An Enhanced Energy Detector for WRAN Systems Using Maximum-to-Mean Power Ratio

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ABSTRACT

Spectrum sensing is the key challenge in implementing cognitive radio system, which enables unlicensed users to identify "white holes" in the spectrum allocated to primary users and utilize them efficiently. Recent studies have proposed three major sensing methods for WRAN systems, including matched filter, energy and feature detector. However, there are some drawbacks along with them. In this paper, we propose an enhanced energy detector that extends the ability of conventional one, which can differentiate the primary users from each other as well as the noise with different maximum-to-mean power ratio. Furthermore, a novel structure of cognitive radio detector employing the proposed algorithm is also analyzed to implement spectrum sensing. The simulation result shows that our proposed scheme performs well in the individual sensing environment and can satisfy the requirement with high detection probability.

Key Words : Cognitive Radio, WRAN, Spectrum Sensing, Energy Detection

Ⅰ. Introduction

From Federal Communications Commission's Spectrum Policy Task Force Report on 2002[1], there are huge temporal and geographic spectrum vacancies in the allocated spectrum, which clearly shows the inefficiency of the fixed license spectrum policy, rather than the physical scarcity of spectrum resource. Cognitive Radio (CR) has been considered as the effective technology to implement the opportunistic spectrum sharing and spectrum efficiency improving. It can sense the spectral environment over a wide frequency band and exploit this information to opportunistically provide wireless service accesses that best meet the requirements of customers[2].

Since cognitive radios are considered as the secondary or lower priority users of spectrum allocated to a primary user (PU), their fundamental requirement is to avoid interference to potential primary users in the neighborhood. Spectrum sensing has been considered as a key functionality to satisfy this requirement. Furthermore, to properly respond to changes in its environment, cognitive radios have to be able to detect and classify the signals in their environment. If deployed in an opportunistic manner, it would be important for the cognitive radios to distinguish between primary spectrum licensees whose signals must be protected from interference and from other opportunistic signals.

Recent studies have proposed three major methods for IEEE 802.22 WRAN systems, including matched filtering, energy and feature detector[3,4].

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Matched filtering detector is an optimal coherent sensing method that detects known primary user signals. However, it requires the perfect knowledge of primary user signaling features to demodulate the received signal. Furthermore, it needs the priori knowledge of all types of signals that operate in the band, which is practically difficult to implement. Energy detector is the most common method, because of its non-coherency and low complexity. However, it also has some limitations, including the inability for differentiating the PU and interference, and the poor performance under low SNR environment. Another sensing method for CR is feature detector, which exploits the distinct feature of each primary user, such as spectral correlation detector[5,6]. Proper utilization of the features can achieve extremely good sensing performance, and even explore the specific type of signal in low SNR regime. However, the complexity of this method is large.

The remainder of this paper is organized as follows: Section II analyzes the characteristics of primary users considered in IEEE 802.22 WRAN systems. In Section III, the enhanced energy detector is proposed and analyzed for detecting and classifying primary users in the operating bands. The simulation result is shown and discussed in section IV. Finally, we make the conclusion in section V.

Ⅱ. Primary Users in WRAN Systems

According to the regulations of IEEE 802.22 WRAN systems, there are a variety of different primary signals, each of which can handle the interference with different level. Considering the case in US where the UHF bands have been suggested for initial cognitive radio deployment, there are currently three primary signals that must be protected, analog TV (NTSC), digital TV (ATSC) and wireless microphone signal (Part 74).

ATSC DTV signal is 8-Vestigial Side Band (VSB) modulated with the spectrum occupying 6MHz bandwidth, as shown in Fig.1. It has the power spread over center 5.38 MHz within a TV channel, where a distinctive pilot tone with 10 KHz bandwidth can be observed in a narrowband receiver. Furthermore, the power of pilot tone is 11.3dB below average power measured in a 6MHz bandwidth[7]. Fig.2 is the spectrum of wireless microphone signal using amplitude modulation. Wireless microphone signal has the bandwidth of 200 KHz which is obviously a narrowband signal, compared to DTV signal.

