Two-stage sequential spectrum sensing detector based on Higher-Order Statistics for Cognitive Radio

Bonny Mgawe
Department of Electrical Engineering, PAN African University, institute of basic Science, Technology and Innovation, Nairobi-Kenya

Vitalice Oduol
School of Engineering, University of Nairobi, Kenya

Abstract: - In cognitive radio (CR), spectrum sensing techniques aim to allow cognitive users to effectively recycle the spectrum resources without interrupting the active primary users. Several detectors have been proposed including the energy detector, matched filters, and the cyclostationary detector but most of these are either too complex or unable to perform efficiently in low signal-to-noise ratio (SNR) environments, as blind detectors. In this paper, a partial two-stage sequential spectrum sensing algorithm based on higher-order statistics and energy detector is introduced to minimize the sensing time, and maximize the probability of detection, particularly for low SNR applications. The method first uses a filter bank to extract multiple narrow-band channels from the received wideband signal then compute the normalized power values using the energy detector in each time slot of sensing for all the sub-bands. These normalized power values are used as weights for the third-order cumulants estimated in those sub-bands. Based on these cumulants, a binary hypothesis testing problem is formulated and a low-complexity sequential probability ratio test (SPRT) is developed. At the constant false alarm rate of 0.1, computer simulation result is showing 37% of improvement in the detection probability of signals at a low SNR of -20 dB.

Key-Words: - Spectrum sensing, filter banks, SPRT, energy detector, higher order statistics, cognitive radio

1 Introduction

With the high demand of multimedia services in wireless communication technology, the use of wireless devices and applications has been experiencing an exponential growth. Meanwhile, the allocation of spectrum resources is still in a wasteful and fixed manner by the International telecommunication union (ITU-R) frequency allocation policy as each frequency band is usually licensed to dedicated wireless services. Spectrum utilization surveys in [1], [2] and [3] have shown that the static spectrum allocation policies have led to heavily under-utilized spectrum. The study done in [4] indicates a number of spectrum bands that may be excellent candidates for re-allocation and/or spectrum sharing and there is a need of dynamic spectrum allocation to overcome this problem and improve spectrum utilization.

The idea of cognitive radio suggested by Mitola and Maguire in [5] has been proposed as the key technology to resolve the electromagnetic spectrum scarcity and improve the spectrum utilization. Cognitive radio significantly improves the spectrum utilization by allowing secondary users to dynamically access spectrum holes (white space) temporally unoccupied by the primary user in the geographical region of interest.

One of the vital and key mechanisms that make possible dynamic spectrum access is the capacity of cognitive radio to sense and detect the spectrum holes. This technique is referred to as spectrum sensing. To design a reliable spectrum sensing technique, several challenges have to be considered such as channel fading, noise uncertainty and sensing time. Tremendous researches on spectrum sensing techniques have been conducted such as energy, feature detection, and matched filter [6].

In matched filter detection [7] and cyclostationary detection [8], detections are designed to attain better sensing performance but the secondary user is required to have some knowledge in advance about the primary user features, to execute coherent detection.
The energy detector (ED) approach has been widely studied and is a non-coherent detector with low implementation complexity as per discussions in [9], [10] and [11]. In addition, with ED no prior knowledge information about the primary users

signal is required. However, under low SNR and noise uncertainty conditions its detection efficiency degrades heavily, which lead to restricting its efficiency for cognitive radio [12] [13].

In [14], Subekti et al suggested a spectrum sensing method which based on higher order statistics (HOS). The spectrum sensing is done by calculating relevant HOS features referred as cumulants. Better performance was achieved at extremely low SNR regions using this statistical approach but to obtain the whole set of cumulants for better detection accuracy a higher sample set is required. This results in a longer sensing time.

In [15], Hsieh et al have suggested the theory of sequential probability ratio test (SPRT) in order to reduce the sensing time. The technique performance well but it searches over a wide bandwidth to determine spectrum holes. For example, in the case of Zigbee, Bluetooth, and WCDMA because they all exist around the same band 2.4GHz, erroneous decisions might have happened on spectrum usage due to out-of-band interference and spectral leakage.

The goal of this paper is to design a partial two-stage spectrum sensing algorithm which tries to minimize the sensing time and maximize the spectrum utilization under a given probability of detection, by splitting the wideband into multiple narrow bands in the first stage using the filter bank.

