Cooperative Sensing of OFDM Signals using Heterogeneous Sensors

by

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***Abstract*—In this paper, we investigate a distributed and heterogeneous cognitive radio network (CRN), comprising of secondary users (SUs) employing either energy detector (ED) or autocorrelation detector (AD) to detect the presence or absence of an orthogonal frequency-division multiplexing (OFDM) based primary user (PU). For the considered heterogeneous cooperative spectrum sensing (CSS), the optimal soft combining rule is derived. The performance of this optimal fusion rule and different hard combining schemes such as OR, AND, and MAJORITY is presented for the case when the noise variance is exactly known. Later, the effect of noise uncertainty is also presented. The proposed heterogeneous CSS is shown to combine the excellent performance of the EDs (when the noise variance is exactly known) and robustness of the ADs to the noise uncertainty.**

I. Introduction

Cognitive radio (CR) is going to be a key enabler for 5G with spectrum-aware applications such as efficient spectrum utilization and interference management [1]. Spectrum sensing is an important component of CR as it provides spectrum awareness required for cognitive processing. In CR literature, local spectrum sensing algorithms have been proposed based on different features such as energy, autocorrelation, cyclostationary, eigenvalue, etc., [2], [3]. However, primary user (PU) detection by a single secondary user (SU) suffers from path loss, shadowing, multi-path fading etc. To minimize these channel effects, cooperative spectrum sensing (CSS) is proposed to enhance sensing performance by exploiting spatial diversity [2]–[4].

Majority of the available literature on CSS considers only homogeneous CR nodes for cooperation. In this paper, by homogeneity, we mean that all the SUs participating in CSS are identical and employ same detection scheme. This assumption makes it easier to analyze the detection performance of the CSS schemes. However, with increasing number of wireless technologies and gradual trend towards coexistence of heterogeneous networks in the same frequency bands, future CR networks (CRNs) may consists of SUs having different resource and power constraints due to their size, complexity, task involved, etc. Moreover, some SUs may possess information regarding PU signal characteristics, while others may not. As such, it is highly probable that different SUs in a CRN would employ different spectrum sensing schemes for PU detection, in order to improve their detection performance. Collaborative sensing using heterogeneous sensors can provide similar gains as in the case of CSS using homogeneous sensors. In a heterogeneous CRN, the nodes participating in CSS can have different resources with respect to each other. In this paper, the term *heterogeneous nodes or sensors*, mean that the nodes employ different algorithm to evaluate the local test statistic from the received observations. In such a situation, it is quite a challenge to design optimal fusion rules for CSS. It is therefore important to study and analyze the performance of heterogeneous CSS schemes for different fusion rules, which is the focus of this paper.

In the recent years, the idea of CSS based on heterogeneous CRs employing dissimilar detection algorithms has been explored to a limited extent [5]–[7]. In [5], a heterogeneous CSS scheme comprising of energy and cyclostationary detectors is considered. The optimal soft combining rule is derived for the considered scenario and its performance is compared with different hard decision combining rules. In [6], a decision statistics-based centralized CSS technique using the joint probability distribution function of the multiple decision statistics is proposed and its performance is compared with various existing cooperative schemes. In [7], a spectrum sensing scheme is proposed where SUs analyze the power in the frequency band of interest to determine whether the PU waveform is known or not. The SU then performs either a combination of energy detector (ED) and cyclostationary detector if the PU waveform is unknown or employs a matched-filter detector otherwise.

Most of the latest communication signals such as LTE, WLAN, etc., are based on orthogonal frequency-division multiplexing (OFDM) signal waveform. Also future wireless systems including 5G are expected to use OFDM. Therefore, detecting OFDM signals is a relevant problem. This paper proposes CSS for OFDM signal in a heterogeneous CRN comprising of energy and autocorrelation feature detectors. ED is a low complexity detector which can detect any signal irrespective of the knowledge of PU signal properties. In case of AWGN with known noise power, the ED is the optimum detector for a random uncorrelated Gaussian signal and at least a generalized likelihood ratio test (GLRT) statistic for completely unknown random signals [8]. However, ED cannot differentiate between signal and noise. Also it suffers from the performance limitation of SNR wall in the presence of noise uncertainty [9]. Autocorrelation detector (AD) considered in this paper is the one suggested in [10] which is robust against noise uncertainty, can classify different OFDM signals, and differentiate between OFDM and non-OFDM signals. In addition, it has much less complexity to cyclostationary based detectors.

