Review of Spectrum Sensing in Cognitive Radio

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Abstract- **The frequency spectrum bandwidth used in modern wireless systems is limited while the number of wireless systems is rapidly increasing. In order to alleviate the spectrum scarcity, secondary systems can opportunistically access the temporarily unused licensed bands of primary systems which are known as spectrum holes or white spaces, by altering their transmitting parameters so that the interference is minimal to primary user while coordinating access to this channel with other cognitive radio (CR) users in the vicinity. Spectrum sensing is necessary to enable dynamic spectrum access without interfering with primary users. This optimizes the use of available radio frequency spectrum while minimizing interference to other licensed or unlicensed users by detecting and utilizing only the white spaces. This paper explores various sensing methods, their performance, applicability and effectiveness under different transmission conditions and advantages and disadvantages incorporated with each sensing method.**

Index Terms—Cognitive radio, Spectrum Sensing

I. INTRODUCTION

Cognitive radio is an intelligent radio which is capable of autonomous reconfiguration by adapting to the communication environment. Since a cognitive radio operates as a secondary user which does not have primary rights to any pre-assigned frequency bands, it is necessary for it to dynamically detect the presence of primary users. In 2004, the IEEE formed the 802.22 Working Group to develop a standard for wireless regional area networks (WRAN) based on cognitive radio technology in response to the Notice of Proposed Rule Making issued by FCC that identifies cognitive radio as the candidate for implementing negotiated/opportunistic spectrum sharing. WRAN systems will operate on unused VHF/UHF bands [24, 27].

Stages of operation in CRs are spectrum sensing (detecting the presence of licensed users and determining which portions of the spectrum are vacant), spectrum management (selecting the best available channel and varying transmission parameters accordingly), spectrum sharing (coordinating access to this channel with other CR users in the vicinity) and spectrum mobility (vacating the channel when a licensed user is detected in the channel).

Sensing of unused spectrum can be based on transmitter detection methods, interference based detection method or cooperative detection methods. Currently investigated transmitter detection methods are matched filter, Eigen-value based detection, cyclostationary and energy detection. Cooperative detection schemes include centralized, distributed and cluster-based sensing methods. While transmitter and cooperative detection methods sense the spectrum so as not cause interference to the primary transmitter, interference based detection shifts its focus to guarantee minimal primary receiver interference.

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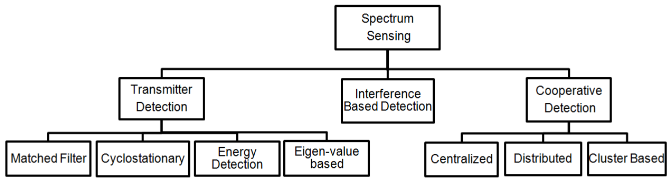

Fig. 1. Classification of cognitive radio spectrum sensing

II. TRANSMITTER DETECTION

A. Energy detection

Energy detection is the widely used spectrum sensing method since prior knowledge of the licensed user signal is not required, performs well with unknown dispersive channels and it has less computational and implementation complexity and less delay relative to other methods. However, this method relies on the knowledge of accurate noise power and hence is vulnerable to the noise uncertainty. Energy detection is optimal for detecting independent and identically distributed (iid) signals in high SNR conditions, but not optimal for detecting correlated signals.

Energy detection compares the energy of the received signal in a certain frequency band to a threshold value(γ) which is defined according to the SNR, to derive the two binary hypothesis; whether the signal present or not [2]. The signal received by the secondary user x(t), can be expressed as follows for the two hypothesis where s(t) is the primary users' transmitted signal, n(t) is the additive white Gaussian noise (AWGN) and h is the amplitude gain of the channel.

$$X(t) = \begin{cases} n(t), & H_0 \text{ (white space)} \\ h * s(t) + n(t), & H_1 \text{ (occupied)} \end{cases}$$

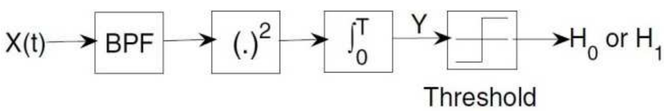

Fig. 2. Block diagram of an energy detector

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Interference, noise uncertainty and varying threshold under low SNR can limit its performance. The minimum SNR threshold below which the detector cannot reliably identify a primary signal is denoted by SNR_{wall} [1, 3]. CRs using energy detection have limited flexibility to choosing reconfigurable parameters such as operating frequency, modulation scheme and transmission power since information about the type of transmission cannot be detected. Another method of detection is the use of a periodigram and averaging the squared magnitudes of the FFT [5].

