1-*out-of*-M becomes the OR rule, and if $z = M$, the M-*out-of*-M becomes the AND rule. If $z \geq M/2$, the z-*out-of*-M becomes the majority-voting rule [3].

CR decisions can be made by applying any detection technique. For those considered here, the test statistics for the i-th CR in the decision fusion (df) scheme can be determined from minor modifications in (7) and (8), leading to:

$$T_{\text{AMED},i}^{\text{df}} = \frac{\lambda_{1,i} + \lambda_{2,i}}{2P_{\mathcal{H}_0}}, \tag{9}$$

$$T^{\text{df}}_{\text{AED},i} = \frac{1}{JP_{\mathcal{H}_0}} \sum_{j=1}^{J} \lambda_{j,i}. \tag{10}$$

It is worth mentioning that the AMED and AED test statistics, as defined in this paper, were determined empirically. This means that it is not guaranteed that they are optimal in the sense of a likelihood ratio test.

III. Simulation Setup

The simulation setup under the discrete-time MIMO model considers that $\mathbf{Y} = \mathbf{H_x X} + \mathbf{H_s S} + \mathbf{V}$ is available to the FC in the sample fusion scheme, and that $\mathbf{Y}_i$ is available to the i-CR in the eigenvalue and decision fusion schemes. Notice that, from a simulation standpoint, $\mathbf{Y}_i$ can be formed by reshaping the i-th row of the matrix $\mathbf{Y}$ from (1).

Matrices $\mathbf{X}$, $\mathbf{S}$, $\mathbf{H_x}$, $\mathbf{H_s}$, and $\mathbf{V}$ are generated as follows: To simulate Gaussian distributed noise-like transmitted signals, $\mathbf{X}$ and $\mathbf{S}$ are formed by i.i.d. zero mean complex Gaussian samples. The choice for the Gaussian distribution is adopted because it accurately models several modulated signals, such as orthogonal frequency-division multiplexing (OFDM) with a large number of subcarriers, which is the preferred modulation technique in most modern wireless technologies, including several digital television standards. The elements in the channel matrices $\mathbf{H_x}$ and $\mathbf{H_s}$ are zero mean i.i.d. complex Gaussian variables that simulate a flat Rayleigh fading channel between each transmitter and sensor, assumed to be constant during a sensing period and independent from one period to another. Therefore, estimated P_{d} and P_{fa} are average values in the flat Rayleigh fading channel. The entries in $\mathbf{V}$ are unitary variance (unitary power), i.i.d. zero mean complex Gaussian variables that represent the additive thermal noise corrupting the received samples. The powers of the PU and the SU signals are determined from their signal-to-noise ratios $\text{SNR}_{\mathbf{X}}$ and $\text{SNR}_{\mathbf{S}}$, respectively.

The test statistics for the AMED and the AED are respectively computed from Equations (3) and (4) for the sample fusion, (7) and (8) for the eigenvalue fusion, and (9) and (10) for the decision fusion. The test statistic of interest is then compared with a threshold computed from the desired false alarm probability, and a final decision upon the occupancy of the sensed channel is reached.

IV. Simulation Results

In this section we present simulation results and discussions concerning the influence of the noise and the SU signal on the performance of the PU signal detection for the AMED and the AED. The ROC (receiver operating characteristic) curves shown hereafter were obtained with a minimum of $30,000$ runs in Monte Carlo simulations implemented in MATLAB according to the setup described in the previous section. Unless otherwise stated, the system parameters are: PU signal-to-noise ratio $\text{SNR}_{\mathbf{X}} = -10$ dB, SU signal-to-noise ratios $\text{SNR}_{\mathbf{S}} = -\infty$ (no SU signal), -5 and 0 dB, number of primary transmitters $p = 1$, number of secondary transmitters $q = 1$ and number of sensors $m = 6$. The choice for a small SNR of the PU signal (-10 dB) is made to represent a more degrading, but yet realistic, situation from the perspective of spectrum sensing performance.

