A COMPREHENSIVE STUDY OF SPECTRUM SENSING TECHNIQUES IN COGNITIVE RADIO

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ABSTRACT

The electromagnetic spectrum is a natural scarce resource. Radio transmission involves the use of part of the electromagnetic spectrum. Use of spectrum is regulated by government agencies such as Federal Communications Commission (FCC) in the United States. Cognitive radio provides solution to the spectrum scarcity problem. Spectrum sensing for CR is an extremely well researched topic. The biggest challenge related to spectrum sensing is in developing sensing techniques which are able to detect very weak primary user signals while being sufficiently fast and low cost to implement. The various spectrum sensing techniques are: classical spectrum sensing, cooperative spectrum sensing, multiple antenna sensing and MIMO spectrum sensing. This paper provides brief overview of all existing spectrum sensing techniques and comparison is evaluated on the basis of their capacity of detecting the presence of primary users. Among these entire spectrum sensing techniques MIMO spectrum sensing is most efficient as it provides higher capacity, low value of probability of false alarm (P_{fa}) *and high value of probability of detection* (P_d).

KEYWORDS

Cognitive radio, spectrum sensing, cooperative spectrum sensing, MIMO spectrum sensing

1. INTRODUCTION

The electromagnetic spectrum is a natural scarce resource. The radio frequency spectrum involves electromagnetic radiation with frequencies between 3000 Hz and 300 GHz. The use of electromagnetic spectrum is licensed by Governments for wireless and communication technologies. Spectrum scarcity is the main problem as the demand for additional bandwidth is going to increase. Measurement studies have shown that the licensed spectrum is relatively unused across many time and frequency slots [1]. The Federal Communications Commission (FCC) published a report prepared by Spectrum Policy Task Force (SPTF) [2].This report indicates that Most of the allotted channels are not in use most of the time; some are partially occupied while others are used most of the time.

The most recommended solution for the problem of spectrum scarcity is cognitive radio (CR) described by Joseph Mitola in his doctoral dissertation [3]. CR technology is considered as the best solution because of its ability to rapidly and autonomously adapt operating parameters to changing requirements and conditions [4]. A cognitive radio can be defined as an intelligent wireless communication system that is aware of its surrounding environment, and uses the methodology of understanding-by-building to learn from the environment and adapt its internal states to statistical variations in the incoming RF stimuli by making corresponding changes in certain operation parameters (e.g., transmit-power, carrier-frequency, and modulation strategy) in real-time[4]. A spectrum hole is a band of frequencies licensed to a primary user but at a particular time and specific geographic location that particular band is not being utilized by that user (PU) [3].

A cognitive radio is a radio frequency transmitter/receiver that is designed to intelligently detect whether a particular segment of the radio spectrum is currently in use, and to jump into the temporarily-unused spectrum very rapidly, without interfering with the transmissions of other authorized users [5].Main functions of cognitive radio are [6]: Spectrum sensing, spectrum management, spectrum mobility and spectrum sharing. Spectrum sensing detects the unused spectrum and shares it without harmful interference with other licensed users. Spectrum Management is the task of selecting the best available spectrum to get user communication requirements. Spectrum Mobility is defined as the process when a cognitive radio user exchanges its frequency of operation. Spectrum Sharing decides which secondary user can use the spectrum hole at some particular time. One of the major challenges in open spectrum usage is the spectrum sharing, which is also known as Dynamic Spectrum Sharing problem.

A number of spectrum sensing methods have been proposed in literature. There are several factors that make spectrum sensing practically challenging. First, the required SNR for detection may be very low. Secondly, multipath fading and time dispersion of wireless channels complicate the spectrum sensing problem. Thirdly, the noise level may change with time and location which yields the noise power uncertainty issue for detection [7-10].

To overcome these challenging factors there is a boom in spectrum sensing methods and a wide scope of research in this area. We can classify these spectrum sensing methods in following three ways: Classical spectrum sensing, cooperative spectrum sensing and Antenna based spectrum sensing (Multiple antenna spectrum sensing and MIMO spectrum sensing). Most of these spectrum sensing methods are briefly reviewed in this paper.

2. CLASSICAL SPECTRUM SENSING TECHNIQUES

There are various classical spectrum sensing techniques in literature. A statistical hypothesis test is a method of making statistical decisions using experimental data. Many techniques were developed in order to detect the holes in the spectrum band. Generally used techniques of this kind are matched filtering, energy detection, cyclostationary, and wavelet and covariance techniques. These techniques provide basic concept of spectrum sensing which is further used in various emerging spectrum sensing techniques. In order to avoid the harmful interference to the primary system, the cognitive radio needs to infer about the availability of the spectrum.

