Robust Two-Stage Spectrum Sensing and Policy Management for Cognitive Radios Using Fourth Order Cumulants

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Abstract- Cognitive radios (CRs) require efficient spectrum detectors that are able to work in low signal-to-noise ratio (SNR) environments. These detectors have little or no information about the signals or noise to utilize the spectrum in an efficient manner. The present paper proposes an autonomous policy-based CR focusing on policy management using spectrum sensing. A separate wireless communication channel known as the sensing policy channel (SPC) is utilized for this purpose. The SPC is monitored for presence of signals. Based on the sensing decision the policy engine loads specific policies onto the CR. By using the theory of higher-order statistics (HOS), a two-stage spectrum sensing method using filter bank based energy detector and fourth order cumulants, is also proposed in this paper. A normalization method for the conventional cumulants is presented using the power values at the energy detection stage. Simulations show that the proposed two-stage method based on energy detection and fourth order cumulants helps to improve the convergence of the conventional cumulants to its true value for a specific signal at low SNRs. Through simulations, this improvement is shown to increase the detection ability of the proposed cumulants over the conventional cumulants for various signals at low SNRs. Typically the proposed cumulants method shows an improvement of 27% in the probability of detection of an OFDM signal at an SNR of -15 dB for a constant false alarm rate of 0.1 when compared with the conventional cumulants method. It is also shown to outperform various conventional methods such as energy detection, cyclostationary feature detection and the conventional two-stage sensing method. Experiments are conducted to determine the average decision time for sensing and policy enforcement. The overall performance of the proposed policy-based CR aided by sensing is shown to be good at the expense of complexity and average decision time.

Keywords- Policy Management; Software Defined Radio; Spectrum Sensing; Higher Order Statistics; Cognitive Radio

I. INTRODUCTION

Over the last decade, various radio technologies requiring more spectral resources have impacted the wireless communication systems. Spectrum scarcity has become a key issue because of the static allocation of electromagnetic spectrum to licensed users known as primary users (PUs). The new class of radios, namely the software defined radios (SDRs), and cognitive radios (CRs) provide flexibility and agility that help in dynamic allocation of spectrum. A survey of the spectrum utilization made by the Federal Communications Commission (FCC) in 2002 suggested that there are regions of licensed spectrum that are regularly utilized, never utilized, or utilized for brief periods of time [1]. This renders the spectrum usage inefficient which facilitates a change in the management of spectrum utilization.

A cognitive radio (CR) [2] is an intelligent communication device that is environment-aware and can adapt by changing its transmission parameters such as carrier frequency, bandwidth, modulation, and transmission power. These secondary user (SU) radios are allowed to access the vacant spectral regions known as spectrum holes in an opportunistic fashion. This aspect of CR is known as dynamic spectrum access (DSA). One of the key features of CR is the ability to sense a wideband spectrum in order to identify these holes. This requires the CR to change its receiver parameters in a dynamic fashion, which is achieved using SDR technology. SDRs can be used to provide control over a variety of modulation schemes, transmission parameters and waveform requirements for various communication standards without changing the hardware.

Spectrum sensing and DSA can be considered as a multi-layer problem involving a lot of parameters such as frequencies, bandwidths of operation, waveforms, power levels, noise scenarios, regulatory environments and application requirements. It is very difficult to develop optimal sensing algorithms that can consider most of these factors, in order to utilize the spectrum in a flexible manner. Instead, a flexible policy mechanism that supports spectrum sharing and usage of various waveforms according to the changes in policies has to be designed [3]. All the radio devices are by definition policy-enabled devices, dealing with their own policies depending on the physical capabilities of the radio and the communication standard. CRs and SDRs offer the ability to create policy-enabled devices that can help in utilizing under-utilized spectrum. Due to hardware constraints, a CR has to deploy a sensing policy that defines when and which frequency band needs to be sensed. Based on the sensing results, the CR decides which waveforms need to be loaded on to the radio. Sensing policies can be determined, in a dynamic fashion, either individually or collaboratively. They can determine which waveform standard need to be used based on a pre-determined rule and hence determine when the spectrum is to be considered available for opportunistic access [4]. Some applications where such a policy-based radio can be
used are public safety radios, emergency situations and aerospace communications.

In this paper, a policy-based CR focusing on policy management by means of spectrum sensing is proposed. A separate channel known as the sensing policy channel (SPC) is allocated for this purpose. The CRs monitor the SPC frequently in order to sense signals at various frequency locations. Depending on these sensed signals, a CR determines which policies need to be loaded. These policies that can be loaded are already pre-defined in the CR. The motivation for a policy-based CR is to support dynamic adaptability which allows it to change policies without stopping or restarting the system. In addition, the authority to change policies resides with the CR. This can have a profound impact on the emerging wireless communication standards, as many waveforms can operate in a reconfigurable fashion using the proposed method. The CRs determine which policy has to be loaded, based on the signals sensed in the SPC. Hence, the detection of the signals has to be accurate and robust so that the CRs load correct policies without causing any interference and/or conflicts. It is in this context that the present paper investigates a filter bank based energy detector and HOS-based two-stage spectrum sensing method, where the sensing policy channel is monitored for signals in a parallel fashion.