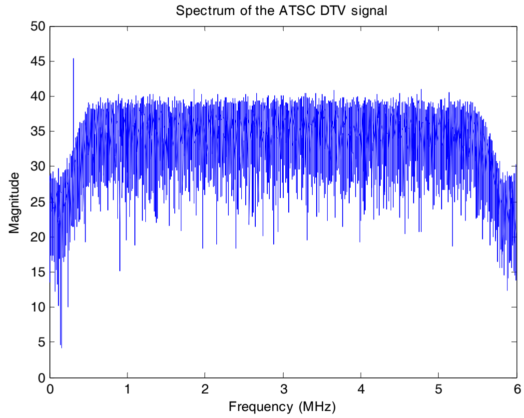

Fig. 1. The spectrum of ATSC DTV signal

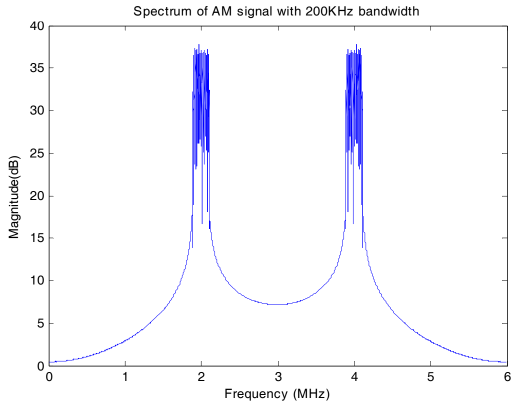

Fig. 2. The spectrum of wireless microphone signal

We assume that for each channel, there is only one kind of user at a time. This paper only considers two primary users, DTV and wireless microphone signal. With regard to the PSD of each PU, the different spectrum characteristics might be able to be utilized to differentiate these two primary users and noise from each other by some kind of criterion. That motivates the idea and the following work in the paper.

Ⅲ. Enhanced Energy Detection Algorithm

As we know, energy based detection is a non-coherent detection method that the receiver does not need any knowledge on primary user signal[8]. It can be easily implemented by calculating the energy of the received signal in frequency domain by Fast Fourier Transform (FFT), and comparing the output of the energy detector with a threshold that depends on the noise floor, as described in Fig.3. If the estimated energy of the received signal is larger than the pre-set threshold, the existence of primary user would be declared. In order to achieve better performance, the collaborative sensing among secondary users based on energy detection has been recently studied in[9]. Because of low computational complexity, energy detector has been considered as the most common way for individual spectrum sensing in secondary users.

However, there are some drawbacks with the detector which may degrade the performance and hinder its implementation. A critical problem is the inability of differentiating the interference from primary user and noise, as well as the type of primary users operating in the band. With the help of conventional energy detector, we can only decide on whether primary user exists or not. The problem might be worse, as the sensing information would play the significant role on frequency allocation in next step. The more sensing information could be obtained, the more efficient operation would be conducted in the following section by secondary users. One alternative way to deal with the problem is a combination of energy detector and feature detector[10].

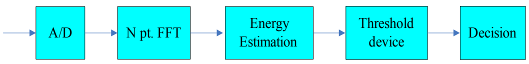

Fig. 3. Conventional energy detector

In this paper, we propose the enhanced energy detector which holds the ability of identifying the type of primary user operating in the band. It utilizes conventional energy detector as an intermediate step for determining the existence of PU efficiently and then employs an enhanced energy detection algorithm to classify the specific type of primary user and the noise. The proposed structure of CR detector is shown in Fig.4, which is illustrated in the following:

Generally, for the low-pass process over the interval (0, T), we can express the noise and PU signal in the form[7]:

$$w(t) = \sum_{i=1}^{2TW} a_i \mathrm{sinc}(2Wt - i) \tag{1}$$

$$s(t) = \sum_{i=1}^{2TW} \alpha_i \mathrm{sinc}(2Wt - i) \tag{2}$$

where T is the observed bandwidth; W is the considered bandwidth; $a_i = w(i/2W)$, $\alpha_i = s(i/2W)$ are Gaussian random variables with zero mean and with the same variance $2N_0W$; N_0 is the two-sided noise power density spectrum.