In this paper, the performance of the proposed CSS is analyzed for different fusion rules such as the optimal soft combining rule (likelihood ratio test (LRT)) and few widely-used hard combining rules (OR, AND, MAJORITY). The Neyman-Pearson detection criteria is adopted which maximizes the probability of detection for a constraint on the false alarm probability. The performance of all schemes is compared in terms of probability of detection for the scenarios when the noise variance is exactly known. For the case of noise uncertainty, the comparison is done only for hard-combining schemes as designing LRT scheme is difficult in this case. The performance of optimal soft-combining homogeneous-CSS schemes using either only ADs or only EDs in the considered heterogeneous CSS is also shown for reference.

The paper is organized as follows. In Section II, the considered system model is explained in detail along with details of ED and AD considered in this paper. In Section III, the optimal soft combining scheme is derived for the heterogeneous case. Section IV presents the hard combining schemes. Section V presents the simulations results and Section VI concludes the paper.

II. Energy and Autocorrelation based Detectors

Fig. 1 shows the system model for the considered CSS with heterogeneous sensors. It consists of K_E SUs employing ED and K_A SUs employing AD for spectrum sensing such that there are total $K_E + K_A = N$ SUs. In Fig. 1, SUs are labeled as SU_n for $n = 1, 2., ..., N$. For convenience, the index n is used for the n^{th} SU (irrespective of ED or AD), while indices i and j are used for the i^{th} ED and j^{th} AD, respectively, so that $i \in [1, \ldots, K_E]$ while $j \in [1, \ldots, K_A]$. The PU signal is assumed to be an OFDM signal. Furthermore, the sensing channels are modeled as AWGN channels while reporting channels are error free. For the sake of simplicity, we assume that the signal-to-noise-ratio (SNR) is same for all the detectors and noise variance σ_w^2 is completely known. The SUs send their respective test statistics to the fusion center (FC) which utilizes a suitable fusion rule to arrive at the global decision. The global decision is then relayed backed to all the SUs and based on the received information, the SUs adjust their operating parameters accordingly.

In spectrum sensing, the presence or absence of a PU on locally observed signal samples can be formulated as a binary hypothesis testing problem. There are two hypotheses: $\mathcal{H}_0$, which denotes the absence of PU signal and $\mathcal{H}_1$, which denotes the presence of PU signal. The considered signal model is

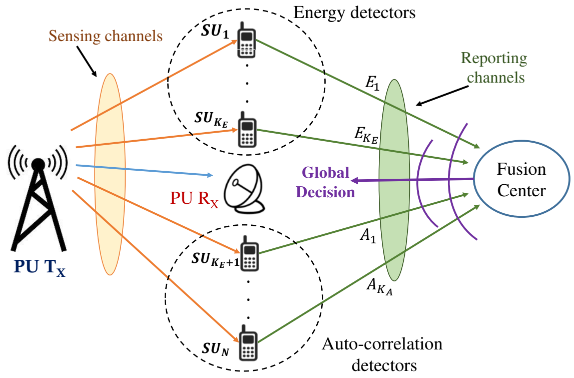

Figure 1. System model for the considered heterogeneous CSS using K_E number of energy detectors (EDs) and K_A number of autocorrelation detectors (ADs).

$$
\begin{aligned}
\mathcal{H}_0 &: x_n[m] = w_n[m] \\
\mathcal{H}_1 &: x_n[m] = s[m] + w_n[m]
\end{aligned}
\tag{1}
$$

for $m = 0, 1, \ldots, M-1$ and $n = 1, 2, \ldots, N$. Here, $x_n[m]$, $w_n[m]$, and $s[m]$ are the samples of received signal, AWGN and PU signal, respectively at the n^{th} SU while M is the number of received signal samples at each SU. Note that the local observation of SUs, conditioned on either of the hypotheses are assumed to be independent of each other. The noise samples $w_n[m]$ are assumed to be zero mean with variance σ_w^2. It is also a complex circularly symmetric Gaussian random variable. Moreover, the noise samples $w_n[m]$ are also assumed to be independent from sensor to sensor. Basically, several PU signals such as OFDM signals, are Gaussian signals [11], therefore, the PU signal $s[n]$ is also assumed as complex circularly symmetric Gaussian random variable with zero mean and variance σ_s^2. Consequently, $x_n[m]$ is also complex circularly symmetric Gaussian random variable and its distributions under different hypotheses are given by

$$
\begin{aligned}
\mathcal{H}_0 &: x_n[m] \sim \mathcal{N}_c\left(0, \sigma_w^2\right) \\
\mathcal{H}_1 &: x_n[m] \sim \mathcal{N}_c\left(0, \sigma_s^2 + \sigma_w^2\right).
\end{aligned}
\tag{2}
$$