This paper is organized as follows. Section II presents various policy management schemes in SDR and spectrum sensing technologies available in the literature. It also elucidates the need for a policy based CR using SDR. Section III introduces the proposed two-stage spectrum sensing method and the proposed policy management describing the design insights used in our method. In Section IV, various simulation results for the proposed spectrum sensing method and experimental analysis of the overall method is presented. Section V provides the conclusions.

II. RELATED WORKS

This section deals with policy management in SDR based CR technology in general, and to DSA in particular. It also elucidates the previous work on various spectrum sensing algorithms and its advantages and disadvantages.

A. Policy Management in Radios

In general, policy management in radios involves managing policies pertaining to the working configuration of a radio. This is performed by specifying certain objectives in the policies that can be interpreted and enforced by the radio. These policies are procedural statements expressing specific conventions like modulation scheme, carrier frequency, bandwidth etc., which are adopted by the communication standard. However in the context of a CR, policies are sensing-based and refer to conventions that define when and which frequency band has to be used for opportunistic access. A policy engine (PE) is defined as a program or process that can deploy these machine-readable policies [5]. The PE must be able to automatically modify the run-time configuration of the CR based on the policies that get loaded. These policies are pre-defined in the PE, and get loaded onto the CR depending on the spectrum sensing unit.

The PE is an inference engine that initiates the change in resource configurations such as change in the operating frequency, the spectral band of interest, and other such device configurations in the case of a CR. The outputs of a PE are generally authorization commands that are specific to a standard. Much of the research in the area of policy-based CR has been focused on developing a formal language for expressing complex policies for various communication standards and network management problems [8-10]. The Defense Advanced Research Projects Agency’s (DARPA’s) Next Generation (XG) radio communications program [3-6] develops novel technologies and system concepts for DSA. The Phase III of the XG program focused on many technical issues, such as the processing power and signal sensing requirements. As part of the XG program, a policy-based network management system for controlling DSA was proposed in [6]. Most of the literature assumes that the CR can be implemented using a SDR platform. However the CR architecture is one of the important issues in the deployment of a CR as it involves software interfaces and application-programming interface (API) that has to be provided by the services on the host platform. Apart from platform integration issues, the policy engine has to be integrated with the CR’s software architecture. Software Communications Architecture (SCA) is one such layered architecture which provides APIs for control and information exchange as well as for integration with new applications that are supported by the core framework [11]. The Joint Tactical Radio System (JTRS) defines the SCA based on Common Object Request Broker Architecture (CORBA) middleware [12]. The PE will be another component in this architecture that can interface with other components supported by the core framework. However, one of the most important architectural considerations is the definition of this interface of PE to the software environment of the radio.

In this paper, we propose an integrated framework for a policy-based CR with spectrum sensing capability. SDR is dependent on the SCA architecture chosen for reconfiguration. However, the main focus of this paper is not on the software architecture, but the spectrum sensing and policy management in such radios. In the next subsection, various existing spectrum sensing algorithms are discussed in detail.

B. Spectrum Sensing Methods

Spectrum sensing and detection methods have been studied extensively in the literature and are broadly categorized as matched filtering, energy detection and cyclostationary feature detection [13].

Matched filtering provides optimal detection but it requires full a priori knowledge about the signal and hence is not a good solution for CR. Energy detection is the most widely used detection method as it requires no knowledge of the input signal and is less complex but it is not robust to
noise, interference and fading. Cyclostationary detection provides better detection accuracy but is computationally more complex and needs longer sensing time than the energy detection method. However, none of these methods is efficient in highly noisy conditions. For this purpose, higher-order statistics (HOS)-based spectrum sensing using higher order signal characteristics was proposed in [14]. It is a robust statistical approach, which can effectively sense the spectrum by calculating the relevant HOS features known as cumulants. They perform better at extremely low SNR environments but the disadvantage is that it requires a higher sample set to obtain the whole set of cumulants and better detection accuracies. This results in a longer sensing time. As a result, the HOS-based spectrum sensing methods cannot be directly applied to the wideband spectrum for real-time sensing.

