Hard Decision-based Cooperative Spectrum Sensing via Sequential Detection in Cognitive Radio Networks

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ABSTARCT
This paper presents a study of hard combination data fusion for cooperative spectrum sensing in Cognitive Radio (CR). Fast and accurate spectrum sensing is crucial in realizing a reliable cognitive network. Cooperative spectrum sensing can help reducing the mean detection time and increasing the agility of the sensing process. However, when the number of cognitive users is large, the bandwidth need for the control channel that are used to report the secondary user nodes' results to the fusion center may become excessively large. This paper presents a hard decision-based cooperative sequential detection scheme to reduce the average sensing time that is required to reach a detection decision. In the scheme, each cognitive radio computes the log likelihood ratio for its every measurement, and quantizes its measurements then sends its hard-decision to base station and the base station sequentially accumulates these log likelihood statistics and determines whether to stop making measurement.

KEYWORDS: Cognitive Radio, Cooperative Sensing, Hard Decision-based Cooperative Sensing, Sequential Detection, Spectrum Sensing.

1. INTRODUCTION

In recent years, cognitive radio (CR) has emerged as a promising paradigm for exploiting the spectrum opportunity, which is restricted by the current rigid spectrum allocation scheme, to solve the spectrum scarcity problem [1][2].

In the U.S.,the spectrum is traditionally assigned by the Federal Communications Commission (FCC) to specific users or applications, and each user can only utilize its preassigned bandwidth for communication. This discipline causes some bandwidth to be overcrowded while some other bandwidth may be underutilized.

Dynamic spectrum access based on cognitive radios has been proposed in order to opportunistically use underutilized spectrum portions of the licensed electromagnetic spectrum [3]. Cognitive radios opportunistically share the spectrum while avoiding any harmful interference to the primary licensed users. Cognitive radio aims at providing a flexible way of spectrum management, permitting secondary users to temporally access spectrum that is not used by legacy users. In this regard, the FCC has taken a number of steps in the U.S. towards allowing low-power devices to operate in the broadcast TV bands that are not being used by TV channels [5]. The U.S. TV bands include the following portions of the VHF and UHF radio spectrum: 54–72, 76–88, 174–216, and 470–806 MHz. Each TV channel occupies a slot of 6-MHz bandwidth. If a TV frequency band is not used in a particular geographical region, it can be used by cognitive radios for transmission. To promote this development, IEEE has established the IEEE 802.22 Working Group to develop a standard for a cognitive radio-based device in TV bands [6]. A key challenge in the development of the IEEE 802.22 standard is that a cognitive radio should be able to reliably detect the presence of TV signals in a fading environment. Otherwise, the radio may use the frequency band that is occupied by a TV channel, and cause interference to the TV receivers nearby. Many sensing and detection schemes have been reported in the IEEE 802.22 community, e.g., [7]–[12]. These schemes can be classified into two categories: single-user sensing and cooperative sensing. Due to the large variation in the received signal strength that is caused by path loss and fading, single-user sensing has proven to be unreliable, which consequently triggered the FCC to require geolocation-based methods for identifying unused frequency bands [13], [14]. The geolocation approach is suitable for registered TV bands; however, its cost and operational overhead prevent its wide use in the opportunistic access to occasional "white spaces" in the spectrum. Cooperative sensing relies on multiple radios to detect the presence of primary users and provides a reliable solution for cognitive radio networks [10]–[12]. In this paper, we focus on how to achieve cooperative sensing in an efficient and robust manner. The performance of spectrum sensing is usually measured by two key factors: probability of detection errors and sensing time. The traditional way to design a sensing strategy is based on the Neyman–Pearson criterion, and the resulting likelihood ratio test (LRT) fixes the number of required samples or the sensing time. In this framework, the probability of false alarm is required to be less than a predefined level, and under this constraint, the probability of miss detection is optimized (minimized) by the proposed test [15]. In contrast to the Neyman–Pearson framework, another design methodology is to minimize the required sensing time, subject to a constraint on the detection errors [16]–[18]. The resulting test is called the sequential probability ratio test (SPRT) and was first developed in the seminal work by Wald [19]. A recent exposition about the theory behind the test can be found in [20]. Some recent papers have applied this technique to spectrum sensing for cognitive radio networks, e.g., [21] and [22]. In the scheme proposed in [21], the autocorrelation coefficient based log-likelihood ratios from different cognitive radios are combined in a sequential manner at the base station for quickly detecting the primary user. In [22], the sequential detection method is applied to the detection of cyclostationary features in the received signals. These techniques can reduce the sensing time and the amount of signal samples required in identifying the unused spectrum. In this paper, we extend previous work on the sequential detection method for collaborative spectrum sensing.

