SpectrumSensing Algorithm: Based On Enhanced Energy Detection Approach to Maximize Spectrum Utilization

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***Abstract*- cognitive radio a novel approach in wireless communication was introduced in 1999 officially by Joseph Mitola and Generald Q. Maguire. Regulatory bodies in various countries (FCC in US and ofcom in UK) found that most of the radio frequency spectrum is inefficiently utilized. The emerging technology of cognitive radio has created a paradigm shift in utilizing the unused spectrum resources without causing interference to the primary users functioning. This is achieved by sensing the spectrum before using it. This paper deals with the efficient spectrum sensing technique to utilize the unused limited spectrum resource thus maximizing spectrum utilization. Here we will consider a spectrum sensing technique which can be applied even without the prior knowledge of transmitter and channel. An enhanced energy detector (EED) for digitally modulated primary signals is presented to maximize the spectrum utilization, without the prior information on the transmitted sequence of the primary signals. The proposed method makes use of the prior statistics of PU activity and the signaling information of the PU such as symbol rate and modulation order to improve the SU throughput and the overall spectrum utilization of both PUs and SUs**.

I. INTRODUCTION

Fixed spectrum allocation results in a large part of frequency band remaining under-utilized. Channels dedicated to licensed (primary) users are out of reach for unlicensed users, while the licensed users hardly occupy the channel completely, at all times [1]. Cognitive radio revolution hopes to tap into this inconsistency and attempts to utilize the channel in its full capacity.Over the past 15 years, notions about radios have been evolving away from pure hardware-based radios to radios that involve a combination of hardware andsoftware. In the early 1990s, Joseph Mitola introduced the idea of software defined radios (SDRs). These radios typically have a radio frequency (RF) front end with a software-controlled tuner. Baseband signals are passed into an analog-to- digital converter. The quantized baseband is then demodulated in a reconfigurable device such as a field-programmable gate array (FPGA), digital signal processor (DSP), or commodity personal computer (PC). The reconfigurability of the modulation scheme makes it a software-defined radio. In his 2000 dissertation, Mitola took the SDR concept one step further, coining the term cognitive radio (CR). CRs are essentially SDRs with artificial intelligence, capable of sensing and reacting to their environment as shown in Fig 1.1 graphically contrasts traditional radio, software radio, and cognitive radio.

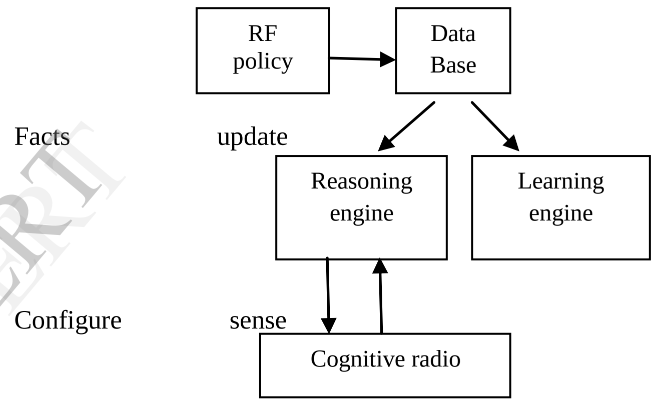

Fig. 1.1 Functional portion of the cognitive radio.

In this paradigm, "either a network or a wireless node changes its transmission or reception parameters to communicate efficiently avoiding interference with licensed or unlicensed users. This alteration of parameters is based on the active monitoring of several factors in the external and internal radio environment, such as radio frequency spectrum, user behavior and network state. While the above description is essentially that of full cognitive radio, the present work will be primarily focused on spectrum sensing cognitive radio. Figure 2 makes out the difference between SDR and Cognitive radio module.

It has been shown that a simple energy detector cannot guarantee the accurate detection of signal presence, calling for more sophisticated spectrum sensing techniques and requiring information about spectrum sensing to be regularly exchanged between nodes[2]. Increasing the number of cooperating sensing nodes decreases the probability of false detection.

