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Engineering

Efficient & Intelligent Spectrum Sensing Scheme for Cognitive Radio Networks

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ABSTRACT Successful deployment of Cognitive radio (CR) can successfully deal with the growing demand and scarcity of the wireless spectrum. To exploit limited spectrum efficiently, CR technology allows unlicensed users to access licensed spectrum bands. Since licensed users have priorities to use the bands, the unlicensed users need to continuously monitor the licensed users' activities to avoid interference and collisions. How to obtain reliable results of the licensed users' activities is the main task for spectrum sensing. Based on the sensing results, the unlicensed users should adapt their transmit powers and access strategies to protect the licensed communications. One of the key effecting factors on the CR network throughput is the spectrum sensing sequence used by each secondary user. In this paper, secondary users' throughput maximization through finding an appropriate and efficient sensing is investigated. The proposed intelligent learning and optimization cycle, based on neural networks, finds the optimal sensing sequence for each secondary user without any prior knowledge about the wireless environment. The structure of the proposed scheme is discussed in detail, and its efficiencies are verified through numerical results.

KEYWORDS : Cognitive radio, Sequential spectrum sensing, neural networks, Sensing sequence, Spectrum holes

1. INTRODUCTION

Cognitive radio network (CRN) concept has been developed to mitigate the lack of frequency resources for the ever growing spectrum demand by allowing secondary users (SUs) to opportunistically share the spectrum with licensed primary users (PUs) [1]. To this end, sensing capability is exploited in the CRNs' nodes, which enables them to find some temporarily available transmission opportunities called white spaces also called Spectrum Holes (SH). The average throughput of the SUs is one of the most important performance metrics, which depends on the candidate primary channels for sensing and transmission. In practice, the unlicensed users, also called secondary users (SUs), need to continuously monitor the activities of the licensed users, also called primary users (PUs), to find the spectrum holes (SHs), which is defined as the spectrum bands that can be used by the SUs without interfering with the Pus [6]. This procedure is called spectrum sensing. There are two types of SHs, namely temporal and spatial SHs, respectively. A temporal SH appears when there is no PU transmission during a certain time period and the SUs can use the spectrum for transmission. A spatial SH appears when the PU transmission is within an area and the SUs can use the spectrum outside that area. To determine the presence or absence of the PU transmission, different spectrum sensing techniques have been used, such as matched filtering detection, energy detection, and feature detection. However, the performance of spectrum sensing is limited by noise uncertainty, multipath fading, and shadowing, which are the fundamental characteristics of wireless channels. To address this problem, cooperative spectrum sensing (CSS) has been proposed by allowing the collaboration of SUs to make decisions. Based on the sensing results, SUs can obtain information about the channels that they can access. However, the channel conditions may change rapidly and the behavior of the PUs might change as well. To use the Spectrum bands effectively after they are found available, spectrum sharing and allocation techniques are important. As PUs have priorities to use the spectrum when SUs co-exist with them, the interference generated by the SU transmission needs to be below a tolerable threshold of the PU system. Thus, to manage the interference to the PU system and the mutual interference among SUs, power control schemes should be carefully designed. In this paper, an intelligent spectrum sensing sequences setting is proposed, which does not need any prior information and presumptions about the wireless media as well as PUs' data traffics. More specifically, a multilayer feed forward (MFF) neural network [9] is exploited to replace the mathematical modeling by learning the actual impact of the design parameters, i.e., the various permutations of elements in the sensing sequences, on the CRN average throughput. Then, a Kennedy-Chua (KC) neural network [10] is used to optimally find the SS of each SU.

2. SYSTEM MODEL

A fully synchronized time slotted secondary and primary networks with Ns SUs, equipped with narrowband sensing capability, and Np PUs, each having one channel, and are assumed. Each SU sequentially senses the channels based on its SS provided by the CRN coordinator, i.e., the SU senses the first channel assigned in its SS for a predetermined time duration (channel sensing time), and then changes its sensing circuitry, which takes a constant time τho, and senses the second channel if and only if the first channel is sensed to be busy. This procedure will continue until a transmission opportunity is found. Efficient Sensing is defined as a matrix with the dimensions of Ns × Np, in which the i-th row contains the SS for the i-th SU [8].

3. RELATED WORK

Spectrum sensing is fundamental for the successful deployment of CRs. The main focus of current spectrum sensing schemes for CRs is divided into two main streams: the first is to improve local sensing performance, and the second is to improve performance by having cooperation between SUs. In local sensing, each SU performs spectrum sensing on the received signal and makes a decision about the presence or absence of a PU. In cooperative spectrum sensing, SUs perform local sensing and send their sensed information to the fusion center, and a final cooperative decision is taken at the fusion center. Therefore, in order to improve cooperative performance, it is necessary to improve local sensing. Many two-stage spectrum sensing schemes are proposed in literature to improve local spectrum sensing.

