ENERGY DETECTION TECHNIQUE FOR SPECTRUM SENSING IN COGNITIVE RADIO: A SURVEY

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ABSTRACT

Spectrum sensing is the basic and essential mechanisms of Cognitive Radio (CR) to find the unused spectrum. This paper presents an overview of CR architecture, discusses the characteristics and benefits of a CR. Energy detectionbased spectrum sensing has beenproposed and used widely because it doesn't require transmitted signal properties, channel information, or even the type of modulation. In this paper, a surveyof energy detector over Additive White Gaussian Noise (AWGN), different fading channels for spectrum sensing methodologies in cognitive radio is presented.Theoretical analysis of time domain energy detection and threshold setting is investigated. Cooperative spectrum sensing and a multiple antenna processing based energy detector receptions are also discussed.

KEYWORDS

Wireless Communication, Cognitive Radio, Energy Detection, Dynamic Spectrum Access.

1. INTRODUCTION

Currently, cognitive radio (CR) is great interest to technologists because of significantly increasing the overall utilization of spectrum efficiency. From the date of publishing paper by Mitola on CR [1], 30 special issue scientific journals and more than 60 dedicated conferences and workshopscustom to CR [2]. This is still a very fresh and interesting research topic, therefore many technical research questions still need to be answered.Energy detection uses a squaring device followed by an Integrator, the output of which gives the decision variable.This variable is then compared with a threshold and if it isabove the threshold, then the result of the detector is that aprimary user is present. Energy detection is very practicalsince it requires no information about the signal needed to detect.

2. MOTIVATION: SPECTRUM SENSING FOR SPECTRUM SHARING

Wireless communication systems were growth significantly over the last twodecades. However, there are limits to growth, because the radio spectrum used for wireless communications is a finite resource. In most countries, the government regulates the usage of the frequency spectrum by national regulatory bodies like the Federal Communications Commission (FCC) in the USA.FCC coordinated allocating frequency bands and issuing exclusive licenses to systems within a geographical area while forbidding or at least regulating other systems with respect to these bands. Figure 1 [3]shows the FCC'sfrequency allocation chart, from where we can observe that a heavily crowded spectrum with nearly all usable radio frequency bands already

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licensed to commercial operators and government units for specific services, making spectrum a scarce resource.

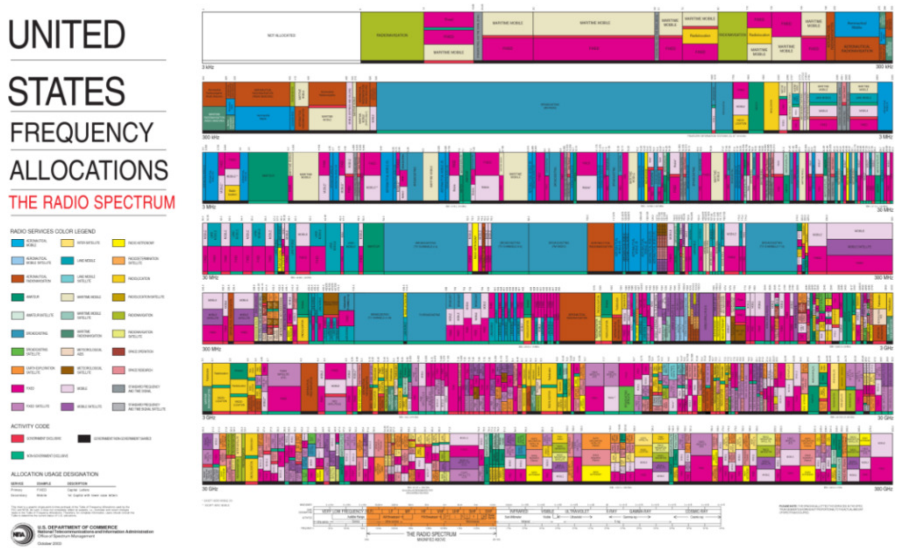

Figure 1. FCC Spectrum Allocation Chart

According to the FCC study of the spectrum utilization shows that licensed spectrum with utilization ranges from 15% to 85%in the bands below 3 GHz [4], which indicates that there is significant scope of improving spectrum utilization. As a solution for the spectrum used inefficiently problem, CR and Dynamic Spectrum Access (DSA) areproposing an opportunistic spectrum usage approach [1]. The basic idea of DSA isin which frequency bands that are not being used by their licensed users, (a.k.a.Primary Users (PUs)), are utilized by CRs, (a.k.a.SecondaryUsers (SUs)) as long as they do not cause any harmful interference to PUs [5].Hence, the key enabling technology of DSA techniques is CR.

The CR enables the usage of temporally unused frequency bands which are commonly known as ***spectrum holes***.Usually spectrum holes are generally categorized into ***temporal spectrumholes*** and ***spatial spectrum holes***. A temporal spectrum hole is unoccupied by the PU during the time of sensing. Hence, this band can be used by SUs in the current time slot. Spectrum sensing of this kind does not require complex signal processing.A spatial spectrum hole is a band which is unoccupied by the PU at some spatial areas; and therefore can be occupied by SUs As well asoutside this area. Spatial sensing of a PUneeds complex signal processing algorithms [6], [7].

In terms of power spectra of incoming RF is classifying the spectrum holes into three broadly defined types [8]

1. ***Black spaces***, which are dominated by high-power “local”interfere some of the time.
2. ***Grey spaces***, which are partially dominated by low-power interference.
3. ***White spaces***, which are free of RF interference except for white Gaussian noise.

Among these three, white spaces and grey spaces can be used by unlicensed operators if accurate sensing technique is designed, and Black spaces cannot be used because usage of this space will cause interference to the PU.

If the band is used more by a PU, the CR moves to another spectrum holeas shown in Figure 2 [9].