It is known that the number of samples and the order of the covariance matrix influence the performance of eigenvalue-based spectrum sensing. Thus, for a fair comparison, both should be the same in all cases analyzed here. However, based on the model proposed in this paper, this is only possible in the case of the eigenvalue and the decision fusion. Then, we have chosen to make the order of the sample covariance matrices the same. The consequence is that the number of collected samples in each CR had to be larger for the eigenvalue and the decision fusion schemes, when compared with the sample fusion. Nevertheless, as a counterexample, we have also carried out simulations assuming an equal number of collected samples per sensed channel in all fusion schemes. For the sample fusion, the number of samples collected by each CR was $n = 60$ and 300 samples. For the eigenvalue and decision fusion schemes, the number of samples collected by each CR was $N = nJ = 60$ and 300 samples. So, we have chosen to compute $J = 5$ eigenvalues in each CR for the eigenvalue and decision fusion schemes. Since $m = 6$, this is also the number of eigenvalues computed by the FC in the sample fusion scenario.

Figures 1–5 show ROC curves relating P_{d} and P_{fa} for the AMED and the AED considering the sample fusion, the eigenvalue fusion and the decision fusion with AND, OR and Majority voting. It can be seen that the classic sensing scheme, in which the SU is not transmitting, outperforms the continuous sensing model in all techniques. However, one must recall that the strength of the continuous sensing is the sensing time flexibility, since it is not necessary to stop sensing to transmit. It means that, for a fixed bandwidth, a much larger number of samples can be used to improve its performance, which is accomplished by setting a longer sensing time.

Comparing the results for no SU signal, the AMED performs better than the AED in the case of the sample fusion. However, the AED outperforms the AMED for the eigenvalue combining and for the decision fusion schemes with majority-voting, AND and OR rules. When compared with the AMED test statistics (7) and (9), the AED test statistics (8) and (10) unveiled more statistical power, indicating that the former ones have margin for further improvements. This behavior naturally leads to the question: Is there any other empirical eigenvalue combination that results in a better performance of the AMED? We have tried combinations other than the arithmetic mean. For instance, we have tried the geometric mean and the harmonic mean of the two largest eigenvalues from each CR; we have also tried just the maximum eigenvalue among all eigenvalues sent to the FC. However, the best ones corresponded to the expressions proposed in this paper.

With the exception of the sample fusion with $n = 300$ samples, one can notice that the eigenvalue fusion outperforms the other fusion methods for all test statistics analyzed in this paper. The performance of the eigenvalue fusion is followed by the OR, MAJ and AND decision fusion, respectively. In all

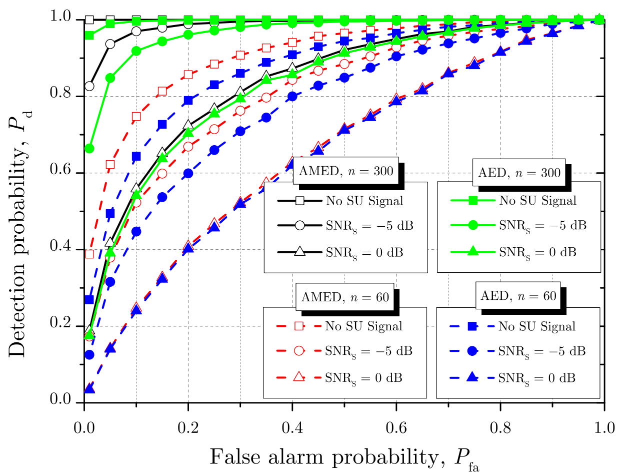

Fig. 1. ROC curves for the AMED and the AED using sample fusion, under variations of the SU SNR.