To improve local spectrum sensing, a number of two stage detection approaches are proposed in [7, 8, 9, 10, 11, 12, 13, and 14]. These are two stage spectrum sensing schemes. In [15], a new dynamic spectrum access approach is proposed which deals with multiple types of primary systems. It performs either matched filter detection if PU waveform is known, or the combination of energy detection and Cyclostationary detection is performed if PU waveform is unknown. A bi-thresholds method is used in energy detection. On the basis of [15], we also incorporate matched filter, energy detection and Cyclostationary feature detection but our approach to sense access spectrum is somewhat different.

It is assumed that multiple PU systems are detected by a CR network and the PU waveform for some of the PU systems is known. In first, since sensing time of matched filter is less than other detection techniques, so matched filter detection is performed by SU to detect the PU signal in those channels whose PU waveforms are known. The SU then performs energy detection if the PU waveform is unknown. The PU signals which are not detected by energy detection and have low

SNR values than SNR wall, are sensed by one order Cyclostationary detection. The idea behind this proposed technique is to mitigate the problems caused by noise power uncertainty of energy detection and reduce the effect of noise uncertainty by implementing Cyclostationary detection for those PU signals which has SNR values less than SNR wall. The rest of the paper is organized as follows. Section 2 presents system model.

4. SYSTEM MODEL

Spectrum sensing is a key element and foremost step in cognitive radio communications as it must be performed before allowing unlicensed users to access a vacant licensed band. The essence of spectrum sensing is a binary hypothesis model and is defined as follows.

$$H_0: y(n) = w(n) \quad (1)$$
$$H_1: y(n) = hx(n) + w(n) \quad (2)$$

Where,(n) is the received signal by the CR user transmitter, $x(n)$ is the transmitted signal by the primary user, $w(n)$ is the noise present in the channel and $\hbar$ is the amplitude gain of the channel. It is assumed that both signal and noise are independent to each other.

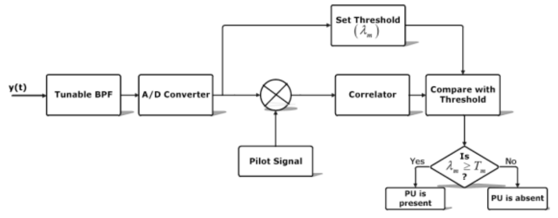
$H0$, represents a null hypothesis, which indicates there is no primary user signal in a certain spectrum band i.e. channel is vacant or idle. $H1$, is an alternative hypothesis, which states that there exists some licensed or PU signal i.e. channel is occupied or busy. This model only helps to identify whether there is any local (primary) user present in the focused geographical location for further processing or not for the usage of virtual unlicensed spectrum.

The following key metrics are characterized to evaluate the performance of spectrum sensing schemes such as:

1. Probability of detection Pd which is shown as $P\ H_1H_1$ i.e. probability of successful decision upon the spectrum sensing process. Actually it verifies the presence of PU signal in a channel on the basis of decision of the spectrum sensing schemes.
2. Probability of miss-detection (Pmd) which is represented as $P\ H_0H_1$ i.e. probability of unsuccessful decision means spectrum sensing process is showing that PU signal is absent in a channel while PU signal present in that channel.
3. Probability of false alarm Pfa which is shown as I H_1H_0 i.e. probability of unsuccessful and false decision upon the spectrum sensing process. In other words, it shows that PU signal is present in a channel while the channel is vacant.

5. LOCAL SPECTRUM SENSING TECHNIQUES

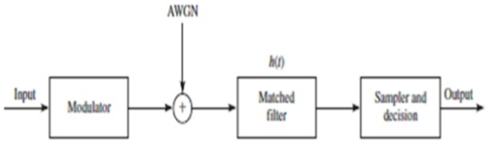
Fig(1):- Spectrum Sensing



The main goal of spectrum sensing is to detect presence or absence of PUs and determines which portion of the spectrum is currently not utilized. There are three basic local spectrum sensing techniques which sense the primary band in which a primary user transmits signal to primary receivers. Matched filter detection, energy detection and Cyclostationary detection are well known sensing techniques.

5.1. Matched Filter Detection

Primary User signals like TV and mobile communication signals have well-defined characteristics, e.g. presence of narrowband pilot for audio and video carriers of TV signal, dedicated spreading codes for pilot and synchronization channels in CDMA, preambles for packet acquisition in OFDM packets. If PU waveform is known and then matched filter detection [5] is performed because of it takes less sensing time. The matched filter correlates the received signal y_n with the known signal i.e. pilot signal $x\ n$ and finally the output of matched filter T_m is compared with a threshold λm to decide about the presence or absence of a primary user (PU) shown in Fig(2).



