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Source Number Detection and Realization of ROC for Spectrum Sensing in Cognitive Radio

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Abstract

Background/Objectives: The pre-assigned spectrum allocation policy that has been adopted by various wireless technologies according to the standards of Federal Communications Commission (FCC), in Cognitive radio, the whole available spectrum is grouped into many different bands and the usage of bands by different applications leads to the existence of spectrum hole(s). **Methods/Statistical Analysis:** High sampling rate is required for cognitive transceiver spectrum sensing applications, multiple analog front-end circuitry, high resolution of Analog to Digital Converters having large and dynamic range, and fast signal processors. Calculating the interference temperature or noise variance over intended Narrow Band (NB) transmission signals is a part of spectrum sensing. **Findings:** The main issue related to cognitive radio applications is to sense the vacant spectrum holes and simultaneously accommodate the unlicensed secondary users in that. For cognitive radio implementation, spectrum sensing is the foremost concern. The paper presents the realization of Receiver Operating Characteristic (ROC) for implementation of proposed source number detection for existing adaptive energy detection scheme. The realization is mapped using comprehensive Monte Carlo simulations that are quantified for detection performance as a received signal to noise ratio. **Application/Improvements:** As per the application point of view, different combinations of the sensing techniques are required for different requirements. For example, in case of quick and coarse scan of broad frequency range, the sensing method can of energy detection type. The present white spaces can further be discovered accurately using feature detection method.

Keywords: Cognitive Radio, Energy Detection, Likelihood Ratio, Source Number Detection, Spectrum Sensing

1. Introduction

Cognitive radio is being introduced in wireless communication world where the basic communication system behaves dynamic by the continuous detection of vacant channels for SU operation. The paper starts with basic discussion of implemented SND based Energy sensing method and later converges towards realization of ROC using Monte-Carlo simulation method for the implemented scheme[1].

The common assumption of Gaussian data seems to lead to some variant of the statistic, as shown, irrespective of the source-detection scheme is based on hypothesis tests or information theoretic criteria,

$$\frac{\left(\prod_{i=k}^{p} l_i\right)^{\left(\frac{1}{p-k+1}\right)}}{\frac{1}{p}-k+1\sum_{i=1}^{p} l_i} \quad k=1,2,3,\ldots\ldots,p-1 \tag{1}$$

which is the ratio of the geometric mean to the arithmetic mean of the smallest sample Eigen values. This can be accomplished by considering the following set of hypothesis tests for determining the number of sources:

$$\begin{aligned} &H_0 : \lambda_1 = \ldots. = \lambda_{p.} \\ &H_k : \lambda_{k+1} = \ldots. = \lambda_p \\ &{}_{..}H_{p-1} : \lambda_{p-1} = \lambda_p \end{aligned} \tag{2}$$

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Hypothesis test procedure used for determining the number of sources:

1. Set $k = 0$
2. Test H_k
3. If H_k is accepted then set q= k and stop.
4. If H_k is rejected and $k<p$-1 then set $k \leftarrow k + 1$ and return to procedure 2 otherwise set q = p -1 and stop, with corresponding alternatives K_k, not H_k, k=0,...,p-2. Acceptance of H_k leads to the estimate q = k. A practical procedure to estimate starts with testing and proceeds to the next hypothesis test only on rejection of the hypothesis currently being tested. Upon acceptance, the procedure stops, implying all remaining hypotheses are true[2,3].

In the proposed method, the primary sources are been estimated through bootstrap based source number detection in the initial stage and the optimization is been performed on the basis of number of sources in the later.

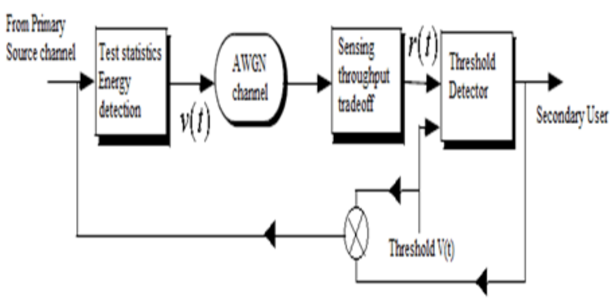

Figure 1. Energy sensing through source number detection.

Figure 1 shows the detection of number of sources through an additional feedback to the traditional energy detection scheme which includes threshold V (t) and the output of energy detector.

The shortcomings of the traditional spectrum sensing along with its optimization has been modified[4,5] which includes improper access of the spectrum efficiently and not being able to identify the presence or absence of PU. To alleviate this problem the primary sources are efficiently detected using SND technique and spectrum sensing is performed with the proposed energy based scheme. The overall model has been modified with detection of spectrum while the primary user and CR user work simultaneously.