Using (1) and (2), we can find the received signal in time domain with the PU signal present as:

$$y(t) = \sum_{i=1}^{2TW} (a_i + \alpha_i) \mathrm{sinc}(2Wt - i) \tag{3}$$

3.1 Band Pass Filter and A/D Converter

The signal arriving at the cognitive radio receiver, say y(t), is first filtered by a band-pass

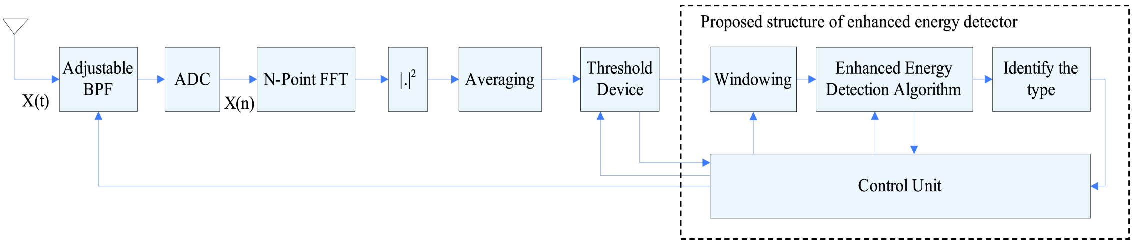

Fig. 4. The proposed structure of CR detector

filter (BPF) with the purpose of extracting the signal in the frequencies of interest. The filter may be adaptable and pre-configured by a control unit. Then we can scan a wider range of spectrum by moving BPF center frequency. The output of BPF is then sampled at Nyquist rate by high-speed A/D converter.

The sampled signal y(n) under binary hypotheses detection test is described in the following:

1) H_0: y(n)=w(n), signal is absent
2) H_1: y(n)=s(n)+w(n), signal is present

where w(n) is additive white Gaussian noise with zero mean and variance σ_w^2; s(n) represents the sampled primary user signal, which may be VSB-modulated DTV signal or amplitude-modulated wireless microphone signal in this paper.

3.2 FFT and Energy Estimation

In order to switch from time domain to frequency domain, N-point FFT is applied to obtain frequency samples,

$$\begin{aligned} H_0 :\ Y(k) &= F[y(n)] \\ &= \frac{1}{2W}\sum_{i=1}^{2TW} a_i . \exp(-j\frac{i\pi k f_0}{W}) \\ H_1 :\ Y(k) &= \frac{1}{2W}\sum_{i=1}^{2TW} (a_i+\alpha_i).\exp(-j\frac{i\pi k f_0}{W}) \end{aligned} \tag{4}$$

where N is FFT size, Y(k) is frequency samples of the received signal, k is the frequency index

Afterwards, the estimated energy is calculated by squaring the magnitude of frequency samples and aggregateing the received power for each frequency bin,

$$\begin{aligned} H_0 :\ E &= \int_0^{2W} |Y(f)|^2 df \\ &= \sum_{k=1}^{N} |Y(k)|^2 = \frac{1}{2W}\sum_{i=1}^{2TW} a_i^2 \\ H_1 :\ E &= \frac{1}{2W}\sum_{i=1}^{2TW} (a_i+\alpha_i)^2 \end{aligned} \tag{5}$$

where N is number of frequency samples, W/f_0.

3.3 Threshold Device

As the final step for the first stage of sensing, threshold device is applied to compare the estimated energy of input signal with the preset threshold. Here, we can decide whether primary user exists or not. The performance would be evaluated with the resulting pair of detection probability and false alarm probability, which is associated with the particular threshold Thr:

1) E $\geq$ Thr, decide signal present
2) E < Thr, decide signal absent

The preset threshold Thr could be dynamically adapted by control unit. If the estimated signal level is lower than the preset threshold, the decision information would be notified to control unit and the absence of primary user would be declared. Then, another sensing period would be prepared to be initiated. Otherwise, if the estimated signal level is larger than the threshold, the second stage of sensing deploying the enhanced energy detection algorithm would start to distinguish the specific type of primary user.

3.4 Enhanced Energy Detection Algorithm

The enhanced energy detection algorithm is introduced as the second step of sensing with the extended ability to classify different primary users and the noise. Because of the distinct spectrum features illustrated in Section II, these two primary users and noise show different maximum-to-mean power ratio (MMPR) values in the considered band, which could be used to identify the specific type of primary signal existing in the band. The flow chart of the proposed algorithm is shown in Fig. 5, which can be implemented in three steps as follows:

