Optimization of Cooperative Spectrum Sensing and Implementation on Software Defined Radios

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***Abstract*—Reliable detection of primary user activity by spectrum sensing is a crucial issue of cognitive radio systems. The objective of cooperative spectrum sensing is to combine the detection results of multiple cognitive radios in order to maximize the probability of detecting unused spectrum while meeting a required reliability of detecting primary user activity. In this paper, a Kullback-Leibler distance-based optimization approach for the local decision thresholds of cooperative spectrum sensing is proposed. It is both computationally efficient and scalable with the number of cognitive radios. To validate the concept, real spectrum sensing results are used. The employed practical setup is based on software defined radio and detects a WiMAX-like OFDM signal. The presented numerical results illustrate the feasibility and effectiveness of the approach.**

I. Introduction

According to recent studies, most of the licensed radio spectrum is severely underutilized in both the time and spatial domain [1]. Spectral efficiency can be significantly improved by sharing the available frequency band between a licensed primary user (PU) and unlicensed secondary users or cognitive radios (CRs). By observing the spectrum domain of interest, CRs are able to detect spectrum holes and adapt radio operations to a dynamically changing environment without introducing harmful interference to the PU. Hence, spectrum sensing is a key enabling functionality of CRs. Besides offering reliable detection of weak PU signals of possibly unknown types, spectrum sensing should also monitor the activation of the PU in order for the CRs to vacate the occupied spectrum portions. There are three traditional spectrum sensing approaches: matched filtering, cyclostationary feature detection and energy detection [2].

If CRs have a priori knowledge of PU signal features (e.g., modulation type, pulse shaping, packet format), then the optimal detection is achieved by correlating the received signal with a pre-stored local copy in a matched filter. Due to coherency, the main advantage of the matched filter is small convergence time and increased reliability, while a significant drawback is the need of a dedicated receiver for every class of PU.

Cyclostationary feature detectors differentiate the PU signal energy from the local noise energy by exploiting periodicity exhibited by the mean and autocorrelation of a particular modulated signal. Increasing the number of cyclostationary features in PU signals improves detection reliability and robustness against multipath fading, which comes at the expense of increased overhead and bandwidth loss of the PU.

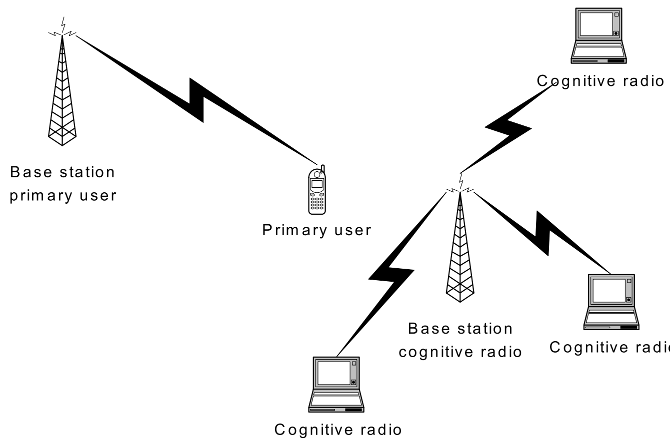

Fig. 1. Considered system setup.

Energy detection is optimal when the CRs have no information of the PU signals. It can be implemented similar to a spectrum analyzer by averaging frequency bins of a Fast Fourier Transform (FFT). The signal detection is performed based on the amount of received energy. This allows for a simple implementation but the performance in low SNR regime can be weak due to noise uncertainty. Moreover, results presented in [3] suggest that the performance of an energy detector severely degrades in fading environments. Additional degradation caused by the hidden terminal problem results from the case when a CR is shadowed by objects with high penetration loss. Not detecting spectrum holes can lead to inefficient spectrum usage, while missing PU signal presence causes harmful interference. The former case is characterized by the probability of miss P_M, while the later performance degradation is described by the probability of false alarm P_F.

The performance of spectrum sensing can be significantly improved by introducing a cooperative sensing approach where the final detection result is based on the combination of local decisions collected from multiple CRs. In such a way sensing time can be decreased and the hidden terminal problem can be avoided. In a cooperative network of CR users, a central unit or fusion center collects individual sensing information from CRs, identifies the available spectrum and broadcast this information over a control channel to other CRs or directly controls the CR traffic as shown in Fig. 1.

The optimal selection of CR users and the way how their decisions are combined can be determined by the means of minimizing the global P_M while maintaining a level of P_F. In this way, the probability of detecting spectrum holes $P_D = 1 - P_M$ will be maximized while restricting interference with the PU on a predetermined level α. Consideration of minimizing the total probability of error can also be found in literature [4].