A. Energy Detector (ED)

In an ED (also referred as a radiometer), the test statistic E_i evaluated from M received samples is given [12] by

$$
E_i = \frac{1}{M} \sum_{m=0}^{M-1} |x_i[m]|^2 \tag{3}
$$

for $i = 1, 2, ..., K_E$. For sufficiently large value of $M (> 100)$, the distributions of E_i under both hypotheses H_0 and H_1 can be approximated to be Gaussian using the *central limit theorem* and are given [12] by

$$
E_i \sim \begin{cases} \mathcal{N}\left(\sigma_w^2, \dfrac{1}{M}\sigma_w^4\right) & : \mathcal{H}_0 \\ \mathcal{N}\left(\sigma_w^2(1+\gamma), \dfrac{1}{M}\sigma_w^4(1+\gamma)^2\right) & : \mathcal{H}_1. \end{cases} \tag{4}
$$

Here, $\gamma = \sigma_s^2/\sigma_w^2$ is the SNR in normal scale with σ_s^2 being the signal power at the receiver.

B. Autocorrelation Detector (AD)

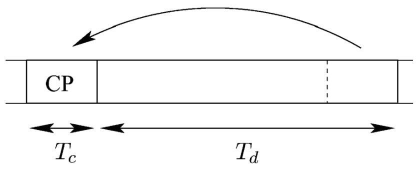

Figure 2. A cyclic prefix of T_c symbols is copied in front of the data block of T_d symbols to create one OFDM symbol or block containing total $T_s = T_d + T_c$ symbols.

In this paper, the PU signal is assumed to be an OFDM signal, in which a cyclic prefix of T_c symbols is copied in front of the data block of T_d symbols to create one OFDM symbol. Due to the presence of cyclic prefix in an OFDM symbol, the autocorrelation value for a lag T_d is not zero, unlike AWGN whose autocorrelation value is zero for any non-zero lag value. In autocorrelation based spectrum sensing, the detector first evaluates the maximum likelihood autocorrelation estimate A_j from M received signal samples as given in [10] by

$$A_j = \frac{\frac{1}{M} \sum_{m=0}^{M-T_d-1} \Re\left\{x_{j+K_E}[m]x^*_{j+K_E}[m+T_d]\right\}}{\hat{\sigma}^2_{zj}}, \tag{5}$$

where $j = 1, 2, ..., K_A$ and $\hat{\sigma}^2_{zj}$ is given in [10] by

$$\hat{\sigma}^2_{zj} = \frac{1}{2M} \sum_{m=0}^{M-1} |x_j[m]|^2. \tag{6}$$

The distributions of the autocorrelation estimate A_j under $\mathcal{H}_0$ and $\mathcal{H}_1$ can be given as in [10] by

$$\begin{aligned} \mathcal{H}_0 : A_j &\sim \mathcal{N}_r\left(0, \frac{1}{2M}\right), \\ \mathcal{H}_1 : A_j &\sim \mathcal{N}_r\left(\rho_1, \frac{(1-\rho_1^2)^2}{2M}\right), \end{aligned} \tag{7}$$

where assumption of $M \gg T_d$ is made while ρ_1 is given in [10] by

$$\rho_1 = \frac{T_c}{T_d + T_c}\left(\frac{\gamma}{1+\gamma}\right). \tag{8}$$

III. Optimal Soft Combining Based CSS

In this section, the optimal soft combining test statistic is derived for the CSS scheme. All the SUs send their respective test statistics to the FC. An ED based SU sends E_i for $i = 1, 2, ..., K_E$ whereas an AD based SU sends A_j for $j = 1, 2, ..., K_A$ as the test statistic to the FC. For mathematical convenience, normalizing E_i such that it becomes standard normal random variable under $\mathcal{H}_0$, we get

$$\tilde{E}_i = \frac{E_i - \sigma_w^2}{\sqrt{\sigma_w^4/M}}. \tag{9}$$

Therefore, the distributions of the transformed test statistic $\tilde{E}_i$ under the two hypotheses are given by

$$\tilde{E}_i \sim \begin{cases} \mathcal{N}(0,1) & : \mathcal{H}_0 \\ \mathcal{N}\left(\sqrt{M}\gamma, (1+\gamma)^2\right) & : \mathcal{H}_1. \end{cases} \tag{10}$$