In the proposed framework, each cognitive radio computes the log-likelihood ratio then quantizes the results with use hard decision output to three levels . then sends these results to base station for its every measurement, and the base station sequentially accumulates the log-likelihood tatisticsand determines whether to stop making new measurement.

Due to uncertainties caused by fading and interference, we normally do not have exact information about some signal parameters, such as signal strength and noise variance. It is thus important to make the sequential detection algorithm sufficiently robust to the uncertainties in unknown parameters. Different from previous work which assumes complete knowledge about the distributions of the measurements, our work modifies the original SPRT in order to handle unknown parameters in the assumed signal models. In our proposed solution, unknown parameters are sequentially estimated by the maximum likelihood estimation, and the sequential detection algorithm is performed by using the estimated parameters. By doing so, the average sensing time depends on the signal conditions, rather than being fixed as in the Neyman–Pearson approach. With proper stopping conditions, the proposed scheme guarantees to achieve the desired sensing performance in terms of the probability of false alarm and miss detection. These ideas are illustrated through two spectrum sensing examples. One assumes both the signal and noise are Gaussian distributed, while the other assumes the target signal is deterministic. Throughout this paper, we adopt the following definitions and notations.

2. SYSTEM MODEL

Unlike censoring model, where each user collects a specific number of samples, in this section, each cognitive radio sequentially senses the spectrum and upon reaching a decision about the presence or absence of the primary user, it sends the result to the FC. The FC then collects the received LLRs and as soon as their sum is larger than an upper threshold or smaller than a lower threshold, the decision is made and the sensors can stop sensing. The LLRs are transmitted in such a way that the larger LLRs are sent sooner. The results are shown that the number of transmissions considerably reduces and particularly when the transmission energy is high, this approach performs very well. The final decision is then made at the FC . Here, a hard decision truncated sequential sensing scheme is employed where each cognitive radio carries on sensing until it reaches a decision while not passing a limit of samples. We define N samples. A network of M cognitive radios is considered under a cooperative spectrum sensing scheme. A parallel detection configuration is employed as shown in Fig. 1. Each cognitive radio senses the spectrum and makes a local decision about the presence or absence of the primary user and informs the FC by employing a censoring policy. The final decision is then made at the FC.

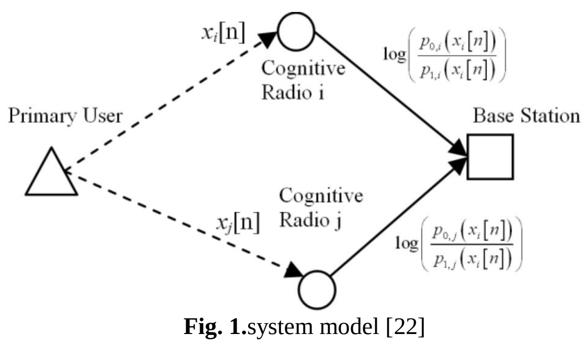

Fig. 1.system model [22]

The two hypotheses corresponding to the signal-absent and signal present events are defined as:

H_0: Target signal is absent.
H_1 : Target signal is present.

The signal acquired by the mth (m = 1, 2,…, M) cognitive radio device is represented by :

H_0 : X_m[n]= $S_{0,m}$[n],
H_1 : X_m[n]= $S_{1,m}$[n], n=1,2,…. (1)

Where $S_{1,m}$[n], is the nth acquired signal sample when the target signal is present and $S_{0,m}$[n] is the nth acquired noise signal sample when the target signal is absent. The samples X_m[n] can be either a scalar or a vector, depending on the application of interest. Throughout the paper, we assume that the samples acquired by different radios are statistically independent, and that the samples acquired by the same radio are independent and identically distributed (i.i.d.).Under H_0 and H_1 , the distributions of the acquired signal at the mth radio are characterized by the probability density functions $P_{0,m}(X_m[n])$ and $P_{1,m}(X_m[n])$ respectively. The performance of detecting against is measured by the probability of false alarm and the probability of miss detection. The error of false alarm refers to the error of accepting H_1 when H_0 is true, while the error of miss detection is the error of accepting H_0 when H_1 is true.
The probability of false alarm is represented by:

$$P_{FA} = \Pr (\widehat{H} = H_1 \mid H_0) \tag{2}$$

and the probability of miss detection is represented by:

$$P_{MISS} = \Pr (\widehat{H} = H_0 \mid H_1) \tag{3}$$

Where $\widehat{H}$ represents the detector output.