2.1. Matched Filter Detection

Matched filtering is known as optimal method for detection of primary users when the transmitted signal is known. It is a linear filter designed to maximize the output signal to noise ratio for given input signal. It is obtained by correlating a known signal, with an unknown signal to detect the presence of the known signal in the unknown signal. This is equivalent to convolving the unknown signal with a time-reversed version of the signal. Convolution is at the heart of matched filters. Convolution does essentially with two functions that it places one function over another function and outputs a single value suggesting a level of similarity, and then it moves the first function an infinitesimally small distance and finds another value [11]. The end result comes in the form of a graph which peaks at the point where the two images are most similar. The matched filter is the optimal linear filter for maximizing the signal to noise ratio (SNR) in the presence of additive white stochastic noise.

Matched filtering requires cognitive radio to demodulate received signals. Hence it requires perfect knowledge of the primary users signalling features such as bandwidth, operating frequency, modulation type, pulse shaping and frame format. A matched filter compares two signals and outputs a function describing the places at which the two signals are most like one another. This is carried out by taking Fast Fourier Transform (FFT) of two signals, then multiplying their coefficients and after that taking Inverse Fast Fourier Transform (IFFT) of the result, the output can be find out [11].

Major advantages and disadvantage of matched filter are illustrated below:-

- Advantage of matched filter is that it needs less time to achieve high processing gain and probability of false alarm and missed detection due to coherent detection [12].
- Disadvantage of matched filter is that it would require a dedicated sensing receiver for all primary user signal types.
- It requires the prior information of primary user signal which is very difficult to be available at the CRs.
- Another disadvantage of matched filtering is large power consumption as various receiver algorithms need to be executed for detection.

Probability of false alarm ($P_{fa,MFD}$) for a given threshold γ_{MFD} given as [13]:-

$$P_{fa,MFD} = Q(\frac{\gamma_{MFD}}{\sigma_n\sqrt{E}}) \quad (1)$$

Probability of detection is given ($P_{d,MFD}$) as [13]:-

$$P_{d,MFD} = Q(\frac{\gamma_{MFD-E}}{\sigma_n\sqrt{E}}) \quad (2)$$

Where Q (.) is the Gaussian complementary distribution functions.

2.2. Energy Detection Method

Energy detection is a non coherent detection technique in which no prior knowledge of pilot data is required. Goal of this paper is to provide a comprehensive study supported with experimental data that addresses the following issues in spectrum sensing based on energy detection [14]:

1. Required sensing time needed to achieve the desired probability of detection and false alarm.
2. Limitations or energy detector performance due to presence of noise uncertainty and background interference.
3. Performance improvements offered by network cooperation.

Depending on the application, the signal to be detected can be either unknown or known. In most of the applications, the signal information is not available for the detector. The detection is based on some function of the received samples which is compared to a predetermined threshold level [14]. If the threshold is exceeded, it is decided that signal(s) is (are) present otherwise it is absent. Energy detectors (radiometers) are often used due to their simplicity and good performance. The energy detection method performs the signal measurements and determines the vacant channel candidates by comparing the power estimated to the predefined threshold levels.

The detection of a weak deterministic signal in additive noise is considered. The signal power is confined inside a priori known bandwidth (B) around central frequency f_c. It is assumed that activity outside of this band is unknown. Two deterministic type of signal are considered: sine wave (pilot tone) and modulated signal with unknown data. In this case a suboptimal energy detector is adopted which can be applied to any signal type.

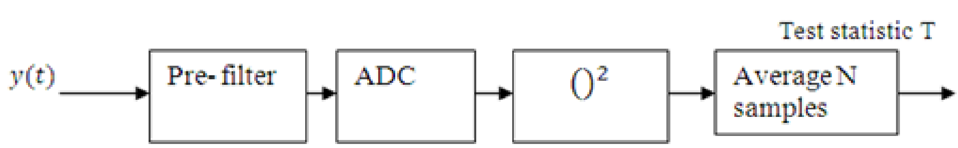

Figure 1 Implementation of energy detection with analogue pre-filter and square law device

The detection is the test of the following two hypotheses:

$H_0: y[n] = w[n]; signal\ is\ absent$

$$H_1: y[n] = s[n] + w[n]; signal\ is\ present,\ where\ n = 1, \ldots N$$

where N is observation interval. Here noise is assumed to be additive white Gaussian noise (AWGN) with zero mean and variance σ_w^2. In the absence of coherent detection, the signal samples can also be modelled as Gaussian random process with variance σ_s^2.Decision statistic for energy detector is:-

$$T = \sum_N (Y[n])^2 \quad (3)$$

This implementation is quite inflexible in case of narrowband signals and sine waves. So to make it flexible for sine waves an alternative approach is implemented in which periodogram method is used to estimate the spectrum via squared magnitude of the FFT.