Three parameters are defined as P_d (probability of detecting the signal when the signal is preset), P_m (Probability of missed detection when the signal is present ($1-P_d$)) and P_f (probability of false alarm; deciding a signal is present when the primary user signal is indeed not present). A high P_f results in low spectrum utilization since the false alarms increase the number of missed opportunities while a high P_m results in missing the presence of primary user and causing interference to the primary user [4 - 6].

The probability density function (PDF) of the integrator output can be written as [6]:

$$f_Y(y) = \begin{cases} \frac{1}{2^u \Gamma(u)}\, y^{u-1} e^{-y/2} & H_0 \\ \frac{1}{2}\left(\frac{y}{2\gamma}\right)^{\frac{u-1}{2}} e^{\frac{2\gamma+y}{2}} I_{u-1}\left(\sqrt{2\gamma y}\right) & H_1 \end{cases} \quad (1)$$

where u is the time bandwidth product and γ is the signal to noise ratio. $I_{m-1}(.)$ is the $(m-1)^{th}$ modified Bessel function of the first kind and the gamma function is given by:

$$\Gamma(a) = \int_0^\infty t^{a-1} e^{-t} dt \quad (2)$$

The probabilities of detection and false alarm in a non fading channel can be derived using the cumulative distribution functions of the central and non-central chi-square distributions as given in [4, 6]:

$$P_f = P\{Y>\lambda |\, H_0\} = \frac{\Gamma(m,\ \lambda/2)}{\Gamma(m)} \triangleq G_m(\lambda) \quad (3)$$

$$P_d = P\{Y>\lambda |\, H_1\} = Q_m(\sqrt{2m\,\gamma}, \sqrt{\lambda}) \quad (4)$$

where the incomplete gamma function is given by:

$$\Gamma(a,b) = \int_b^\infty t^{a-1} e^{-t} dt \quad (5)$$

and generalized Marcum Q-function is given by:

$$Q_m(a,b) = \int_b^\infty \frac{x^m}{a^{m-1}} e^{-\frac{x^2+a^2}{2}} I_{m-1}(ax) dx \quad (6)$$

P_f is independent of the fading channel conditions, but P_d is dependent on the instantaneous SNR(γ) and can be expressed as [4]:

$$P_d = \int_\gamma Qm\left(\sqrt{2m\gamma}, \sqrt{\lambda}\right) f_Y(x)\, dx \quad (7)$$

where $f_\gamma(x)$ is the probability density function of the signal under fading. There are different types of fading models applicable to urban and rural environments. Nakagami fading model is suitable for urban environments with multipath propagation and can be used in mobile communication. Rayleigh fading model is applicable to urban areas where there is no line of sight communication and the signal is received after several reflections and scattering. Rician fading model can be applied when line of sight communication exists yet the signal suffers from multipath interference. Probability functions for each fading model are described as below [30].

Rayleigh channel:

$$f(\gamma) = \frac{1}{\bar{\gamma}} e^{-\gamma/\bar{\gamma}} \quad , \gamma \geq 0 \quad (8)$$

Nakagami-m channel:

$$f(\gamma) = \frac{1}{\Gamma(m)} \left(\frac{m}{\bar{\gamma}}\right)^m \gamma^{m-1} e^{-\gamma m/\bar{\gamma}} \quad , \gamma \geq 0 \quad (9)$$

Rician channel:

$$f(\gamma) = \frac{K+1}{\bar{\gamma}} e^{-K-\frac{(K+1)\gamma}{\bar{\gamma}}} I_0\left(2\sqrt{\frac{K(K+1)\gamma}{\bar{\gamma}}}\right) \quad , \gamma \geq 0 \quad (10)$$

where K is the Rician factor

From (4) the average probability of detection over Rayleigh, Nakagami and Rician fading channels has been derived in [4,6,7].