3. RELATED WORK TO SEQUENTIAL SENSING

Sequential detection as an approach to reduce the average number of sensors required to reach a decision is also studied comprehensively during the past decades [14]–[19]. In [14], [15], each sensor collects a sequence of observations, constructs a summary message and passes it on to the FC and all other sensors. A Bayesian problem formulation comprising the minimization of the average error detection probability and sampling time cost over all admissible decision policies at the FC and all possible local decision functions at each sensor is then considered to determine the optimal stopping and decision rule. Further, algorithms to solve the optimization problem for both infinite and finite horizon are given. In [16], an infinite horizon sequential detection scheme based on the sequential probability ratio test (SPRT) at both the sensors and the FC is considered. Wald's analysis of error probability, [20], is employed to determine the thresholds at the sensors and the FC. A combination of sequential detection and censoring is considered in [17]. Each sensor computes the LLR of the received sample and sends it to the FC, if it is deemed to be in a certain region. The FC then collects the received LLRs and as soon as their sum is larger than an upper threshold or smaller than a lower threshold, the decision is made and the sensors can stop sensing. The LLRs are transmitted in such a way that the larger LLRs are sent sooner. It is shown that the number of transmissions considerably reduces and particularly when the transmission energy is high, this approach performs very well. However, our paper employs a hard fusion scheme at the FC, our sequential scheme is finite horizon, and further a clear optimization problem is given to optimize the energy consumption. Since we employ the OR (or the AND) rule in our paper, the FC can decide for the presence (or absence) of the primary user by only receiving a single one (or zero). Hence, ordered transmission can be easily incorporated in our paper by stopping the sensing and transmission procedure as soon as one cognitive radio sends a one (or zero) to the FC. A truncated sequential sensing technique is employed in [19] to reduce the sensing time of a cognitive radio system. The thresholds are determined such that a certain probability of false alarm and detection are obtained. In this paper, we are employing a similar technique, except that in [19], after the truncation point, a single threshold scheme is used to make a final decision, while in our paper, the sensor decision is censored if no decision is made before the truncation point. Further, [19] considers a single sensor detection scheme while we employ a distributed cooperative sensing system and finally, in our paper an explicit optimization problem is given to find the sensing parameters.

4. SEQUENTIAL SENSING FOR SIMPLE HYPOTHESES

To begin with, assume that the number N_{fix} of samples (acquired by each cognitive radio) is fixed. To detect H_0 and H_1 , the likelihood ratio test (LRT) is performed according to :

Accept H_1 if LLR $\geq$ A
Accept H_0 if LLR $\leq$ B (4)

Where the log-likelihood ratio (LLR) is computed by the base station as:

$$\text{LLR} = \sum_{n=1}^{N} \sum_{m=1}^{M} \ln\left(\frac{P1,m(X[n])}{P0,m(X[n])} \right) \tag{5}$$

The threshold value η and the sample size N_{fix} are selected such that the probability of false alarm and the probability of miss detection are bounded by some pre-assigned values $0 < \alpha < 1$ and $0 < \beta < 1$, respectively, i.e.

$$P_{FA} \leq \alpha \text{ and } P_{MISS} \leq \beta \quad (6)$$

To do so, the distributions of the test statistic, i.e., the LLR, under H_0 and H_1need to be determined. The computation of the distributions is usually not easy and may involve complex numerical computations or simulations. To reduce the number of required samples, instead of using a fixed sample size N_{fix} , we can implement the LRT for every acquired sample in a sequential manner motivated by Wald's work [19]. That is, for N=1, 2,…, we perform the following test:

Accept H_1 *and determine* if LLR ≥ A
Accept H_0 *and determine* if LLR ≤ B

Take one more sample to Repeat the test if
$B \leq LLR_N \leq A$

Where

$$LLR_N = \sum_{n=1}^{N}\sum_{m=1}^{M} \ln\left(\frac{P_{1,m}(X_m[N])}{P_{0,m}(X_m[N])}\right) \quad (7)$$

A > 0 and B < 0 are predetermined constants according to the sensing objective (2). In the context of cooperative sensing, each radio computes the log-likelihood ratio for its every acquired sample, and the base station sequentially accumulates the log likelihood statistics and performs the above test, as described in Algorithm 1.

4.1. Algorithm: Cooperative Sequential Sensing for Simple Hypotheses

0: Set N=0, and let $LLR_0 = 0$ at the base station.
1: repeat
2: N=N+1.
3: The mth (m=1,2,..,M) radio acquires sample X_m[N] and computes $\ln\left(\frac{P_{1,m}(X_m[N])}{P_{0,m}(X_m[N])}\right)$.
4: Each radio compute its $\ln\left(\frac{P_{1,m}(X_m[N])}{P_{0,m}(X_m[N])}\right)$,then sends its hard decision results to the base station.