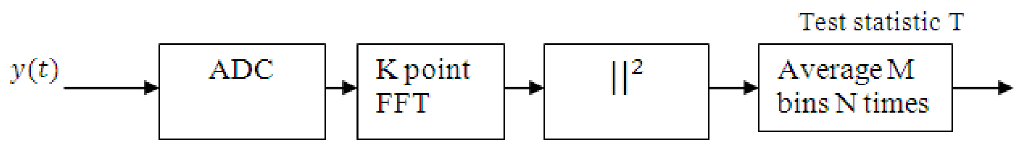

Figure 2 Implementation of energy detection with periodogram; FFT magnitude squared and averaged

Probability of false alarm ($P_{fa,ED}$) for a given threshold γ_{ED} given as [13]:-

$$P_{fa,ED} = 1 - P\left(\frac{\gamma_{ED}}{2}, L\right) \tag{4}$$

where $P(a,x)$ is the lower incomplete gamma function.
Similarly, probability of detection is given ($P_{d,ED}$) as [13]:-

$$P_{d,ED} = 1 - Q_{x^2}\left(\gamma_{ED}, 2L, \frac{MLP_s}{2\sigma_w^2}\right) \tag{5}$$

Where $Q_{x^2}(x, v, \delta)$ is the non central x^2 cumulative distribution function of x with v degrees of freedom and positive non-centrally parameter δ.

2.3. Cyclostationary Detection

Cyclostationary feature detection is a method for detecting primary user transmissions by exploiting the cyclostationary features of the received signals. A signal is said to be cyclostationary, if its autocorrelation is a periodic function of time t with some period. A zero-mean continuous signal $x(t)$ is called cyclostationary if its time varying autocorrelation function $R_{xx}(t,\tau)$ defined as [16]:-

$$R_{xx}(t,\tau) = E[x(t)x^*(t,\tau)] \tag{6}$$

is periodic in time t for each lag parameter τ and it can be represented as a Fourier series

$$R_{xx}(t,\tau) = \sum_{\alpha} R_{xx}^{\alpha}(\tau) exp^{j2\pi\alpha t} \tag{7}$$

Where the sum is taken over integer multiples of fundamental cyclic frequency α for which cyclic autocorrelation function (CAF) is defined as:-

$$R_{xx}^{\alpha}(t,\tau) = \lim_{t\to\infty} \left(1/_T\right) \int_{-\frac{T}{2}}^{\frac{T}{2}} R_{xx}(t,\tau) exp^{-j2\pi\alpha t} dt \tag{8}$$

The Fourier transform of $R_{xx}^{\alpha}(t,\tau)$ is called the cyclic spectrum (CS) which is defined as:

$$S_{xx}^{\alpha} = \int_{-\infty}^{\infty} R_{xx}^{\alpha}(\tau) exp^{-j2\pi f t} d\tau \tag{9}$$

The detection of the presence and absence of signal is performed based on scanning the cyclic frequencies of its cyclic spectrum or its cyclic autocorrelation function. The decision is made very simple i.e. at a given cyclic frequency if the cyclic spectrum or its cyclic autocorrelation function is below the threshold level, the signal is absent otherwise signal is present [16]. The detection performance is investigated under white Gaussian noise channel.
Probability of false alarm ($P_{fa,CSD}$) for a given threshold γ_{CSD} given as [13]:-

$$P_{fa,CSD} = (1 - \gamma_{CSD})^{(L-1)} \tag{10}$$

Similarly, probability of detection is given ($P_{d,CSD}$) as [13]:-

$$P_{d,CSD} = 1 - P_{CDF}(\gamma_{CSD} | L, |\sigma|^2) \tag{11}$$

The performance of this method is worse than energy detector when noise is stationary. It is robust to noise uncertainty than energy detector. If the signal of PU exhibits strong cyclostationary probabilities, it can be detected at very low SNR values by exploiting information embedded in the received signal.