Similarly, normalizing the autocorrelation test statistic $\tilde{A}_j$ such that it follows standard normal distribution under $\mathcal{H}_0$, we have

$$\tilde{A}_j = \frac{A_j - 0}{\sqrt{1/2M}}.$$

The distributions of the new test statistic A_j under $\mathcal{H}_0$ and $\mathcal{H}_1$ are

$$\tilde{A}_j \sim \begin{cases} \mathcal{N}(0,1) & : \mathcal{H}_0 \\ \mathcal{N}\left(\rho_1\sqrt{2M}, (1-\rho_1^2)^2\right) & : \mathcal{H}_1. \end{cases} \tag{11}$$

Let $\mathbb{T} = [\tilde{E}_1, \tilde{E}_2, ..., \tilde{E}_{K_E}, \tilde{A}_1, \tilde{A}_2, ..., \tilde{A_{K_A}}]^T$ denote the vector of test-statistics after normalization. The observations at the SUs are assumed to be independent and hence their respective test statistics are also independent from one another. In such scenario, the optimal fusion rule at the FC is the likelihood ratio test (LRT) given [8] by

$$\begin{aligned} \mathcal{L}(\mathbb{T}) &= \prod_{i=1}^{K_E} \frac{p\left(\tilde{E}_i|H_1\right)}{p\left(\tilde{E}_i|H_0\right)} \cdot \prod_{j=1}^{K_A} \frac{p\left(\tilde{A}_j|H_1\right)}{p\left(\tilde{A}_j|H_0\right)} \\ &= \mathcal{L}(\tilde{E}) \cdot \mathcal{L}(\tilde{A}). \end{aligned} \tag{12}$$

Now taking log on both sides, the log likelihood ratio (LLR) is obtained as

$$\begin{aligned} \ln(\mathcal{L}(\mathbb{T})) &= \ln(\mathcal{L}(\tilde{E}) \cdot \mathcal{L}(\tilde{A})) \\ Z &= \Lambda(\tilde{E}) + \Lambda(\tilde{A}), \end{aligned} \tag{13}$$

where, $\Lambda(\tilde{E}) \triangleq \ln \mathcal{L}(\tilde{E})$, $\Lambda(\tilde{A}) \triangleq \ln \mathcal{L}(\tilde{A})$ and $Z \triangleq \ln(\mathcal{L}(\mathbb{T}))$ for convenience.

A. LLR for SUs Employing ED

Using (10), the probability density functions (pdfs) of $\tilde{E}_i$ under $\mathcal{H}_0$ and $\mathcal{H}_1$ can be expressed as

$$p\left(\tilde{E}_i|\mathcal{H}_0\right) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{\tilde{E}_i^{\,2}}{2}\right), \tag{14}$$

$$p\left(\tilde{E}_i|\mathcal{H}_1\right) = \frac{1}{\sqrt{2\pi}(1+\gamma)} \exp\left(-\frac{(\tilde{E}_i - \sqrt{M}\gamma)^2}{2(1+\gamma)^2}\right). \tag{15}$$

Using (14) and (15), the closed form expression of $\Lambda(E)$ can be obtained as

$$\Lambda(\tilde{E}) = K_E \ln\left(\frac{1}{1+\gamma}\right) - \frac{M\gamma^2}{2(1+\gamma)^2} K_E + \frac{\gamma}{2(1+\gamma)^2}\left\{\sum_{i=1}^{K_E} \tilde{E}_i^{\,2}(\gamma+2) + 2\tilde{E}_i\sqrt{M}\right\}. \tag{16}$$