Many two-stage methods have been proposed in literature by combining the methods discussed above [15-18]. For example, a two-stage sensing based on energy detection in both the stages with different signal bandwidths was proposed in [15]. A CR first searches over a larger bandwidth in the coarse sensing stage using a simple method such as energy detection. Once the energy detector detects a spectrum hole, it goes to the fine sensing stage using a more robust detector such as cyclostationary detection. Fine sensing stage is activated to decide whether the channel is empty with confidence or the PU was present but missed in the detection during the coarse sensing stage. In a largely subscribed spectrum scenario such as the commercial mobile communications, the number of PUs is more. In such a case, determining spectrum holes becomes an even more difficult task because of out-of-band interference and spectral leakage that might lead to erroneous decisions on the spectrum usage. Using a two-stage sensing scheme for such a scenario will offer good detection accuracy. As mentioned above, in the coarse sensing stage, the spectrum is sensed over a large bandwidth consisting of many PU channels using energy detection. If the detection determines the presence of signal, the fine sensing stage is not activated. However, some vacant bands may have been missed because the coarse sensing stage operates on a larger bandwidth.

In order to find the spectrum holes, there is a need to perform sensing at the channel bandwidth in real-time. Fine sensing stage performs sensing at the channel bandwidth but only if coarse sensing fails to determine the presence of a PU. The CR not only has to sense the spectrum in real time but also move away from the band if there is any PU requesting channel access. This provides a bottleneck on the sensing time and poses a challenge in real-time spectrum sensing causing an inherent trade-off between sensing time and sensing accuracy. We propose a sensing policy channel that has to be sensed regularly to understand the utilization of a spectral region. There is a need for robust, less complex spectrum sensing methods for deployment of CR. However, the accuracy in sensing is affected when there is an upper bound on the sensing time. In order to reduce the overhead in performing spectrum sensing accurately and robustly at channel bandwidth, we decided to employ a separate sensing policy channel that has pre-defined policies regarding the spectrum usage. The CRs check for specific signals in the sensing policy channel. Based on the signal sensed at various frequencies in the SPC, the corresponding policy is loaded. This policy contains the information on the waveform and the frequency band to be used for communication. The CR then loads the required waveform in the SDR without causing any interference in the specific band.

In order to facilitate the use of automatic policy management in CRs and to improve sensing performance, the present paper investigates a two-stage spectrum sensing method. The first stage is the filter bank based energy detector where the sensing policy channel is split into various subbands. The use of a filter bank is two-fold. Firstly, it helps in reducing the time taken for sensing the SPC when compared to serially sensing the spectral region. Secondly, the sampling rate of the incoming signal can be reduced by moving the decimator closer to the ADC. The power value of each subband is calculated in a parallel fashion. This power value is used as a normalization factor for the fourth-order cumulants calculated in the next stage. The second stage consists of the cumulants operation on all the subbands based on HOS. Although the proposed scheme has two stages of operation, it differs from the conventional two-stage methods in [15-17] in two ways. Firstly, the methods in [15-17] perform sensing by attempting to detect the signals using binary hypotheses in both the first and second stage, whereas in this paper, the hypothesis testing is performed only at the end of the second stage. Secondly, in this paper the cumulant values calculated are normalized using the subband power values calculated in the first stage. This is performed to remove the effects of noise on the cumulant and improve the detection accuracy of the proposed cumulants based sensing method at very low SNR conditions. In the next section, we discuss the proposed policy-based CR and the two-stage spectrum sensing in detail.

III. PROPOSED POLICY-BASED COGNITIVE RADIO

The proposed policy-based cognitive radio with its various components is shown in Fig. 1(a). The proposed model comprises of three main components for deployment of a CR namely; policy engine, policy control interface and the SCA-based SDR.
Fig. 1(a) shows that the policy engine serves three main policy management functions: policy definition files, policy decisions, and policy enforcement. The policy definition files maintain all the policies that need to be enforced to decide which waveform to be instantiated in the SDR. It also performs operations such as parsing and keeping track of policies that are enabled and disabled. The policy decision function determines which of the existing policies have to be enforced. In order to make these decisions, it requires information about the communication conditions and/or the spectral scenario. It communicates with the spectrum sensing unit in the policy control interface that reports real-time information on the spectrum policy channel. The policy enforcer function acts as the control interface to constrain the radio’s behavior according to the policy and communicates with the SCA framework through its components. It also performs actions that are defined in the policy. The SCA framework is the core framework for an SDR. The focus of this work is on the PE and spectrum sensing, and the details regarding the SCA framework for SDRs are considered out of scope of this paper. While [4] deals with an extensive set of policy models and engines for policy management and decision making for policy-based CRs, in this paper we focus on the deployment of a policy engine. For the sake of simplicity, we propose a policy engine that encompasses the most essential functions of policy definition, deployment, and enforcement.

As previously mentioned, the policies required for the CR are pre-defined in the PE. These policies, known as the policy definition files, are loaded depending on the spectrum sensed by the CR in the sensing policy channel. The sensing policy channel consists of different signals that have a one-to-one mapping with the policies defined in the policy definition files. In this paper we use an open source software project named Apache Imperius as the PE. It uses the Simple Policy Language (SPL) for the policy definition files [18]. SPL is an object-oriented policy language that allows expression of management policies using simple condition-action rules. The PE Imperius provides an extensible set of operations for expressing these conditions and actions. We use JavaSPL (Imperius with Java binding) which extends SPL to interact with Java objects directly. The JavaSPL is wrapped to python using JPy [19] which allows full access to all the Java class libraries. The policy enforcer communicates with the SCA framework and loads the corresponding waveform defined in the policy database or the policy definition files. In the next subsections various policies and the sensing policy channel are described in detail.

