A HOS-Based Blind Spectrum Sensing in Noise Uncertainty

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Abstract. Spectrum sensing for cognitive radio is a challenging task since it has to be able to detect the primary signal at a low signal to noise ratio (SNR). At a low SNR, the variance of noise fluctuates due to noise uncertainty. Detection of the primary signal will be difficult especially for blind spectrum sensing methods that rely on the variance of noise for their threshold setting, such as energy detection. Instead of using the energy difference, we propose a spectrum sensing method based on the distribution difference. When the channel is occupied, the distribution of the received signal, which propagates under a wireless fading channel, will have a non-Gaussian distribution. This will be different from the Gaussian noise when the channel is vacant. Kurtosis, a higher order statistic (HOS) of the 4th order, is used as normality test for the test statistic. We measured the detection rate of the proposed method by performing a simulation of the detection process. Our proposed method's performance proved superior in detecting a real digital TV signal in noise uncertainty.

Keywords: *blind spectrum sensing; cognitive radio; HOS; kurtosis; noise uncertainty; normality test; spectrum sensing.*

1 Introduction

The main advantage of software defined radio (SDR) implementation is its support for reconfigurable communication systems. In SDR, the electronic circuit is replaced by software. Changing transmission parameters, such as modulation or transmission frequency, is easily solved by configuring the software; a new electronic circuit is not required. SDR is the enabler for shifting ordinary radio to cognitive radio. Cognitive radio is a radio that understands the context in which it finds itself and as a result it can tailor the communication process in line with that understanding [1]. Compared to ordinary radio, cognitive radio has cognitive capability and reconfigurability [2]. Cognitive capability refers to its ability to sense the environment (e.g. to find the unused

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spectrum). Once it finds the opportunity to transmit in an unused frequency, the communication system can easily be reconfigured to switch to that frequency.

Cognitive radio has several potential applications, for example incognitive radar [3]-[4], satellite communication [5], and wireless communication [6]. The most popular application of cognitive radio is for spectrum sharing in wireless communication. The recent radio access standard based on the cognitive radio concept follows the rule that allows transmission on a vacant channel (i.e. a channel that is not being used) [7]. This application comes from the fact that while the spectrum is fully allocated, its utilization can be low. It is expected that the use of the cognitive radio concept will increase spectrum utilization. In this paper, the term cognitive radio refers to spectrum-sharing cognitive radio.

There are two co-existing users in cognitive radio, the primary user and the secondary user. Before transmitting, the secondary user has to find a spectrum hole. It must be ensured that when the secondary user occupies a spectrum hole, its transmission will not cause harmful interference to the primary user. Spectrum sensing has to accurately detect spectrum holes. If the occupied spectrum is detected as vacant, this will cause harmful interference, whereas if a vacant channel is detected as occupied, it will result in lower spectrum holes utilization.

One of the most challenging tasks in spectrum sensing is the ability to detect a very weak signal while dealing with some constraints, such as wireless fading, noise fluctuation and limited knowledge of the signal's parameters. As such, several proposed sensing methods provide various levels of performance and complexity. Performance is usually measured by probability of detection (P_d) and probability of false alarm (P_f). Spectrum sensing in the IEEE 802.22 standard, for example, requires stringent sensing. For a maximum false-alarm probability of 10%, a sensing algorithm should achieve a detection probability of 90% for a signal as low as -20 dB SNR. Beside performance, the complexity is also important. The complexity can be measured based on computation and implementation complexity.

A blind sensing algorithm that does not require primary signal parameters usually gives lower implementation complexity. Energy detection, covariance and correlation based algorithm are examples of blind spectrum sensing. Energy detection is easy to implement. Unfortunately, due to noise uncertainty, its performance is worse at low SNRs. In this paper, we propose a method based on higher order statistics (HOS) to enhance the energy detection method's performance. Kurtosis of the received signal is used as test statistics. Their values are compared with a predefined threshold to distinguish between occupied spectrum and white space. Empirical estimation of the system's noise is used to find the threshold. Experimental validation showed that its performance is better than energy detection in noise of uncertain power. The rest of this paper is organized as follows: related previous work is presented in Section 2, a system model of the spectrum sensing problem in Section 3, an explanation of the proposed method in Section 4, the results of the performance evaluation in Section 5, and finally the conclusion in Section 6.

2 Related Work

Several sensing methods have been proposed, such as: matched filtering, feature detection and energy detection [8]-[9]. In the matched filtering method a matched filter is used to recognize the presence of the primary signal. Its detection accuracy is high at low SNRs. However, this method requires different filters for different primary signals and the filter design itself requires information such as the pilot and frame structure of the primary signal. Similarly, for the feature detection method that relies on cyclostationarity, sufficient signal information must be given as well. In practice, a cognitive radio should be able to perform spectrum sensing in case of limited knowledge of the primary signal's structure and other related parameters.

The energy detection approach differs from both other methods in that it works without knowledge of the primary signal's parameters to be detected [9]. This method exploits the energy difference between the occupied and vacant channel condition. It compares the energy of the received signal with a pre-defined threshold. This method is simple to implement. The works reported in [10] and [11] are examples of ED implementation for spectrum sensing. Due to its low complexity, energy detection is the most preferable and popular method. However, its performance decreases at low SNRs due to noise uncertainty [12] and its performance is much lower than that of the matched filtering and feature detection method.