5: The base station updates the sequential log-likelihood ratio LLR_N according to:

$$LLR_N = LLR_{N-1} + \sum_{n=1}^{N}\sum_{m=1}^{M} \ln\left(\frac{P_{1,m}(X_m[N])}{P_{0,m}(X_m[N])}\right)$$

6: until $LLR_N \geq A$ or $LLR_N \leq B$.

7: If $LLR_N \geq A$, "H_1: target signal is present" is claimed; if , $LLR_N \leq B$, " H_0: target signal is absent" is claimed.

5. RESULTING SIMULATION

In this section, we evaluate the average sample number of sequential spectrum sensing with use likelihood ratio test by computer simulations. also we simulate the proposed cooperative sequential sensing scheme .The simulated network has twelve cognitive radios for spectrum sensing. i.e. M=12. We also suppose thirty samples for each cognitive radio, i.e.N=30. In the simulations, the sensing objective is set according to (6) with $\alpha = \beta = 0.1$.
In this scenario, the noise is Gaussian distributed with zero mean and the target signal is Gaussian distributed too. The base station has full knowledge of the distributions of the signal and noise. In fig.3-6 are shown histogram of the required sample in the proposed scheme in different SNRs .It is observed that the sequential method substantially reduces the sensing time with reducing the number of samples.

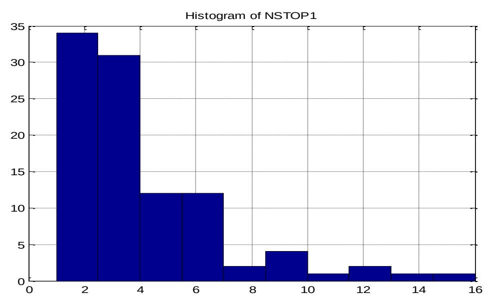

Fig. 2. -histogram of Nstop in 10dB

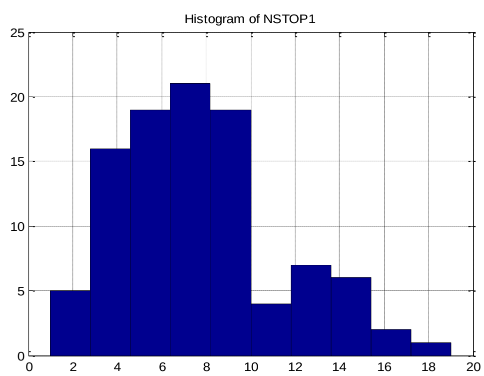

Fig. 3.histogram of Nstop in 0dB

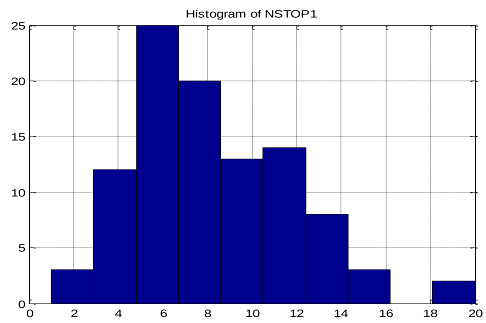

Fig. 4. histogram of Nstop in -10dB

The simulation results are shown in Fig. 6. Note that with shown sequential method, result of probability detection is optimizing. In Fig.5 shown with increase number of CRs probability of miss-detection will be low.

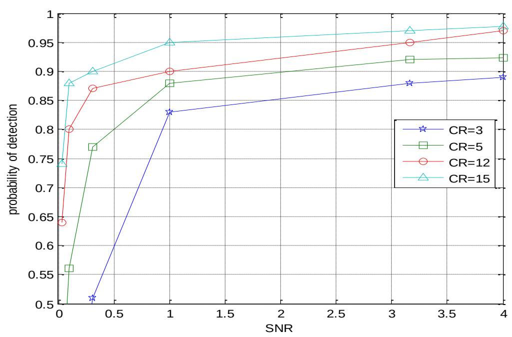

Fig. 5.probability of detection with increasing number of cognitive radio in sequential detection

6. CONCLUSION

In this study, we have proposed a hard decision-based sequential spectrum sensing scheme by combining hard decision-based cooperative sensing and sequential probability ratio test and likelihood ratio test. It has been found that sequential detection significantly reduces the average sample number and sensing time while retaining comparable detection performance compare energy detection.

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