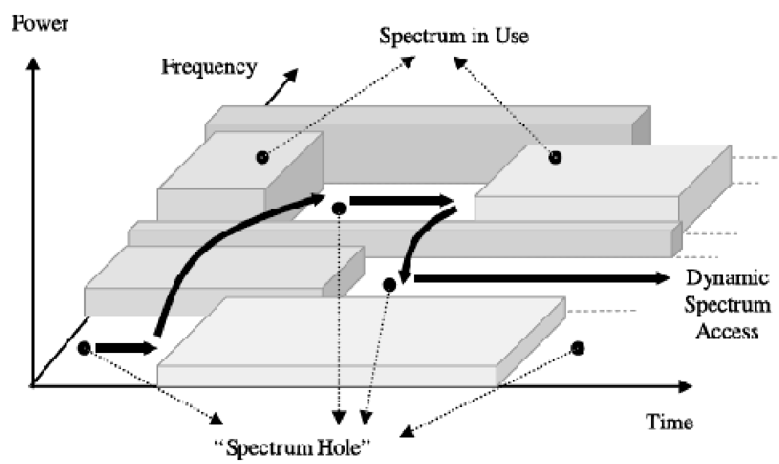

Figure 2. Spectrum Holes

Figure 3 illustrates a simpleand yettypical DSA networkthat consists of a pair of PU and a pair of SU. They operate at the same frequency band. The PU has higher priority accessing the spectrum. The SU has to sense the spectrum and communicate only if it identifies a spectrum hole. Miss detections from the SU will cause interference to the PU as shown in the figure. The key enabling technology of DSA techniques is CR.

The FCC ruled in November 2008 that unused TV channels 21 to 51, with the exception of channel 37, be made available for SU [10].

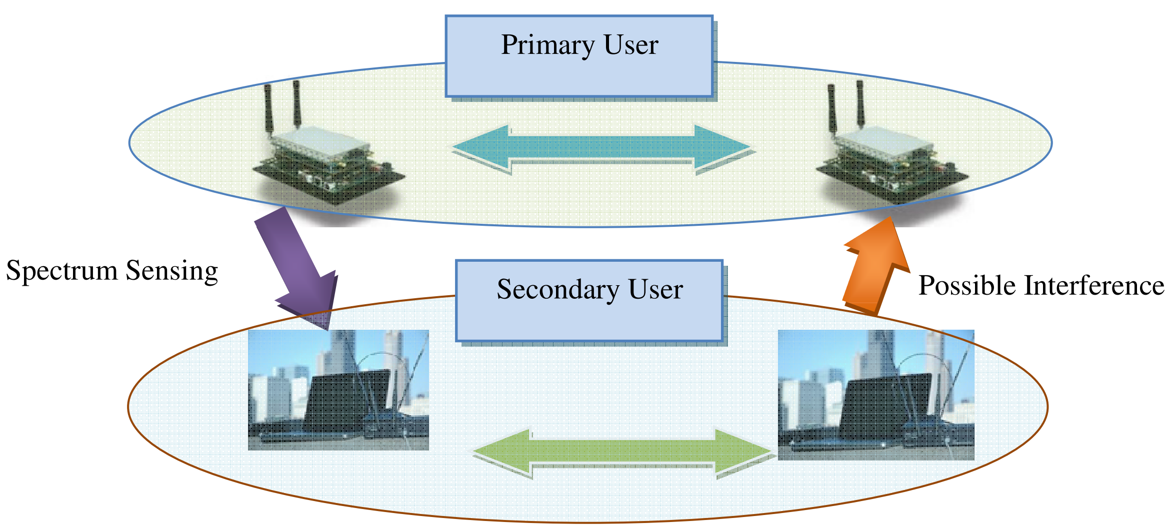

Figure 3. Illustration of DSA

3.DEFINITIONS

The words cognitive have become buzzwords that are applied to many different networking and communications systems. From the Oxford English dictionary, one of the most used definitions of cognitive is: "*pertained to cognition or to the action or process of knowing"*the word cognition means:"*the mental process of getting knowledge through thought, experience and the senses*."Thus, Term CR could be defined as *a radio that is cognitive*.

In the 1999 paper that first invented the term "cognitive radio", Mitola defines a cognitive radio as [1]: "*A radio that employs model based reasoning to achieve a specified level of competence in radio-related domains*."

Six years after Mitola's first article on CR, Simon Haykin in his invited paper to IEEE Journal on Selected Areas in Communications, summarized the idea of CR as [11]: "*An intelligent wirelesscommunication system that is aware of its surrounding environment (i.e., outside world),and uses the methodology of understanding-by-building to learn from the environmentand adapt its internal states to statistical variations in the incoming RF stimuli by makingcorresponding changes in certain operating parameters (e.g., transmit-power, carrierfrequency,and modulation strategy) in real-time, with two primary objectives in mind:*

· *Highly reliable communications whenever and wherever needed;*

· *Efficient utilization of the radio spectrum.*

Coming from a background where regulations focus on the operation of transmitters, theFCC has defined a cognitive radio as [12]: *"An intelligent wirelesscommunication system capable of changing its transceiver parameters based oninteraction with the environment in which it operates."*

IEEE USA presented thefollowing definition [13]: *"A type of radio in which communication systems are aware of their environment and internal state and can make decisions about their radio operating behaviour based on that information and predefined objectives."*

By using only these common characteristics of all these definitions we reach at the definition of CR given in: "*Is a technology that provides a promising new way to improve the efficiency of the use of the electromagnetic spectrum that available, by using spectrum sensing for detection of spectrum holes (unused bands), and instantly move into vacant bands while avoiding occupied ones without harmful interference to the PU*."

4.CHARACTERISTICS

CR has two importantcharacteristic concepts should be featured [14]:

4.1 Cognitive capability

The cognitive capability of a CRis a process of observing the outside environment in order tofind unused radio spectrum and determine appropriate communication parametersto adapt to the dynamic radio environment.Metola first who explain the cognitive capability in term of the cognitive cycleduring which "*a cognitive radio continually observes the environment, orients itself, creates plans, decides, and then acts"*, as shown in figure 4 [15, p. 48].

