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SPECTRUM SENSING WITH ENERGY DETECTION TECHNIQUES FOR COGNITIVE RADIO SYSTEM

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ABSTRACT

A cognitive radio by virtue of its ability to sense and adapt to the dynamic spectrum scenario, can increase the spectral efficiency .In order to be non invasive, a cognitive radio must adhere to strict benchmark in the quality of spectrum sensing for primary users of a band.Thus, spectrum sensing has a major role to play in cognitive radio .Many algorithms have been proposed to enable spectrum sensing such as energy detection and cyclostationary detection. IEEE 802.22, the first standard for cognitive radio devices, imposes strict requirements for the detection and false alarm probability on all spectrum sensing devices at SNR up to -20 dB. This requires use of robust spectrum sensing techniques.

Energy detection is the simplest and near optimum technique that is widely used for spectrum sensing. However its performance is drastically affected by uncertainty in noise variance due to SNR wall [1]. Cyclostationary detection can exploit detection spectral correlation present in most modulated signals to reliably detect signal even at low SNR .All general QAM signals exhibit distinct cyclic frequency depending on their carrier frequency, baud rate etc. which can help to distinguish between the SOI (signal of interest) and interference.

The filter structures for optimum MSME estimation of cyclostationary signals are frequency shift (FRESH) filters. The theory of cyclic Wiener filtering theory, developed by Gardner [2], forms the basis of LCL (Linear Conjugate Linear) filtering used in fresh filters. By adding appropriately frequency shifted versions of a cyclostationary signals ,fresh filter can provide significant gains for cyclostationary detection .Hence is it intuitive to apply FRESH filter for spectrum sensing in the cognitive radio context . For upcoming wireless standard like WI-MAX and LTE, OFDM (Orthogonal Frequency Division Multiplexing) is used because of the advantage of multicarrier transmission . Spectrum sensing for OFDM signals is specially challenging due to the cancellation of cyclostationary features and efficient detection algorithm for OFDM need to be developed.

INTRODUCTION

It was on this day that the European Union approved the introduction of a unified system for communication codenamed GSM (Global System for Mobile Communications), a technology that spearheaded the development of wireless services and devices, and exposed us to the immense opportunities and concomitant challenges that lay in harnessing its potential for future. Starting from the need to communicate information over a long range, our needs in the present day have risen exponentially to include voice, data and multimedia communication. This spiralling need has imposed an immense pressure on a precious resource, the radio spectrum. While this has led to many frequency bands being overused, such as the ISM band, studies [5] suggest that many frequency bands remain underutilized i.e. they remain free from their primary users for a substantial amount of time. This opportunity can be exploited to serve the growing demand for spectrum by allowing unlicensed users to transmit their own data on licensed bands with the precondition that the quality of service (QoS) of primary transmission is not compromised in any way. Such kind of opportunistic spectrum access forms the basis of a cognitive radio.

Cognitive Radio

Joseph Mitola coined the term `Software Defined Radio', while pursuing his doctoral dissertation work at KTH Sweden in 2000 [6]. He called these radios up to 80% programmable beyond the antenna output terminals and thus capable of doing RF, IF, baseband and bitstream operations using high speed Analog to Digital to Analog (A/D/A) converters and microprocessors. Subsequently he extended the concept of a Software Radio to Cognitive Radio' [7],[8] as follows.

"(A cognitive radio is) a radio frequency transceiver designed to intelligently detect whether a particular segment of the radio spectrum is in use, and to jump into (and out of) temporarily unused spectrum very rapidly ,without interfering with the transmission of other authorizes users".

Such an intelligent radio would be able to learn about the network condition and structure. It could detect unused frequency bands and allow unlicensed to opportunistically access licensed bands without causing any interference to the primary user. This would intuitively improve the spectrum utilization. In the terminology of cognitive radio, users who do no have not obtained prior permission for accessing a band are referred to as secondary users while the authorized users of a band are called primary users. Studies have suggested that while most frequency bands are licensed to primary users, many of these like military, marine communication, amateur radio etc. remain highly underutilized giving rise to a virtual scarcity in spectrum [5]. Fuelled by such revelations along with exponentially increasing number of wireless devices in the market like cordless telephones, remote surveillance cameras, the interest in cognitive radios has been growing at an amazing pace. Cognitive radios require unlicensed users who what to use the licenised bands opportunistically, to be highly adaptive in their parameters like frequency of operation, modulation technique, power allocation etc. Figure 1.1 shows the opportunistic scenario in which a cognitive user operates.