Previous works have adapted a blind sensing method to improve the performance of energy detection by increasing the square factor of its statistic test [13]-[15]. Other methods exploit the distribution difference. These methods are based on the assumption that the distribution of mixed signals and noise is different from the sole distribution of noise [16]-[17]. A recent HOS based detection of DTV signals using 4th to 6th order cumulants has become the recommended sensing method in the IEEE 802.22 standard [7]. The latest refinement of this method, based on goodness of fit testing, uses the Jarqur-Bera statistic test [16]. Although the proposed methods have impressive performance results, they have a high complexity.

3 System Model

There are numerous existing wireless systems and standards for communication, wireless sensor netwok, broadcasting, and radar. Each wireless system requires a dedicated frequency channel. The available frequency is fully allocated. This causes frequency scarcity for future new applications. While the available frequency is fully allocated, a paradox exists when some measurements show that the frequency utilization by the license holder is quite low, only to up 30%. The cognitive radio concept is a solution to increase the efficiency of spectrum usage.

Figure 1 depicts two coexisting systems in spectrum sharing cognitive radio, i.e. a primary user network and a cognitive radio network. As a license holder, the primary user has the right to transmit on the frequency band at any time. Secondary users are allowed to transmit only when the channel is vacant or when the channel is not being used by primary users. A secondary user has to cease transmission on the vacant channel when a primary user returns to use the band. If the secondary user fails to stop transmission, this will cause harmful interference to the primary user.

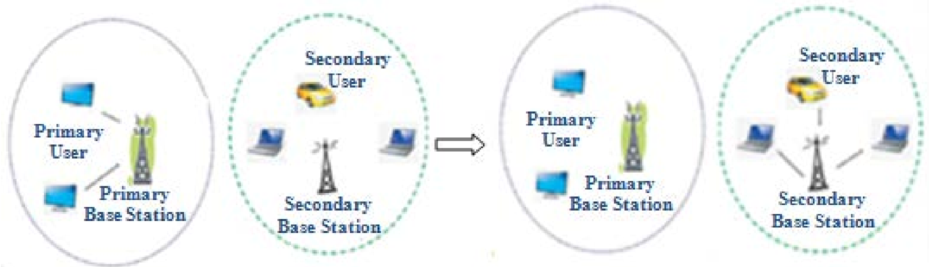

Figure 1 Secondary user uses the vacant channel.

The primary task of cognitive radio is to perform spectrum sensing. The aim of spectrum sensing is to find the unused frequency spectrum by a continuous sensing of the primary user's transmission activity on a certain band. If the channel is being used, the spectrum-sensing module will receive the primary user's signal. The received signal may fluctuate due to several factors, such as the distance from the primary user, multipath fading and shadowing. This fluctuation may make the received signal level fall below the receiver's thermal noise. As such, it is difficult to detect the presence of the signal.

Suppose **r** is the received signal. When transmission of a primary signal exists, this will comprise the primary user's signal **s** and thermal noise **w**. Hence, we have:

$$r(n) = s(n) + w(n) \tag{1}$$

$S(n)$ is the primary signal, which is received by spectrum sensing. Wireless channel fading effects are already contained in it. $S(n) = 0$ if there is no transmission from the primary signal. $W(n)$ is the receiver noise, which is mostly modeled as additive white Gaussian noise (AWGN).

Spectrum sensing decides which condition of the received signal is the true condition. There are two possible conditions at each detection time instance. The first condition is H_0, when the signal is absent. The second condition is H_1, when the signal is present. Suppose N samples are used for detection. The problem can be modeled as an equation for hypothesis testing [18]:

$$H_0 : r(n) = w(n) n = 0, 1, \dots, N-1 \tag{2}$$

$$H_1 : r(n) = s(n) + w(n) n = 0, 1, \dots, N-1 \tag{3}$$

Based on N samples, spectrum sensing has to make the decision: H_1 or H_0.

Hypothesis testing in spectrum sensing produces two possible detection results: true detection or false detection. The spectrum sensing will give true detection if condition H_1 is detected by the spectrum sensing as H_1. True detection should be high because it is important to ensure that active transmission from the primary user is detected, even when the received signal is very low. If primary user transmission is incorrectly detected as vacant, a secondary user can start to transmit a signal. This will cause harmful interference to the primary user. Conversely, if a vacant channel (H_0) is detected as occupied (H_1), the secondary user will miss the opportunity to transmit.

The detection algorithm aims to maximize the true decision, which is measured by the probability of detection (P_d). This is the conditional probability of $P_d = P\big((H_1)\big|(H_1)\big)$. Spectrum sensing also has to minimize false decisions (probability of false alarm). Probability of false alarm is the probability of making a false H_1 decision. This is the conditional probability of $P_f = P\big((H_1)\big|(H_0)\big)$. Due to the limited knowledge of the probability distribution of each condition in cognitive radio, the spectrum-sensing algorithm is a class of detector which works based on the Neyman-Pearson theorem [18]. P_d, maximized in the condition of P_f, is set to a certain fixed value. For example, the IEEE 802.22 standard requires a maximum P_f of 10% [6],[7]. As a performance metric, P_d should achieve 90% for the proposed sensing method.