It is generally understood that certain kinds of spectrum users have significant variability in their spectrum use and much of their allocated spectrum is under-utilized during non-peak

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periods[3]. It is reported that the temporal and geographical variations in the utilization of the assigned spectrum range from 15% to 85%. The measurement results suggest that most of the allocated frequencies (ranging from 80 MHz to 5850 MHz) are heavily under-utilized except for the frequency bands allocated for broadcasting and cell phones. The similar observation also shows that there is a high probability that the primary users are likely idle for most of the time. Using Cognitive Radios (CRs), the Secondary Users (SUs) are allowed to use the spectrum originally allocated to Primary Users (PUs) as long as the primary users are not using it temporarily[5]. This operation is called Opportunistic Spectrum Access (OSA).

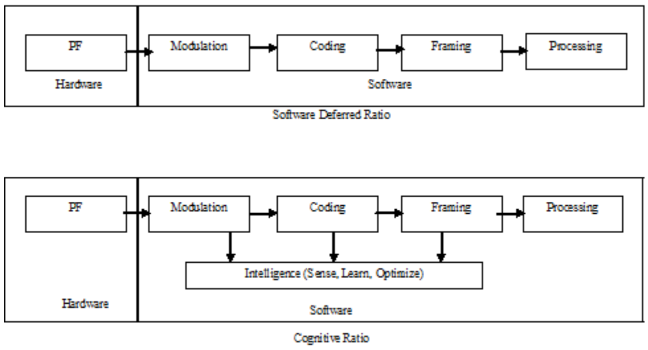

Fig 1.2 Module of SDR and Cognitive radio

To avoid interference to the primary users, the SUs have to perform spectrum sensing before their attempts to transmit over the spectrum [5]. Primary user is highly likely idle and the primary signals are digitally modulated, an optimal energy detector for spectrum sensing to achieve higher spectrum utilization in cognitive radio networks is proposed. We derive the optimal detector structure for MPSK modulated primary signals with known order over AWGN channels and give its corresponding suboptimal detectors in both low and high SNR (Signal-to-Noise Ratio) regimes. In high SNR regime, it is shown that, for BPSK signals, the test statistic is the sum of signal magnitudes, but uses the real part of the phase-shifted signals as the input. Through approximations, it is found that, in low SNR regime, for MPSK (M >2) signals, the suboptimal detector is the energy detector, while for BPSK signals the suboptimal detector is the energy detection on the real part[6]. We provide the performance analysis of the suboptimal detectors in terms of probabilities of detection and false alarm, and selection of detection threshold and number of samples. The simulations have shown that detector has a performance similar to the energy detector in low SNR regime, but has better performance in high SNR regime in terms of spectrum utilization and secondary user's throughput.

Although enhanced energy detector structure is the same as or similar to that of energy detector after approximation, due to the difference in detection threshold, such detector has the advantage over both energy detector and Neyman-Pearson detector which maximize the detection probability for a given false alarm probability, in terms of overall spectrum utilization and secondary users throughput, when primary users underutilize the spectrum.

The proposed enhanced energy detector has the performance similar to the energy detector that is designed to maximize the spectrum utilization, for complex MPSK signals in the low SNR regime. But they are different in high SNR regime, where enhanced energy detector has a better performance in terms of spectrum utilization and secondary users' throughput.

The simulation results confirm that energy detector is not optimal in high SNR regime. It is also observed that due to the chosen detection threshold, probability of false alarm for the detector that maximizes the spectrum utilization is not monotonically increasing with SNR, which is counterintuitive. In section II system model is described along with some assumptions. The suboptimal energy detector structure for low and high SNR regimes is derived un section III. The two probabilities namely probability of detection and probability of false alarm, detection threshold and other performances related parameters are defined in section IV followed by conclusion in section V.