A. Proposed Sensing Policy Channel

The proposed sensing policy channel consists of $M$ discrete frequency bands with center frequencies $\{f_1, f_2, ..., f_M\}$. The wideband bandwidth of the sensing policy channel is assumed to be 1 MHz. The corresponding policies that need to be loaded for the specified frequency bands are denoted as $\{P_1, P_2, ..., P_M\}$ respectively. These policies load waveforms $\{W_1, W_2, ..., W_M\}$ respectively, when they are enforced. The SDR based CR can reconfigure between $M$ waveforms based on the policies that are being loaded. The policy condition is defined below:

1. Policy $P_i$ allows the policy-based CR to operate using the waveform $W_i$, if it can detect a signal in $f_i$ for all $i$’s, given $1 \leq i \leq M$. For e.g. policy $P_1$ is loaded when a signal is detected at a center frequency $f_1$. $P_i$ instructs the policy-based CR to operate using the waveform $W_i$.

2. The policy also has the information on transmission parameters such as the bandwidth and frequency of operation for a specific policy depending on which waveform instance is instantiated in the SCA framework.

3. Although the proposed detection is called two-stage, the detection is performed at the end of second stage. The cumulant estimates (second stage) calculated are error corrected using the power values of subbands (energy detection) calculated in the first stage.

The proposed two-stage method is different from conventional two-stage methods in the sense that binary hypothesis detection is performed only once at the end of second stage. However, it is computationally complex because of the HOS moments calculated for all the cumulant estimates. The present paper does not focus on reducing the complexity of the method but on improving the performance of sensing. The two-stage method in [20] can be used with our method to reduce the complexity. It is shown in [20] that in case of scenarios where the SNR is high, the detection performance of energy detection alone is equivalent to that of complex methods such as cyclostationary feature detection. Thus, if the SNR is known to the receiver, the second stage can be used sparingly to detect the signal. The complexity incurred in using two stages for sensing can be minimized in this manner. In [20], the authors perform a two-stage spectrum sensing using energy detection in the first stage and cyclostationary feature detection in the second stage. In contrast, the proposed two-stage spectrum sensing algorithm uses fourth-order cumulants in the second stage.

The proposed method is discussed in detail in the next subsection, to showcase the difference between the proposed method and a conventional two-stage method as in [20].

B. Proposed Spectrum Sensing Method

The overall block diagram of the detection method is illustrated in Fig. 1(b).
It is illustrated in Fig. 1(b) that the filter bank is used to separate the observed sensing policy channel into uniform frequency channels. The filter bank consists of an M-channel uniform discrete Fourier transform filter bank (DFTFB) to split the sensing policy channel into multiple subbands of uniform bandwidths. For simplicity sake, we assume both the number of policies and subbands to be equal to M. Power values, as in the case of energy detection, are calculated for all the subbands and this is considered as the first stage of the detection. The energy detector accumulates the power of N samples in each band in this stage to locate possible signals in the frequency locations \{f_1, f_2, ..., f_M\} in a parallel fashion. The normalized power values of the subbands obtained in the first stage are used as weights for the fourth order cumulants estimated in the next stage. Thus, at the end of both stages, a test statistic based on the new estimate of fourth order cumulants for each of the channels are compared with a threshold \( \gamma \), to decide whether the channel is empty or occupied. It is this threshold which determines the performance metrics; probability of detection \( P_d \), and probability of false alarm \( P_{fa} \) of the system. The hypothesis testing performed on the test statistic is defined as

\[
H_0: r(n) = \eta(n) \quad H_1: r(n) = s(n) + \eta(n)
\]

(1)

where \( r(n) \) is the general expression for received signal, \( H_0 \) testifies the presence of zero mean additive white Gaussian noise (AWGN) \( \eta(n) \) alone, while \( H_1 \) testifies the presence of a signal \( s(n) \) corrupted by AWGN respectively. The conventional fourth order cumulant method estimates the cumulant values of the received signal. Ideally, if the signal is corrupted by AWGN, the corresponding fourth order cumulants are zero. Typically, a Gaussianity test, where the calculated cumulant values are compared with zero as threshold, is performed using the estimates of the conventional cumulants value. In low SNR cases, the energy detection fails due to the uncertainty in noise and also under the effects of fading. Moreover, the values of the estimated cumulant are very low in the case of low SNRs that the detector decides that it is purely noise. By calculating the power values and using them as weights for the cumulant values of the subbands, we propose a new set of cumulant estimates in this paper. This aspect is shown in the following analysis of the proposed two-stage sensing method.