4 Proposed Method

The spectrum sensing unit comprises of RF, IF and detection sections. The secondary user can perform spectrum sensing in the time domain or frequency domain. The more efficient alternative is spectrum sensing in the frequency domain using digital implementation of FFT [19], as described in Figure 2.

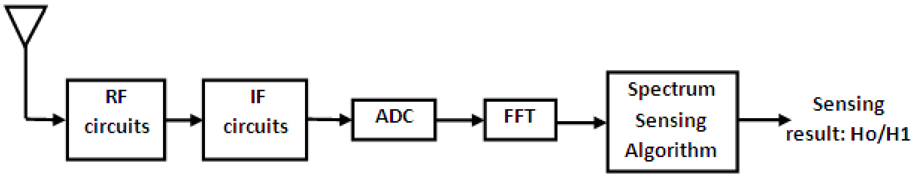

Figure 2 Spectrum sensing system block diagram.

Detection is done by comparing received signal r with a certain threshold λ. This threshold is generated from the probability of false alarm. The probability of false alarm can be defined as:

$$P_f = \int_{r:L(r)>\lambda} p(\boldsymbol{r}|H_0)dr \tag{4}$$

We have to adjust the threshold (λ) so that P_f will be bounded to a certain maximum predefined value, for instance 10%.

After we get λ, we can define a maximum likelihood ratio test (LRT) equation as follows:

$$L(r) = \frac{p(\boldsymbol{r}|H_1)}{p(\boldsymbol{r}|H_0)} > \lambda \tag{5}$$

Likelihood ratio $L(r)$ in Eq. (5) expresses the likelihood of the received samples tending to the condition of H_1 or H_0.

It is assumed that $\boldsymbol{s}$ is a vector of WSS Gaussian random variables with variance σ_s^2. And w is AWGN with the variance σ^2. Then likelihood ratio $L(r)$ in Eq. (5) is:

$$L(r) = \frac{\frac{1}{\left(2\pi(\sigma_s^2+\sigma^2)\right)^{\frac{N}{2}}}\exp\left(-\frac{1}{2(\sigma_s^2+\sigma^2)}\sum_{n=0}^{N-1} r^2(n)\right)}{\frac{1}{(2\pi\sigma^2)^{\frac{N}{2}}}\exp\left(-\frac{1}{2\sigma^2}\sum_{n=0}^{N-1} r^2(n)\right)} \tag{6}$$

If we take the logarithmic differentiation for both sides of Eq. (6), we will get the log-likelihood ratio:

$$l(r) = \frac{N}{2}\ln\left(\frac{\sigma^2}{\sigma_s^2+\sigma^2}\right) + \frac{1}{2}\frac{\sigma_s^2}{\sigma^2(\sigma_s^2+\sigma^2)}\sum_{n=0}^{N-1} r^2(n) \tag{7}$$

Based on Eq. (7), the detector will decide H_1 if $\sum_{n=0}^{N-1} r^2(n) > \lambda$.

Energy detection is a straightforward and less complex spectrum sensing method based on Eq. (7). The power of the received signal is compared with a predefined threshold (λ). The energy detection algorithm computes the test statistic:

$$T(\boldsymbol{r}) = \|\boldsymbol{r}\|^2 = \frac{1}{N}\sum_{n=0}^{N-1} r^2(n) \tag{8}$$

Probability of detection can be expressed as$P_d = P\big(T > \lambda\big|(H_1)\big)$and the probability of false alarm as $P_f = P\big(T > \lambda\big|(H_0)\big)$. We need to find the distribution of each possible condition in order to find the analytical expression of P_f andP_d.

Under the hypothesis H_0, only $w(n)$ is assumed to exist in the received signal. As $w(n)$ has Gaussian distribution with variance σ^2, $T(\boldsymbol{r})$ will be a chi-squared random variable with 2N degrees of freedom and hence the probability of false alarm can be expressed as:

$$P_f = P(T(\boldsymbol{r}) > \lambda|H_0) = 1 - F_{2N}\left(\frac{2\lambda}{\sigma^2}\right) \tag{9}$$

Under the H_1 hypothesis, suppose the signal's average power or its variance is σ_s^2, $T(\boldsymbol{r})$ is a chi-squared randorm variable with 2N degrees of freedom, and the probability of false alarm is:

$$P_d = P(T(\boldsymbol{r}) > \lambda|H_1) = 1 - F_{2N}\left(\frac{2\lambda}{\sigma_s^2+\sigma^2}\right) \tag{10}$$

Suppose $\boldsymbol{r}$ comprises of identically independent distribution (i.i.d.) samples, for the large number of $\boldsymbol{r}$, using the central limit theorem, we can make an approximation so that:

$$F_{2N}(r) \approx 1 - Q\left(\frac{r-2N}{2\sqrt{N}}\right) \tag{11}$$

where $Q(x) = \frac{1}{\sqrt{2\pi}}\int_x^\infty exp\left(\frac{v^2}{2}\right)dv$ is the Marqum Q-function.