2.4. Wavelet Detection

It is known from Fourier theory that a signal can be expressed as the sum of a possibly infinite, series of sines and cosines [17]. This sum is also referred to as a Fourier expansion. The big disadvantage of a Fourier expansion is that it has only frequency resolution and no time resolution.
The frequency resolution is inversely proportional to the duration of the signal for the FFT spectrum; it depends on the order and on the signal-to-noise ratio for spectra [18]. To overcome this problem in the past decades several solutions have been developed which are more or less able to represent a signal in the time and frequency domain at the same time [17].
The wavelet transform or wavelet analysis may be the most recent solution to overcome the drawbacks of the Fourier transforms [17].

A wave is an oscillating function of time or space and is periodic while wavelets are localized waves in which the energy is concentrated in time or space. In wavelet analysis the use of a fully scalable modulated window solves the signal-cutting problem. The window is shifted along the signal and for every position the spectrum is calculated. Then this process is repeated many times with a slightly shorter (or longer) window for every new cycle. In the end the result will be a collection of time-frequency representations of the signal, all with different resolutions.
There are two types of wavelet transform in literature:-

1. Continuous Wavelet Transform:-

The Continuous Wavelet Transform (CWT) is provided by the following equation [19]:

$$X_{wt}(\tau, s) = \frac{1}{\sqrt{|s|}} \int x(t).\, \psi^* \frac{(s)}{t-\tau}\, dt \tag{12}$$

Where $x(t)$ is signal to be analyzed, $\psi(t)$ is the mother wavelet or the basis function. All the wavelet functions used in the transformation are derived from the mother wavelet through shifting and scaling.

2. Discrete Wavelet Transform: - The Discrete Wavelet Transform (DWT), which is based on sub-band coding, is found to yield a fast computation of Wavelet Transform. It is easy to implement and reduces the computation time and resources required.

In CWT, the signals are analyzed using a set of basic functions which relate to each other by simple scaling and translation. In the case of DWT, a time-scale representation of the digital signal is obtained using digital filtering techniques. The signal to be analyzed is passed through filters with different cut-off frequencies at different scales [19].
There are a number of basic functions that can be used as the mother wavelet for Wavelet Transformation. As the mother wavelet produces all wavelet functions used in the transformation through translation and scaling, it determines the characteristics of the resulting Wavelet Transform [19]. So, the details of the particular application should be taken into account and the appropriate mother wavelet should be selected in order to use the Wavelet Transform effectively. Due to the tremendous increment bandwidth demand and increasing spectrum scarcity, wideband spectrum sensing has been introduced to provide better opportunity of detecting spectrum opportunities.

2.5. Covariance Detection

Covariance is a measure of the strength of the link between two random variables. Given two such random variables are X_1 and X_2, two extreme situations can be here [21]:

- There is no link between X_1 and X_2 . Knowing the value of X_1 provides the no idea about the value of X_2. The two variables are said to be independent.
- The link is so strong that it is functional. There is a completely deterministic function $y = f(x)$ such that :

$$X_2 = f(X_1) \tag{13}$$

The concept is about knowing the value of X_1 which determines the value of X_2 without any uncertainty. Most often, the link between two random variables is "somewhere in between"; knowing the value taken by X_1 reduces to a certain extent where it will take the uncertainty about the value of X_2 . There is no universal way to define and measure the strength of the link in this intermediary situation. Covariance is one way to do it, and is very useful in many practical situations despite of its limitations. Instead of measuring the values of X_1 and X_2 , measurement will be made from reference points that translate along with the probability distributions and these reference points are their respective means μ_1 and μ_2. Now the ideas can be [20]:

- Whenever (X_1-μ_1) is positive, then (X_2-μ_2) is likely to be positive too.
- Whenever (X_1-μ_1) is negative, then (X_2-μ_2) is likely to be negative too.

The product (X_1 - μ_1)*(X_2 - μ_2) is then likely to be often positive because either both quantities are positive or both quantities are negative. As the product (X_1 -μ_1)*(X_2 -μ_2) is a random variable, and a fixed number is desired. But a random variable that spends most of its time taking positive values is likely to have a positive expectation. So the expectation of (X_1 -μ_1)*(X_2 -μ_2) is considered, and named as the covariance of X_1 and X_2:-

$$\mathrm{Cov}\,(X_1, X_2) = \mathrm{E}\,[(X_1 - \mu_1)*(X_2 - \mu_2)] \tag{14}$$

Two types of covariance detection methods are proposed in literature:-

- covariance absolute value (CAV) detection
- covariance Frobenius norm (CFN) detection

The threshold and probability of false alarm are also found. This method can be used for various signal detection application without having any prior knowledge of signal, channel and noise power.
Staying with qualitative arguments for given and fixed probability distributions of X_1 and of X_2 it can be noticed:-

- The Covariance may be low because the link between the two variables is weak.
- But there exist a strong, non linear link between the two variables, the nature of this link making the Covariance low.