The rest of this paper is organized as follows. The system model and the proposed sequential spectrum sensing method are presented in Section II. Computer simulation, results and conclusions are drawn in Section III and IV respectively.

2 Problem Formulation

At its core, the spectrum sensing is a binary hypothesis testing problem and can be formulated as follows:

$$H_0 : r_m = n_m$$

$$H_1 : r_m = g_m s_m + n_m \quad m = 1\ 2\ 3 \dots M \quad (1)$$

Where r_m s_m n_m and g_m denotes the received signal, the primary signal which is non-Gaussian random variable, additive white Gaussian noise signal and the frequency-flat channel between the primary transmitter and a cognitive (CR) node at a time instant m. H_0 denotes the primary user (PU) signal is absent, and H_1 denotes the PU signal is present. From equation *(1)*, the filter bank splits the received signal into its polyphase components and the i^{th} branch of the polyphase filter bank has an impulse response $h_i(z)$ given by:

$$h_i(z) = h(zP + i) \quad (2)$$

Note $h(z)$ is the impulse response of the prototype filter of length L. The output signal at the i^{th} branch is given by:

$$x_i(j) = \sum_{z=0}^{L-1} h_i(z) r(j-z) e^{\frac{2\pi ij}{P}} \quad (3)$$

From equation *(3)*, the normalized third-order cumulant of the received signal can be estimated as follow [16]:

$$K_3^r = \frac{\sqrt{N(N-1))}}{N-2} \frac{\sum_{j=1}^{N} \frac{\left(x_j - K_1\right)^3}{N}}{\sigma^{3/2}} \quad (4)$$

Where K_3^r denote the estimated normalized third-order cumulant, K_1 denote first order cumulant, σ represent variance and N represent the number of samples.

$$K_1 = \sum_{j=1}^{N} \frac{x_j}{N} \quad (5)$$

Now if we consider the i^{th} branch from equation *(1)* and *(4)*, when the hypothesis H_1 occur the estimated cumulant K_3^e becomes:

$$K_3^e = \frac{\sqrt{N(N-1)}}{N-2} \sum_{j=1}^{N} \frac{\left(\sum_{z=0}^{L-1} h_i(z)(gs+n)(j-z) e^{\frac{2\pi ij}{P}} - K_1\right)^3}{N} \quad (6)$$

$$\begin{aligned} K_3^e = {} & \frac{\sqrt{N(N-1)}}{N-2} \sum_{j=1}^{N} \frac{g^3 s^3}{N} \sum_{z=0}^{L-1} h^3 \\ & + 3\frac{\sqrt{N(N-1)}}{N-2} \sum_{j=1}^{N} \frac{g^2 s^2}{N} \sum_{z=0}^{L-1} h^2 \left(n \sum_{z=0}^{l-1} h \right. \\ & \left. - K_1 \right) \\ & + 3\frac{\sqrt{N(N-1)}}{N-2} \sum_{j=1}^{N} \frac{gs}{N} \sum_{z=0}^{L-1} h \left(n^2 \sum_{z=0}^{L-1} h^2 \right. \\ & \left. - 2nK_1 \sum_{z=0}^{L-1} h + K_1^2 \right) \\ & - 3\frac{\sqrt{N(N-1)}}{N-2} \sum_{j=1}^{N} \frac{n}{N} \sum_{z=0}^{L-1} h \left(K_1 \sum_{j=1}^{N} \frac{n}{N} \sum_{z=0}^{L-1} h \right. \\ & \left. + K_1^2 \right) - \frac{K_1^3}{N} \end{aligned}$$

$$K_3^e = K_3^s \sum_{z=0}^{L-1} h^3 + \Delta_1 \quad (7)$$

$$K_3^e = K_3^{s_1} + \Delta_1 \quad (8)$$

Where $K_3^{s_1}$ in equation *(8)* is the third-order cumulant value of the faded transmitted signals which depends on the type of modulation used and filter banks coefficients. Δ_1 referred as the variation of K_3^e due to the noise, Rayleigh fading, and filter banks coefficients.