Denoting that the primary signal's power is σ_s^2 and the test statistic T is Gaussian, distribution of H_0 becomes:

$$T(r)\big|H_0 \sim N\left(\sigma^2, \tfrac{1}{N}2\sigma^4\right) \tag{12}$$

And distribution in condition H_1 will follow

$$T(r)\big|H_1 \sim N\left(\sigma_s^2 + \sigma^2, \tfrac{1}{N}2(\sigma_s^2+\sigma^2)^4\right) \tag{13}$$

From Eq. (12) we can express the probability of false alarm in the form of the Marqum Q-function as:

$$P_f = Q\left(\frac{\lambda - \sigma^2}{\sqrt{\frac{2}{N}}\sigma^2}\right) \tag{14}$$

And the probability of detection in the form of:

$$P_d = Q\left(\frac{\lambda - (\sigma_s^2 + \sigma^2)}{\sqrt{\frac{2}{N}}(\sigma_s^2 + \sigma^2)}\right) \tag{15}$$

Eqs. (14) and (15) provide an easy means to measure the performance of energy detection (ED). The performance is a function of received signal power and noise variance. We can find a closed form of the required number of samples for a certain value of signal to noise ratio (SNR) from Eqs. (14) and (15). The SNR is defined here as $\gamma = \frac{\sigma_s^2}{\sigma^2}$

$$N = \frac{2\left[Q^{-1}(P_f) - Q^{-1}(P_d)(\gamma+1)\right]^2}{\gamma^2} \tag{16}$$

Eq. (16) shows the relationship between number of samples (N), SNR, P_f and P_d. For spectrum sensing in cognitive radio, the fixed value of P_f is 0.1. The rest we can always adjust by increasing N to achieve a certain P_d. In other words, we can always achieve a desirable performance even at low SNRs by increasing the number of samples taken for detection. However, noise uncertainty will decrease P_d at low SNRs regardless of the number of samples taken (N) [12].

Eq. (15) shows that the performance of energy detection at various SNRs depends on the threshold value. The threshold can be found from a known noise variance. However, there is a limitation because it is not possible to know the variance exactly. Its value varies for each time instance. This lack of knowledge is a factor known as noise uncertainty (Δ). In practice, the noise variance level varies due to several factors that affect noise uncertainty, such as: calibration errors, thermal noise change due to temperature changes, amplifier gain changes due to temperature changes, or interference during calibration [20]. Noise uncertainty due to these factors is at least 0.7 dB without considering interference. It will be acceptable if it is rounded up to 1 dB.

If noise variance varies with uncertainty factor ρ, then it will have a possible value of $\sigma^2 \in \left[\frac{1}{\rho}\sigma^2, \rho\sigma^2\right]$. The robust statistics approach is used to model and measure the effect of this noise uncertainty on detection performance. This approach can be thought of as a worst-case scenario. The upper limit of the noise's PSD $\rho\sigma^2$ is used to calculate the probability of false alarm, while the lower limit $\frac{1}{\rho}\sigma^2$ is used to calculate the probability of detection. Then, the probability of false alarm is:

$$P_f = Q\left(\frac{\lambda-\rho\sigma^2}{\sqrt{\frac{2}{N}}\rho\sigma^2}\right) \tag{17}$$

and the probability of detection considering noise of uncertain power is:

$$P_d = Q\left(\frac{\lambda-\left(\sigma_s^2+\frac{1}{\rho}\sigma^2\right)}{\sqrt{\frac{2}{N}}\left(\sigma_s^2+\frac{1}{\rho}\sigma^2\right)}\right) \tag{18}$$

We have to modify Eq. (16) to include the noise uncertainty factor. The number of samples equation then will be:

$$N = \frac{2\left[\rho Q^{-1}(P_f)-Q^{-1}(P_d)\left(\gamma+\frac{1}{\rho}\right)\right]^2}{\left(\gamma-\left(\rho-\frac{1}{\rho}\right)\right)^2} \tag{19}$$

When the SNR γ makes the denominator in Eq. (19) close to zero, N will increase to an asymptotic value. This asymptotic value exists in an SNR wall of $SNR_{wall} = \frac{\rho^2-1}{\rho}$. If we receive a low-level primary signal so that its corresponding SNR is lower than SNR_{wall}, it will not be possible to detect it, regardless of the number of samples. This SNR_{wall} phenomena, which is caused by noise uncertainty, is a factor that makes energy detection perform poorly at very low SNRs. We have to find another feature of the received signal to make the decision, such as its distribution.

We propose a spectrum sensing method based on distribution difference. When the channel is idle, the real condition will be $H_0: r(n) = w(n)$. The noise $w(n)$ is AWGN (additive white Gaussian noise). Its probability distribution is $N(\mu_w, \sigma_w^2)$, i.e. a Gaussian random variable with the probability density function (pdf):

$$p(w) = \frac{1}{\sqrt{2\pi\sigma^2}}\exp\left(-\frac{1}{2\sigma^2}(w-\mu_w)^2\right) \tag{20}$$

When the channel is occupied, $H_1: r(n) = s(n) + w(n)$.$s(n)$ is the received signal propagating from the primary user, which already includes the wireless channel effects. The probability of $s(n)$ will have several possibilities depending on the multipath fading channel model, such as rician, rayleigh, etc. Rayleigh can be considered a general condition in wireless environments. The rayleigh random variable has a probability density function (pdf) of:

$$p(s) = \frac{s}{\sigma_S^2} \exp\left(-\frac{s^2}{2\sigma_S^2}\right) \tag{21}$$