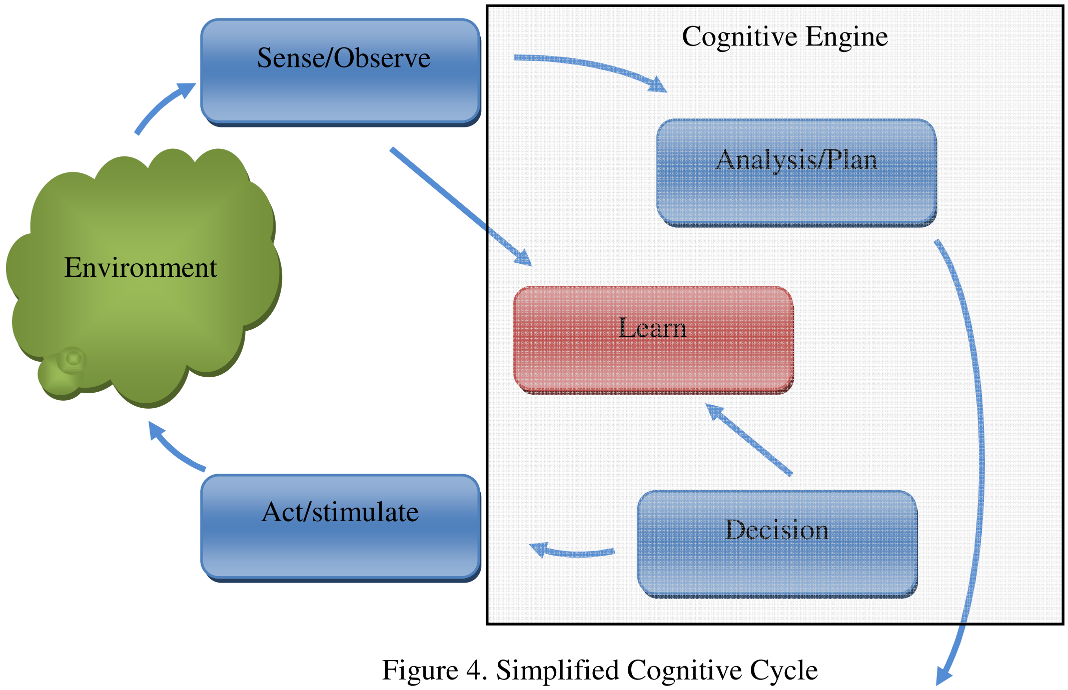

Figure 4. Simplified Cognitive Cycle

The process of *sensing* the outside world determines the presence of spectrum hole. The observations taken by the sensing will be supply into *plan* cycle processes in which further used, but they also supply to *learn* module to learn and remember.The *learning* allows the system to learn from the experiences. The *analysis* process is responsible for generating and analysingwork streams which may be taken, i.e. determines data rate, bandwidth, frequency, power, modulation, etc. At the*decision* stage of the cycle,the CRis chosen appropriate spectrum band for transmission of the signal.The *analysis,decision*and *learn*modules compose the inner part of the system, the intelligence which governs the entire CR: the *Cognitive Engine*. We consider a cognitive engine (similar to a human brain) to enable intelligence in the radio device. Finally the decision is put into *action* and the operation of the cognitive radio is actually influenced.The *sensing* (or *observation*) and *action* modules represent the interfaces of the CR with the real world. Similar cycles are used to describe the operation of cognitive radio by [11], [16],[17].

4.2Reconfigurability

Reconfigurabilityshows the radiocapability to change the functions accordingto enclosing i.e. cognitive radio can change the radio frequency, transmission power,modulation scheme, communication protocol in order to reach the optimal working [9], [11], [12].

5.EVOLVE TO BUILD COGNITIVE RADIO

The term ***radio*** refers to the wireless transceiver device, used the RadioFrequency (RF) as a part of the electromagnetic spectrum to transfer of information.

TraditionalHardware Defined Radio (HDR) can perform only a single or a very limited set of radio functionality, and can only be modified through physical intervention, all of modulation and demodulation is performed in the analog domain.This results in higher production budgets and smallest flexibility in supporting multiple signal standards.Over the pasttwo decades, analog radio systems are being substituted by digital radio systems for several radio applications in military, civilian and commercial spaces. As a result, Mitolainvented theidea of SoftwareDefined Radios (SDR) [18]-[20].SDR Forum [21] defines SDR technology as "*radios that provide software control of a variety of modulation techniques, wideband or narrowband operation, communications security functions (such as hopping), and waveform requirements of current & evolving standards over a broad frequency range.*"

SDR technology facilitates implementation of some of the radio functionality such as modulation/demodulation, signal generation, coding etc. in software modules running on a common hardware platform. SDR contains the same basic functional blocks as any other digital radio, but most, if not all, are implemented in software instead of hardware (e.g. mixer, filters, modulators, demodulators) [14],[22].

SDR architecture (a.k.a. physical layer) consists of three main units, which are software tunable RF front end, wideband Analog to Digital Converter (ADC) andDigital to Analog Converter (DAC) conversionthe implementation ofthe Intermediate Frequency (IF)section and software reconfigurable digital baseband radio,as shown in figure 5[22],[23].

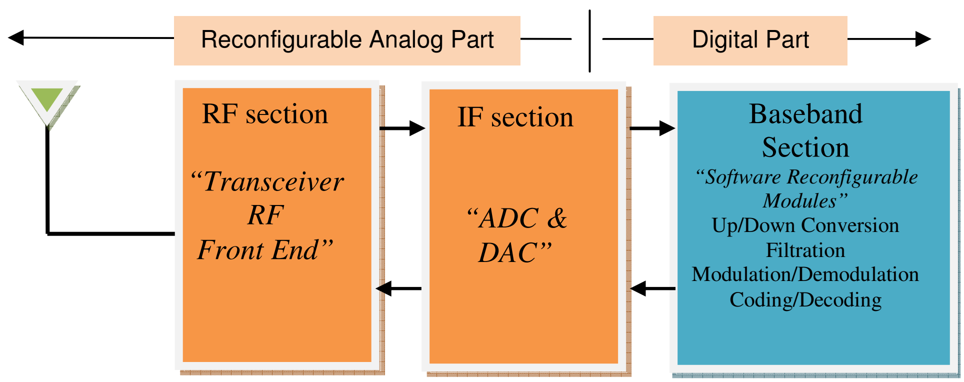

Figure 5. Block Diagram of SDR Transceiver.

The RF front-end is a term referring to the analog circuitry between the antenna and the data converters. The main functions of the RF front end are to modulate and demodulate the carrier with and from the data, respectively.

The ADC and DAC are theconnection between the physical world of continuous analog signals and the world of discrete digital samples handled by software.Baseband signal processing operations are defined by programmable designs running on digital hardware.This device is available in various forms on single-chip custom Integrated Circuits (ICs), of which the most commonly used for software radio are Digital Signal Processors (DSPs), Field Programmable Gate Arrays (FPGAs), General-Purpose Processors (GPPs), Application Specific Integrated Circuits (ASICs), and System-on-Chip (SoC) with hardware accelerators [21], [24], [25].