According to the properties of higher order cumulants, a typical \( p^{th} \) order-\( q^{th} \) conjugate cumulant is defined as follows

\[
L_{pq}(x) = \sum_{r-q}^{\infty} \sum_{s-q}^{\infty} \sum_{t-q}^{\infty} \ldots \sum_{x-q}^{\infty} \left( x \ldots x^{*} \ldots x^{*} \right)
\]

(2)

where \( x \) is a random variable, associated with the random process for the transmitted data sequence \( s(n) \). \( x^{*} \) denotes the complex conjugate of \( x \). \( L_{pq}(x) \) is the defined as the zero-lagged cumulant value. A fourth order cumulant yields a three dimensional matrix of values. However, the most significant is the zero-lagged cumulant value. In order to reduce the complexity involved in dealing with 3-D matrix, we used the simple zero-lagged cumulant value. Expressions for the second and fourth order cumulants according to the moment-to-cumulant formula are given by the following relations respectively:

\[
L_{(1,1)}(x) = \sum_{m=0}^{N} (x_m)^2
\]

(3)

\[
L_{(1,2)}(x) = \sum_{m=0}^{N} x_m x_{m+1}
\]

(4)

It can be noted that \( L_{(1,1)}(x) \) is actually the power of the signal \( x \). The normalized fourth order cumulant is given as

\[
\overline{L_{(1,1)}}(x) = \frac{L_{(1,1)}(x)}{\left( L_{(1,1)}(x) \right)^{1/2}}
\]

(5)

The filter bank splits the received signal into its polyphase components and the \( i^{th} \) branch of the polyphase filter bank has an impulse response \( h_i(m) \) given by

\[
h_i(m) = h(mM + i)
\]

(6)

where \( h(m) \) is the impulse response of the prototype filter of length \( L \). The output signal at the \( i^{th} \) branch is given below:

\[
x_i(n) = \sum_{m=0}^{N} h_i(m) n(n-m) e^{j2\pi m \theta M}
\]

(7)

In this method, fourth-order cumulants based on higher order statistics are used for detection. We choose fourth-order cumulants over third-order cumulants or higher order moments. The reason for this is that for a random process which is symmetrically distributed, both the third-order cumulant equals zero. Moreover, some processes and signal modulations have extremely small third-order cumulant value and larger fourth-order cumulant value. Hence, we prefer to use fourth-order cumulants over the third-order cumulants.

Note that the present paper also utilizes higher order cumulants instead of higher order moments for sensing. Based on practical issues, there are two reasons we work with cumulants over moments. Firstly, the fourth-order cumulants of AWGN are ideally zero; whereas various known signals have non-zero value. Secondly, the cumulants possesses the property that the cumulant of two statistically independent random processes equals the sum of the cumulants of the individual random processes (see Equations (8)-(10)), whereas the same is not true for higher order moments. These two properties of cumulants motivated us to work with fourth-order cumulants. However, the variances of the estimates of such cumulants are large and increase as the order increases for a constant data size. This may lead to error in detection. In order to reduce the error, higher data sizes have to be considered. This in turn will increase the computational complexity, which will lead to increased sensing time and power consumption. Calculating the value of cumulants involves computing averages of several samples from the real data over many dimensions (three in the case of a fourth order cumulant). In order to minimize the computational complexity involved in
calculating a multidimensional matrix for cumulants, we use the zero-lag value of the cumulant as a test statistic in the proposed sensing scheme.

Applying the zero-lagged fourth order cumulants on the output in (7) we can obtain the expression for the cumulant estimate of the transmitted signal as shown in Equations (8)-(10).

\[
\overline{L}_{42}(s) = \frac{L_{42}(s(n))}{L_{22}(s(n))} \left( \sum_{m=0}^{N-1} h(m)(s(n-m) + \eta(n-m)) \right)^{2m} \left( \sum_{m=0}^{N-1} h(m)(n-m) \right)^{2m} \]

\[
\frac{L_{42}(s(n))}{L_{22}(s(n))} = \left( \sum_{m=0}^{N-1} h(m)(s(n-m) + \eta(n-m)) \right)^{2m} \left( \sum_{m=0}^{N-1} h(m)(n-m) \right)^{2m} \]

\[
\overline{L}_{42}(s) = \frac{L_{42}(s(n))}{L_{22}(s(n))} \left( \sum_{m=0}^{N-1} h(m)(n-m) \right)^{2m} \left( \sum_{m=0}^{N-1} h(m)(n-m) \right)^{2m} \]

Equation (10) was obtained by applying the cumulant operation on (9) [10]. If the noise is AWGN, then the fourth order cumulant is zero according to higher order statistics. Thus the equation can be easily modified to obtain the estimate of the cumulant of the transmitted sequence, \( \overline{L}_{42}(s) \).