$$\sigma = \sum_{j=1}^{N} \frac{(x_j - K_1)^2}{N} \quad (9)$$

$$\sigma = \sum_{j=1}^{N} \frac{x_j^2 - x_j K_1 + K_1^2}{N}$$

$$= \sum_{j=1}^{N} \frac{\sum_{z=0}^{L-1}\big(h(z)(gs+n)\big)^2 - \sum_{z=0}^{L-1} h(z)(gs+n)K_1 + K_1^2}{N}$$

$$= \sum_{j=1}^{N} \frac{g^2 s^2}{N} \sum_{z=0}^{L-1} h^2 + \sum_{j=1}^{N} \frac{gs}{N} \sum_{z=0}^{L-1} h^2 (n \sum_{z=0}^{L-1} h - K_1) + K_2^n \sum_{z=0}^{L-1} h^2 - 2K_1 \sum_{j=1}^{N} \frac{n}{N} \sum_{z=0}^{L-1} h$$

$$\sigma = K_2^s \sum_{z=0}^{L-1} h^2 + K_2^n \sum_{z=0}^{L-1} h^2 + \Delta_2$$

$$\sigma^{3/2} = \left(K_2^s \sum_{z=0}^{L-1} h^2 + K_2^n \sum_{z=0}^{L-1} h^2 + \Delta_2 \right)^{3/2}$$

$$\sigma^{3/2} = \left((K_2^s + K_2^n) \sum_{z=0}^{L-1} h^2 + \Delta_2 \right)^{3/2} \quad (10)$$

Now substituting equation *(7)* and *(10)* into *(4)*. Noticing the Gaussian noise statistical properties, both the variation terms Δ_1 and Δ_2 can converge to zero if the block size *N* is large enough.

$$K_3^r = \frac{K_3^s \sum_{z=0}^{L-1} h^3 + \Delta_1}{\left((K_2^s + K_2^n) \sum_{z=0}^{L-1} h^2 + \Delta_2 \right)^{3/2}}$$

$$K_3^r = \frac{K_3^s \sum_{z=0}^{L-1} h^3}{\left((K_2^s + K_2^n) \sum_{z=0}^{L-1} h^2 \right)^{3/2}}$$

$$K_3^r = \frac{K_3^s}{\left((K_2^s + K_2^n) \right)^{3/2}} \frac{\sum_{z=0}^{L-1} h^3}{(\sum_{z=0}^{L-1} h^2)^{3/2}}$$

$$K_3^r = K_3^{ns} \frac{1}{\left(1 + \frac{K_2^n}{K_2^s}\right)^{1/2}} \quad (11)$$

It is observed in equation *(11)* that the third-order cumulant of the received signal is inversely proportional to the third over two of the SNR and it does not dependent on the coefficients of the filter bank.

But in the case where the noise variance is not known or calculated, mitigating this error would be a tedious process. For this reason, we propose an algorithm where the power values of each sub band normalized to the received signal power are used as weights on the cumulant value calculated on the sub band. The normalized third-order cumulant values of each sub band using the weights are calculated as shown below:

$$W = \frac{P \times E_i}{E_{tot}} \quad (12)$$

Where W denote weight P is the number of sub-bands and E_i is the computed power of the i^{th} branch and E_{tot} is the computed power of the received signal.

$$K_3^r = K_3^{ns} W \quad (13)$$

In the same way, when the hypothesis H_0 occurs, the estimated cumulant K_3^r can be expressed as:

$$K_3^r = \frac{\sqrt{N(N-1)}}{N-2} \frac{\sum_{j=1}^{N} \frac{(n)^3}{N}}{\sigma^{3/2}} = \Delta_0 = 0 \quad (14)$$

Now the equivalent binary hypothesis testing can be written as:

$$K_3^r = \begin{Bmatrix} K_3^{ns} W & H_1 \\ \Delta_0 & H_0 \end{Bmatrix} \quad (15)$$

Based on the estimated cumulant in *(4)* and the binary hypothesis testing in *(15)*, The decision rule that minimized the probability of false alarm for a given probability of detection is designed based on SPRT (sequential probability ratio test) in order to reduce the computational complexity and improve the sensing time. The log-likelihood ratio (LLR) of the k^{th} estimated third-order cumulant is given by:

$$L_k = log \frac{p\left(K_3^{r_k} | H_1\right)}{p\left(K_3^{r_k} | H_0\right)} \quad (16)$$