Where σ_S^2 is the signal's variance/power. As s and w are independent, the probability density function of the received signal will be $p(r) = p(s) * p(w)$ [21]. The pdf of $r(n)$ can be calculated as:

$$p(r) = \frac{\sigma_S r}{\sqrt{(\sigma_S^2+\sigma^2)^3}} \exp\left(-\frac{r^2}{2(\sigma_S^2+\sigma^2)}\right) \phi\left(\frac{\sigma_S}{\sigma} \frac{r}{\sqrt{\sigma_S^2+\sigma^2}}\right) + \frac{\sigma}{\sqrt{2\pi(\sigma_S^2+\sigma^2)}} \exp\left(-\frac{r^2}{2\sigma^2}\right) \tag{22}$$

where $\phi(\ldots)$ is a cumulative distribution function of a standard normal random variable. Based on the distribution difference, the hypothesis testing equation becomes:

1. $H_0: dist. of\ r(n)\ will\ follow\ N(\mu_w, \sigma_w^2)$
2. $H_1: dist. of\ r(n)\ will\ not\ follow\ N(\mu_w, \sigma_w^2)$

Based on the distribution of received samples $\boldsymbol{r} = [r_1 \quad r_1 \quad \cdots \quad r_{N-1}]$ we have to draw a decision. Our goal is to design an efficient spectrum sensing method, which works based on this distribution difference.

In this paper we propose kurtosis as a means to differentiate between Gaussian and non-Gaussian samples. Kurtosis is one of several means to measure Gaussianity [22]. Kurtosis is defined as:

$$kurt(r) = E(r^4) - 3\big(E(r^2)\big)^2 \tag{23}$$

Suppose *r* has zero mean and r has been normalized so that its variance is equal to one $E(r^2) = 1$, then Eq. (23) becomes:

$$kurt(r) = E(r^4) - 3 \tag{24}$$

Since r is Gaussian, its fourth moment is equal to:

$$E(r^4) = 3\big(E(r^2)\big)^2 = 3 \tag{25}$$

So, for samples with Gaussian distribution, the corresponding kurtosis is 0. This value will not be exactly equal to 0 if the sample number (*N*) is not large enough. For limited samples of *N*:

$$kurt(r) = \frac{1}{N}\sum_{n=0}^{N-1}(r_n - \bar{r})^4 - 3\left(\frac{1}{N}\sum_{n=0}^{N-1}(r_n - \bar{r})^2\right)^2 \tag{26}$$

In terms of digital implementation of spectrum sensing, this offers more flexibility by using DFT-based spectral estimation [19]. We have to arrange an N-point FFT on $r(n)$ to get $R(k)$:

$$R(k) = \sum_{n=1}^{N-1} x(n) \exp\left(-j2\pi(k-1)\frac{(n-1)}{N}\right) \tag{27}$$

$R(k)$ is complex valued sample $R = Re(R) + j\, Im\,(R)$. A kurtosis test can be applied to $Re(R)$, $Im\,(R)$, or $\|R\|$. When the condition is H_0, the distribution of $Re(R)$ and $Im\,(R)$ should be Gaussian. We use a kurtosis test on both $Re(R)$ and $Im\,(R)$ in order to maximize the available information. Then, the test statistic (T) in the proposed method is:

$$T = \frac{kurt\big(Re(\boldsymbol{R})\big)+kurt\big(Im(\boldsymbol{R})\big)}{2} \tag{28}$$

We propose a sensing algorithm, to be applied as follows:

1. Step 1: We perform FFT operation to the received sample $r(n)$. The output is complex valued $R(k)$
2. Step 2: Kurtosis is calculated to each frame of real $kurt\big(Re(\boldsymbol{R})\big)$ part using Eq. (26).
3. Step 3: Kurtosis is also calculated to each frame of imaginary part or $kurt\big(Im(\boldsymbol{R})\big)$
4. Step 4: Calculation of the test statistic according to Eq. (28) is performed by using the absolute value of each kurtosis,
5. Step 5: if $T > \lambda$ threshold then the detector will decide condition H_1, if $T < \lambda$ threshold then the decision will be condition H_0.

In the proposed method, the detector works blindly as it does not need any information of DTV signal parameters. The threshold is taken empirically from noise samples. To get the threshold, the detector will perform detection in the condition of H_0. Detection events will be counted and divided by the number of frames to produce probability of false alarm. Its value should be under 10%. The threshold is adjusted until the false alarm probability reaches 10%. The resulting threshold will then be used as detection threshold to be compared with the test statistic from Eq. (28).

5 Performance Evaluation

The performance of the proposed spectrum sensing method was evaluated by simulation of the detection process. The goal of the evaluation was to measure the sensitivity of the proposed method in the condition of noise uncertainty. The sensitivity is shown by the probability of detection (P_d) when the received signal level is low compared to the noise level (low SNR). We also tested two other blind spectrum sensing methods for comparison: the well-known energy detection [9] and Jarqur-Bera (JB) detection [16]. While energy detection exploits differences in the signal's power, JB detection is a method recently proposed that is based on the distribution of the signal.