II. ENHANCED ENERGY DETECTOR APPROACH FOR MPSK MODULATED PRIMARY SIGNALS

The efficiency of the detector mainly depends on how effectively it detects the vacant frequency slots to*acces*s them for secondary users without disturbing the primary users. In this proposed model we consider time slotted primary signals with N primary signals are used to detect the presence of primary user's activity. The detection of primary user's presence is modeled by binary hypotheses testing:

$$r(k) = \begin{cases} H0: \ n(k), \\ H1: \ h(k) + n(k), \end{cases} \quad (1)$$

Assuming that r(k) is the received signal, n(k) is a complex white Gaussian noise with variance N0 and is given by $n(k)=n_c(k)+jn_s(k)$ where $n_c(k)$ and $n_s(k)$ are real and imaginary part respectively. h(k) is the signal from licensed users and is given by $h(k)=he^{j\emptyset_n(k)}$, $\emptyset_n(k) = \frac{2n\pi}{M}$, n=0,1………, M-1 with equi-probability, h is the propagation constant of a channelwith in the sensing period.

A. SPECTRUM SENSING PROBLEM

Spectrum sensing is based on two decisions D_0 when the detector detects the sensed channel to be vacant and D_1 when occupied. These are the two decisions which can be made by a cognitive radio. When the detected signal is sensed as noise signal, the frequency slot is vacant and can be allotted for secondary users.

There can be two possible detections error. The misdetection when a primary user is communicating so that the channel is occupied, however, it declares that the sensing area is a white free space. The probability of misdetection is defined as:

$$P_{misd} = P(D_0|H_1) = 1\text{-}P_D \quad (2)$$

To avoid any interference with primary user, the probability of detection Pdshould be as high as possible. The false alarm when a primary user is not communicating so the channel is vacant, however, it declares the presence of the primary user. The probability of false alarm is defined as follows:

$$P_F = P(D_1|H_0) \quad (3)$$

To guarantee an efficient use of the spectrum resource and a possible dynamic access scheme, the probability of false alarm, according to the Neyman-Pearson criterion, should be kept as small as possible with a highest probability of detectionBased on all these parameters the spectrum utilization is defined as

$$P(H_0)(1\text{-}P_F) + P(H_1)P_D \quad (4)$$

and normalized SU throughput as

$$P(H_0)(1\text{-}P_F), \quad (5)$$

Note that $P(H_1)P_D$ is PU throughput when there are primary signals and the SUs detect the presence of the primary signals. To determine whether the spectrum is being used by the primary user, the detection statistic T_D is compared with a predetermined threshold ϵ. Probability of false alarm PF is the probability that the hypothesis test chooses H_1 while it is in fact H_0:

$$P_F = P(T_D>\epsilon|\, H_0). \quad (6)$$

Probability of detection P_D is the probability that the test correctly decides H_1 when it is H_1:

$$P_D = P(T_D>\epsilon|H_1). \quad (7)$$

B. CHANNEL MODEL AND DETECTION THRESHOLD

We consider time-slotted primary signals where N primary signal samples are used to detect the existence of PU signals. The PU symbol duration is T which is known to the SU and the received signal r(t) is sampled at a rate of 1/T at the secondary receiver. For MPSK modulated primary signals, the received signal of kth symbol at the CR detector, r(k), is:

$$r(k) = \begin{cases} n(k), & H_0 \\ h(k)+n(k), & H_1 \end{cases} \quad (8)$$

where $n(k) = n_c(k)+jn_s(k)$ is a complex AWGN signal with variance N_0, $n_c(k)$ and $n_s(k)$ are respectively the real and imaginary part of n(k), $\emptyset_n(k) = \frac{2\pi n}{M}$, n= 0,1, ..., M-1with equi-probability, h is the propagation constant of channel within the sensing period. we will describe r = [r(0) r(1).........r(N-1)]. Assume that the SU receiver has no information with regards to the transmitted signals by the PU and$\emptyset_n(k)$,k = 0, 1, ⋯ ,N -1 are independent and identically distributed (i.i.d.) and independent of the Gaussian noise[7].