Since, SDR is built around software based digital signal processing along with software tunable radio frequency components, therefore , SDR represents a very flexible and general radio platform that is capable ofoperating with many different bandwidths over a wide range of frequencies and using many different modulation and waveform formats. As a result, SDR can support multiple standards, i.e., GSM, EDGE, WCDMA, CDMA2000, Wi-Fi, WiMAX and multiple access technologies such as Time Division Multiple Access (TDMA), Code Division

Multiple Access (CDMA), Orthogonal Frequency Division Multiple Access (OFDMA) [24], [26], [27].

A CR transceiver is senseradio environment and capable of adapting its physical layer parameters according to the environment. In order to achieve the highly flexible reconfigurable physical layer where communication features,thus, an SDR with all the latest communication techniques is the core of cognitive radio.In Figure 6 is evidenced the strict relationship between SDR architecture and CR one: by adding an artificial intelligence module to an SDR architecture, is feasible to obtain an adaptive, flexible device able to learn independently and to react to the external stimuli in a suitable manner [28], [29].

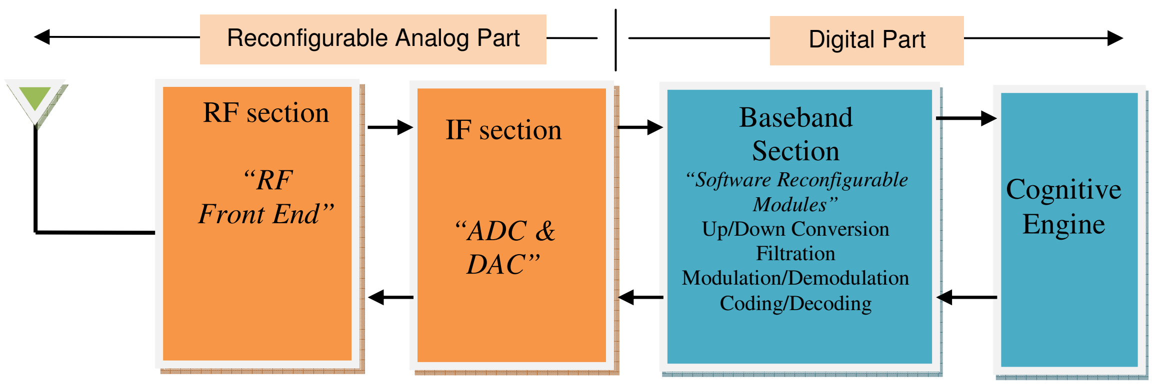

Figure 6. Block diagram of CR transceiver.

Depending on the set of criteria taken into account when deciding on the changes transmission and reception, there are two main types of CR:

- ***Full CR***(***Mitola radio***): In which every possible parameter observable by a SUtakes into account [1].
- ***Spectrum Sensing CR (Haykin radio)***: In which only the radio frequency spectrum is considered [11].

Mitola radio is not expected to be completely implemented until 2030, until the whole SDR hardware become available in a suitable size [30].The work presented here is for configuring the SDR for spectrum sensing CR.

We can also distinguish types of CR in terms of the parts of thespectrum available as:

- ***Licensed band CR:***is CR used in the bands that are used and sold by license. The IEEE 802.22 standard defines a system for a Wireless Regional Area Network (WRAN) that uses spectrum holes within the TVbands between 54 and 862 MHz. To achieve its aims, the 802.22 standard utilizes CR technology to ensure that no undue interference is caused to television services using the television bands. The standard is under development and is currently in draft form[31], [32].
- ***Unlicensed band CR:***can only utilize unlicensed parts of the radio frequency spectrum. There is one system in the IEEE 802.15 Coexistence Task Group 2 (TG2), which focuses on the coexistence of WLAN and Bluetooth [33].

6.SPECTRUM SENSING

Spectrum sensing (a.k.a.spectrum detection technique)is the main task in cognitive cycle and the main challenge to the CRs. In spectrum sensing studying the spectrum and find the unused bands and sharing it while avoiding the spectrum that is occupied by PU. It can be defined as [34]"*action of a radio measuring signal feature*". To enhance the detection probability many spectrum detection techniques can be used,as shown in Figure 7[17].

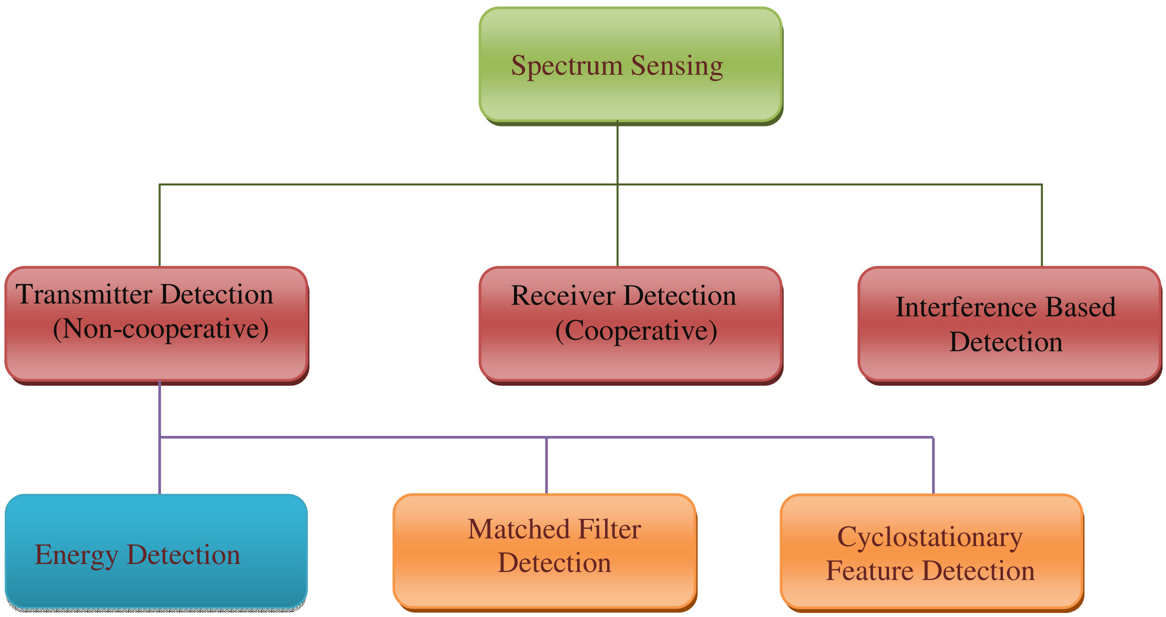

Figure 7.Spectrum Detection Techniques

1.5.1 Transmitter detection (Non-cooperative Detection)

In transmitter detection each CR must independently have the ability to determine the presence or absence of the PU in a specified spectrum.A hypothesized model for transmitter detection is defined in [17], [22], [35]-[37],that is, the signal detected by the SU is:

$$\begin{cases} H_0: y(t) = w(t) \\ H_1: y(t) = h.x(t) + w(t) \end{cases} \quad (1)$$

whereH_0 represents the hypothesis corresponding to "no signal transmitted", and H_1 to "signal transmitted", $y(t)$ is received signal, $x(t)$ is transmitted signal, $w(t)$ is an Additive White Gaussian Noise (AWGN) with zero mean and variance σ_n^2, and h amplitude of channel gain (channel coefficient).