In our simulation, we tested real captured digital television (DTV) signals from [23]. Figure 3 shows the power spectral density of the primary signal. Its frequency was 545 MHz, the signal's bandwidth 6 MHz and it was sampled at 50 MHz. With an oversampling speed of $\frac{8}{7}$, the number of samples in 1 ms was 6857. If we have to perform sensing and have to make a decision in 5 ms, this will be equal to sensing about 30,000 samples.

Previously, we derived the expression for the performance limit of energy detection in noise of uncertain power. As the performance limit depends on the uncertainty factor ρ (Eq. (19)), if the noise uncertainty is considered in the detector, the noise variance will be unstable. It will fluctuate between $\frac{1}{\rho}\sigma^2$ to $\rho\sigma^2$. To verify the phenomena expressed in the equation, we performed a simulation of the energy detection where the noise $w(n)$ includes the condition of 1 dB noise uncertainty. Noise uncertainty of 1 dB is a common acceptable worst case condition.

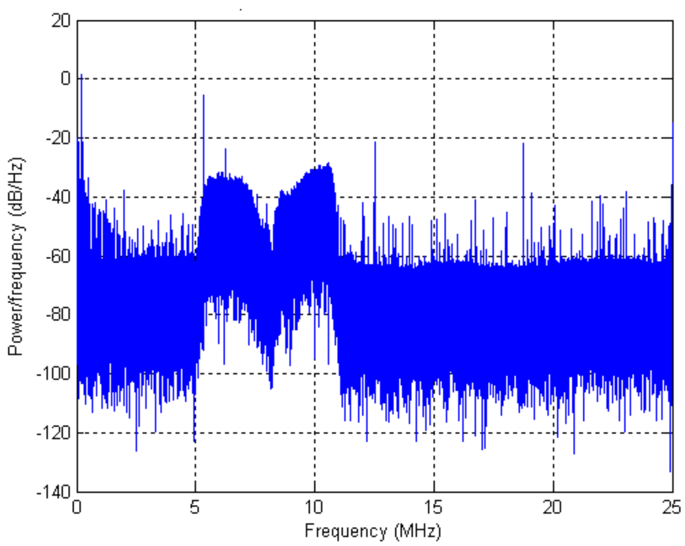

Figure 3 Power spectral density of received signal $r(n)$.

First, we have to find the threshold to be able to detect the primary signal. In this step, the white Gaussian noise (WGN) samples are the input for the simulation. The threshold is the value of the sample's energy, which makes the probability of false alarm equal to a predefined value. Based on robust statistics, the threshold is found by using noise with 1 dB higher power spectral density. The purpose of this setting is to include the noise uncertainty factor into the simulation. The energy of the samples in a frame that consists of N samples is calculated as the test statistic. The test statistic for each frame is then compared to the threshold. The frames that have energy more than the threshold are added up and then divided by the total number of frames to find the probability of false alarm (false alarm rate). The threshold is adjusted so that the probability of false alarm will be bounded to 0.1.We can get the threshold for a certain value of P_f.

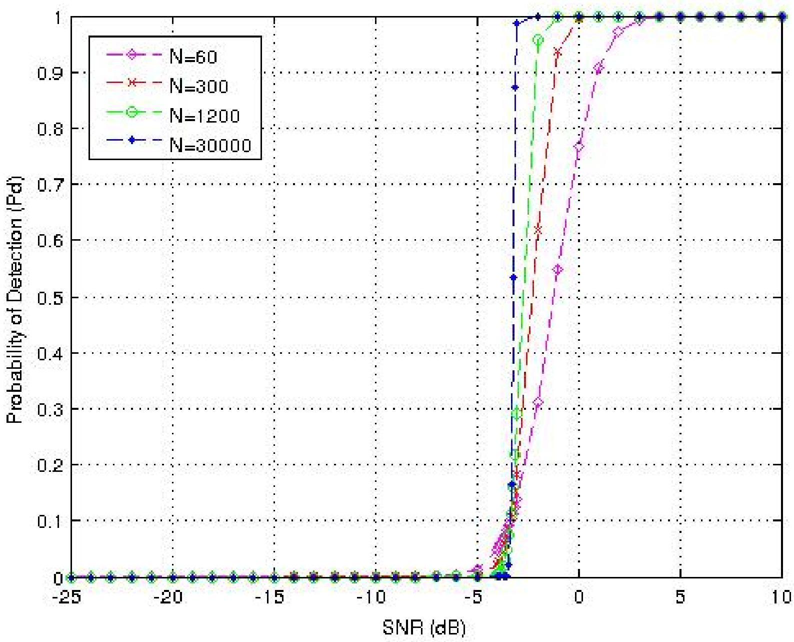

Figure 4 Energy detection performance, noise uncertainty=1 dB.

After the threshold was set, the energy detection method was tested using a DTV signal in noise of uncertain power. The signal was scaled to represent a certain SNR. The probability of detection for SNRs from -25 dB to 10 dB was evaluated for number of samples (N): 60, 300, 1200, and 30000. Figure 4 shows the detection results. Here, the probability of detection is the mean of the test statistic, which was higher than the threshold. The probability of detection will increase if we use more samples for detection. There is an asymptotic SNR in which increasing the number of samples will not improve performance. The result in Figure 4 confirms the existence of an SNR wall at around -3.3 dB. Increasing N will not increase detection performance below the SNR wall. In this case, the limitation of energy detection in noise uncertainty needs to be improved.