B. *Matched filter detection*

Matched filter detection can achieve a shorter sensing time for a certain probability of false alarm or probability of detection but it requires the accurate synchronization and the priory knowledge of primary user's features such as bandwidth, modulating type and order, operating frequency and pulse shaping [8], which would be possible only if the licensed user intends leveraging cooperation. For demodulation it has to achieve coherency with primary user signal by performing timing, carrier synchronization and channel equalization and power is consumed to demodulate the signal. Detecting above features and implementing matched filter detection is possible when primary users have pilots, preambles, synchronization words or spreading codes that can be used for coherent detection.

C. *Cyclostationary detection*

Transmitted signals have cyclostationary features which are caused by periodicity or statistics of mean or autocorrelation of the signal and cyclostationary detector exploits these features to detect the presence of the primary user. Modulated signals in general are associated with periodicities such as digital sequences in the form of pulse trains, sine wave carriers, repeating spreading or having cyclic prefixes which result in an inherent autocorrelation in these communication signals. A cyclostationary detector detects the presence of a signal based on the periodicity of the transmission by using a spectral correlation function (SCF) instead the power spectrum density (PSD). Noise, in general, is wide sense stationary and indicates no periodicity; hence the cyclostationary detector can differentiate the permanent user signal easily from the noise pattern [8].

Unlike the matched detector, cyclostationary feature detector does not require transmitter information at the CR. Under uncertain noise powers and low SNR it can perform better than the energy detector. Nevertheless cyclostationary detector requires excessive signal processing capabilities and is computationally very complex to implement.

D. *Eigen-value based detection*

Eigen value based detection is a novel method which is based on the Eigen values of the covariance matrix of the received signal at the secondary users. The expression for decision threshold has been derived based on the random matrix theory (RMT) which is also under research and in a developing stage [21].

This method achieves both high Pd and low Pf without requiring information of the primary user signals, channel and noise power as a priori hence it can overcome the noise uncertainty problem faced by energy detectors[22] Further, no synchronization is needed as in matched filter detection. Since the covariance matrix incorporates the correlations among the signal samples, the Eigen value based detection outperform the energy detection in the presence of correlated signals while its performance is comparable to that of the energy detector in the presence of independent and identically distributed (iid) signals [23]. But it is computationally more complex than the energy detector [24].

There are three main Eigen value based detection methods under study, which are classified according to the test statistic used to detect the signal [22]. The test statistic is compared against a computed threshold [26] .The three methods are the maximum minimum Eigen value (MME), energy with minimum Eigen value (EME) and maximum Eigen value detection (MED). MME method uses the ratio of the maximum Eigen value to minimum Eigen value of the sample covariance matrix as the test statistic [25, 26] while EME method employs the ratio of the average power of the received signal to minimum Eigen value [22,24]. In MED method the maximum Eigen value is used as the test statistic to be compared against a threshold [22, 23].

However the results derived so far in this field are based on asymptotical assumptions which would make them inaccurate in many practical scenarios [25].

E. *Other detection methods*

There are some other detection methods proposed in the literature such as multi taper spectrum estimation, filter bank spectrum estimation, combined energy detection, likelihood ratio test, covariance based sensing, wavelet-based sensing and waveform-based sensing [28,31-37] of which the latter two has been of great research interest. Waveform-based sensing or coherent sensing analyses the received signal by correlating it with a known signal pattern or a template [34]. This approach can outperform the energy detector in convergence time and reliability. Moreover, it requires short sensing time and it has been shown that the performance of the sensing algorithm improves as the length of the signal templates increases. However, this method is susceptible to synchronization errors and can be applied only to systems with known signal patterns. The other significant method, wavelet-based approach can scan over a wide bandwidth simultaneously. Wavelet-transform of the spectrum's PSD can characterize the local regularity of signals. The wideband under consideration is divided into consecutive frequency sub bands where the power spectral characteristic within each sub band is smooth but exhibits a discontinuous change between adjacent sub bands. By analyzing these discontinuities information on the locations and intensities of spectrum bands can be extracted. Once the PSD edges are detected the powers within bands between two edges are estimated. Using this information and edge positions, the frequency spectrum can be characterized as occupied or empty. Solutions based on the local maxima of both gradient wavelet modulus and multiscale wavelet products are derived and tested in the literature. The type of wavelet used determines the efficiency of this system [32, 32].