The drawback of covariance is that its value depends on the units used express the values of X_1 and X_2, whereas a practical measure of the strength of the link between two variables certainly shouldn't depend on it.

3. COOPERATIVE SPECTRUM SENSING TECHNIQUES

Multi-path fading is a very important factor which make spectrum sensing less reliable and it cannot be ignored. It is difficult to reducing the effective error rate in a multipath fading channel. The improvement in SNR cannot be made by higher transmit power or additional bandwidth because this is against the requirements of next generation systems [20].Before transmitting any signal, cognitive radio should estimate the power spectral density of the radio spectrum so as to check which bands are in use and which bands are not utilized. However, there might be another user of that spectrum behind the next building, transmitting to a tower on the hill. Because the building is between the users, the cognitive radio user does not receive another user signal and so concludes the spectrum is unoccupied. The "hidden terminal problem" must be overcome to ensure that primary users of a band are protected from interference.
The solution to this hidden terminal problem is cooperative spectrum sensing technique. For contemplation of recent advances in cooperative spectrum sensing, readers are referred to [22]-[32]. Cognitive radio cooperative spectrum sensing occurs when a group or network of cognitive radios share the sense information they obtain with each other. Cooperation allows achieving the robustness against severe fading without drastic requirements on individual radios. Cooperative sensing rely on the variability of signal strength at various locations is made. It is expected that a large network of cognitive radios with sensing information exchanged with each other would have a better chance of detecting the primary user compared to individual spectrum sensing.
The operation of this technique can be performed as follows [33]:-

- Every CR calculates its own local spectrum sensing measurements independently through sensing channels and then makes a binary decision (1or 0) on whether the PU is present or not.
- All of the CRs forward their decisions to a common receiver through reporting channels.
- The common receiver fuses the CR decisions using some fusion logic (Xoring or ORing) and makes a final decision to infer the absence or presence of the PU.

3.1 Cluster Based Cooperative Spectrum Sensing

An idea of cluster based cooperative spectrum sensing is explained in [34]. In this cognitive users collaborate with each other to perform spectrum sensing. There are a number of clusters of cognitive users which cooperate with each other within a cluster. The scenario is same; Primary user, cognitive user and a common receiver. But in case of cluster based techniques there should be the cluster of cognitive users in spite of single cognitive users. It is assumed that channels between cognitive users and common receiver (i.e. Reporting channels) are perfect and decision fusion is employed at the common receiver.The channel between any two users in the same clusters is perfect since they are closer to each other. In this case every cognitive user within the same cluster makes its own local decision on the basis of its observations and sends its decision to the cluster head. The cluster head gets the local decisions from all the cognitive users of that cluster and then make a single decision on the basis of some fusion function. This single decision is transmitted over the reporting channel to common receiver. It exploits user selection diversity within the cluster and decreases the reporting errors due to imperfect reporting channels as compared to conventional spectrum sensing.

3.2 Collaborative Spectrum Sensing

For many emerging wireless standards, it will be important for radios to be able to detect and classify signals in its environment to ensure proper network behaviour. Statistics courses teach that an increasing number of independent observations reduce the variance of estimated parameters. Thus the decisions as to if a signal is present and what kind of signal is present could be improved by incorporating more observations from other devices. Collaborative sensing should be able to help overcome the hidden node problem to most standards.

3.3 Transmit and Relay Diversity in Cooperation Technique

Another idea is provided for cooperation technique in [34]. This Paper assumes that the reporting error is of large value on imperfect reporting channels. So to overcome this problem the cooperation between the CRs is exploited. In case of transmit diversity let's take the case of two cognitive users. Now both the cognitive users make their decision about the availability of primary user. Then both cognitive users transmit their decisions to each other. Common receiver receives the decision of both cognitive users from the both secondary user. But in relay diversity, the secondary user which is at larger distance from the common receiver can transmit its decision to another secondary user which is nearer to the common receiver. Now the secondary user transmits its own decision along with the decision of farther cognitive user. The wireless network is assumed to operate over independent and not necessarily identically distributed Rayleigh fading channels. As the primary user starts using the band, cognitive radios receive the signal of the primary user. Therefore in the first phase, all cognitive relays listen to the primary user signal. Instead of making individual hard decision about the presence of the primary user, relay-based cognitive radios simply amplify and retransmit the noisy version.