\[
\overline{L}_{42}(s) = \overline{L}_{42}(\eta) \left( \sum_{m=0}^{N-1} h(m)(n-m) \right)^{2m} \left( \sum_{m=0}^{N-1} h(m)(n-m) \right)^{2m} \]

It is seen from (12) that the expression for estimated cumulant of the transmitted signal depends on three factors, namely; calculated cumulant value on the received signal, the SNR and filter coefficients of the filter bank. The effect of SNR on the cumulant value is denoted as \( \alpha \). When the signal power is very low compared to the noise (low SNR conditions), \( \alpha \) can be approximated as given below:

\[
\alpha = \left( 1 + \frac{L_{42}(\eta)}{L_{22}(s)} \right)^{2} \approx \left( \frac{L_{42}(\eta)}{L_{22}(s)} \right)^{2} \]

In cases where the noise variance is not known, or cannot be calculated, mitigating this error would be a tedious process. For this purpose, we propose an algorithm where the power values of each subband normalized to the received signal power are used as weights on the cumulant value calculated on the subband. In order to estimate the cumulant value of the transmitted sequence, the wideband signal is split into \( M \) subbands using the DFTFB. The signal power of the received signal is calculated as \( P_{nb} \). The power of each subband, namely \( P_{i} \), is calculated. The normalized fourth order cumulant values of each subband are calculated using (5) and are used to calculate the cumulant estimate of the transmitted sequence, denoted as \( \text{est}(\overline{L}_{42}(s)) \) using the weights as shown below.

\[
w_{i} = \frac{P_{i}}{P_{nb}} \]

\[
\text{est}(\overline{L}_{42}(s)) = w_{i} \cdot \overline{L}_{42}(s) \]

This estimate is used to determine the presence or absence of a signal in the received spectrum. When a signal is present in a specific subband, the power value of the subband is higher than that of the power of the received signal. This is because the averaging of samples is done over a smaller bandwidth in the case of a subband, as compared to the wideband bandwidth of the input signal. Thus the weight, which is the ratio of the power of the subband to the power of the received signal, has a value more than unity. This improves the value of the cumulant when the signal is present. When there is no signal, however, the value of the weight is dependent only on the variance of the noise and this will not increase the estimated cumulant value of the noise. In order to understand this effect, the proposed method is analyzed through simulations and compared with various conventional methods of spectrum sensing in the next section.

IV. SIMULATION RESULTS AND EXPERIMENTAL ANALYSIS

In this section, the proposed method is analyzed through various simulations. Two sets of simulations are performed; the effect of the proposed normalization process, and the performance comparisons in terms of probability of detection and false alarm. An experimental setup showing the functionality of the proposed policy-based CR is also illustrated in the later part of this section.
A. Analysis of the Proposed Two-stage Sensing Method

In this subsection, simulations are performed to analyze the proposed sensing scheme for performance comparisons. Case 1 shows how the proposed cumulant estimates are error-corrected for cases of low SNRs. Case 2 deals with the detection probability of the proposed sensing method.

Case 1: A specific modulation scheme was selected for the input signal, but the number of channels was randomly chosen. Three sets of simulations involving BPSK, 16-QAM and 64-QAM were selected separately at Channels 3 and 6. Fig. 2(a), shows the estimated cumulant value for the proposed method as compared to the conventional cumulant method, both plotted against the channel numbers for an SNR of -10 dB. The number of observation samples for each block is 1024 samples. The number of Monte Carlo simulation is set as 3000. It is evident from Fig. 2(a) that at a low SNR of -10 dB, the conventional cumulant values of the modulations are close to zero, which would force the spectrum sensing unit to decide wrongly that there is no signal present. However, by employing the proposed detection scheme, it is seen that the cumulant values are improved.

The true fourth order zero-lagged cumulant values for [BPSK, 16-QAM, 64-QAM] are \([-2, -0.68, -0.6191]\) respectively \([22]\). This will reduce the error in detection at the second stage of sensing in cases of low SNRs. The proposed two-stage method and the algorithm based on weights helps in converging the value of the estimated cumulant closer to the true value of the cumulant for various types of signals analyzed. It is also clear from the above plot that the improvement in the cumulant value for 64-QAM is better than that of 16-QAM and BPSK. This is because all the symbols of these three constellations were considered with a constant minimum distance between the symbols as 2. Since 64-QAM has 64 symbols it is spread out more than 16-QAM or BPSK and hence, the convergence probability of a received symbol into one of those 64 symbols is high. Intuitively, for a constant average power, the constellation with more symbols has shorter distance between their symbols. This would mean a high symbol error rate. For a fair comparison between modulation schemes we chose symbols such that the minimum distance between them is a constant for all modulations.

The impact of this improvement in the cumulant value of the proposed method reaches 0.12 dB on an SNR of 0 dB. This will reduce the error in detection at the second stage of sensing unit to decide wrongly that there is no signal present. However, by employing the proposed detection scheme, it is seen that the cumulant values are improved.