Several methods have been proposed, such as, matched filter detection, energy detection, and cyclostationary feature detection[17], [35]-[37].

1.5.1.1 Matched Filter Detection

The matched filter detector that can use as CR has been first proposed in [38].The matched filter (also referred to as coherent detector), it can consider as a best sensing technique if CR has knowledge of PU waveform. It is very accurate since it maximizes the received signal-tonoise ratio (SNR).Matched filter correlates the signal with time shifted versionand compares between the final output of matched filter andpredetermined threshold will determine the PUpresence.Hence, if this information is not accurate, then the matched filter operatesweakly [17], [35]-[38].

1.5.1.2 Cyclostationary Feature Detection

Implementation of a cyclostationary feature detector, has been first presented in [39],as spectrum sensing which can differentiatethe modulated signal from the additive noise.A signal is said to be cyclostationary if its mean and autocorrelation are a periodic function. Feature detection denotes to extracting features from the received signal and performing the detection based on the extracted features. cyclostationary feature detection can distinguish PU signal from noise, and used at very low Signal to Noise Ratio (SNR) detection by using the information embedded in the PU signal that are not present in the noise. The main drawback of this method is the complexity of calculation. Also, it must deal with all the frequencies in order to generate the spectral correlation function, which makes it a very large calculation. The benefit of feature detection compared to energy detection is that it typically allows different among dissimilar signals or waveforms[17], [35]-[37], [39].

1.5.1.3 Energy Detection

Energy detection (also denoted as non-coherent detection), is the signal detection mechanism using an energy detector (also known as radiometer) to specify the presence or absence of signal in the band. The most often used approaches in the energy detection are based on the Neyman-Pearson (NP) lemma. The NP lemma criterion increases the probability of detection (P_{d}) for a given probability of false alarm(P_{fa}).

It is an essential and a common approach to spectrum sensing since it has moderate computational complexities, and can be implemented in both time domain and frequency domain. To adjust the threshold of detection, energy detector requires knowledge of the power of noise in the band to be sensed. Compared with energy detection, matched filter detection andcyclostationary detection require a priori information of the PUs to operate efficiently, which is hard to realizepractically since PUs differ in different situation.Energy detection is not optimal but simple to implement, so itis widely adopted.The signal is detected by comparing the output of energy detector with threshold which depends on the noise floor[2], [17], [35]-[37].

1.5.2 Receiver Detection (Cooperative Detection)

A collaborative spectrumsensing method has been first proposed by Ghasemi and Sousain [40].

CR cooperative spectrum sensing occurs when a group or network of CRs share the sense information they gainfor PU detection. This provides a more accurate spectrum sensing over the area where the CRs are located.Cooperative spectrum sensing plays a very importantrole in the research of CR due to its ability inimproving sensing performance especially in the fading, shadowing and noiseuncertainty[41], [42].

Figure 8illustrated multipath fading, shadowingand receiver's uncertainty. As shown in thefigure, CR1 and CR2 are placed inside the transmissionrange of the PU transmitter (PU TX) while CR3 is outsidethe range. Due to multiple attenuated copies of the PU signal and the blocking of a house, CR2 experiences multipath and shadow fading such that the PU’s signal may not be correctly detected. Moreover, CR3 suffers from the receiver uncertainty problem because it is unaware of the PU's transmission and the existence of the primary receiver (PU RX). As a result, the transmission from CR3 may interfere with the reception at PU RX. If CR users, most of which observe a strong PU signal like CR1 in the figure, can cooperate and share the sensing results with other users, the combined cooperative decision derived from the spatially collected observations can overcome the deficiency of individual observations at each CR user [17], [35].

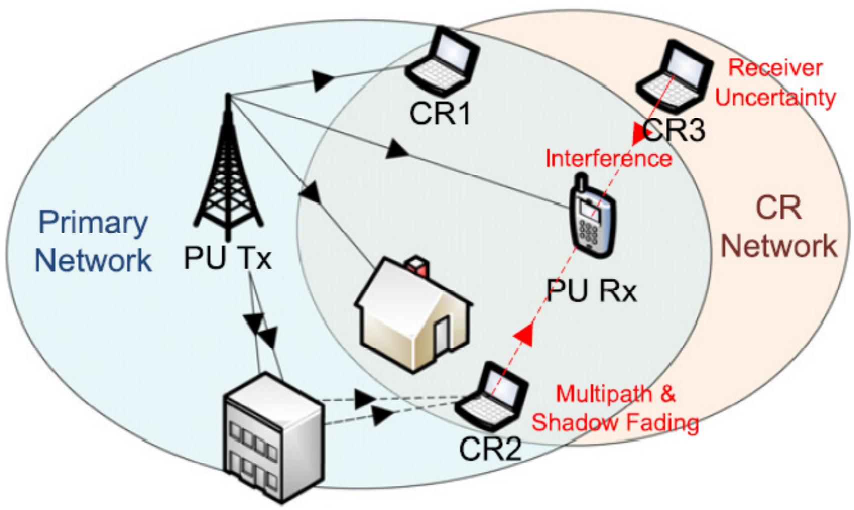

Figure 8. Receiver Uncertainty and Multipath/Shadow Fading

There are broadly two approaches to cooperative spectrum sensing [35], [43]:

1. **Centralised approach:** In this approach to CR cooperative spectrum sensing, there is a centralCRcalled fusion centre (FC) within the network that collects the sensing information from all the sense CRs within the network.For data cooperative, all CRs are tuned to a control channel where a physical point-to-point link between each cooperating CR and the FC for sending the sensing results is called a reporting channel as shown in Figure 9 (a). FC then analyses the information and determines the bands that can and cannot be used.