3.4 Advantages of cooperative spectrum sensing

Naturally cooperative spectrum sensing is not applicable in all applications, but where it is applicable, considerable improvements in system performance can be gained [35]:-

1. Hidden node problem is significantly reduced.
2. Increased in agility.
3. Reduced false alarms
4. More accurate signal detection

3.5 Disadvantages of cooperative spectrum sensing

Significant requirements of cooperative spectrum sensing are:

- Control Channel
- System Synchronization
- Suitable geographical spread of cooperating nodes.

4. MULTIPLE ANTENNA SPECTRUM SENSING TECHNIQUE

As we proceed towards the edge of new ideas; technologies grow up more effectively and most efficiently. In the same way multiple antenna spectrum sensing is a new idea in cognitive radio technology. It is indicated that if multiple antennas are mounted at secondary user than high value of probability of detection can be obtained [36]. A Generalized Likelihood Ratio detector (GLRD) is proposed which do not have any primal information about the parameters like; channel gains, noise variance, and primary user signal variance in [36]. It is supposed that the SU has M receiving antennas and each antenna receives L samples. It is also assumed that the PU signal samples are independent zero-mean random variables with complex Gaussian distribution.

This assumption is valid for an Orthogonal Frequency Division Multiplexing (OFDM) signal in which each carrier is modulated by independent data streams. It is assumed that the additive noise samples at different antennas are independent zero-mean Gaussian random variables. It is assumed that the channel gain vector, i.e., h, is a constant parameter at each sensing time. The optimal detector needs to know the values of channel gains, noise and PU variances. Detection methods for signals with correlation between the received symbols in noise and interference are of special importance in the implementation of a communication system. Signal activity detection is an important stage in real communication systems, since the performance of the succeeding stages, such as demodulation and decoding, depends on correct knowledge of the signal activity. The signal symbols are either independent or correlated with some known/unknown properties. The correlation between the received symbols in a transmission system may be because of the coding on the transmitted information or due to the Inter-Symbol Interference (ISI) imposed on the signal, as the signal goes through the channel. The computational complexity of the proposed detectors comes from two major operations: computation of sample covariance matrix and eigenvalue decomposition of the covariance matrix. Here we consider the computational complexity of a trashy approach in which the largest root of the sample covariance matrix is calculated.

5. MIMO SPECTRUM SENSING TECHNIQUE

The gains achievable by a MIMO system in comparison to a Single Input Single Output (SISO) one can be described stringently by information theory. A lot of research in the area of MIMO systems and Space Time Coding is based on this mathematical proof given by Shannon [37]. So major benefits from MIMO are [38]:-

- Higher capacity (bits/s/Hz). (spectrum is expensive; number of base stations limited)
- Better transmission quality
- Increased coverage
- Improved user position estimation

These benefits are achieved due to spatial multiplexing gain, diversity gain, and array gain and interference detection. . According to Shannon, the capacity C of a radio channel is dependent on bandwidth B and the signal-to-noise ratio S/N. The following applies to a SISO system:

$$C = B\log_2(1+\frac{S}{N}) \qquad (15)$$

Theoretically, the capacity C increases linearly with the number of antennas (M) in case of MIMO [39].

$$C = MB\log_2(1+\frac{S}{N}) \qquad (16)$$

In case of MIMO capacity is proportional to minimum of number of transmitter antennas and receiver antennas [40].

5.1 MIMO Model

A MIMO system typically consists of n_T transmit and n_R receive antennas (as shown in figure). By using the same channel, every antenna receives not only the direct components intended for it, but also the indirect components intended for the other antennas [41]. A time-independent channel is assumed. Figure 2.9 represents MIMO model where multiple antennas are used both on transmitter and receiver.