B. LLR for SUs Employing AD

Using (11), the pdfs of $\tilde{A}_j$ under $\mathcal{H}_0$ and $\mathcal{H}_1$ are given by

$$p(\tilde{A}_j|\mathcal{H}_0) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{\tilde{A}_j^{\,2}}{2}\right), \tag{17}$$

$$p(\tilde{A}_j|\mathcal{H}_1) = \frac{1}{\sqrt{2\pi}} \frac{\exp\left(-\frac{\left(\tilde{A}_j - \rho_1\sqrt{2M}\right)^2}{2\left(1-\rho_1^2\right)^2}\right)}{\left(1-\rho_1^2\right)}. \tag{18}$$

Using (17) and (18), the closed form expression of $\Lambda(\tilde{A})$ is obtained as

$$\Lambda(\tilde{A}) = K_A \ln\left(\frac{1}{1-\rho_1^2}\right) - \frac{M\rho_1^2}{(1-\rho_1^2)^2}K_A + \frac{\rho_1^2}{2(1-\rho_1^2)^2}\sum_{i=1}^{K_A}\left\{\tilde{A}_j^{\,2}(\rho_1^2-2) + \frac{2\tilde{A}_j\sqrt{2M}}{\rho_1}\right\}. \tag{19}$$

C. LLRT statistic at the FC

Using the LLRT statistic Z, the decision is made on the following decision rule

$$Z = \Lambda(\tilde{E}) + \Lambda(\tilde{A}) \underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\gtrless}} \eta, \tag{20}$$

where η is a threshold under Neyman-Pearson criterion while $\Lambda(\tilde{E})$ and $\Lambda(\tilde{A})$ are given by (16) and (19). Now taking constants of $\Lambda(\tilde{E})$ and $\Lambda(\tilde{A})$ to the right hand side and rearranging, we get equivalent LLRT statistic

$$Z' = \frac{\gamma(\gamma+2)}{2(1+\gamma)^2}\sum_{i=1}^{K_E}\tilde{E}_i^{\,2} + \frac{\sqrt{M}\gamma}{(1+\gamma)^2}\sum_{i=1}^{K_E}\tilde{E}_i + \frac{\rho_1^2(\rho_1^2-2)}{2(1-\rho_1^2)^2}\sum_{j=1}^{K_A}\tilde{A}_j^{\,2} + \frac{\rho_1\sqrt{2M}}{(1-\rho_1^2)^2}\sum_{j=1}^{K_A}\tilde{A}_j. \tag{21}$$

Now, letting

$$a \triangleq \frac{\gamma(2+\gamma)}{2(1+\gamma)^2} \quad ; \quad b \triangleq \frac{\sqrt{M}\gamma}{(1+\gamma)^2}$$
$$c \triangleq \frac{\rho_1^2(\rho_1^2-2)}{2(1-\rho_1^2)^2} \quad ; \quad d \triangleq \frac{\rho_1\sqrt{2M}}{(1-\rho_1^2)^2}.$$

Therefore, Z' in (21) can be expressed as

$$Z' = \sum_{i=1}^{K_E}\left(a\tilde{E}_i^{\,2} + b\tilde{E}_i\right) + \sum_{j=1}^{K_A}\left(c\tilde{A}_j^{\,2} + d\tilde{A}_j\right). \tag{22}$$

The decision is made according to the following decision rule

$$Z' \underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\gtrless}} \eta', \tag{23}$$

where η' is the threshold of a Neyman-Pearson detector and is found empirically in this paper.

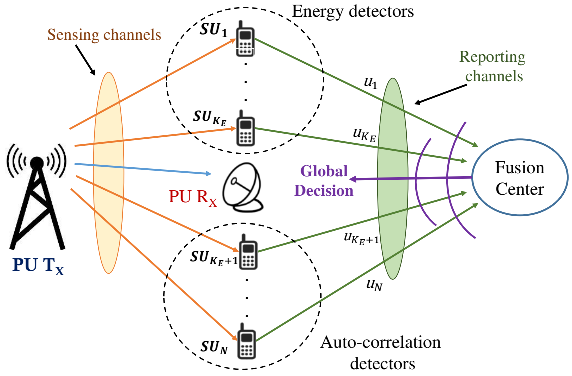

Figure 3. Hard decision based heterogeneous CSS.