3.4.1 Sliding Window Function

In this step, the window function is applied in frequency domain. With the squared magnitude of the frequency bins passing through the window, the power of each window is estimated and stored, as presented in Eq.(6) and (7),

$$\begin{aligned} P(m)_{H_0} &= \sum_{k=1}^{N_W} |Y(k+(m-1)*N_W)|^2 \\ &= \frac{1}{4W^2}\sum_{k=1}^{N_W}\left[\left|\sum_{i=1}^{2TW} a_i * \exp(-j\frac{i\pi(k+(m-1)*N_W)f_0}{W})\right|^2\right] \end{aligned} \tag{6}$$

$$P(m)_{H_1} = \frac{1}{4W^2}\sum_{k=1}^{N_W}\left[\left|\sum_{i=1}^{2TW}(a_i+\alpha_i)*\exp(-j\frac{i\pi(k+(m-1)*N_W)f_0}{W})\right|^2\right] \tag{7}$$

where N_w is the window size, m indicates the window index. According to the simulation test, we find $P(m)_{H0}$ has a chi-square distribution with 2TW degrees of freedom, while $P(m)_{H1}$ has a non- central chi-square distribution with 2TW degrees of freedom and a non-centrality parameter SNR.

In order to estimate the different MMPR for each primary user and noise, the sliding window size is required to be properly set. Different window sizes would bring on different levels of performance. Normally, it could be preset as 10 KHz, which is equal to the bandwidth of DTV pilot tone.

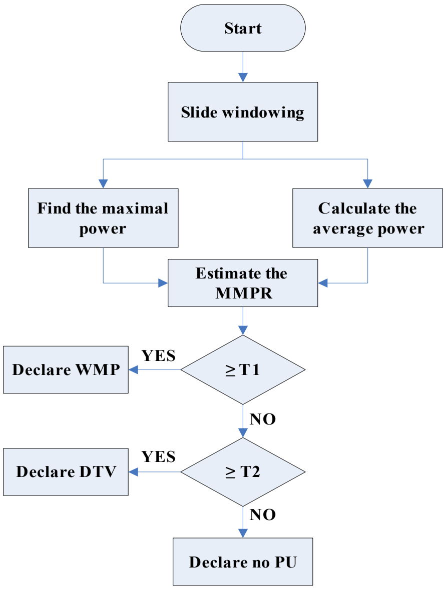

Fig. 5. The flow chart of the proposed detection algorithm

3.4.2 MMPR Calculation

The maximum power can be found through comparing the power of each sliding window. Because of the different spectrum features, two primary users and noise displays different peak power levels. Usually, DTV signal with the pilot tone always shows higher peak than wireless microphone signal, while Gaussian noise has a stationary PSD. Then, we can find the maximum-to-mean power ratio according to Eq.(8) in the following:

$$V_{MMPR} = \frac{Max(P(m))}{Mean(P(m))} \tag{8}$$

3.4.3 Decision

This step gives the important part of the proposed algorithm to solve with the classification problem. First of all, the MMPR is chosen as the test statistic in the threshold device. Based on the analysis on the primary users in frequency domain, the fact is that different primary users and the noise exhibit different MMPR levels. We can estimate the MMPR value of the received signal, and then determine the type of primary user by threshold device. In this paper, the specific MMPR levels for DTV, wireless microphone signal and noise is estimated and stored in control unit, by which they are differentiated from each other. In this paper, we observe a 6MHz band and normalize the power of primary user signal on the transmitter side. Therefore, wireless microphone signal can achieve the highest MMPR level due to its comparatively narrow band, while the noise has the lowest one.

In order to satisfy the sensing requirement of WRAN systems, the threshold level should be carefully installed. In this paper, we consider two thresholds T_1 and T_2 (Assume $T_1 > T_2$), as shown in Fig.5. If the estimated MMPR is larger than T_1, wireless microphone signal would be declared to be present by threshold device. Otherwise, if the estimated MMPR is larger than T_2, the existence of DTV signal can be announced to control unit. Due to the variation of MMPR level along with SNR, there is possibility that the MMPR of WMP might fall into the range of DTV at low SNR environment, which then causes the false alarm. The performance of Enhanced Energy Detector would be evaluated by a pair of probabilities P_d and P_f. P_d is the probability of detection of primary user that really exists. P_f is the probability of wrongly declaring the existence of the primary user that is actually absent.

Ⅳ. Simulation Results

In order to evaluate the performance of the Enhanced Energy Detector, both DTV and wireless microphone signal are evaluated under AWGN and ITU-R pedestrian channel A fading environment with pairs of P_d and P_f, respectively. The simulation parameters are listed in table I. In the simulation, we consider the fixed noise level, -163dBm/Hz. Meanwhile, any PU signal would be normalized before passing through channel.