In [5], AND, OR and k-out-of-N methods for combining local decisions from different CRs are investigated. In [6], the optimal linear function of weighted local decisions has been derived. The optimal likelihood ratio test considering the influence of the channels between CRs and the fusion center has been studied in [7]. The local detection reliability of each CR is taken into account in [8], where the final decision is made by jointly considering the local decisions of each CR and their credibility transmitted by CRs along their decisions.

For maximizing the probability of detecting unused spectrum P_D while jointly meeting a required reliability α of detecting primary user activity, optimal local CR decision rules and an optimal combining rule have to be found. In the general case, the jointly optimum solution for the local decision rules and the fusion rule is very difficult to obtain and does not scale with the number of CRs [9]. In this paper, we propose a novel optimization approach for cooperative spectrum sensing. To determine the local decision thresholds the Kullback-Leibler distance between the local detection probabilities is maximized at the CRs. By this procedure, the joint optimization problem is decoupled. After the local CR decision thresholds have been determined, the optimal fusion rule can be derived. This decoupling results in an optimization procedure which is scalable with the number of CRs. To validate this approach, we employ real spectrum sensing results obtained in a typical office environment. The results are obtained by software defined radios, which are used to detect a WiMAX-like OFDM signal assumed as PU. Numerical results show that spectrum holes can be reliably detected, while the required reliability of detecting primary user activity is guaranteed to be met.

The remainder of the paper is organized as follows. In Section II, the system model of cooperative spectrum sensing is stated. The proposed optimization procedure is introduced in Section III and the setup for practical spectrum sensing is described in Section IV. Finally, in Section V numerical results are presented and conclusions are drawn.

II. System model

The problem of cooperative spectrum sensing can be formally modelled as follows. We consider a binary hypothesis testing problem with hypotheses H_0 and H_1 indicating whether the spectrum is occupied (H_0) or free (H_1). In order to detect the presence of a spectrum hole, a network of N CRs obtains random observations

$$(X_1, \ldots, X_N)' \in \mathcal{X}_1 \times \cdots \times \mathcal{X}_N, \tag{1}$$

which are generated according to either H_0 or H_1. In case of energy detection, e.g., X_j models the energy that is received by the jth CR in the spectrum of interest. The random observations $X_1, \ldots, X_N$ are assumed to be conditionally independent given the underlying hypothesis, i.e., the joint conditional probability density function of all the observations factorizes according to

$$f(x_1, \ldots, x_N | H_k) = \prod_{j=1}^{N} f_j(x_j | H_k), \quad k = 0, 1. \tag{2}$$

The observations do not have to be identically distributed, which means in practice, that the SNR of the observed PU signal can vary between the CRs. According to the distributed nature of the problem, the jth CR performs independent spectrum sensing and processes its respective observation X_j by forming a local decision $U_j = \delta_j(X_j)$ about the absence or presence of the signal.

A. CR decision rules

In case of binary local decisions, the CR decision rules δ_j are mappings

$$\delta_j \colon \mathcal{X}_j \to \{0, 1\}, \quad j = 1, \ldots, N. \tag{3}$$

As is known from the distributed detection literature, local decision rules leading to jointly optimal configurations under the Neyman-Pearson criterion are log-likelihood ratio tests [10] according to

$$L_j \underset{U_j = 0}{\overset{U_j = 1}{\gtrless}} \tau_j \tag{4}$$

where $L_j = \log(f_j(X_j|H_1)/f_j(X_j|H_0))$ is the local log-likelihood ratio of observation X_j. In this way, each CR has a local probability of false alarm according to

$$P_{f_j} = P(U_j = 1 | H_0) = P(L_j > \tau_j | H_0) \tag{5}$$

and a local probability of detection according to

$$P_{d_j} = P(U_j = 1 | H_1) = P(L_j > \tau_j | H_1). \tag{6}$$

An optimization procedure to determine the local decision threshold τ_j is presented in Section III.