2. **Distributed approach:**Unlike centralized approach, distributed cooperative sensing does not depend on a FC for making the cooperative decision.Using the distributed approach for CR cooperative spectrum sensing, no one CR takes control. Each CR sends its specificdata of sensing to other CRs, merges its data with the received data of sensing, and decides whether or not the PU is present by using a local condition as shown in Figure 9 (b). However this approach requires for the individual CRs to have a much higher level of independence, and possibly setting themselves up as an ad-hoc network.

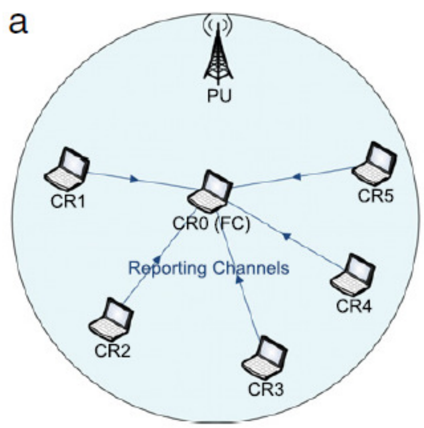

Figure 9. Classification of Cooperative Sensing: (a) Centralized, (b) Distributed

1.5.3 Interference Based Detection

Under the assumptions that if a signal *A* can interfere with signal *B*, then signal*B* is within the communication range of signal*A*.Asignal can be detected by checking the interference with the detector's signal[12], [17], [36].

From the viewpoint of detection of signals, techniques of sensing can be categorized into two categories: coherent and non-coherent detection. In coherent detection, the PU signal can be coherently detected by comparing the received signal characteristics with a priori knowledge of PU signals. Another way to classify sensing techniques is based on the bandwidth of the spectrum of interest for sensing: narrowband and wideband as shown in Figure 10 [35].

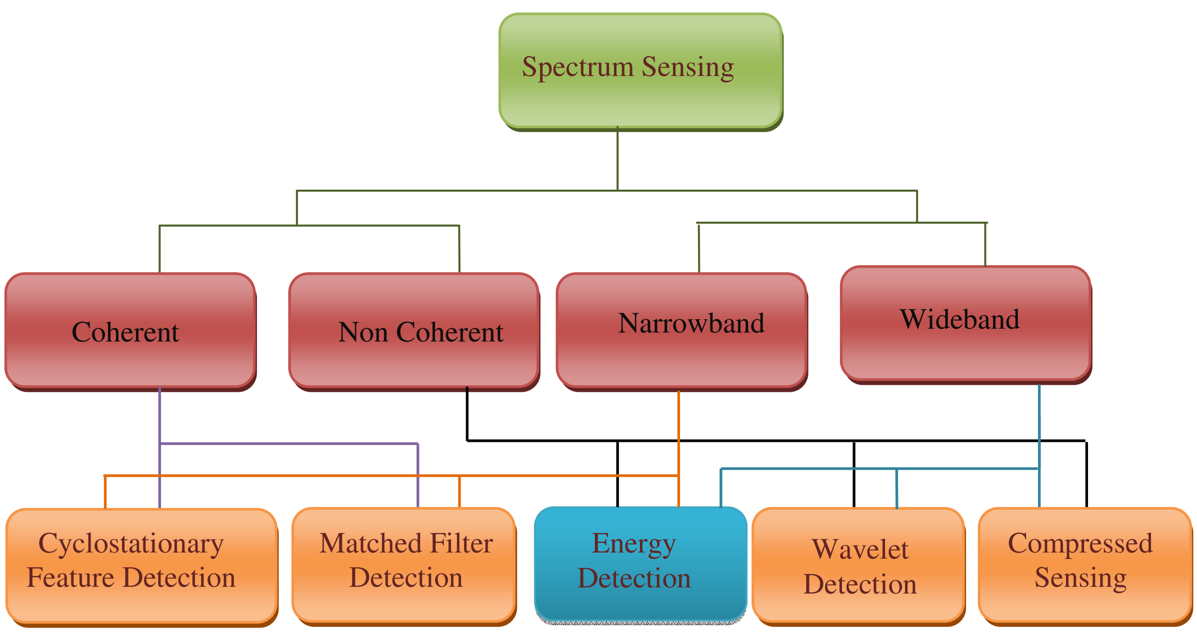

Figure 10.Another way to Classify Sensing Techniques

7. ENERGY DETECTION UNDERAWGNCHANNELS

Energy detection is the most popular signal detection method due to its simple circuit in practical implementation. The principle of energy detector is finding the energy of the received signal and compares that with the threshold [2].In the literature, we come across various algorithms indicating that energy detectioncan be implemented both in time and also frequency domain using Fast FourierTransform(FFT).

7.1 Time Domain Energy Detection

The most important preliminary work for the general analysis of energy detector in time domain was presented in the landmark paper [44], the Urkowitz proposed the model as shown in Figure 11.

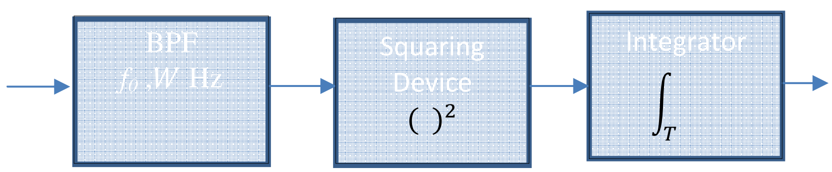

Figure 11.Time Domain Representation of Energy Detection

Urkowitz classic work was based on detection of a deterministic signal in an AWGN, and exact noise variance is known a priori. The input signal $y(t)$is first passed through an ideal BandpassFilter (BPF) with center frequency f_0 and bandwidth W, with transfer function

$$H(f) = \begin{cases} \frac{2}{\sqrt{N_0}}, & |f - f_0| \leq W \\ 0, & |f - f_0| > W \end{cases} \tag{2}$$

whereN_0 is the one-sided noise power spectral density, this normalizes it found convenient to compute the false alarm and detection probabilities using the related transfer function. After that the signal squared, and integrated in the observation interval T to produce a test statistic, V, is compared to a threshold λ. The receiver makes a decision that the target signal has been detected if and only if the threshold is exceeded.