Fig. 2(a) Proposed cumulant value and conventional cumulant value plotted against the channel numbers for BPSK, 16-QAM and 64-QAM signals at SNR=10 dB

The positive effect of the normalization process can be illustrated in terms of the histogram of the estimated cumulant value. 3000 simulations were conducted and the histogram of the proposed cumulant value and conventional cumulant value for a 64-QAM signal \((H_s)\), and AWGN \((H_0)\) are plotted in Fig. 2(b). In the case of only AWGN, the value of cumulant does not change drastically from its true value of zero. However, in the case of a signal immersed in AWGN the value of the cumulant is shown to have improved. The impact of this improvement in the cumulant value is elucidated below through simulations.

Fig. 2(b) Histogram comparisons of the proposed cumulant value and the conventional cumulant value for the binary hypothesis for a 64-QAM signal

The positive effect of the normalization process can be illustrated in terms of the histogram of the estimated cumulant value. 3000 simulations were conducted and the histogram of the proposed cumulant value and conventional cumulant value for a 64-QAM signal \((H_s)\), and AWGN \((H_0)\) are plotted in Fig. 2(b). In the case of only AWGN, the value of cumulant does not change drastically from its true value of zero. However, in the case of a signal immersed in AWGN the value of the cumulant is shown to have improved. The impact of this improvement in the cumulant value is elucidated below through simulations.

Fig. 3(a), 3(b) and 3(c) show the performance improvement in the probability of detection for the proposed two-stage method over the conventional cumulants method versus SNR for a 64-QAM, 16-QAM and BPSK signal, respectively. The number of simulations conducted is set at 3000, with a signal block of 1024 symbols per simulation. The threshold for the test statistic was calculated by keeping the probability of false alarm constant at 0.1 for the conventional cumulants method. This calculated threshold was used to perform detection for both the proposed and conventional method. It is evident from these three plots that the false alarm rate of the conventional cumulants method is at 0.1. Fig. 3(a) suggests that the proposed method and the conventional method provide a high detection ability of 99.87% for SNRs ranging from -20 dB to 0 dB for a 64-QAM signal. However, the false alarm rate of the proposed method reaches zero from -12 dB onwards for the same threshold value. Fig. 3(b) shows that the present method outperforms the conventional cumulants method for SNR values lower than -12 dB at a lower false alarm rate. At an SNR of -16 dB the proposed cumulants method gives 75% improvement in the detection ability when compared with the conventional cumulants method.
Fig. 3(a) Probability of detection and false alarm versus SNR for a 64-QAM signal using the conventional and proposed cumulants method.

Fig. 3(b) Probability of detection and false alarm versus SNR for a 16-QAM signal using the conventional and proposed cumulants method.

Fig. 3(c) Probability of detection and false alarm versus SNR for a BPSK signal using the conventional and proposed cumulants method.

The proposed method outperforms the conventional cumulants methods by 27% approximately, for an SNR as low as -15 dB. It also outperforms the two-stage method proposed in [20] by 58% approximately. The proposed method gives a detection ability of 96.7% for an SNR of -15 dB for the OFDM signals considered.

B. Experimental Setup and Analysis

In this subsection, the experimental setup for the proposed policy engine and spectrum sensing is elucidated. These experiments are designed to evaluate the performance of the proposed scheme in a real world scenario. In order to capture and analyze the signals, we have used a Universal Software Radio Peripheral 2 (USRP2) [23] board with an indoor Thomson ANTD120 DVB-T antenna. The hardware setup required to capture the signal is summarized in Table I.

<table>
<thead>
<tr>
<th>Processor</th>
<th>Intel Pentium 2.26 GHz (Core 2 Duo), 4 GB RAM</th>
</tr>
</thead>
<tbody>
<tr>
<td>OS</td>
<td>Ubuntu 10.04 LTS</td>
</tr>
<tr>
<td>GNU Radio</td>
<td>3.3 or later</td>
</tr>
<tr>
<td>SDR RF hardware</td>
<td>USRP2</td>
</tr>
<tr>
<td>RX Antenna</td>
<td>Thomson ANTD120 DVB-T (4.0 MHz to 862 MHz)</td>
</tr>
</tbody>
</table>

The proposed two-stage method was simulated for detecting OFDM signals with signal parameters given in [20]. The noise uncertainty is assumed to be known to the receiver for a fair comparison between these methods. The performance of the sensing method was evaluated in terms of the variation of its probability of detection versus the SNR, as compared to the probability of detection of various other sensing methods.

detection depends on the number of samples considered for simulation. For a fair comparison, we took the number of symbols to be 1024 for all the modulation schemes. The proposed cumulant method gives 80% detection ability at an SNR of -4 dB which is 60% more than the conventional cumulants method for the same false alarm rate of 0.1.

