

# Adaptive double-threshold energy detection algorithm for cognitive radio

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**Abstract:** Due to the fact that the conventional spectrum sensing algorithm is susceptible to noise, an adaptive double-threshold energy detection algorithm for a cognitive radio is proposed. Based on double-threshold energy detection, the algorithm can adaptively switch between one-round sensing and two-round sensing by comparing the observations with the pre-fixed thresholds. Mathematical expressions for the probability of detection, the probability of false alarm, and the sensing time are derived. The relationships including signal to noise ratio (SNR) vs. the probability of detection and SNR vs. the sensing time are plotted using Monte Carlo simulation and the algorithm is verified in a real cognitive system based on GNU Radio and universal software radio peripheral (USRP). Simulation and experimental results show that, compared with the existing spectrum sensing method, the proposed algorithm can achieve a higher probability of detection within a reasonable sensing time.

**Key words:** energy detection; software radio; probability of detection; sensing time

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Unlicensed bands are becoming increasingly scarce, especially those under 3 GHz. Cognitive radio (CR) has been highlighted as a possible candidate in improving spectrum utilization by providing an opportunistic spectrum access<sup>[1]</sup>. In the CR-based system, the secondary user (SU) exploits the spectrum opportunity, which is defined as the frequency channel that is temporarily not used by the primary users (PUs). These “free” areas are termed as “holes” in Ref. [2]. Therefore, as the heart of the cognitive radio techniques, the spectrum sensing is so critical that it determines the throughput and the agility of the CR networks.

The energy detection (ED) is the most common technique for spectrum sensing. The ED has been generally adopted in recent work because it does not require information of the primary user signal (a priori knowledge), which means that it is easy to implement. In Ref. [3], a double-threshold method is used to perform spectrum sensing, while a fusion center makes the final decision. Since there is a control channel to be maintained, this collaborative method is complicated to implement. In Ref. [4], a two-step spectrum sensing

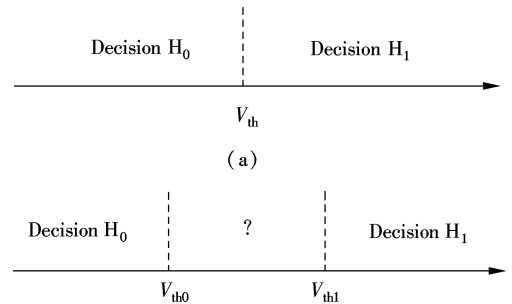
scheme based on energy detection and maximum eigenvalue detection was proposed. The proposed scheme can achieve a better performance under dense noise conditions. However, when there are no PUs, the proposed scheme will always perform a two-round spectrum sensing, thus being time consuming. Ref. [5] proposed a three-threshold decision based cooperative spectrum sensing algorithm with two rounds cooperation and eliminated the probability of failure sensing which might happen in Ref. [6] when not any local decision was reported to the common receiver. But there is no further description about the performance of sensing time.

In this paper, an adaptive double-threshold energy detection (AED) algorithm for cognitive radio is proposed. The algorithm can adaptively switch between one-round sensing and two-round sensing by comparing the observations with the pre-fixed thresholds. Mathematical expressions for the probability of detection, the probability of false alarm, and the sensing time are derived. Both simulation and experimental results are provided to compare the performance of the proposed scheme with that of the conventional ED scheme.

## 1 Algorithm Description

### 1.1 Conventional energy detection

It is assumed that the wideband frequency range is divided into  $K$  sub-channels with the same bandwidths. We consider the problem of detecting the presence of one PU at a given sub-channel based on the signal observed by the SU. In the conventional ED, the SU makes its local decisions by comparing its observation with a pre-fixed threshold, as illustrated in Fig. 1(a).



**Fig. 1** Spectrum sensing scheme. (a) Conventional energy detection; (b) Adaptive double-threshold energy detection

A sub-channel is either free ( $H_0$ ) or occupied by a PU ( $H_1$ ). Decision  $H_0$  or  $H_1$  will be made when the energy of the PU signal in this sub-channel is greater or less than the threshold value  $V_{th}$ , respectively. In the  $i$ -th sub-channel, the received signal  $y_i(n)$  of the  $n$ -th sampling result can be described as

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$$\begin{aligned} H_0: y_i(n) &= w_i(n) && \text{band free} \\ H_1: y_i(n) &= s_i(n) + w_i(n) && \text{band occupied} \end{aligned}$$

where  $w_i(n)$  is the real additive, white Gaussian noise (AWGN), which is independent and identically distributed (iid), with zero mean and variance  $\sigma_w^2$ ;  $s_i(n)$  denotes the PU signal in the  $i$ -th sub-channel ( $i = 1, 2, \dots, K$ ;  $n = 1, 2, \dots, N$ ). The test statistic of energy detection is given as<sup>[7]</sup>

$$Y_{\text{ed}} = \frac{1}{N_{\text{ed}}} \sum_{n=1}^{N_{\text{ed}}} |y_i(n)|^2 \quad (1)$$

where  $N_{\text{ed}}$  denotes the sample number of the ED.