$T_{i,j} = l_i - l_j$,

where i= k+1 .... p-1 and j= i+1,...,p

These differences will be small when both l_i and l_j are considered to be noise Eigen values but relatively large if any one or both of l_i and l_j are source Eigen values. The pair wise comparisons represented in a hypothesis testing framework gives

$$H_{ij} : \lambda i = \lambda j \tag{3}$$

$$K_{ij} : \lambda i \neq \lambda_j, \tag{4}$$

where i= k+1,...., p-1. and j= i+1,...,p

The hypotheses H_k can be reformulated as intersections between the pair wise comparisons

$$H_k = \bigcap_i^j H_{ij} \quad and \qquad K_k = \bigcup_i^j K_{ij} \tag{5}$$

$$K_k = \bigcup_i^j K_{ij} \tag{6}$$

where i= k+1,...., p-1 and j= i+1,...,p

One of the most popular approaches for composite hypotheses testing stands to be the generalized likelihood ratio test[6]. By their maximum likelihood estimates, the Generalized Likelihood Ratio Test (GLRT) replaces any unknown parameters. The GLRT can generally have the form

$$\hat{T}(X_N) = \frac{f_1(X_N;\hat{\theta}_1)}{f_0(X_N;\hat{\theta}_0)} \begin{cases} > \tau, & accept\ H_1 \\ < \tau, & accept\ H_0, \end{cases} \tag{7}$$

where $\hat{\theta}_1$ is the MLE of θ_1 assuming H_1 is true, and $\hat{\theta}_0$ is the MLE of θ_0 assuming H_0 is true.

As in the simple hypotheses, the threshold τ is found from the nominal value of the probability of false alarm Pfa.

Figure 2 shows the likelihood ratio of the miss-detection when comparing it with the threshold of each channels. The crossing of the blue and red line from the graph shows the optimum number of primary sources that is 10 sources. The existing path loss model suggests that the power that is experienced by any PU or other SU as interference, is determined by the channel of propagation. The process of sensing of spectrum is concerned upon the channel of propagation[7,8]. The path loss determines the level of signal at the sensor end which in turn decides upon condition of missed detection and condition of false alarm. However in wide band sensing at various frequencies, level of signal are different for the impact of small scale fading and its frequency selectivity and frequency being dependent on path loss[9], formulated with power transmitted to the channel and power received follows as

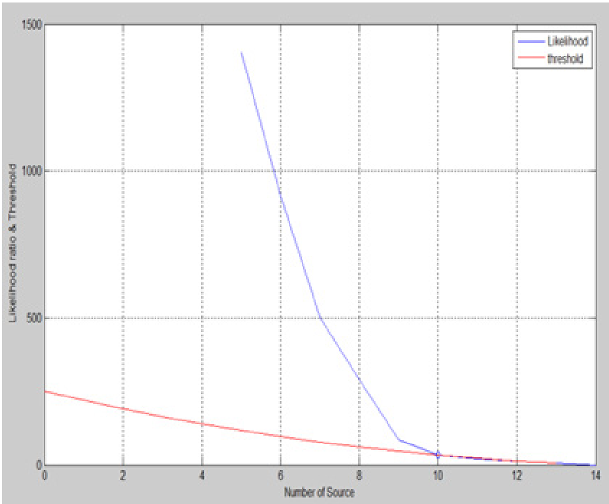

Figure 2. Likelihood and Threshold versus Calculated number of sources.

PL= Pt/Pr (8)

Path loss in terms of SNR considering noise figure as a function of signal power only can be described as

PL = SNRi/SNRo (9)

Where SNRi is the transmitted signal to noise ratio in a propagation channel. In distributed sensing, information, involving this path loss and statistics of shadowing correlation, of characteristics of channel in PU and sensing element is needed unlike Blind spectrum sensing using Independent Component Analysis (ICA)[19]. In case array of antenna is used, the signals correlation at the various antenna elements are determined by angular speed, and hence the in the process of optimum detection[10].

The fact that a sensor can experience only the presence of PU transmitter and not PU receiver, to draw inferences from these observations seems significant like interference to PU with SU power levels.