The detection statistics of energy detector (ED) can be defined as the average energy of observed samples as

$$T_{ED} = \frac{1}{N}\sum_{k=1}^{N} |r(k)|^2 \quad (9)$$

Although energy detector does not require the knowledge of the symbol rate, we assume that the sample rate is identical to the symbol rate [8]. It is well-known that the optimal detector for binary hypothesis testing based on Neyman-Pearson theorem is to compute the likelihood ratio and then make its decision by comparing the ratio with the threshold. The likelihood ratio test (LRT) of the hypotheses H1 and H0 can be defined as:

$$T_{LRT}(r) = \frac{p(r|H1)}{p(r|H0)} \quad (10)$$

Denote C_{ij} as the cost associated with the decision that accepts H_i if the state is H_j, for i, j = 0, 1. Based on Bayesian decision rule [21] to minimize the expected posterior cost which is defined as

$$\sum_{i=0}^{1}\sum_{j=0}^{1} C_{ij}\ P(H_j)P(H_i|H_j) \quad (11)$$

Now the enhanced energy detector is defined as,

$$T_{LRT}(r) \underset{H0}{\overset{H1}{\gtrless}} \epsilon, \quad (12)$$

The predefined threshold € is given by,

$$\epsilon = \frac{P(H_0)(C_{10}-C_{00})}{P(H_0)(C_{01}-C_{11})} \quad (13)$$

If $C_{00} = C_{11} = 0$ and $C_{01} = C_{10}$, which is a uniform cost assignment (UGA),

$$\epsilon = \frac{P(H_0)}{P(H_1)}, \quad (14)$$

It is most obvious in CR networks that $P(H_0)>P(H_1)$. this happens because of spectrum underutilization. Considering equations (4)and (11) decision rule can be reduced to,

$$\text{Max } P(H_0)(1\text{-}P_F)+P(H_1)P_D \quad (15)$$

This is also a equation to maximizes the spectrum utilization.

Now

the new decision rule is given as,

$$\max P_D(\epsilon) \text{ S.T. } P_F(\epsilon) \leq \overline{P_F}, \quad (16)$$

Where $\overline{P_F}$ is maximum bound of P_F.The structure of detector should in such a way to reduce the probability of false alarm and should enhance the detection probability.

For designed energy detector considering MPSK modulated primary signals over AWGN channels in low SNR regime we have,

$$P_F = \frac{1}{x}\frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}x^2} \quad (17)$$

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$$P_D=1+\frac{x}{1+x^2}\frac{1}{\sqrt{2\pi}}e^{-\frac{1}{2}x^2} \quad (18)$$

where x>0 and is given by,

$$x=\begin{cases}\frac{\ln\epsilon}{\gamma\sqrt{2N}}, & M>2,\\ \frac{\ln\epsilon}{\gamma\sqrt{N}}, & M=2.\end{cases} \quad (19)$$

III. THEORETICAL ANALYSIS

Sum of all the independent identical distributed random variables can be approximated by Gaussian distribution. This is done only if the N is very much large. This is given by central limit theorem. The proposed detector can be structured depending on some approximation in both low and high SNR region.

A. Approximations in low and high SNR region.

For MPSK modulated signals in low SNR regime we will approximate $x \to 0, \ln(1+x)\approx x$, $\cosh(x)=\frac{1}{1+x^2}$. From this approximation we get,

$$T_{EED}=\frac{1}{N}\sum_{K=0}^{N-1}|r(k)|^2 \underset{<}{\overset{>}{}} \frac{N_0}{\gamma}\left(\gamma+\frac{\ln\varepsilon}{N}\right) \quad (20)$$

And in high regime when x>>0, $\cosh(x)\approx\frac{e^{-x}}{2}$

$$T_{EED}=\frac{1}{N}\sum_{K=0}^{N-1}\ln\left(\sum_{n=0}^{M/2-1} e^{\frac{2}{n_0}R[R(K)h^* e^{-j\phi_n(k)}]}\right)\underset{H_0 <}{\overset{H_1 >}{}}\gamma+\ln M\frac{\ln\varepsilon}{N}$$
(21)

1V. SIMULATION AND RESULTS

Setting up number of samples to 5000 and detection threshold is obtained by approximating $P(H_0)=0.85$ AND $P(H_1)=0.15$, the simulation results of probability of detection and probability of false alarm is obtained