The received signal $y(t)$of SU under the binary hypotheses testing can represent as

$$\begin{cases} H_0: y(t) = w(t) \\ H_1: y(t) = x(t) + n(t) \end{cases} \tag{3}$$

whereH_0 represents the hypothesis corresponding to “no signal transmitted”, and H_1 to “signal transmitted”, $x(t)$ is the unknown deterministic transmitted signal, and $w(t)$ assumed to be an AWGN with zero mean and variance $\sigma_n^2 = WN_0$is known a priori. The SNR is denoted as $\gamma = \frac{\sigma_s^2}{\sigma_n^2}$ where σ_s^2 variance of signal and σ_n^2 variance of noise. By using Shannon’s sampling formula, we can obtain the reconstructed noise signal

$$n(t) = \sum_{i=-\infty}^{+\infty} n_i \, sinc(2Wt - i) \tag{15}$$

where$sinc(x) = \frac{\sin \pi x}{\pi x}$ is the normalized $sinc$ function and $n_i = n(\frac{i}{2W})$ is the i-th noise sample. The test statistic under hypothesis H_0 as follows

$$V = \int_0^T (n(t))^2 dt \approx \frac{1}{2W} \sum_{i=1}^{2TW} n_i^2 \quad . \tag{16}$$

If we take the BPF effect and simplify, the decision rule which is employed by the energy detector can be obtained as

$$V = \frac{1}{WN_0} \sum_{i=1}^{2TW} |y[i]|^2 = \sum_{i=1}^{2TW} {y'}_i^2 \underset{H_0}{\overset{H_1}{\gtrless}} \lambda . \tag{17}$$

The same approach can be applied under hypothesis H_1 when the signal $x(t)$ is present, by replacing each n_i by $n_i + x_i$where $x_i = x(\frac{i}{2W})$.
The test statistic for both cases can be expressed as

$$V \sim \begin{cases} H_0: \chi^2_{2TW} \\ H_1: \chi^2_{2TW}(2\gamma) \end{cases} \tag{18}$$

whereχ^2_{2TW} chi-square distribution with the $2TW$ degree of freedom (DOF), and $\chi^2_{2TW}(2\gamma)$, noncentral chi-square distribution with the same number of DOF and a noncentrality parameter equal to 2γ. The probability of detection and probability of false alarm can be computed if $2TW > 250$ by

$$P_d = \frac{1}{2} \text{erfc}\left[\frac{\lambda - 2TW - \gamma}{2\sqrt{2}\sqrt{TW + \gamma}}\right] \tag{19}$$

$$P_{fa} = \frac{1}{2} \text{erfc}\left[\frac{\lambda - 2TW}{2\sqrt{2}\sqrt{TW}}\right] . \tag{20}$$

Based on Urkowitz'swork and some other related results,Mills and Prescott [45], presentedsix common radiometer models for the wideband radiometer. Comparisons with exact results showedthat these models touchwith the exact results for very large time-bandwidth (TW).

In recent year, Lehtomaki [46]has done a lot of research work in signal detection based on the ideal energy detector. His main goal was to develop energy based detectors. Different possibilities for setting the detection threshold for a quantized total power energy detector are analysed.

Ciftci and Torlak[47], compare energy detector models in [45] in both AWGN and Rayleigh channels. These models are very suitably and easily available for theoretical analysis when one model is utilizing the energy detector for spectrum sensing.

Lee and Akyildiz [48], in order to solve both the interference avoidance and the spectrum efficiency problem, an optimal spectrum sensing framework is based on the maximum a posteriori probability (MAP) energy detection and its decision criterion based on the primary user activities. The PU activities can be assumed as a two state birth-death process, death rate $\alpha$and birth rate β. Where each transition follows the Poisson arrival process meaning that the length of ON (Busy) and OFF (Idle) intervals of primary network are exponentially distributed. We can estimate the a posterioriprobability as follows

$$P_{\text{off}} = \frac{\alpha}{\beta + \alpha} \tag{22}$$

$$P_{\text{on}} = 1 - P_{\text{off}} = \frac{\beta}{\beta + \alpha} \tag{23}$$

where$P_{\text{on}}$is the probability of the period used by primary users and $P_{\text{off}}$is the probability of the idle period. From the definition of MAP detection, the $P_{\text{d}}$and P_{fa}can be expressed as follows

$$P_{\text{d}} = P[V > \lambda |\ H_1]P_{\text{on}} \tag{24}$$

$$P_{\text{fa}} = P[V > \lambda |\ H_0]P_{\text{off}} \tag{25}$$

where$\lambda$is a decision threshold of MAP detection.

The improved performance of the energy detector for random signals corrupted by Gaussian noise is derived. The derivation is based on a simple modification to the conventional energy detector in [44],Chen [49], by replacing the squaring operation of the signal amplitude with an arbitrary positive power operation.

$$V = \sum_{i=1}^{2TW} \left(\frac{y[i]}{\sigma_n}\right)^p . \tag{21}$$

Moghimi andSchober[50], propose a novel hybrid coherentenergy detection scheme for spectrum sensing whichdeveloped a corresponding low–complexity locally optimal decision metric.This hybrid metric is a linear combination of coherent and energy detection metric and combines the advantages of these individual metrics as it exploits both the pilot and the data symbols emitted by the PU.

Dhope et al.[51], describethe hybrid detection method which takes the advantages oftwomethods, energy detection performs well in high SNR value and not dependent on the correlation of incoming signal but suffers from the noise uncertainty problem. Covariance Absolute Value (CAV) outperforms in high correlation environment. The simulation and comparison is made betweenCAV and energy detection for differenttypes of input. The simulation shows that the proposed hybriddetection method outperformed energy detection and CAV method and is more insensitive to the type ofinput data.

Guicai YU et al. [52], a new energy detection algorithm based on dynamic threshold is presented. Theoretic results and simulations show that the proposed scheme removes the falling proportion of performance and detection sensitivity caused by the average noise power fluctuation with a choice threshold, and also improves the dislike of the average noise power fluctuation in a short time and obtains a good performance.

7.1 FrequencyDomain Energy Detection

In order to measure the signal energy in frequency domain, the received signal is first selects the interesting bandwidth by a band pass filter and sampled, then converted to frequency domain taking FFT followed by squaring the coefficients and then taking the average over the observation band. Finally, according to a comparison between the average andthreshold, the presence or absence of the PU can be detected as shown in figure 12.