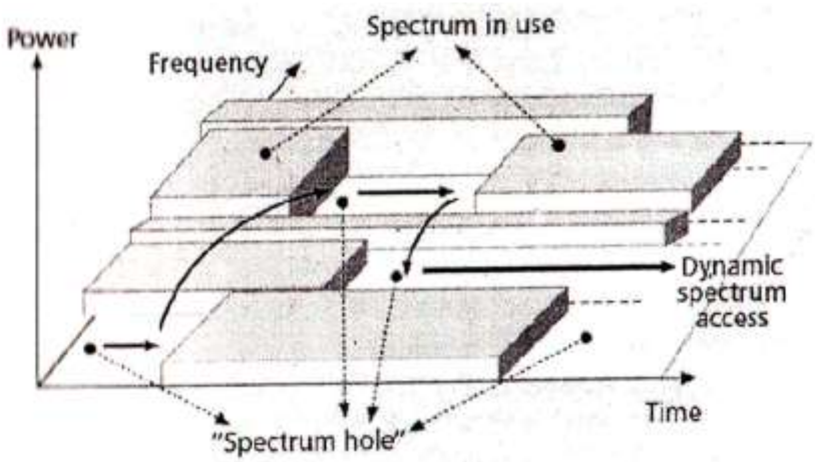

Figure : Dynamically changing spectrum scenario for a cognitive radio with black dots representing spectrum opportunities [3].

Haykin [4] states that a Cognitive Radio has to perform three basic tasks as listed below.

(1)Radio–scene analysis: This consist of two main tasks, namely,

- Estimation of interference temperature of the radio environment;
- Detection of spectrum holes.

The interference temperature in a band is a measure of the total RF interference present at the receiver with no primary signal present. This helps define a limit on the maximum interference power a band can accommodate without adversely affecting the primary transmission. Following the measurement of interference temperature, the RF spectrum is categorized as either white or black depending on whether it is occupied by high power signals or contains only ambient noise signals. This categorization may be performed through many methods such as the MTM-SVD (Multi Taper Method Singular Value Decomposition) [9], energy detection [10] and cyclostationary detection [11]. A while spectrum signifies a spectrum opportunity. This task of detecting spectrum holes or vacant spaces in the spectrum is called spectrum sensing.

(2) Channel identifications: This consists of the following two tasks, namely,

- Estimation of channel-state information (CSI)
- Prediction of channel capacity for use by the transmitter.

Channel state information can be estimated at the receiver by using pilot transmission or semi-blind approaches. Subsequently the channel coefficients must be tracked at the receiver through a mathematical model such as Kalman or particle filter. The estimate of CSI must be fed back to the transmitter to enable adaptive modulation.

(3) Transmit power control and dynamic spectrum management: Once the spectrum holes have been identified and their CSI estimates are available, a cognitive radio transmitter must choose its transmission bands accordingly and dynamically adjust them as and when the RF scenario changes. It also needs to optimize the transmit power in each band, in sync with the interference temperature limit for that band.