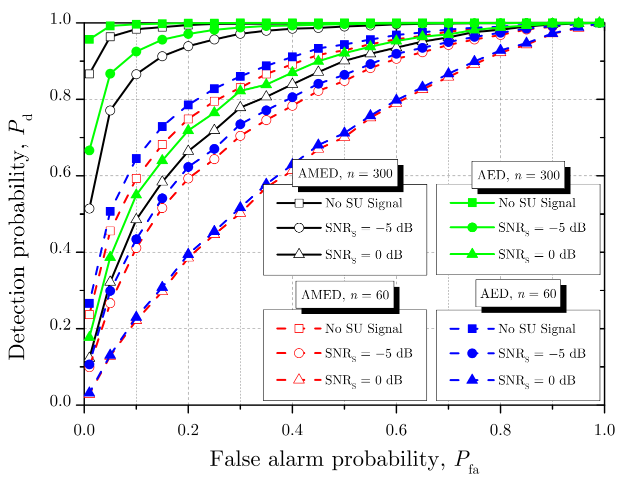

Fig. 2. ROC curves for the AMED and the AED using eigenvalue fusion, under variations of the SU SNR.

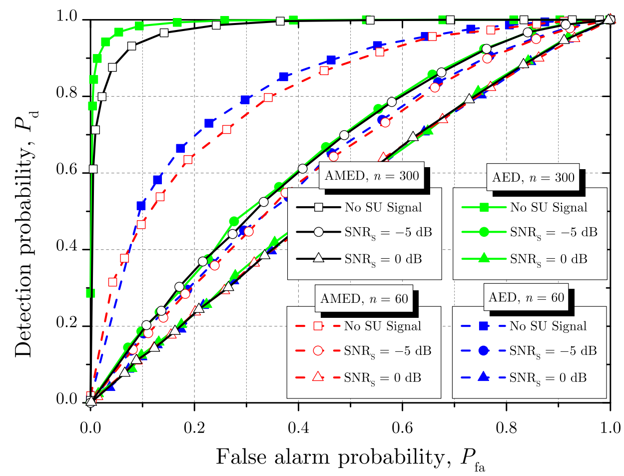

Fig. 3. ROC curves for the AMED and the AED using decision fusion with the OR rule, under variations of the SU SNR.

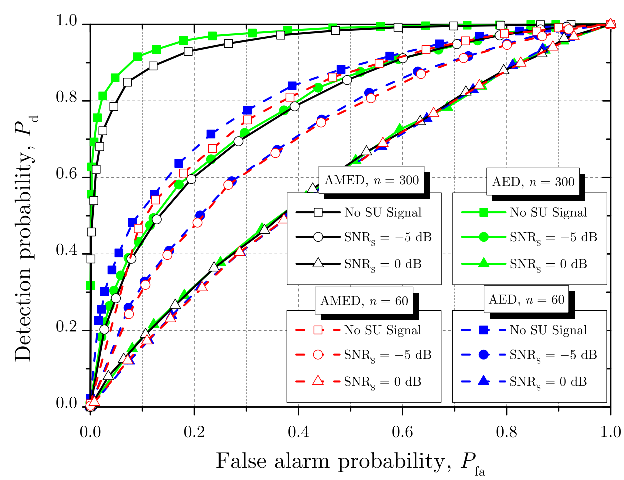

Fig. 4. ROC curves for the AMED and the AED using decision fusion with the Majority-voting rule, under variations of the SU SNR.

fusion schemes, the AMED and the AED show a diminishing detection performance as the SU signal power increases, which is an expected result.

An alternative way to compare the detection methods is by measuring the number of samples required to meet a target performance. To this end, we have varied the number of samples and estimated P_d for a fixed $P_{fa} = 0.1$. The results are depicted in Figures 6 and 7, considering low PU signal power ($SNR_{\mathbf{X}} = -10$ dB), high SU signal power ($SNR_{\mathbf{S}} = 0$ dB) and no SU transmission ($SNR_{\mathbf{S}} = -\infty$ dB). The remaining parameters were kept as before. As expected, we clearly see that the number of samples required to achieve a given P_d is always larger in the continuous sensing model, no matter the adopted sensing technique or fusion scheme. The required number of samples to reach $P_{fa} = 0.1$ and $P_d = 0.9$ for each technique and sensing model is listed in the Table I.