Fig(2):-Block Diagram of Matched Filter

If x_n is completely known to the receiver then the optimal detector for this case is:

$$T_m = \frac{1}{N_m}\sum_{n=0}^{N_m-1} y(n)x(n) \begin{array}{ll} >\lambda_m & ,H_1 \\ <\lambda_m & ,H_0 \end{array} \quad (3)$$

Where,, is the detection threshold of matched filter detection and $N\,m$ is the number of samples.

$$P_{f,MD} = Q\left(\frac{\lambda_m}{\sqrt{P_s\sigma_n^2/N_m}}\right)$$
$$P_{d,MD} = Q\left(\frac{\lambda_m - P_s}{\sqrt{P_s\sigma_n^2/N_m}}\right)$$

Where, is the standard Gaussian complementary cumulative distribution function, P_s is the signal power and σ_n^2 is the noise power.

5.2. Energy Detection

Energy Detection (ED) is generally adopted for spectrum sensing in recent work because of no need of a priori information of the primary signal and its low computational and implementation complexities [4]. The ED computes the energy T_e of PU signal present in a channel and if T_e is greater than predetermined threshold , then it is hypothesized that channel is in use.

For energy detection T_e is as follow: The test statistic T_e is as follow

$$Te = \frac{1}{N_e}\sum_{n=0}^{n-1} |Y(n)|^2 \quad (5)$$

Where (n) is the received signal and Ne is the number of samples which is N_e=2TW, for simplicity we assume that time-bandwidth product,W, is an integer.

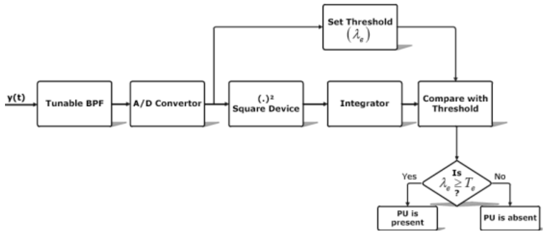


Fig (3):- Energy Detection

5.3. Cyclo-stationary Detection

Common analysis of Cyclostationary signal is based on autocorrelation function in frequency domain. In frequency domain, Cyclostationary detection mainly focus on two-order Cyclostationary i.e. auto-correlation function. These features are detected by analysing a spectral correlation function in frequency domain. One of major drawback of CFD in frequency domain is that it is computationally complex because of all the frequencies should be searched in order to generate the spectral correlation function, so the calculation complexity is huge. To reduce the complexity and power consumption, we perform first order Cyclostationary detection in time domain which shows mean of the signal is periodic.

In the transmission of (t) through an AWGN channel, t =x(t) +n(t). The mean function of (t) can be written as

$$M_y(t)_T = E[y(t)] = x(t) \quad (6)$$

Where, denotes the expectation operator. The above equation shows that the mean is time-varying, if signal x(t) is periodic with period $T0$, then mean of received signal y(t) will be also periodic with period T0 i.e. we can say that $M\,y\,t$ is also periodic with period $T0$

$M_y(t)=M_y(t+kT_0)$ for $k=0,\pm1,\pm2,\pm3\ldots\ldots$ (7)

Such a characteristic is called one-order Cyclostationary detection which block diagram is shown in Fig

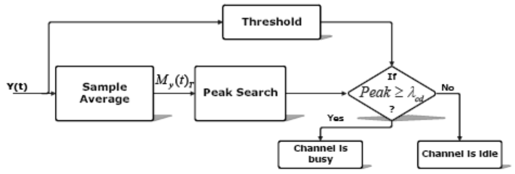


Fig (4):- One-Order Cyclostationary Detection

For a particular threshold λcd, an approximate expression for the probability of false alarm P_f and the detection probability $P_{d,cd}$ of one-order Cyclostationary detection over AWGN channel can be obtained.

6. PROPOSED SCHEME

6.1. Model

The proposed scheme is assumed that

- A band of interest, B, is considered, in which there are N channels to be sensed. Each channel has bandwidth W.
- For some channels, the information of PU waveforms are known enough (most probably completely known) to perform matched filter detection while for others, the PU signal structure is unknown.
- SNR γ value of PU signal present in each channel is given as input in this scheme.

In this proposed scheme, the cognitive radio or SU will sense serially the N channels present in the band of interest and detect whether or not there is a spectrum hole or idle channel available. In the first stage, scheme will check whether complete knowledge of PU waveform is known. If PU waveform is unknown, the second stage will work in which combined energy detection and Cyclostationary detection will be performed. At first, energy detection is chosen because of its low computational and implementation complexities and it can also maintain a low constant false alarm even at low SNR conditions.