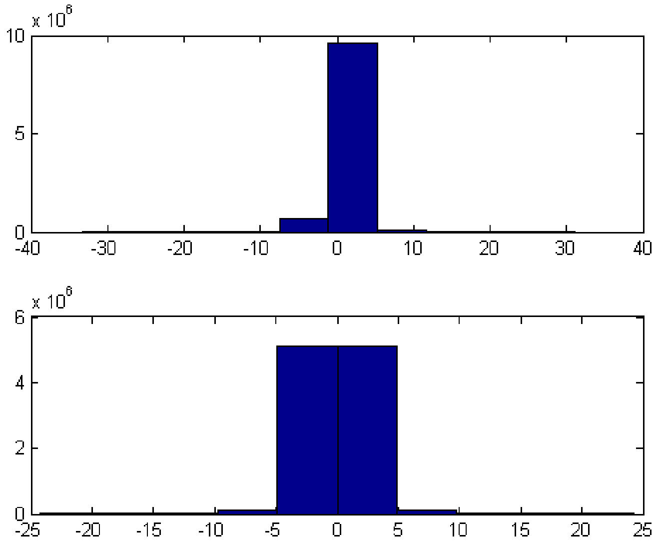

Figure 5 Histogram of $R(k) = S(k) + W(k)$.

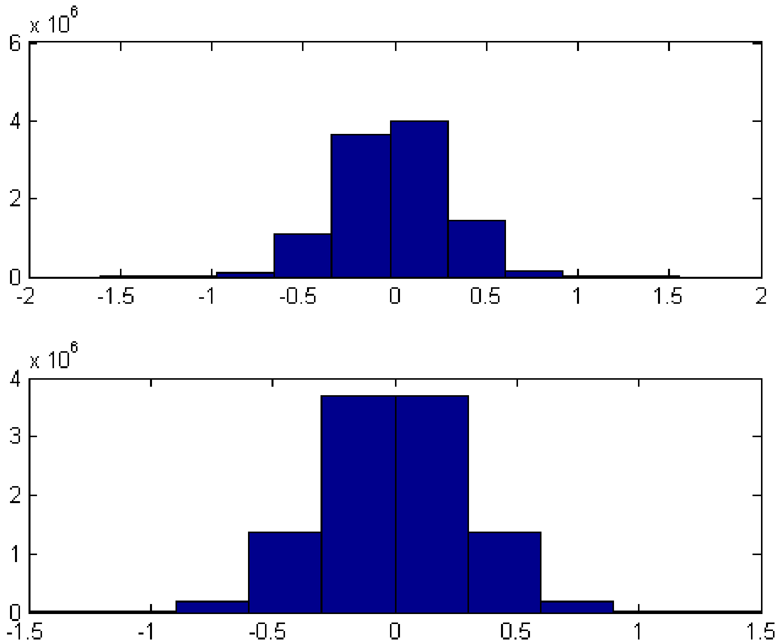

Figure 6 Histogram of received signal $W(k)$.

While energy detection exploits the energy difference between the conditions of H_1 and H_0, our method exploits the distribution difference. Eqs. (20) and (21) explain that the distribution of received signal will be different for each condition. Before continuing with the performance of the proposed method, we present a histogram of the received signal at the FFT output: $R(k)$. Figure 5 shows the histogram of $R(k)$ when the primary signal exists in the received signal. Figure 6 is the distribution of $R(k)$ when only $W(k)$ exists in the inspected band. In both histograms, the upper graph is the real part while the lower graph is the imaginary part. The histogram represents the respective distributions of the signal in both conditions. Figure 6 shows that $W(k)$ as additive white Gaussian noise (AWGN) has a Gaussian distribution. On the other hand, Figure 5 shows that the distribution of the mixture of the primary signal and noise can be considered non-Gaussian. The difference in the shape of the histograms in Figures 5 and 6 supports our assumption with regards to the usage of distribution for spectrum sensing.

In the second simulation, we performed detection using the proposed method. We calculated the kurtosis of $Re(R)$, $Im\ (R)$ and test statistic T (Eq. (28)) for every frame of N samples. The same procedure was performed to get the threshold as in the experiment with energy detection. The threshold is taken empirically from real noise samples. First, we conduct the detection process with noise variance set to 1 dB higher than the input for the simulation. The result of detection is the false alarm rate. The threshold has to be adjusted to get a false alarm rate of 10%. Then we use the threshold for the detection process. The simulations use a sample number of N=30,000 and are repeated for about 1000 times to ensure that the experimental results are statistically correct.

Once the threshold is set, the detection process using the same DTV signal added with noise is ready. The signal is scaled to achieve a certain signal to noise ratio. The noise's variance is 1 dB lower than the respected value to model the worst-case scenario of noise uncertainty. The test statistic is counted for every N = 30000 samples. The average number of frames with its test statistic higher than the threshold is the detection rate. We repeated the experiment 1000 times to ensure statistical correctness.

The performance of the proposed method was compared with two existing methods: energy detection and Jarqur-Berra (JB) test based detection [16]. Similar to our method, the authors in [16] exploited the distribution difference by using the JB statistic of the norm of $R(k)$ to distinguish between both conditions. The detection threshold in their method is calculated analytically. The performance is described using the graph of probability of detection versus SNR. The performance is evaluated at SNR -25 dB to 0 dB. The number of samples in each frame is N = 30,000.