The eigenvalue and sample fusion schemes, when the AED technique is considered, need almost the same number of samples in order to achieve a given probability of detection. The performance of the AED is better than the AMED, for the same number of samples.

TABLE I
NUMBER OF SAMPLES REQUIRED FOR $P_{fa} = 0.1$ AND $P_d = 0.9$.

	AMED (AED)	
	$SNR_{\mathbf{S}} = 0$ dB	No SU signal
Sample fusion	$n = 1280$ (1000)	$n = 84$ (125)
Eigenvalue fusion	$n = 1315$ (1020)	$n = 219$ (170)
Decision fusion OR	$n \to \infty$	$n = 266$ (10)
Decision fusion MAJ	$n \to \infty$	$n = 388$ (273)
Decision fusion AND	$n \to \infty$	$n = 1200$ (7500)

The best performance of the AED in terms of the number of samples in the continuous sensing and transmission model is consistent with the ROC curves in Figures 1–5. Its advantage is even more pronounced in comparison with the AMED when a higher performance standard is set, e.g. when $P_{fa} = 0.1$ and

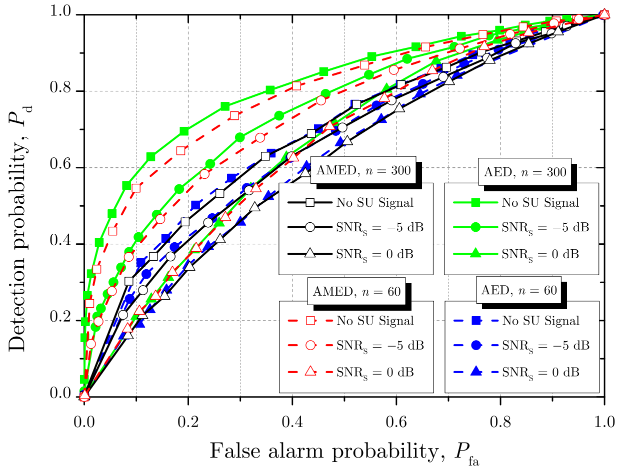

Fig. 5. ROC curves for the AMED and the AED using decision fusion with the AND rule, under variations of the SU SNR.

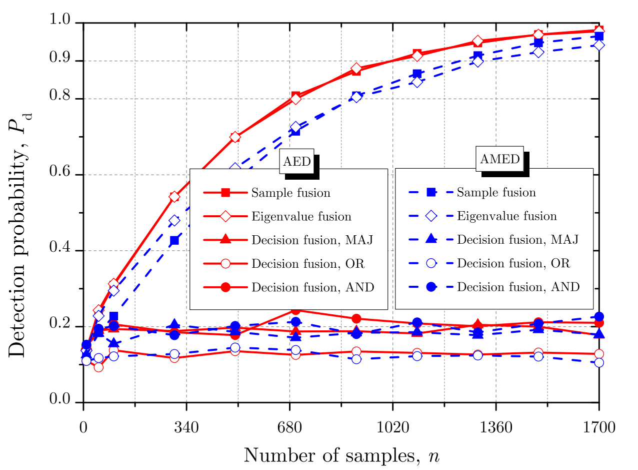

Fig. 6. P_d as a function of the number of samples for $P_{fa} = 0.1$, $SNR_{\mathbf{X}} = -10$ dB and $SNR_{\mathbf{S}} = 0$ dB.

$P_d = 0.9$.

Notice that all the decision fusion rules clearly suffer from a severe performance degradation in the presence of the SU. Under the parameters adopted here, we were not able to improve P_d by increasing the number of samples when a decision fusion rule is adopted. This result is consistent with the ROC curves in Figures 3–5 for $SNR_{\mathbf{S}} = 0$ dB.