MATERIALS AND METHODS

Any cognitive radio must be able to reliably sense the presence of unused spectrum resources which could be opportunity used for unlicensed transmission and concurrently also protect any incumbent licensed user from harmful interference .this necessitates that a cognitive user follow a listen before talk protocol. Such a protocol apart from setting up a definite framework for unlicensed access, would also lay down strict regulation on the QOS that must be met. the QOS in a cognitive radio context depend on parameter like probability of detection promised to the primary user ,rate of sensing to detect an upcoming in band primary user(how often is sensing performed),the duration of sensing and the response time for spectrum handoff in case a primary user is detected ,among others .the first global standard to legalise operation of cognitive devices IEEE 802.22 in tv which spaces has specified strict constraints on all the above mentioned parameter that all cognitive device used to adhere to. It states that all such devices will provide P_d >0.9 and , P_f<0.1 .it also states that all DTV SIGNALS OF RSS greater than 116 db and all wireless microphone signals above 107dn m must be detected .while the maximum detection time for an incoming in band primary user is around 1 minute in case of DTV signals, for low power wireless microphone signals that operate in the same frequency band ,that threshold is set at .5-2 sec. robust spectrum sensing at such low signals level in a short time requires efficient spectrum sensing techniques in the following section, we consider energy detection technique ,its mathematical model and its detection performance under low SNR wall. Following this, sensing using cyclostationary detection is discussed and its mathematical background is presented along with simulation examples .it is a shown that cyclostationary detection is more robust than energy detection.

Energy Detection

Energy detection is the simplest technique in terms of implementation complexity .its detects the presence of a signal by measuring the total incumbent energy in the band of interest and comparing it to a predefined threshold .this threshold must be decided in a manner, so as to limit to false alarm rate, and it can be set independent of the traditional signal energy. Once a noise and signal variance are known, the problem of spectrum sensing can be formulated as a binary hypothesis ,the received and transmitted signals are represented by their complex low pass equivalent .the two hypothesis may be formulated as follows:

$$H_0 : y(n)=w(n)$$
$$H_1 : y(n)= S(n) +w(n)$$

Where y[n]is the received sample, w[n] is an AWGN sample with variance and s[n] is the transmitted signal value .At the receiver the test statics used is defined as the energy of N received samples.

$$E= \sum_{i=1}^{N} \|y(i)\|^2$$
$$=\sum_{i=1}^{N} |y_R(i)|^2+|y_i|^2$$

Where N is the number of complex observation samples and y(n) denote the real and imaginary part of y [i]each having a variance of σ_w^2 /2 .Under both the hypothesis the test statistic E is a sum of square of 2N real Gaussian random variable with equal variance .Hence the distribution of random variable E is the chi square distribution with a non centrality parameter 0 under H_0 and 2γ under H_1.

$$E= \begin{cases} \aleph_{2N}^2 \ , H_0 \\ \aleph_{2N}^2 \ (2\gamma), H_0 \end{cases}$$

Where γ is the average SNR given by $\gamma = \frac{P}{\sigma_w^2}$ and $P = \frac{1}{N}\sum_{i=1}^{N}|s(i)|^2$ .The probability of detection and false alarm are defined as

$$P_f = \Pr\{\, E > \lambda \mid H_0$$

$$P_d = \Pr\{\, E > \lambda \mid H_1 \}$$

There are two ways of obtaining closed form expression for these probabilities. the first which is through direct integration of the chi-square distribution over the tail of the distribution function giving us the following results[28],

$$P_f = \frac{\Gamma(N,\frac{\lambda}{2})}{\Gamma(N,0)}$$

$$P_d = Q_N(\sqrt{2\gamma}, \sqrt{\boldsymbol{\lambda}})$$

Where $(\boldsymbol{\Gamma}.,.)$ is the incomplete gamma function given by $\boldsymbol{\Gamma}$(s,x)= $\int_x^\infty t^{s-1}e^{-t}dt$ and Q_M(..,.0 is the generalised Marcum Q function given by $Q_M(\alpha\beta) = \frac{1}{\alpha^{M-1}}\int_\beta^\infty x^M e^{-\frac{x^2+a^2}{2}} I_{M-1}(\alpha x)dx$ where is the modified Bessel function of first kind [29].Another way of computing the probabilities in(2,4) is through application of the central limit theorem assuming that the number of samples in question(N)is high, in which case the resultant distribution become normal and hence expression for P4 and p can be obtained by finding the area under the Gaussian tail for which standard expression are available in terms of Q function .We first find the probability values assuming that N real samples y[n] are being used for energy detection in real samples Under this assumption, the mean of test statistic E under the hypothesis H_0 and H_1 can be found mathematically by observing the equation (2.2)and (2.1).the mean real values are given by μ_0=Nσ_w^2 and μ_1 =N(σ_w^2 + P). To find the variance of E under H0 , we computing the following,