First, we analyze the detection performance of wireless microphone signal by the proposed detector compared to conventional energy detector. For an arbitrary received signal, a preset threshold is first estimated in the case of no PU to satisfy the required false alarm probability which should be less than 10% in WRAN systems. Then, the threshold is applied to calculate the detection probability in the proposed algorithm. Because of the much higher MMPR level of wireless microphone signal, properly setting of T_1 will lead to the good performance on both Pd and P_f. As shown in Fig.6, false alarm probability P_f which are caused by no PU case, DTV under AWGN case and DTV under fading channel case are all satisfied with the requirement, respectively. At the

Table 1. Simulation Parameters for Spectrum Sensing

Parameter	Value
Noise level	-163 dBm/Hz
Considered Bandwidth	6.0 MHz
E_bN_0	-25 dB ~ 25 dB
Probability of Detection	> 90%
Probability of False Alarm	< 10%
Fading model	ITU-R M.1225 Ped A
Speed	3 km/hr
Central frequency	2.0 GHz
Doppler frequency	5.56 Hz
Sliding window size	10.0 kHz

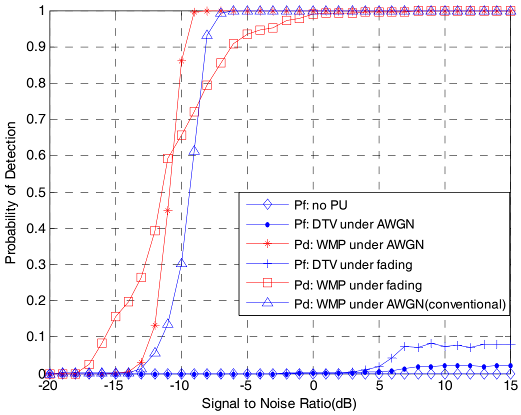

Fig. 6. Enhanced energy detector for wireless microphone signal(Average time: 0.015ms, window size: 10KHz)

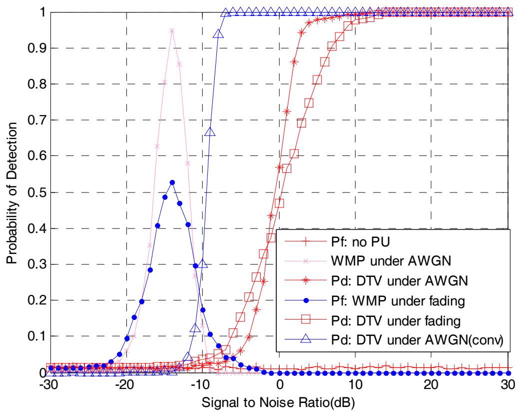

Fig. 7. Enhanced energy detector for DTV signal(Average time: 0.015ms, window size: 10KHz)

target of 90% P_d, the proposed detector has about 2dB SNR improvement as compared to conventional one. Moreover, it holds the ability of identifying the WMP which is significant to implement the efficient sensing in CR users.

The performance of DTV signal detection is also illustrated in Fig.7. From the figure, we can see that there are significant false alarms between -20dB and -9dB under both AWGN and fading channel, which are caused by wireless microphone signal. Due to the monotony of MMPR level with SNR, the MMPR level of WMP decreases as SNR lowers, which inevitably makes it fall into the detection range of DTV and leads to the mis-detection. Considering the practical case, if detection probability P_d is small enough in a low SNR regime, the detector becomes futile and its performance can be ignored. Here, P_f can be ignored along with the very low Pd in the SNR less than -10dB. Fig.7 also shows that there are about 10dB SNR degradation of proposed detector at the target of 90% P_d compared to conventional one.

Then, we are also interested in the effect of window size on the performance of proposed detector. Considering the case of wireless microphone signal detection in Fig.8, we can see that P_d monotonically increases as the window size decreases. Furthermore, at the target P_d of 90%, about 9dB SNR gain is achieved through decreasing windowing size from 50KHz to 2KHz. When window size increases to be 6MHz same as the observed bandwidth, the worst P_d is achieved. As a contrast, the best performance is achieved when the window size approaches to only one frequency bin, whereas, it results in high computational complexity and additional processing time. However, for the case of DTV, as indicated in Fig.9, the performance suffers from the obviously increasing MMPR value due to the decrease of window size. In this case, the threshold needs to be reset according to the different window size.

Lastly, we analyze the effect of average time and measure how much the performance can be improved by averaging the consecutive symbols.