B. Fusion of local decisions

Under the assumption of conditionally independent local decisions $U_1, \ldots, U_N$ at the CRs, the optimal fusion rule at the fusion center which makes a binary global decision U_0 about the state of the observed spectrum can be implemented by a linear threshold rule [9]. It is given by

$$\sum_{j=1}^{N} \lambda_j U_j \underset{U_0 = 0}{\overset{U_0 = 1}{\gtrless}} \vartheta \tag{7}$$

with weights

$$\lambda_j = \log\left(\frac{P_{d_j}(1 - P_{f_j})}{P_{f_j}(1 - P_{d_j})}\right) \tag{8}$$

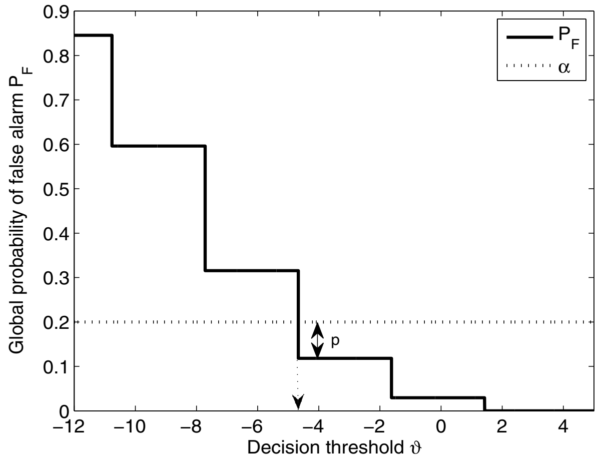

Fig. 2. Global probability of false alarm P_F depending on the decision threshold ϑ before randomization. Confidence level α is exploited by adjusting probability p.

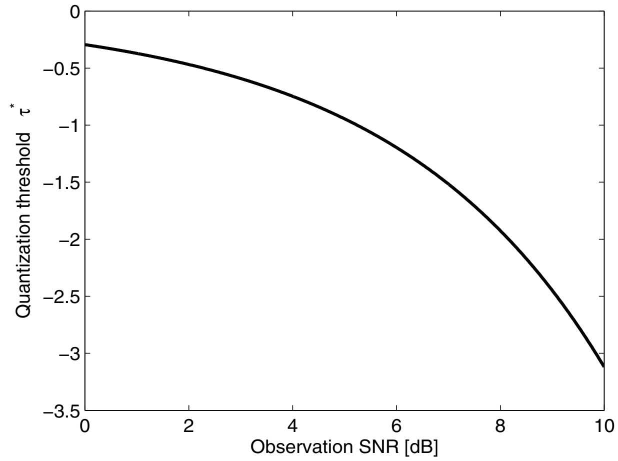

Fig. 3. Optimal local decision threshold τ^* for the Gaussian detection problem obtained by the Kullback-Leibler distance approach depending on the observation SNR.

for $j = 1, \ldots, N$, and a decision threshold $\vartheta = \vartheta(\alpha)$ which depends on the desired value of α (see Fig. 2). The tie-breaking is done in a randomized way such that the whole confidence level α is exploited. For the case $\sum_{j=1}^{N} \lambda_j U_j = \vartheta$, we formally define

$$\sum_{j=1}^{N} \lambda_j U_j = \vartheta \colon \begin{cases} U_0 = 1, & \text{with probability} \quad p \\ U_0 = 0, & \text{with probability } 1-p \end{cases} . \quad (9)$$

The value of p can be calculated as

$$p = \frac{\alpha - P(\sum_{j=1}^{N} \lambda_j U_j > \vartheta | H_0)}{P(\sum_{j=1}^{N} \lambda_j U_j = \vartheta | H_0)}. \quad (10)$$

III. Optimization of Decision Rules

In this section, we motivate and present a scalable optimization procedure for the CR decision rules (3). To determine the local decision thresholds τ_j the Kullback-Leibler (KL) distance between the local detection probabilities (5) and (6) is maximized. The rationale behind the presented approach is that the KL distance arises as asymptotic error exponent in Neyman-Pearson hypothesis testing [11].

A. Hypothesis testing and Kullback-Leibler distance

If we assume conditionally independent and identically distributed (i.i.d.) observations $X_1, \ldots, X_N$, the local conditional probability density functions $f_j(\cdot|H_k)$ are the same for all $j = 1, \ldots, N$, and we can write

$$\begin{aligned} H_0 &\colon X_j \sim f_0, \\ H_1 &\colon X_j \sim f_1, \end{aligned} \quad (11)$$

where f_k is the conditional probability density function under hypothesis H_k for all sensors. The KL distance between the two distributions f_0 and f_1 is defined as

$$D = D(f_0||f_1) = \int f_0(x) \log \frac{f_0(x)}{f_1(x)} dx. \quad (12)$$

If the fusion center has access to the unquantized observations $X_1, \ldots, X_N$ and uses the Neyman-Pearson decision rule, for the probability of miss P_M it asymptotically holds that [11]

$$\lim_{P_F \to 0} \lim_{N \to \infty} \frac{\log P_M}{N} = -D. \quad (13)$$

For small P_F and large N we obtain

$$P_M \approx \exp(-ND), \quad (14)$$

i.e., the KL distance $D = D(f_0||f_1)$ is the asymptotic error exponent in Neyman-Pearson hypothesis testing. Intuitively, in the unquantized case considered above, every cognitive radio contributes with the full KL distance $D(f_0||f_1)$ to the exponent in (14). The higher the contributed KL distance $D(f_0||f_1)$, the lower the global probability of miss P_M and thus the higher the global probability of detection $P_D = 1 - P_M$. This motivates the approach that in the case of quantization of measurements at the cognitive radios, the local decision thresholds τ_j should be determined such that the KL distance between the local probability distributions described by the probabilities (5) and (6) is maximized.