From equation *(16)*, the LLR for receiving q observation samples is given by:

$$R_q = \sum_{k=1}^{q} L_k \quad (17)$$

Decision rule will be formed as suggested in [17]:

$$\eta_0 \geq R_q \quad Accept\ H_0$$

$$\eta_1 \leq R_q \quad Accept\ H_1$$

$$\eta_1 > R_q > \eta_0 \quad Take\ another\ sample$$

Where the two thresholds η_1 and η_0 of SPRT can be derived from the targeted false alarm probability α and miss probability β as follows:

$$\eta_1 \leq log(\frac{1-\beta}{\alpha}) \quad (18)$$

$$\eta_0 \geq log(\frac{\beta}{1-\alpha}) \quad (19)$$

3 Computer simulation results

The simulation parameter values are tabulated in table *1* below; the modulation type adopted is 8PSK because it carries data over RF signal more efficiently and is less susceptible to errors. The signal sample size and Monte Carlo size both are set to 1000. The channel fading varies slowly with Doppler frequency given by 27Hz, and the sample period is set as 90 nanoseconds.

Table 1: Simulation Parameters

Simulation parameters	**Values**
Modulation type	8PSK
Signal sample size	1000
Number of Monte Carlo simulation	1000

The performance improvement under various SNRs is shown in figure *1*. From -20 dB to -8 dB great performance is archived by the proposed method relative to conventional method for the probability of false alarm (Pf) =0.1. This is due to the minimization of the level of interference caused by the filter bank since the sensing is performed at the channel level.

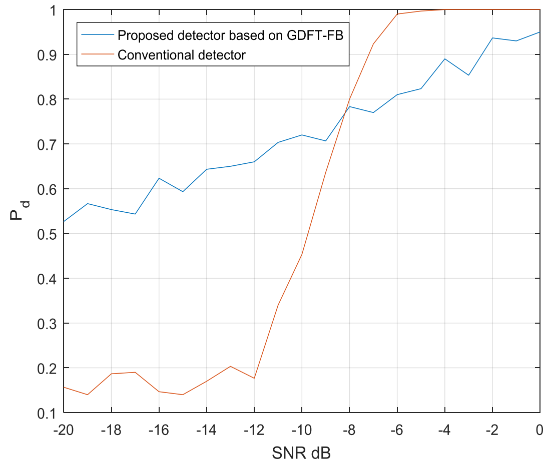

Figure 1: Performance comparison between the proposed detector and Conventional detector for 8-PSK

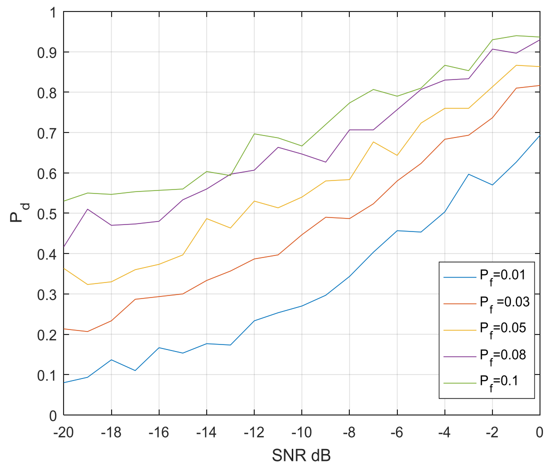

Figure 2: ROC of the proposed detector and Conventional detector for 8-PSK

Next in figure *2* the effect of increasing the probability of false alarm on the probability of detection for the proposed detector is explored. Simulation result depicts that, a 10% increase in the probability of false alarm (i.e. 0.01 to 0.1) increase the probability of detection by 43% (i.e. 0.25 to 0.68) for a given value of SNR= -11 dB.

4 Conclusion

In this paper, a partial two-stage sequential spectrum sensing detector for cognitive radio was presented using a filter bank based energy detector and HOS in which the third-order cumulant is estimated and applied for binary hypothesis testing. This scheme is blind which means no prior knowledge about primary signal and noise is required and it allows spectrum sensing operations even at extremely low SNR environments. Filter bank adopted for extracting uniform narrow bands from the wideband helps to reduce the probability of false while the SPRT helps to improve the sensing time. Superior performance gain in term of detection probability and the probability of false alarm has been shown by the proposed method, particularly at low SNR. This work can be improved by introducing a filter bank that is capable of extracting both uniform and non-uniform bands. This will allow the cognitive radio to co-exist between different systems.

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