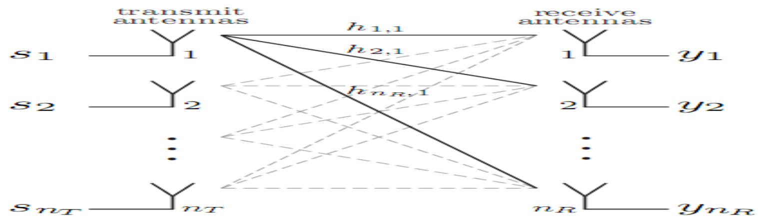

Figure 3 A MIMO channel with n_T transmit and n_R receive antennas.

The direct connection from antenna 1 to 1 is specified with h_{11}, etc., while the indirect connection from antenna 1 to 2 is identified as cross component h_{21}, etc.,. from this a transmission matrix **H** with the dimensions ***n x m***.

It is assumed that the elements of the channel matrix **H** are complex Gaussian random variables with zero mean. This assumption is made to model the fading effects induced by local scattering in the absence of a line of-sight component, as most of the time there is no any line of sight communication between the transmitter and receiver.

However, the magnitudes of the channel gains $\{|h_{mn}|\}$ have a Rayleigh distribution and are exponentially distributed as $\{|h_{mn}|^2\}$. The presence of a line-of-sight component can be modelled by letting $\{|h_{mn}|\}$ have a Gaussian distribution with a non-zero mean. Another assumption on **H** is that its elements are statistically independent of one another. Practically, the elements of **H** are correlated by an amount that depends on the propagation environment as well as the polarization of the antenna elements and the spacing between them. For MIMO model, it can also be written as:

$$Y = HS + N \tag{17}$$

The noise is assumed to be spatially white circular Gaussian random variables with zero mean and variance σ^2:

$$e_n = N_c(\sigma^2, I) \tag{18}$$

The additive white Gaussian channel is the simplest of all channels to model.

5.2 MIMO Spectrum Sensing In Cognitive Radio

Introducing this new technique of spectrum sensing can provide a better way to sense the vacant bands. As , in case of multiple antenna spectrum sensing there is one antennas at primary user and multiple antennas at secondary user; this is the case of SIMO (single input and multiple output), while in MIMO spectrum sensing, multiple antennas are employed at both on primary user and secondary user.

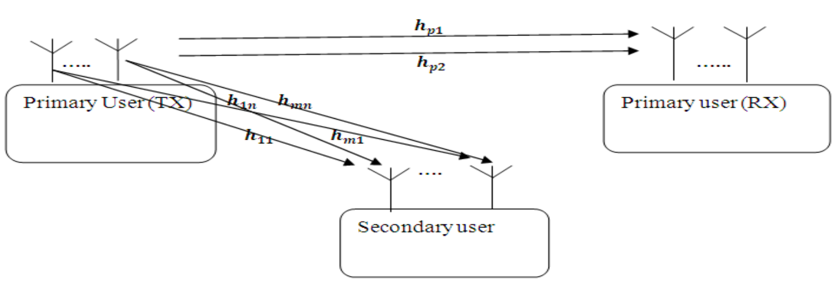

Figure 4 MIMO spectrum sensing techniques

5.2.1 MIMO Spectrum Sensing

1. **For independent channel:**

To evaluate the performance of MIMO, optimal detector is used. Assumption is that optimal detector needs to know the noise and PU signal variances and channel gains.

To reduce the complexity of the system here only 2 antenna system is consider for implementation. Two antennas at transmitter and two at receiver are mounted.
Mathematically, it can be given as:-
$Y = HX + N$
Here, H is channel matrix and its elements are assumed to be independent.
Let's assume that the signals received to the secondary user from the primary user after sensing its surrounding environment is (x_1, x_2). After applying hypothesis at these two symbols i.e.

$$\begin{cases} H_0: Primary\ user\ is\ absent; \\ H_1: Primary\ user\ is\ present \end{cases}$$

For this it's necessary to find out its probability density function. It is assumed that the signals are Gaussian distributed with zero mean and channel is independent in this case.
The PDF of a Gaussian distribution function is given as:

$$f(t) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(t-\mu)^2}{2\sigma^2}} \tag{19}$$

where μ is the mean and σ^2 is variance of the signal.
Let $X = [x_1, x_2, \dots\dots\dots . x_L] \in C^{M\times L}$ is a complex matrix containing the observed signals at M antennas (in this case M=2). L is the number of samples which each antenna receives and σ_n^2 and σ_s^2 are the noise variance and signal variance respectively.

$$\begin{cases} H_0: X \sim N(0, \sigma_n^2) \\ H_1: X \sim N(0, \sigma_s^2 + \sigma_n^2) \end{cases} \tag{20}$$