IV. Hard Decision Combining Based CSS

In this section, we present hard decision combining rules while using heterogeneous sensors. In hard decision combining, instead of sending E_i or A_j to the FC as was done in soft decision combining scheme, each SU makes a local decision based on E_i or A_j and sends a one-bit decision either 1 or 0 depending on presence or absence of PU respectively to the FC as shown in Fig. 3. In the figure, one-bit hard decision is denoted by u_n for the n^{th} SU. At the FC, K-out-of-N rule is used to make a global decision such that we decide H_1 if

$$\sum_{n=1}^{N} u_n \geq K, \tag{24}$$

and H_0 otherwise. The K-out-of-N fusion rules encompass a general class of fusion rules that includes widely used OR, AND, and MAJORITY. Boolean fusion rules as special cases. In addition, the optimal fusion rule at the FC is of the form of a K-out-of-N fusion rule under the assumptions of conditional independence of observations at the SUs and identical detectors. For $K = 1$, the fusion rule is termed as OR rule. For $K = N$ fusion rule is termed as AND rule and for $K = \lceil \frac{N+1}{2} \rceil$ the fusion rule is termed as MAJORITY rule.

Let $P_{f,fc}$ denote the global probability of false alarm at the FC and P_{fn} denote the local probability of false alarm. For the K-out-of-N fusion rule, $P_{f,fc}$ for CSS at the FC is given [13] by

$$P_{f,fc} = 1 - \mathcal{B}\left(K-1, N, P_{fn}\right), \tag{25}$$

where $P_{fn} = P_f \ \forall n$ and $\mathcal{B}(\cdot)$ denotes the binomial cumulative distribution function. Using (25), $P_{fn} = P_f$ can be found using

$$P_f = \mathcal{B}^{-1}\left(K-1, N, 1-P_{f,fc}\right). \tag{26}$$

Therefore, the local threshold λ corresponding to the local false alarm rate P_f for the ED and AD can be expressed as in [10], [14] by

$$\lambda = \sqrt{\sigma_0^2 Q^{-1}(P_f)} + \mu_0, \tag{27}$$

where $\mu_0 = \sigma_w^2$, $\sigma_0^2 = \frac{1}{M}\sigma_w^4$ for the ED and $\mu_0 = 0$, $\sigma_0^2 = \frac{1}{2M}$ for the AD.

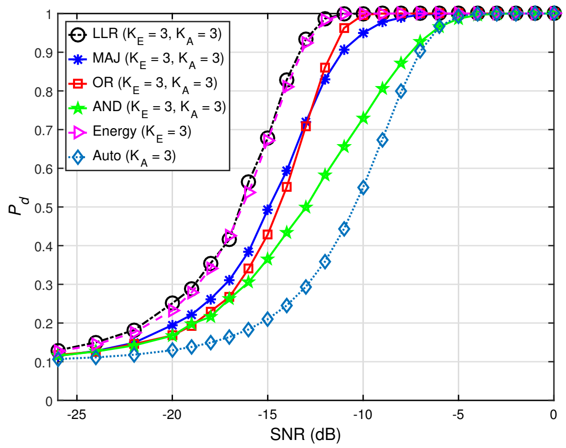

Figure 4. Comparison of soft and hard combining schemes for $P_{f,fc} = 0.1$ when noise variance is exactly known.

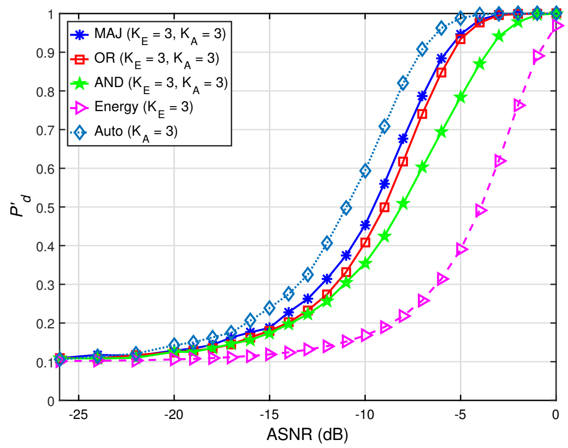

Figure 5. P_d vs SNR (dB) plot showing comparison of soft and hard combining schemes in the presence of noise uncertainty with $\sigma_\Delta^2 = 0.1$ and average $P'_{f,fc} = 0.1$