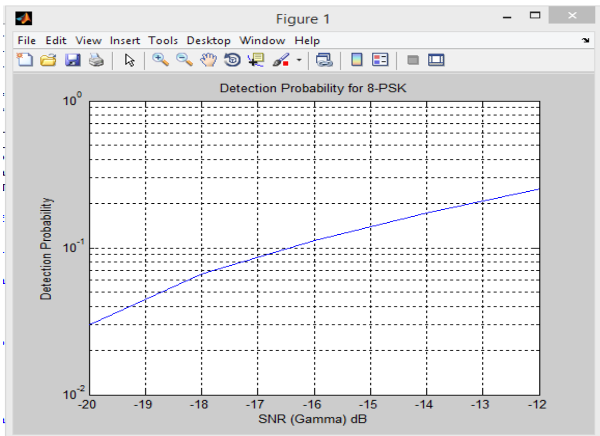

Fig 4.1 detection probability of EED for 8PSK modulated primary signals over AWGN channel

The curves in graph denote the performance of the detector. From these simulation results it is found that the proposed detector can enhance the spectrum utilization in a better acceptable way by increasing the detection probability for defined false alarm probability. Fig 4.1 gives the P_D for 8PSK modulated primary signals over AWGN channels while 4.2 give same for P_F.

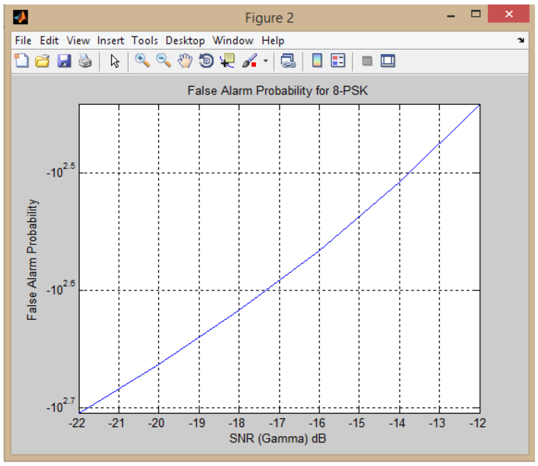

Fig 4.2 False alarm probability for 8PSK modulated signals over AWGN channels

V. CONCLUSION

As the proposed detector structure for modulated primary signals is a combination of energy detector and Neyman-Pearson detector, it can maximize the detection probability for a given false alarm probability. It has a performance similar to energy detector but in a better way. It is observed that this EED has better performance in low SNR and high SNR regime in terms of overall spectrum utilization and secondary users throughput.

REFERENCES

[1] Y. Zeng, Y.-C. Liang, A. T. Hoang, and R. Zhang “A review on spectrum sensing for cognitive radio: challenges and solutions,” EURASIP Journalon Advances in Signal Processing, Article Number: 381465, 2010.
[2] A. Annamalai, O. Olabiyi, S. Alam, O. Odejide, and D. Vaman,“Unified Analysis of Energy Detection of Unknown Signals overGeneralized Fading Channels,” to appear in *Proc. IEEE IWCMC 2011*Conference , Sept, 2011, Turkey, Intanbul.
[3] Z. R. Cao, U. Tureli, Y. D. Yao, and P. Honan, “Frequencysynchronizationfor generalized OFDMA uplink,” in Proc. IEEE Globecom, 2004,pp. 1071–1075.
[4] Y. H. Zeng, Y.-C. Liang, A. T. Hoang, and R. Zhang, “A review onspectrum sensing for cognitive radio: challenges and solutions,” EURASIPJ. Advances in Signal Process., no. 1, pp. 1–15, 2010.
[5] A. Sahai, N. Hoven, and R. Tandra, “Some fundamental limits on cognitiveradio,” in 2004 Allerton Conference on Communication, Control,and Computing.
[6] H. V. Poor, An Introduction to Signal Detection and Estimation (Springer Texts in Electrical Engineering), Springer.
[7] J. G. Proakis, Digital Communications, 4th edition. McGraw-Hill, 2001.
[8] H. L. Van-Trees, Detection, Estimation and Modulation Theory. John Wiley & Sons Inc., 2001.