III. COOPERATIVE DETECTION

The transmitter detectors operate as individual nodes. Depending on the spatial distribution, secondary nodes have access to different primary users and hence face problems imposed by hidden node, shadowing, multipath and receiver uncertainty (inability of a CR to detect a primary transmitter due to weakness of its signal but CR's transmission is adversely affecting the reception of the primary receiver). Information collected at each individual CR can be combined in decision making to address the above mentioned issues and cooperative detection employs this technique.

Advantages of cooperative detection methods are their ability to prevent hidden node, shadowing, multipath and receiver uncertainty problems and high accuracy [11]. These are achievable at the cost of traffic overhead caused by the implementation complexity, the need for a control channel and the delay incorporated with the communication between CRs and data processing. In a cooperation based spectrum sensing scheme, the measurements of several secondary users are combined and examined together in order to determine the presence of the primary user.

When fusing the data cooperative schemes can either use hard decisions or soft decisions [13, 11] to evaluate whether the primary signal is present. In hard decision making, individual CRs make the decisions regarding the existence of the primary user and the final decision is made by fusing these decisions from individual cognitive users together. The hard decision can be made using either the OR rule or the

AND rule. Under the OR rule, if one of the sensing cognitive users decides that the primary user is present then all the cooperating CRs accept that the primary signal is present whereas under the AND rule, only if all the cognitive users decide that the primary user is present, entire system will accept that the primary is present. An optimum value for P_d or P_f can be obtained by considering only the decisions of CRs with higher SNR, for the decision making [11, 12]. Other sub-optimal hard decision schemes in use are the Counting Rule and Linear quadratic detector. In counting rule a threshold value is determined and if the number of users that decide that the primary user is present is above a threshold value, then this decision is accepted by the entire system, else it is rejected. Linear quadratic detector uses partial statistical knowledge, without ignoring the correlation information completely, to give a general suboptimal solution to the fusion problem and gives a better performance than the one obtained by ignoring the correlation information entirely [13, 16].

In soft decision making, the decision is made by correlating the measurements collected by the individual users rather than the decisions of the individual users. It has been shown that soft decision making has much better results when compared to hard decision making. A weighted linear combination of the measurements of cognitive users is taken for decision making. The weights are chosen so as to maximize the value of P_d for a given value of P_f. Larger weighting coefficients are assigned to secondary users which receive high SNR signals and are likely to make their local decisions consistent with the real hypothesis, allowing more contribution to the global decision making. Lesser weights would be assigned to secondary users experiencing deep fading, limiting their contribution to the global decision making [4, 12].

A. Centralized cooperative detection

Centralized cooperative spectrum sensing uses regulator dependent management where a central unit collects sensing information from CR devices and identifies the available spectrum and allocate the unused spectrum to the secondary users that require access to the spectrum by the use of methods such as spectrum pooling and spectrum leasing. But if the number of devices is large, the data traffic between nodes would be highly crowded and a larger bandwidth would be required [11].

B. Distributed cooperative detection

Distributed cooperative spectrum sensing does not require a backbone infrastructure and final information is learnt from the closest node, hence it has less traffic over head compared to centralized cooperative detection. Still it has disadvantages such as network information overhead and band width consumption. In distributed cooperative detection, cognitive nodes share information among neighbors but they make their own decisions as to which part of the spectrum they can use [16].

C. Cluster-based cooperative spectrum sensing

In cluster based spectrum sensing, the most favorable user with the largest reporting channel gain in a cluster is selected as the cluster head. The cluster heads collect the sensing results from all the other users in the same cluster and forward them to the common receiver, which coordinates the CRs. After receiving the authorization from the common receiver, through cluster heads, all the cognitive users initiate the spectrum sensing independently. The cluster heads collect local observations in the same cluster and make a cluster decision according to a fusion function. If the control channel bandwidth is low, radios exchange decisions or summary statistics rather than long vectors of raw data. On the other hand if the control channel bandwidth is high, CRs can exchange entire raw data. Next the cluster decisions are reported to the common receiver, which would make a final decision according to a fusion function. After determining the occupancy of the spectrum the common receiver transmits back the final decision to the CRs via cluster heads and informs which secondary users are allowed to transmit [14, 15].