The AND rule demonstrated to be the worst among all fusion rules and test statistics under analysis. The results concerned with decision rules are not meant to state that the relative performances will always be kept the same. The performance ranking of AND, OR and majority-voting can vary with different system parameters or scenarios, as also stated in [3].

V. Final Remarks and Suggestions for New Research

In this paper we have compared the performances of eigenvalue spectrum sensing techniques in a multiple sensor

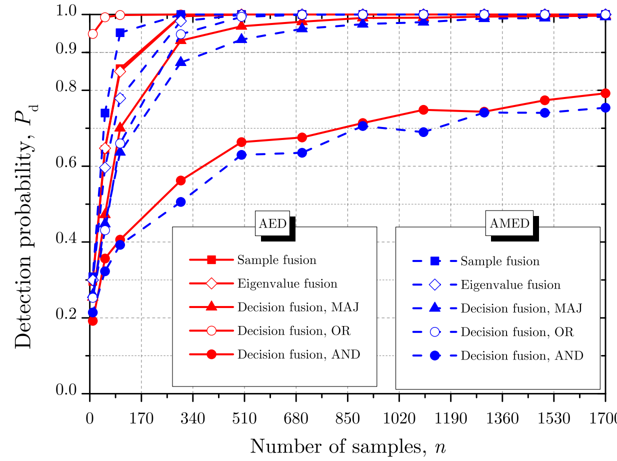

Fig. 7. P_d as a function of the number of samples for $P_{fa} = 0.1$, $SNR_{\mathbf{X}} = -10$ dB and $SNR_{\mathbf{S}} = -\infty$ dB (no SU signal transmission).

cognitive radio network that uses the concept of continuous sensing and transmission. We have considered collaborative centralized spectrum sensing with sample, eigenvalue and hard decision combining. It has been shown that the decision fusion rules are the worst options for detecting the PU signal when the SU signal is transmitting at the same time. The proposed empirical test statistics for the AED unveiled more statistical power than the ones proposed for the AMED, demonstrating an interesting future research opportunity seeking for further improvements in the AMED expressions. The use of the decision fusion schemes in the presence of the SU signal has led to a low probability of detection even for high number of samples. As a natural and necessary future development, it will be a deeper analysis of the sensing-throughput tradeoff by performing spectrum sensing and data transmission at the same time as proposed in this paper.

References

[1] R. Engelman, "Report of the spectrum efficiency working group," Federal Communication Commission, Tech. Rep., Nov. 2002.

[2] S. Haykin, "Cognitive radio: brain-empowered wireless communications," *IEEE J. Sel. Areas Commun.*, vol. 23, no. 2, pp. 201–220, Feb. 2005.

[3] I. F. Akyildiz, B. F. Lo, and R. Balakrishnan, "Cooperative spectrum sensing in cognitive radio networks: A survey," *Elsevier Physical Comm.*, vol. 4, pp. 40–62, Mar. 2011.

[4] W. Hu, D. Willkomm, M. Abusubaih, J. Gross, G. Vlantis, M. Gerla, and A. Wolisz, "Cognitive radios for dynamic spectrum access - dynamic frequency hopping communities for efficient IEEE 802.22 operation," *IEEE Commun. Mag.*, vol. 45, no. 5, pp. 80–87, May 2007.

[5] S. Boyd, J. Frye, M. Pursley, and T. Royster, "Spectrum monitoring during reception in dynamic spectrum access cognitive radio networks," *IEEE Trans. Commun.*, vol. 60, no. 2, pp. 547–558, Feb. 2012.

[6] R. Bizerra, A. Braga, and G. de Carvalho, "A spectrum sensing model for continuous transmission in cognitive radio network," in *Wireless Telecommunications Symposium (WTS), 2012*, Apr. 2012, pp. 1–7.

[7] A. J. Braga, R. A. A. de Souza, and D. A. Guimarães, "Eigenvalue-based techniques for continuous sensing model in MIMO CR networks," in *Communications (LATINCOM), 2013 IEEE Latin-America Conference on*, Nov. 2013, pp. 1–6.