V. Simulation and Results

In this section, we compare the performance of different combination rules for the heterogeneous CSS. The PU signal is assumed to be an OFDM signal. The input to the IFFT at the transmitter are chosen from a 4 QPSK constellation. The IFFT size is chosen to be 32. Therefore, $T_d = 32$. The cyclic prefix is chosen as $T_c = T_d/4 = 8$. Monte-Carlo realizations considered for simulation is $10,000$. The number of received signal samples is chosen as $M = 1000$. The total number of SUs in the CRN is taken as $N = 6$ where the number of EDs $K_E = 3$ and the number of ADs $K_A = 3$. For the performance comparison of different combination rules, the P_d vs SNR (dB) curves are plotted for global probability of false alarm $P_{f,fc} = 0.1$. First the P_d vs SNR curves are plotted for the case when the noise variance is known perfectly. Next, results are presented for the case when there is noise uncertainty. In addition to the performance of fusion rules discussed in this paper for heterogeneous CSS, the performance of optimal soft-combining homogeneous-CSS schemes using either only EDs (i.e.,$K_E = 3, K_A = 0$) or only ADs (i.e.,$K_A = 3, K_E = 0$) in the considered heterogeneous scenario is also shown for reference.

A. Noise variance exactly known

Fig. 4 shows the P_d vs SNR (dB) comparison for different combination rules when the noise variance is exactly known. First observation from this plot is that for the case of heterogeneous CSS, LLR based optimal fusion rule gives the best performance followed by MAJORITY, OR, and AND fusion rules in that order. However, it is evident from the plot that homogeneous CSS with only EDs $(K_E = 3)$ leads to same performance as LLR $(K_E = 3, K_A = 3)$ when noise variance σ_w^2 is exactly known. The least performance is seen for homogeneous CSS with only AD with $(K_A = 3)$.

B. Effect of Noise Uncertainty

In order to show the effect of noise uncertainty on ED's performance, we consider a scenario where the noise variance is modeled as a random variable following a Gaussian distribution having a nominal mean σ_n^2 and standard deviation σ_Δ as was done in [14]. Therefore, the pdf of σ_w^2 is given by

$$f(\sigma_w^2) = \frac{1}{\sqrt{2\pi}\sigma_\Delta} \exp\left(-\frac{(\sigma_w^2 - \sigma_n^2)^2}{2\sigma_\Delta^2}\right). \tag{28}$$

In this case, the average probability of false alarm P'_{fn} is given as

$$P'_{fn} = \int_0^\infty Q\left(\frac{\eta'_{E_n} - \mu_0}{\sigma_0}\right) f(\sigma_w^2)\, d\sigma_w^2, \tag{29}$$

Fig. 5 shows the P_d vs SNR curves for different fusion rules in the presence of noise uncertainty of $\sigma_\Delta^2 = 0.1$ and constraint on the average $P'_{f,fc} = 0.1$. Note that the LLR based soft combining is not attempted in this paper as finding LLR in the presence of noise uncertainty is an open problem and will be dealt in our future work. It can be seen that there is significant performance degradation for homogeneous ED based CSS with $K_E = 3$ which had the best performance when the noise variance was perfectly known. On the other hand, the performance of homogeneous CSS using AD with $K_A = 3$ gives the best performance. In fact, there is no change in the performance of AD detectors even in the presence of noise uncertainty as the AD detectors do not assume the knowledge of noise variance and are totally robust to any noise uncertainty. This clearly shows that while the performance of the ED falls drastically even for a slight deviation of noise variance from the assumed value, the AD is immune to the noise uncertainty. This is the reason, the performance of MAJORITY, OR, and AND with $K_E = 3$ & $K_A = 3$ lies in between homogeneous ED based CSS with $(K_E = 3)$ and homogeneous AD based CSS with $(K_A = 3)$.

These results highlight the benefit of heterogeneous CSS using AD and ED detectors.

VI. Conclusion

In this paper, we have investigated a heterogeneous CSS comprising of SUs employing either an ED or an AD. The PU signal has been assumed to be an OFDM signal. The optimal soft combining rule for this heterogeneous CSS has been derived and its performance compared to the K-out-of-N based hard combination rule. It has been shown that the proposed LLR based CSS outperforms the performance of hard decision combination rules. Moreover, it has been seen that the performance of the ED is excellent when there is no noise uncertainty while the AD provides robustness in the presence of noise uncertainty. Thus, the results presented in this paper provide excellent motivation for cooperation among these heterogeneous detectors.

Acknowledgement

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