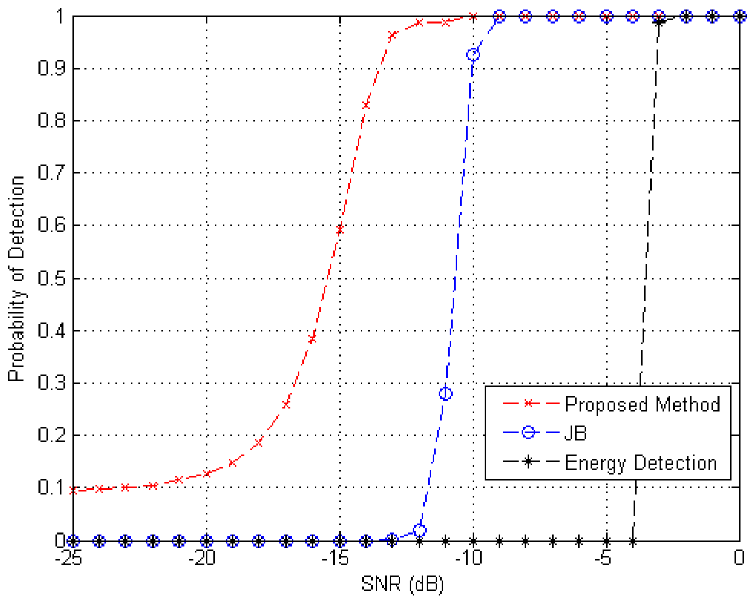

Figure 7 Proposed detection performance, noise uncertainty = 1 dB.

Figure 7 shows the performance of the 3 methods. The graph describes the comparison of sensitivity, as represented by the lowest detectable primary signal's level. The graph describes a comparison of sensitivity with regards to the lowest primary signal's level at which it can still be detected by the respective methods. Energy detection gave the lowest performance due to its vulnerability to noise uncertainty, as described before. Our proposed method also gave a higher detection rate compared to the JB test based method. There are two different things that make our method perform better: the test statistic and the threshold. Originally, the JB test based method is a normality test. The method in [16] uses the norm of $R(k)$. Even if $R(k) = W(k)$, the distribution of the norm will not be normal. This makes the method suboptimal compared to our method. The second reason is that the threshold in our method is empirically found, so it can adapt to different noise characteristics, while in the JB test based method, the threshold is from a fixed formula.

Lastly, we used different FFT sizes for comparison. Figure 8 describes the simulation results of the proposed method for two different FFT sizes. The graph shows that if we increase the FFT points, the detection rate will also increase. The reason is that by using a higher number of FFT points, the $R(k)$ reveals more signal characteristics in a higher resolution. Spectrum sharing cognitive radio standardized by IEEE 802.22 defines white space in the digital television spectrum. In DVB-T there are 2 alternatives for the number of FFT points, i.e. 2048 and 8196. For spectrum sensing purposes, the same FFT module for modulation may be used as well.

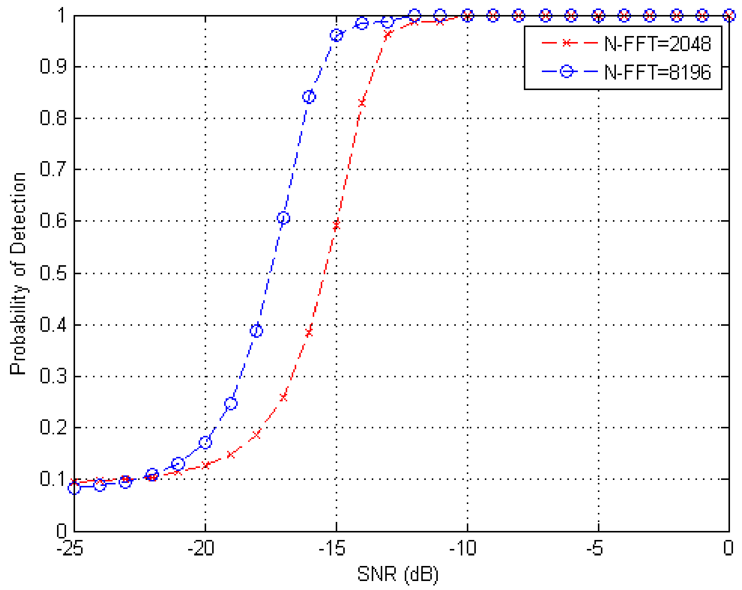

Figure 8 Effect of FFT size on detection performance noise uncertainty = 1 dB.

6 Conclusion

The performance limitation of the energy detection method in noise of uncertain power has been discussed in this paper. The weakness of the energy detection method is improved by our proposed spectrum sensing method. It exploits the distribution difference of the received signal. Our method is able to perform the spectrum sensing blindly because it works without primary signal knowledge. In the case of noise of uncertain power it outperforms the energy detection method as well as the JB based detection method, particularly for SNRs lower than the SNR_{wall}. Increasing the N-FFT improves the performance significantly. The proposed method can adapt to various noise characteristics because the threshold is taken empirically from the system's noise.

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