$$E\{\mathbb{E}\}^2 = E\{(\textstyle\sum_{i=1}^{N}|w(i)|^2)(\sum_{j=1}^{N}|w(j)|^2)\},$$

$$= \textstyle\sum_{k=1}^{N} E\{|w(k)|^2|w(k)|^4\} + E\{\sum_{i=1}^{N} \sum_{j=1}^{N-1}|w_i(n)|^2\,\left|w_j(n)\right|^2\}, (i\neq j)(k \text{ is an integer})$$

$$= N{*}E\{|w(n)|^4\} + N{*}(N-1)E\{|w(i)|^2|w(j)|^2\}, (i\neq j),$$

$$= 3N\sigma_w^4 + N^2\sigma_w^4 - N\,\sigma_w^4,$$

$$= 2N\sigma_w^4 + N^2\sigma_w^4$$

$$\sigma_0^2 = E\{\mathbb{E}\} - E\{\mathbb{E}\}^2,$$

$$= 2N\sigma_w^4 + N^2\sigma_w^4 - N^2\sigma_w^4$$

$$= 2N\sigma_w^4$$

Through a similar analysis assuming independence of the signal and noise samples, the variance of the test statistic under H1 can be derived as σ_1^2 =2N(σ_w^2 + P) ^{2}.Using these expression in the integral OF GAUSSIAN function from $\boldsymbol{\lambda}$ to infinity and using Q(x)=$\frac{1}{\sqrt{2\pi}}\int_x^\infty e^{\frac{-x^2}{2}}$ dx ,we get the following ,

$$P_f = \frac{1}{\sqrt{2\pi\sigma_0^2}}\int_\lambda^\infty e^{\frac{-(x-\mu)^2}{2\sigma_0^2}}dx$$

$$= Q\{\frac{\lambda-\mu}{\sqrt{\sigma_0^2}}\}$$

$$= Q\,(\frac{\lambda-N}{\sqrt{2N\sigma_w^4}}),$$

$$P_d = \frac{\mathbf{1}}{\sqrt{\mathbf{2\pi\sigma_1^2}}}\int_{\boldsymbol{\lambda}}^\infty \mathbf{e}^{\frac{\mathbf{-(x-\mu)^2}}{\mathbf{2\sigma^2}}}$$

$$= Q(\frac{\lambda-\mu}{\sqrt{\sigma_1^2}})$$

$$= Q(\frac{\lambda - N(\sigma_w^2+P)}{\sqrt{2N(\sigma_w^2+P)^2}})$$

Where $\boldsymbol{\lambda}$ is the threshold to be calculated .now, when incoming samples are complex ,the sum of square of N complex Gaussian random variable with variance σ_w^2 is equivalent to the sum of squares of 2N real Gaussian random variables with variance $\frac{\sigma_w^2}{2}$ .Hence the complex signal case become a special case of real signal and correct probabilities for complex case are derived by replacing N by 2N and σ_w^2 by $\frac{\sigma_w^2}{2}$.

$$P_f = Q(\frac{\lambda - N\sigma_w^2}{\sqrt{N\sigma_w^4}})$$

$$P_d = Q(\frac{\lambda - 2N(\frac{\sigma_w^2}{2} + P}{\sqrt{4N(\frac{\sigma_w^2}{2} + P)^2}})$$

For a constant false alarm rate (CFAR) test also known for Neyman-Pearson test, we can select a desired maximum value for P_f , calculate the corresponding threshold $\boldsymbol{\lambda}$ and use this threshold to compute the resulting $P_d$this gives us a mechanism to observe the probability of detection,also reffered to here from as detection performance ,of energy detection for different values of the parameters P_f ,N (number of complex samples being averaged ,σ_w^2 (the noise variance) and P (the signal power). The two formulas in (2.8)can be solved together to eliminate and yield an expression for N in terms of P_f & P_d .Eliminating $\boldsymbol{\lambda}$ we get,