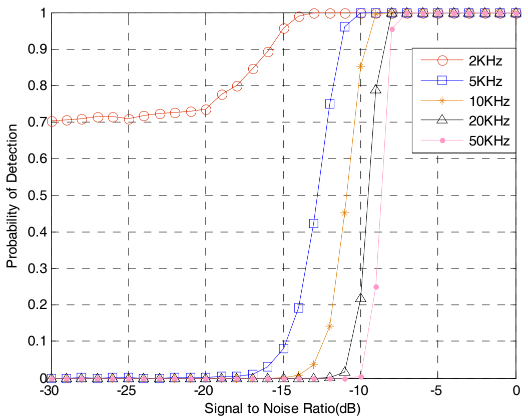

Fig. 8. Wireless microphone signal detection with different window size(Average time: 0.015ms, AWGN)

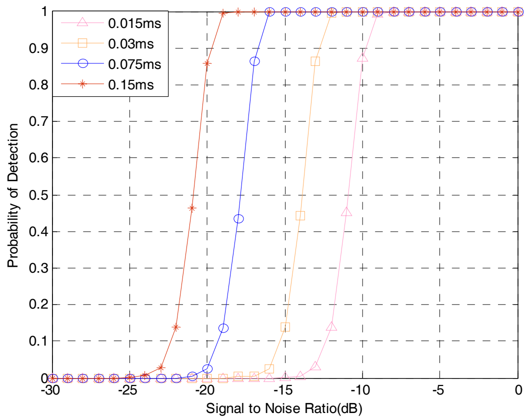

Fig. 10. Wireless microphone signal detection with different average time(Window size: 10KHz, AWGN)

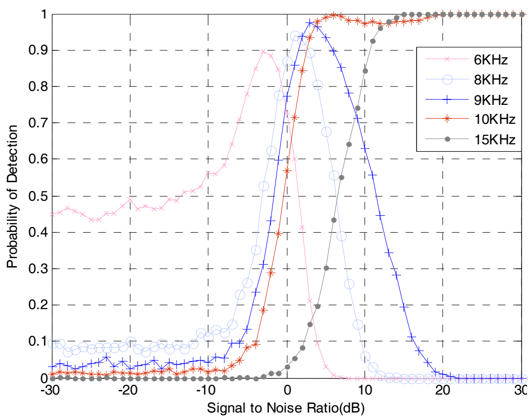

Fig. 9. Digital TV signal detection with different window size(Average time: 0.015ms, AWGN)

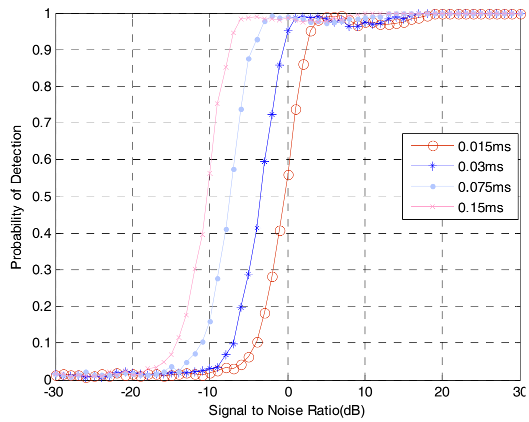

Fig. 11. Digital TV signal detection with different average time(Window size: 10KHz, AWGN)

Fig.10 and Fig.11 show that at the target of 90% Pd, 10dB SNR gain is achieved through increasing the average time from 0.015ms to 0.15ms, for the case of wireless microphone and DTV signal, respectively. This is due to the consecutive symbols combining and averaging, the interference by AWGN is largely reduced. Therefore, it is beneficial to increase average time to improve sensing performance while make the trade-off of increasing the processing time.

V. Conclusion

In this paper, we explore the spectrum sensing which is one of the most challenges in implementation of CR. Motivated by the desire for an effective sensing method, we propose an enhanced energy detector to perform spectrum sensing for the IEEE 802.22 WRAN systems. Different from conventional one, the proposed detector utilizes the spectrum features of the primary users to differentiate each primary user from the other as well as the additive white Gaussian noise with different MMPR levels. Finally, our simulation result shows that with properly setting two thresholds T_1 and T_2, the window size and the average time, the proposed detector can perform well in the individual sensing of CR users and satisfy the requirements of WRAN systems. Further work is undergoing to identify more signals and better test statistic.

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