IV. INTERFERENCE BASED DETECTION

Transmitter detection and cooperative detection methods focus on reducing the interference to the primary transmitter. Interference based detection shifts its focus to minimize the interference to the primary receiver irrespective of the primary transmitter's operation. The signal power received at the primary receiver reduces exponentially with the distance, until it reaches a level of noise floor. At this point, although the primary transmitter is operating, the primary receiver treats this communication as simply noise and not transmission; hence the secondary user can utilize the channel since no interference is introduced to the primary user's communication, as the primary receiver is not in the receiving mode. An interference cap is introduced above the maximum noise level, known as interference temperature; below this level the primary receiver will treat this transmission as simply noise. If the detected primary signal level is below the interference temperature, the secondary user may utilize that channel. Further if the transmission power of a CR remains below the interference cap, it may utilize any frequency parameters of its choice. A main challenge faced in implementation of this method is the receiver interference temperature determination.

Another approach is to detect the primary receiver through the local oscillator reverse leakage power which couples back through the input port and radiates out of the antenna. If no primary receiver is around, a CR may use any frequency band of its choice irrespective of primary transmitters in the vicinity. Detecting leakage power directly with a CR would be impractical due to difficulty of detecting leakage over large distances and variable local oscillator leakage power. As a solution low cost sensor nodes can be mounted close to the primary receivers. The nodes would first detect the local oscillator leakage to determine which channel the receiver is tuned to and then transmit this information to the CR through a separate control channel [9].

V. SUMMARY

In this literature review we explored the field of spectrum sensing in cognitive radio implementation which is a rapidly developing technology area in telecommunication. The CRs should be able to detect signals in the wideband regime and the performance of the sensing should be adequate to ensure efficient use of available spectrum and limited interference to the licensed primary users' communication within an acceptable amount of time. We analyzed the sensing techniques available in current literature and their advantages, disadvantages and applicability.

Energy detection is the most common scheme of spectrum sensing with low implementation and computational complexities. If the receiver cannot gather sufficient information about the primary user signal but the power of the random Gaussian noise is only known to the receiver, the optimal detector is an energy detector. However, the performance of the energy detector is susceptible to uncertainty in noise power and fading channels. Also, energy detectors often generate false alarms triggered by unintended signals because they cannot differentiate signal types and has poor performance under low SNR.

When the information of the primary user signal such as the pulse shape, packet format and modulation type and order is available, matched filter is the optimal detector. Since most wireless network systems have pilots, preambles, synchronization word or spreading codes, these can be used for the coherent detection. It has high accuracy and the minimum sensing time. Nonetheless it involves high complexity and need for receivers for all signal types of wide band regime.

Cyclostationary feature detection is to detect the target users by utilizing the cyclostationary features of the observed signals. These features are detected by analyzing the SCF. It can distinguish not only interference from the target users but also among different types of transmission scenarios and users and is robust to uncertainty in noise power and propagation channel. Nevertheless, it is computationally complex and requires significantly long observation time.

Eigen value based detection is a blind sensing method that does not need either the information of the source signals or the propagation channels. Unlike the energy detector Eigen value based detector is invulnerable to noise uncertainty and can perform well under low SNR conditions. Complexity of this method depends on the computation of the covariance matrix and the Eigen value decomposition. Nevertheless, this method has not yet been tailored to practical scenarios.

Cooperative detection mitigates the uncertainty in a single user's detection through collaboration. Detection probability is improved by reducing the multipath fading, hidden node and shadowing effects. This method can employ either data fusion or decision fusion depending on the available channel resources. If enough bandwidth can be allocated for the control channel, raw data can be exchanged; otherwise the decisions would be exchanged. Further it is categorized according to the inter-cognitive radio communication architecture as distributed, centralized and cluster based. However, this method introduces additional operations and traffic overhead. Furthermore, reliable information exchanges among the cooperating users must be guaranteed and practical fusion algorithms should be robust to data errors due to noise, interference and channel impairments.

The interference based detection shifts its attention to avoiding interference to primary receivers. As long as CR users do not exceed the interference temperature limit, which is the amount of new interference the receiver could tolerate by their transmissions, they can use this spectrum band. The difficulty of this model lies in accurately determining the interference temperature limit and reliably detecting the weak LO leakage signals of the primary receivers.

CR systems for dynamic spectrum access is an emerging technology which is still in its early stages of development and research is being carried out to achieve high accuracy of detection, minimal sensing time, less computational and implementation complexities and detection of spread spectrum primary users. Furthermore, novel algorithms and sensing methods are being proposed in this field.

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