$$N = \frac{[Q^{-1}(P_f) - Q^{-1}(P_d)(1+2SNR)]^2 SNR^{-2}}{4}$$

The expression in [10] which holds for only real samples can be derived from this expression by doubling the value of N and replacing $\sigma_{\frac{w}{2}}^2$ by $\sigma_{\frac{w}{2}}^2$. in this expression for any arbitrary SNR a corresponding N can be derived from that satisfies the constraints of P_f *and* P_d. Hence ideally energy detector can robustly detect a signal at any signal to noise to noise ratio given an appropriate number of samples .figure 2.1 shows that P_{md} vs P_f plots for two different values OF SNR and number of samples N also known as receiver operating curves (roc) where P_{md} denotes probability of miss detection gives as ($P_{md} = 1 - P_d$. These curves have been obtained using equation (2.8)by calculating the detection probability corresponding to a range of value of the false alarm probability. As expected,with decreasing SNR also increasing for the same P_f while increasing the limit P_f causes P_{md} to decrease concurrently also detection probability. It may be observed from figure 2.1 that for a given number of samples N ,as the signal power decreases from 10db to -15 db ,the miss detection probability increases meaning thereby the detection probability has decreased. Similarly for a given SNR increasing the number of samples available for sensing improves the average detection probability .this represents the fundamental trade off in a cognitive radio system. To counter the effect of a worse channel ,a cognitive radio must either increasing its sensing time ,or be ready to accommodate a higher number of false alarm in order to maintain the same average probability of detection of primary user. Alternatively, the cognitive radio must sacrifice some data rate to continue operation below the channel capacity .as a final recourse ,the cognitive radio may look to opt for a more efficient sensing techniques. it is the last choice that has been the motivation to design more efficient and robust spectrum sensing techniques.

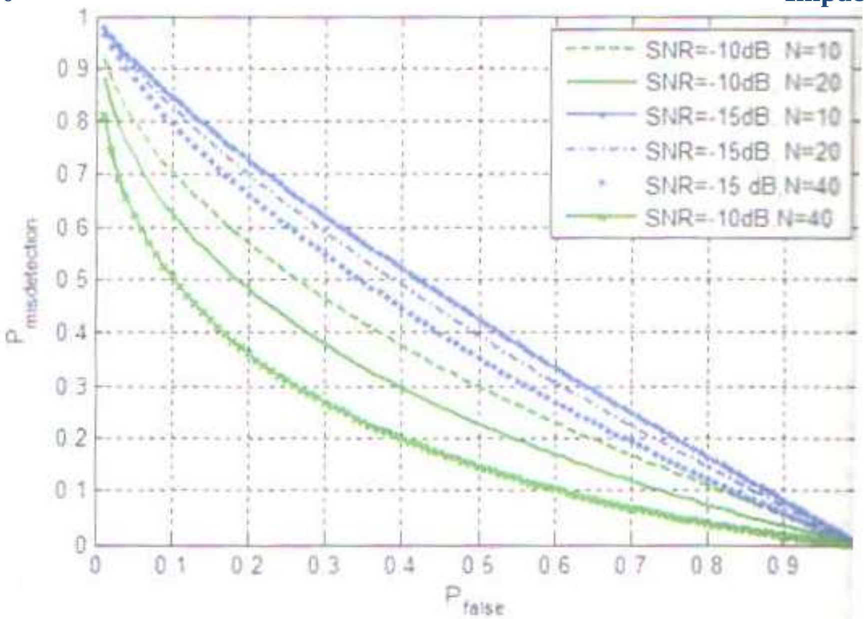

Figure : ROC curves for energy detector for different SNR and N (number of samples).

CONCLUSION

It presents a comparative analysis of 3 spectrum sensing techniques viz. energy detection, cyclostationary detection and FRESH filter based detection .As energy detection is widely used and suffer many limitation ,the contribution of this thesis is to develop cyclostationary spectrum sensing technique to robustly detect a signal in the low SNR regime .IT presents the application of FRESH filter for spectrum sensing and present simulation result to substantiate the claim that FRESH filter based detection can outperform other detection technique in signal carrier AWGN environment .For the multicarrier environment ,this thesis develops an optimal detector for induced cyclostationary in cyclic prefixed OFDM ,and varies its superior performance over energy and cyclostationary detection techniques through simulation

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