Case 2: The proposed two-stage method was simulated for detecting OFDM signals with signal parameters given in [20]. The noise uncertainty is assumed to be known to the receiver for a fair comparison between these methods. The performance of the sensing method was evaluated in terms of the variation of its probability of detection versus the SNR, as compared to the probability of detection of various other sensing methods.
In these over-the-air tests, signals were sent in the sensing policy channel using the signal generator with an antenna connected to its RF output and received by the USRP2 board which is connected to the processor where the detection is performed. The signal generator transmits the signal at known signal power level of -20 dBm. The receiving antenna, which is connected to the USRP2, is positioned at a distance of approximately 3m from the transmitting antenna. This setup is shown in the Fig. 5(a) and Fig. 5(b). In these tests, we have no control over the noise channel. The noise need not be purely AWGN and there is also the effect of multipath/fading on the transmitted signal although we tried to provide a clear line of sight. To perform energy detection in such a case, we need to have a clear idea on the noise characteristics such as variance, and hence the noise power. The frequency band of operation was chosen arbitrarily as 649.5 MHz to 650.5 MHz in the TV white space region. This region of spectrum corresponds to the sensing policy channel which determines the policy to be loaded onto the SDR. The main objective of the experiment was to control policies for an SDR based CR using the spectrum sensing unit. Our main challenges, therefore, were to implement a fully operational PE along with signal processing on the received signal in the sensing policy channel. The number of policies was varied to check the performance of the proposed system in terms of average decision time (ADT). It is calculated by performing 1000 experiments for a specific number of policy changes and calculating the time taken to instantiate the policy each time. This is averaged over the number of experiments to give the ADT for a specific number of policy changes. Similarly, experiments for different number of policy changes were conducted and ADT was calculated and tabulated in Table II. XG DARPA in [6] performed similar experiments to obtain the average decision time for policy enforcement. However, they considered dynamic frequency selection (DFS) as a benchmarking policy as it is currently the only policy defined by FCC for SDRs. In Table II, we have shown the ADTs of both the methods for a fair comparison. It is clear that the proposed policy engine combined with the two-stage based spectrum sensing provides sensing and policy management with by utilizing slightly more time for decision as compared to an existing methodology for DSA. In this method, we provide a policy strategy for spectrum sensing in SDR enabled CRs. The ADT includes the time taken to sense the signals in the sensing policy channel and the time taken for the policy to be enforced in the PE.

<table>
<thead>
<tr>
<th>Number of policies</th>
<th>Proposed method</th>
<th>XG DARPA [6]</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>23.24</td>
<td>21</td>
</tr>
<tr>
<td>2</td>
<td>25.78</td>
<td>22</td>
</tr>
<tr>
<td>4</td>
<td>29.3</td>
<td>25</td>
</tr>
<tr>
<td>8</td>
<td>31.62</td>
<td>29</td>
</tr>
</tbody>
</table>

V. CONCLUSIONS

In this paper, a policy-based CR, which loads policies based on the sensing of a specific channel known as sensing policy channel, was presented. The sensing policy channel consists of signals that have to be sensed at various pre-defined frequencies. These signals are sensed in order to determine the working configuration (i.e., which waveform to be selected for communication) of the SDR. This is expected to have a profound impact on the deployment of CR as many standards can operate in a reconfigurable fashion using the proposed method. By keeping a separate sensing policy channel to determine which waveform is to be loaded, we provide a policy strategy for CR based on sensing. It allows policies to be dynamically changed and controlled. The proposed PE concept is implemented using an off-the-shelf Java Imperius policy engine and the SCA architecture. The proposed sensing method is a two-stage filter bank based energy detector and higher order cumulants. The filter bank used for channelization is used for spectrum sensing as well, resulting in complexity reduction. The two-stage spectrum sensing method involves calculation of HOS based fourth order cumulants. These cumulant values are normalized using weights obtained by the power values of the corresponding subbands. Applying binary hypothesis testing, it is shown through simulations that the normalization method helps in improving the cumulant value to its true value. This improvement is shown, through simulations, to increase the detection ability of the proposed cumulants over the conventional cumulants methods for BPSK, 16-QAM and 64-QAM signals. The proposed cumulants method shows an improvement of 27% in the probability of detection for an OFDM signal at an SNR of -15 dB for a constant false alarm rate of 0.1, when compared with the conventional cumulants method. It is also shown to outperform various conventional methods such as energy detection, cyclostationary feature detection and the conventional two-stage sensing method. In this paper the fourth order zero-lag cumulant was considered for high sensing performance. The performance of the sensing
method comes at the cost of the computational complexity involved in calculating higher order moments. However, the average decision time of the proposed method indicates that the proposed method takes only slightly more time than the conventional XG DARPA policy based SDR. Spectrum sensing based policy management for CRs is considered in this paper. The proposed methods have been shown to be better or on par in performance with various existing methods in the literature. Reduction of the computational complexity of the method is of interest for future improvement in this direction, as the cumulants considered are of higher order.

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