In this case it is assumed that, the SU knows the channel gains, noise and PU signal variances. So under H_0 the PDF of matrix X, can be given as:-

$$f(X; H_0, \sigma_n^2) = \frac{1}{(2\pi\sigma_n^2)^{L/2}} \exp\left\{\frac{-tr(X)^2}{2\sigma_n^2}\right\} \tag{21}$$

Where tr (.) is the trace of the matrix.
By taking logarithm of PDF of observation matrix H:

$$L_0(X) = \frac{-tr(X)^2}{2\sigma_n^2} - L\ \ln\pi - \frac{L}{2}\ln\sigma_n^2 \tag{22}$$

For H_1 the PDF of matrix X, can be given as:-

$$f(X; H_1, \sigma_n^2, \sigma_s^2) = \frac{1}{(2\pi(\sigma_n^2+\sigma_s^2))^{L/2}} \exp\left\{\frac{-tr(X)^2}{2(\sigma_n^2+\sigma_s^2)}\right\} \tag{23}$$

By taking logarithm of PDF of observation matrix H:

$$L_1(X) = \frac{-tr(X)^2}{2(\sigma_n^2+\sigma_s^2)} - L\ \ln\pi - \frac{L}{2}\ln(\sigma_n^2 + \sigma_s^2) \tag{24}$$

Let's calculate the likelihood ratio function:

$$LLR = \ln\frac{f(X; H_1, \sigma_n^2, \sigma_s^2)}{f(X; H_0, \sigma_n^2)} = L_1(X) - L_0(X) = \frac{tr(X)^2}{2\sigma_n^2}\left(\frac{1}{1+\frac{\sigma_n^2}{\sigma_s^2}}\right) - \frac{L}{2}\ln\sigma_s^2 \tag{25}$$

Comparing the LLR function with a threshold results as:-

$$\frac{tr(X)^2}{2\sigma_n^2}\left(\frac{1}{1+\frac{\sigma_n^2}{\sigma_s^2}}\right) - \frac{L}{2}\ln\sigma_s^2 \gtrless \eta \tag{26}$$

Where η is the decision threshold and $\frac{\sigma_n^2}{\sigma_s^2}$ is the SNR of the signal
For independent channel in MIMO case; P_f and P_d expressions can be written as:-

$$P_f = \frac{\Gamma(L, \frac{\eta}{||h||^2\sigma_n^2})}{\Gamma(L)} \tag{27}$$

Where $\Gamma(L, \frac{\eta}{||h||^2\sigma_n^2})$ is upper incomplete and $\Gamma(L)$ is complete gamma functions.

$$P_d = \frac{\Gamma(L, \frac{\eta}{||h||^2(||h||^2\sigma_s^2+\sigma_n^2)})}{\Gamma(L)} \tag{28}$$

In terms of SNR:

$$P_d = \frac{\Gamma\left(L, \frac{\eta}{||h||^2 \sigma_n^2 (L+\gamma)}\right)}{\Gamma(L)} \quad (29)$$

Where γ is SNR of received signal and given by:-

$$\gamma = \frac{||h||^2 \sigma_s^2}{\sigma_n^2} \quad (30)$$

2. For correlated channel:

In multiple antennas spectrum sensing technique PU has single antenna and SU has multiple antennas while in that case channel is considered independent. But by using multiple antennas at SU, practically it is very difficult for the channels to be completely independent. There exists some correlation between the channels. If two electromagnetic waves originating from two different antennas are reflected by the same object then the propagation coefficients of these waves will be correlated with each other. The degree of correlation depends upon the propagation environment and the polarization of the antenna elements and the distance gap between them. If fading correlation is taken in account then it can be divided in two independent components:-

- Receive correlation
- Transmit correlation

6. CONCLUSIONS

Cognitive radio is a novel approach that basically improves the utilization efficiency of the radio spectrum. This paper presents an extensive analysis of spectrum sensing techniques in cognitive radio. Cooperative spectrum sensing is better than classical spectrum sensing as it overcomes the hidden node problem, reduces false alarm and gives more accurate signal detection. In multiple antenna spectrum technique no prior information of signal is needed. It provides more accurate signal detection in less sensing time than cooperative sensing technique. Theoretical analysis on test statistic distribution and threshold setting has been evaluated. Calculations show that value of probability of false alarm is low and probability of detection is high for MIMO spectrum sensing technique. As, number of antennas increases; it provides higher capacity, better transmission quality and increased area coverage.

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