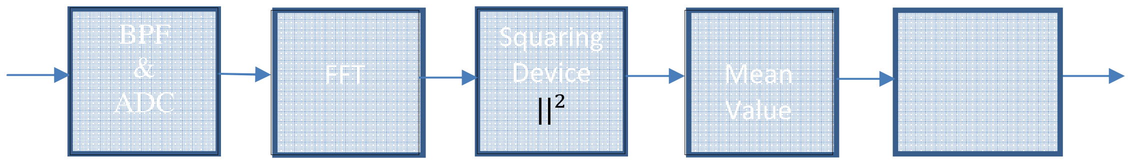

Figure 12.FrequencyDomain Representation of Energy Detection

The energy detection can be implemented in the frequency domain using periodograms and the Welch's periodogram.The periodogram method is a Discrete Fourier Transform (DFT) based method to estimate Power Spectral Density(PSD).The idea of the Welch's periodogram is to divide the data sequence into segmentswith windowing. In the Welch's method these data segments can be overlapping andnon-overlapping.Using overlapped windows that decreases the noise variance compared to single periodogram estimation.

The use ofspectrum sensing based on the frequencydomain energy detection hasbeen studied for cognitive radio systems in[53]-[58]. Cabric et al. [53],using a periodogram to estimate the spectrum viasquared magnitude of the FFT. The testbed used in the experiments is built around theBerkeley Emulation Engine 2 (BEE2).Mustonen et al. [54], the performance of spectrum sensing basedon the Welch'speriodogram was studied for cooperatingnodes in AWGN channel.

Zayen et al. [55], the smoothing was applied to the Welch's periodogrm based sensing, increasing the performance whilekeeping the complexity in relatively low level. Chen et al. [56], the Welch's periodogram basedspectrum sensing algorithm called FAR is introduced. It is thebeauty of the algorithm that the decision variable is insensitive tonoise level.

EIRamly et al.[57], a Modified Energy Detection (MED)technique uses for spectrum sensing of narrow-band FMsignal in the Wireless Microphone (WM) silent mode.Spectrum sensing using themodified periodogram and Welch method for different windowtypes.

Miar and Aboulnasr [58], new methods of spectrum sensing based onsimplified DFT matrices are introducedfor PSD estimation for CR.The methodis less computationallycomplex than DFT techniques since no multiplications arerequired in the time-to-frequency domain conversion process.

8. ENERGYDETECTIONUNDERFADINGCHANNELS

Energy detection has been used widely for spectrum sensing unknown deterministic signals [44]. However, the performing analysis of energy detection over fading channels is heavy, because it is hard to derive closed-form expressions for the average probability of detection involving the generalized Marcum Q-function and the log-normal distribution.

8.1 Time Domain Energy Detection

Kostylev [59], analysis a signal with random (Rayleigh, Rice, and Nakagami) amplitude.$P_d$andP_f are derived for Rayleigh, Rice and Nakagami fading channels. Digham et al. [60], presents another analysisof the problem of energy detection of unknown signals over different fading channels. The analysis focuses on no-diversity case under Rayleigh, Rice and Nakagami fading channels, and quantify the improvement in the probability of detection when multiple antennas (diversity) methods for energy detection based systems like equal gain combining (EGC), selection combining (SC), and switch and stay combining (SSC) are used. Digham et al. [61] the focus is on different a multiple antenna processing based energy detector receptions such as maximal ratio combining (MRC), selection combining (SC), switch-and-stay combining (SSC), square-law combining (SLC) and square-law selection (SLS) under Rayleigh fading channels. The average probability of detection over Rayleigh, Nakagami and Rician fading channels has been derived. Pandharipande and Linnartz [62], derived closed-form expressions for the probability of detection and expressions for the probability of false-alarm for each multiple antenna processing based energy detection scheme (SC and MRC) to analyse the detection performance gain as compared to a single antenna energy detection scheme. Herath andRajatheva [63], The energy detector with equal gain combining (EGC) reception under Nakagami-m fading channels is analysed

Torrieri [64], a practical energy detector (energy detector with bandpass sampling) is described and analysed for the AWGN and Rayleigh channels with and without diversity combining. The noise power at the radiometer output can be measured quite accurately if the measurement interval is sufficiently long.

Li et al. [65], studies the PU signaldetection methods over Rayleigh fading channel in CR system. Double threshold detection proposes withchannel selector. In this method, the cognitive user receivessignals by selecting the maximum SNR channel, so it caneffectively detect the PU signal in Rayleighfading environment.

Atapattu etal. [66], Inthis paper, the detection performance of an energy detector usedfor spectrum sensing in CR networks is investigatedunder such very low SNR levels. Theanalysis focuses on the derivation of a closed-form expression forthe average missed-detection probability over Rayleigh fadingand Nakagami-m fading channels.

8.2Frequency Domain Energy Detection

Matinmikko et al. [67], evaluated the performance of spectrum sensing using Welch's periodogram in Rayleigh fading channels for CR systems. The performance measures considered were the receiver operating characteristics that quantify the relations of the $P_d$and P_f.

The energy detection method remains the most common detection mechanism currently in use in cooperative sensing [35].This is because some of its performance degradation due to the noise uncertainty can be mitigated by the diversity gain resulting from cooperation. Atapattu et al. [68], Detection performance of an energy detector used for cooperative spectrum sensing in a CR network is investigated over channels with both multipath fading and shadowing.Harjulaet. al. [69], cooperativespectrum sensing based on the Welch periodogramstudies in the frequency selective fading environment. The work focused on OFDM signal detection. The effect of the frequency selective channel was also studied for both single and multicarrier signals. The cooperation impact and the differences between the decision-making rules of the sensing nodes were also studied for the aforementioned scenarios. Hekkala et al. [70], extend previous research done in [69] by focusing on the practical implementation-related topics. In order to reduce the computational complexity of the spectrum sensing, smaller FFT size uses in the Welch'speriodogram. The implementation complexity of the Welch'speriodogram and the required processing power are therefore estimated.

Gismalla and Alsusa, [71], provide a performance analysis of cognitive radio systems employing energy detection based on PSD estimation. Mathematical expressions are derived for the probability of false alarm, and the probability of miss for i.i.d Rayleigh and Rician channels. In comparison with time-domain energy detection, find that the probability of false alarm at a specific frequency is not affected by changing the observations length.

9. CONNCLUSIONS

In this paper a review of the CRs technology was presented. Energy Signal Detection is introduced as a figure of merit on which to base quantitative assessment of a radiometer's design including its calibration architecture and algorithm. The problem of the spectrum detection schemes was formulated which include Energy detection in time and frequency domain. Energy detection has been adopted as an alternative spectrum sensing method for CRs due to its simple circuit in the practical implementation and no information requires about the signal needed to detect.

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