6.2. Evaluation of Proposed Scheme

The agility of proposed model is evaluated by comparing overall detection time of proposed model with energy detection, matched filter detection and Cyclostationary detection. The overall detection time of proposed sensing scheme is

$$T_0=T_m+T_e+T_c \qquad (8)$$

Where T_m, T_e and T_c are the sensing times of the matched filter detection, energy detection and one-order Cyclostationary detection, respectively.

$$T_m=N(1-P_r)T_1 \qquad (9)$$

where T_1 is sensing time for each channel by matched filter detection. T_e and T_c can be derived as follows

$$T_e=E[K_1]T_2 \qquad (10)$$

where $E[K1]$ is the mean number of channels reported to energy detector and $T2=Ne2W$ is the mean sensing time for each channel, in which Ne is the number of samples for detection and W is the channel bandwidth. $K1$is the random variable which follows a binomial distribution, with parameters N and Pr, where Pr is the probability that a channel would be reported to the energy detector. Hence the detection time of the energy detection is

$$T_e=NP_rT_2 \qquad (11)$$

T_c can be derived as follows:

$$T_c=E\,[K_2]\,T_3 \qquad (12)$$

where $E\ K2$ represents the mean number of channels reported to one order Cyclostationary detector and $T_3=Nc2W$ is the mean sensing time for each channel where Nc is the number of samples for detection. $K_2$is the random variable which follows a binomial distribution, with parameters N and $1-P_r$. Hence the mean detection time of the one order Cyclostationary detection is

$$T_e=NP_rT_3 \qquad (13)$$

So, overall detection time of proposed model to detect signals present in N channels is

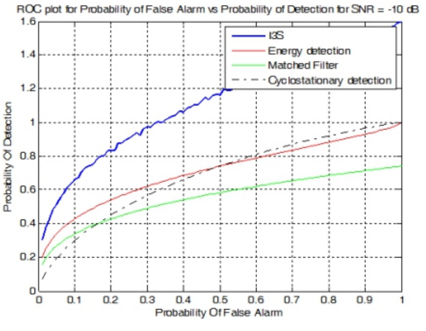
$$T0=(\,1-Pr)\,T_1+NPrT_2+NPrPT_3 \qquad (14)$$

7. SIMULATION RESULTS

In this section, the proposed sensing scheme is compared with energy detection, matched filter detection and one order Cyclostationary detection. The parameters used for simulation are given in Table(1).

Parameter	Value
Signal type	BPSK
Carrier frequency	1MHz
Number of samples	5000
Number of channels, N	10
Probability of false alarm for each detection	0.01

Table(1):- Parameter Values For Simulation



Fig(5):- Result Showing Different Curves of Sensing Schemes

One can see that how the performance of probability detection degrades when noise uncertainty increases in energy detection techniques. For noise uncertainty factor ρ=1.02, ED stops detecting authorized signal below -9dB which degrades performance of ED in comparison of ρ=1 (in case of no noise uncertainty) where primary signal is detectable up to -10dB.

Fig, 5 shows the performance of the different basic local spectrum sensing techniques at different value of SNR 10 . For probability of detection, Pd=0.9, ED is limited to -7.5dB while MFD and CD can sense up to SNR value -18.5dB and -33.5dB, respectively. It shows that at low SNR Cyclostationary feature detection outperforms the matched filter detection and energy detection.

An SU senses these channels serially. For simulation purposed, we already defined SNR value dB of each channel. The performance of proposed spectrum sensing scheme is shown in Fig.5 , for which already defined SNR for each channel is given in Table. For ED, SNR wall is taken as -10dB which corresponds to ρ=1.2 approximately. For simulation, we assume that channel numbers 5 and 6 have prior knowledge of PU waveform and we apply matched filter detection. Rest of channels work is mentioned in section.

8. CONCLUSION

A new local spectrum sensing scheme for a single user is proposed in this article to improve detection efficiency and to decrease sensing time. The proposed scheme is compared with the existing transmitter detection schemes and it is found that the proposed scheme takes less time and reliable for sensing even if low SNR values. Concept of SNR wall is discussed to mitigate the problems caused by noise uncertainty faced by ED at low SNRs.

Channel No.	1	2	3	4	5	6	7	8	9	10
SNR in dB	-42	-35	-30	-25	-20	-18	**-10**	-7	1	5

Table(2):- SNR value input to different channel for simulation

It is observed that detection performance of the proposed scheme is very near to Cyclostationary detection, but the overall sensing time is quite less than that of Cyclostationary detection.

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