B. Kullback-Leibler distance-based optimization of CR decision rules

Analogously to definition (12), the KL distance between the local probability distributions described by the probabilities (5) and (6) can be calculated by

$$D_j = (1 - P_{f_j}) \log \left(\frac{1 - P_{f_j}}{1 - P_{d_j}} \right) + P_{f_j} \log \left(\frac{P_{f_j}}{P_{d_j}} \right). \quad (15)$$

Based on the local observation statistics $f_j(\cdot|H_k)$, the local decision threshold τ_j of the jth CR is determined in such a way that the KL distance D_j is maximized

$$\tau_j^* = \underset{\tau_j}{\operatorname{argmax}}\, D_j \quad (16)$$

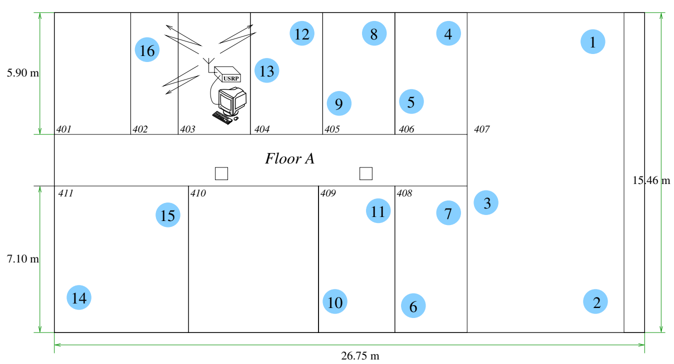

Fig. 4. Measurement floor plan.

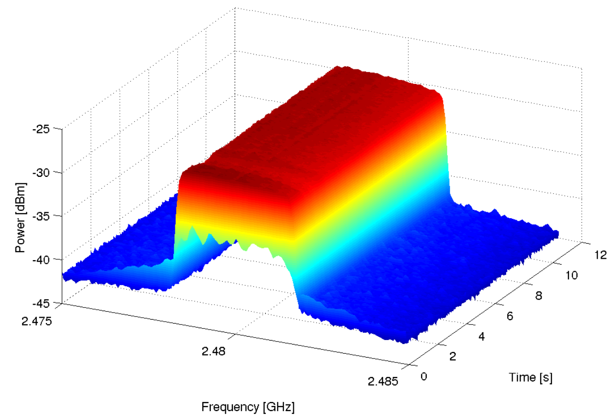

Fig. 5. Observed spectrum of the 5 MHz OFDM signal.

As an illustrative example, we consider the problem of detecting the presence or absence of a deterministic signal in Gaussian noise [12].

For this example, the resulting optimal local decision threshold τ_j^* leading to the maximum KL distance D_j^* can be easily computed numerically. In Fig. 3 the optimal threshold is depicted depending on the value of the local observation SNR. In practice, the CRs can use look-up tables with the optimal threshold values for a reasonable range of observation SNRs. In this way, a computation of the numerical optimization on the CR hardware is not required.

IV. Practical Spectrum Sensing

To evaluate the validity of the proposed approach in practice, we conduct a cooperative sensing campaign of an OFDM signal in an indoor office environment. For the measurements, a total of 16 CRs are distributed over a floor of the Institute for Theoretical Information Technology at RWTH Aachen University as shown in Fig. 4. The transmitter broadcasts an OFDM signal of 5 MHz bandwidth at 2.48 GHz. The considered test-case is used to emulate distributed spectrum sensing in the presence of an indoor WiMAX base station.

TABLE I
Observation SNRs of the measurement points in Fig. 4

Point	SNR [dB]
1	−4.05
2	−9.90
3	−4.76
4	2.81
5	0.40
6	0.16
7	3.95
8	6.28
9	6.56
10	7.49
11	8.84
12	9.40
13	8.69
14	5.46
15	8.03
16	9.38

The measurement setup is based on a Software Defined Radio (SDR) platform. The OFDM transmitter and the CRs are composed of a host commodity computer and general purpose RF hardware, Universal Software Radio Peripheral (USRP) equipped with omnidirectional antennas. The baseband signal processing at the host computers is implemented in the GNU Radio framework [13], an open source free software toolkit that provides a library of signal processing blocks. Computationally intensive operations such as filtering or up- and down-conversion are performed on the USRP. The considered OFDM transmitter is a part of a GNU Radio based adaptive OFDM framework [14].