Path loss models for free space propagation like shadowing fading model suggests statistics of shadowing model with first order supported by well-defined data and the model can be defined as

$$\langle S(x)S(x+\triangle x)\ \rangle = \sigma^2 \exp\left(-\frac{|\triangle x|}{X_c}\right) \tag{10}$$

Where Xc can be defined as distance of correlation of shadowing fading and values of Xc typically varies from 10m to 500m. σ stands to vary with respect to some indoor ranging from 3-12db, typically to be 8db[11,12,13,14,15]. While median path-loss model the loss grows as large as 20log10 f, as in effect of radio antenna aperture. Again, at receiver, model of delay dispersion equals narrated exponential model which is

P(r) = exp[-Yt] for t>= 0, (11)

where 1/Y stands the decay instance constant. The bandwidth efficiency in terms of SNR for an AWGN channel can be described as

$$\left(\frac{C}{B}\right)_{AWGN} = \log_2\left(1+SNR_0\right) \tag{12}$$

And the path loss over a distance of set of wavelengths and taking the expression of SNR termed bandwidth specified above needs to estimate probability of detection P(d)[16]. Assumptions are made for P(d) (which is again to be justified through uniform distribution of number of sources taking Monte Carlo approach) so that it equals a uniform surface distribution, related as:

$$p(d\,|\,1) = \frac{P(d,l)}{p(l)} = \frac{p(l\,|\,d)\,p(d)}{p(l)} \qquad p(d) = \frac{2.d}{R^2_{simul}} \tag{13}$$

where Rsimul is an arbitrarily great analysis radius (i.e. 10 km). We have for P(l)

$$P = \int_0^{R_{simul}} \left[p\left(\frac{1}{d}\right) p(d)\partial d = \int_0^{R_{simul}} \frac{1}{\sqrt{2.\pi.\sigma^2}} \exp\left(\frac{-(1-Lm)^2}{2.\sigma^2}\right)\right] \cdot \frac{2d}{R^2_{simul}} \partial d \tag{14}$$

However the constraint is that the integration should be made for Rsimul ∞. But as the propagation model does not hold valid after a certain range of distance, Rsimul have to be finitely integrated[17–19]. Therefore, certain approximation is needed. The calculation of P(d|l) is decided to be limited depending upon the range of L which is included with a bound of [min(Lm)+3σ; max(Lm)-3σ].

2. Simulation Results and Discussion

Here, the proposed approach for spectrum sensing with SND based energy detection and the realization of Receiver Operating Characteristic (ROC)[20] are been shown and discussed. Sensing performance of the approach is been quantified by the Receiver Operating Characteristic (ROC) earlier[21,22] and these are modified in terms of Probability of false alarm (Pf) versus Probability of missed detection (Pm), detection performance versus obtained SNR and more accurate mean sensing time. Monte Carlo simulation has been used for simulations under following settings taken for system under operation: There are 10 random distributed Gaussian channels having zero mean and unity variance, and one Secondary User looking for spectrum vacancies in those channels.

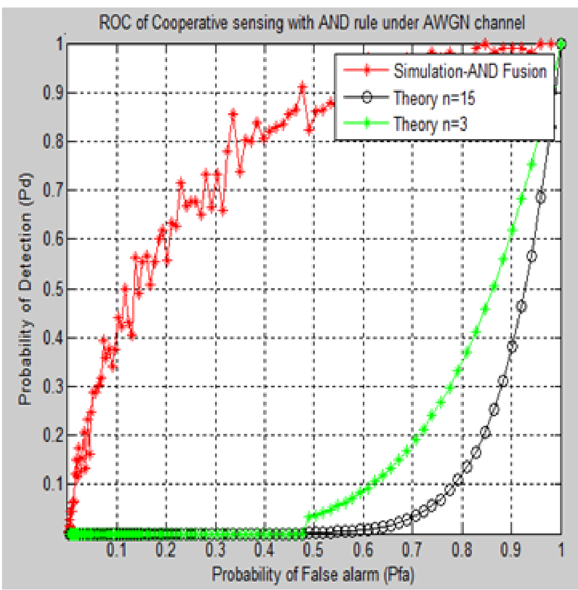

Figure 3. ROC realisation with 20 number of Monte Carlo Simulation.

The figure 3 describes the Probability of Detection (Pd) for the proposed scheme varies in a stable region while being the probability of false alarm in a tiny variation. Here we have taken 20 number of Monte Carlo simulation for optimal result with respect to sensing time. For more accurate result, number of Monte Carlo simulations can be increased but it would result into greater sensing time which again can lead to delay in sensing by the time, there is every possibility of the spectrum being occupied by the primary used.

3. Conclusion

With a view to evaluate more about detection time, mean detection time for single-order cyclostationary based detection is presented and proposed adaptive SND based spectrum sensing with varying received power (Pr). The mean detection instance of single-order cyclostationary detection is invariant irrespective of received power (Pr). Whereas in the proposed scheme, where dynamic number of primary source is to be sensed with respect to ratio of Probability of miss-detection and Probability of false alarm is to be maximum. With minimum detectable value of SNR, PUs are to be sensed in a differentiation of respective path loss calculated in terms of SNR and the ROC of cooperative scheme shows a stable region of Probability of detection(Pd) with less variation in Probability of false alarm.

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