Each of the distributed CRs, experiencing different signal attenuations, observes the absence or presence of the OFDM signal in a 5 MHz wide frequency range. The spectrum sensing is based on energy detection which is implemented by averaging the squared FFT magnitude of the observed signal. The achieved observation SNRs of the different measurement points in Fig. 4 are summarized in Table I. An exemplary spectrum utilization with presence of the OFDM signal as observed by a CR with high observation SNR is shown in Fig. 5. For each measurement the CR sums up the energy of the observed signal. The received energy of the jth CR is modelled by X_j introduced in Section II. The received energy differs from measurement to measurement due to additive noise. The upper part of Fig. 6 shows 250 measurements for the case of occupied and unoccupied spectrum for measurement point 7. At each CR, these measurements are used to estimate the local conditional probability density functions $f_j(\cdot|H_0)$ and $f_j(\cdot|H_1)$ and to determine the optimal local decision threshold τ_j^* which maximizes the KL distance (15). Estimates of the conditional densities $f_j(\cdot|H_0)$ and $f_j(\cdot|H_1)$ for measurement point 7 are shown in the lower part of Fig. 6.

V. Numerical Results and Conclusions

In this section we present numerical results obtained by applying the proposed optimization method from Section III

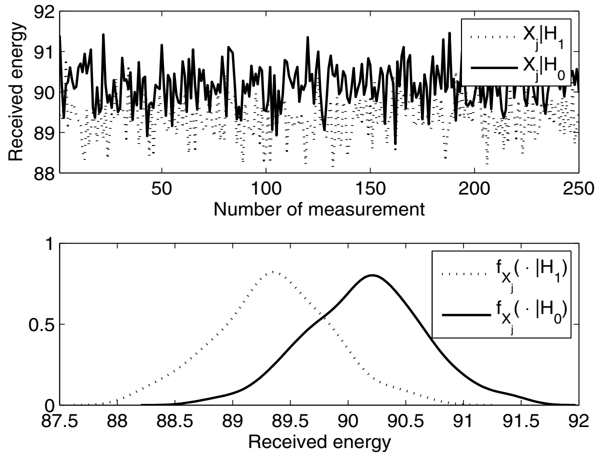

Fig. 6. Received energy at measurement point 7 for signal present and absent (upper part). The lower part shows estimates of the corresponding conditional densities $f_j(\cdot|H_0)$ and $f_j(\cdot|H_1)$.

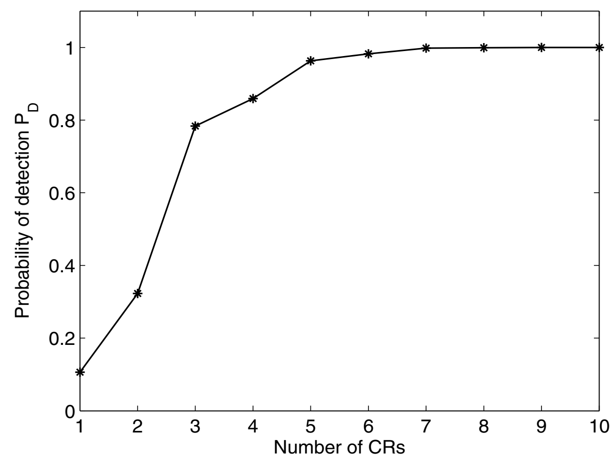

Fig. 7. Global probability of detection P_D depending on the number of cognitive radios N.

to the practical spectrum sensing measurements as described in the previous section. Fig. 7 shows the global probability of detecting unused spectrum P_D depending on the number of CRs.

For each number of CRs the value of P_D is obtained by averaging the detection results of 100 different randomly chosen subsets of the measurement points in Fig. 4. The global probability of false alarm P_F is restricted by $P_F \leq \alpha = 0.05$. This means that the probability of interfering with the PU does not exceed 0.05. The global probability of detection P_D is monotonically increasing with the number of CRs. For 5 CRs P_D is already higher than 0.963 and for 7 CRs higher than 0.998.

These results illustrate the feasibility of the presented scalable optimization approach. As a final remark, we point out that the method can easily be extended to soft decisions, i.e., the local CR decisions about the state of the observed channel can have more than one bit. This may further improve the system performance.

Acknowledgment

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