For simplicity, we assume that the PU signal is a real Gaussian process with zero mean and variance  $\sigma_s^2$ . When the sample number of energy detection is very large, the test statistic  $Y_{\text{ed}}$  in a sub-channel can be approximated as a normal variable. Hence,  $Y_{\text{ed}}$  follows a normal distribution under  $H_0$  and  $H_1$ :

$$Y_{\text{ed}} \sim \begin{cases} N(\sigma_w^2, 2\sigma_w^4/N_{\text{ed}}) & H_0 \\ N(\sigma_s^2 + \sigma_w^2, 2(\sigma_s^2 + \sigma_w^2)^2/N_{\text{ed}}) & H_1 \end{cases} \quad (2)$$

Then, the probability of detection  $P_{\text{d,ed}}$ , the probability of false alarm  $P_{\text{fa,ed}}$ , and the probability of missing  $P_{\text{m,ed}}$  for the ED can be formulated as<sup>[4]</sup>

$$P_{\text{d,ed}} = P\{Y_{\text{ed}} > V_{\text{th}} \mid H_1\} = Q\left(\sqrt{\frac{N_{\text{ed}}}{2}} \frac{\bar{V}_{\text{th}} - (1 + \gamma)}{1 + \gamma}\right) \quad (3)$$

$$P_{\text{fa,ed}} = P\{Y_{\text{ed}} > V_{\text{th}} \mid H_0\} = Q\left(\sqrt{\frac{N_{\text{ed}}}{2}} (\bar{V}_{\text{th}} - 1)\right) \quad (4)$$

$$P_{\text{m,ed}} = P\{Y_{\text{ed}} < V_{\text{th}} \mid H_1\} = 1 - P_{\text{d,ed}} \quad (5)$$

where  $Q(a) = \int_a^{+\infty} \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{x^2}{2}\right) dx$ .  $\bar{V}_{\text{th}} = V_{\text{th}}/\sigma_w^2$  denotes

the threshold to noise variance and  $\gamma = \sigma_s^2/\sigma_w^2$  represents the same SNR in each sub-channel. Therefore, from Eqs. (3) and (4), it is found that  $P_{\text{fa,ed}}$  is independent of  $\gamma$ , and  $P_{\text{d,ed}}$  is a function of  $\gamma$  for given  $\bar{V}_{\text{th}}$  and  $N_{\text{ed}}$ .

## 1.2 Adaptive double-threshold energy detection

Based on the ED, we propose an adaptive double-threshold energy detection scheme. Two thresholds  $V_{\text{th1}}$  and  $V_{\text{th2}}$  are used to help the decisions of the SU. Decision  $H_1$  will be made when the collected energy value  $Y_{\text{aed}}$  is greater than the threshold value  $V_{\text{th2}}$  while decision  $H_0$  will be made when  $Y_{\text{aed}}$  is less than the threshold value  $V_{\text{th1}}$ . Otherwise, if  $Y_{\text{aed}}$  is between  $V_{\text{th1}}$  and  $V_{\text{th2}}$ , we first save the energy value as  $Y_{1,\text{aed}}$  and then do spectrum sensing again to obtain  $Y_{2,\text{aed}}$ . In the situation that either  $Y_{2,\text{aed}}$  is greater than  $V_{\text{th2}}$  or the average of  $Y_{1,\text{aed}}$  and  $Y_{2,\text{aed}}$  is greater than  $V_{\text{th1}}$ , decision  $H_1$  will be made. Otherwise, decision  $H_0$  will be made. The AED algorithm is described as follows:

### Algorithm 1 AED algorithm

For SUs

Begin

Perform local sensing and obtain  $Y_{1,\text{aed}}$

if  $0 < Y_{1,\text{aed}} \leq V_{\text{th1}}$  then

Band free

else if  $Y_{1,\text{aed}} \geq V_{\text{th2}}$  then

Band occupied

else perform local sensing and obtain  $Y_{2,\text{aed}}$

if  $Y_{2,\text{aed}} > V_{\text{th2}}$  or  $(Y_{1,\text{aed}} + Y_{2,\text{aed}})/2 > V_{\text{th1}}$  then

Band occupied

else

Band free

end if

end if

End

## 2 Performance Analysis and Simulation

### 2.1 Performance analysis

Let  $P_{\text{fa,aed}}$  and  $P_{\text{d,aed}}$  denote the probabilities of false alarm detection for the AED, respectively. Then,

$$\begin{aligned} P_{\text{fa,aed}} &= P\{Y_{1,\text{aed}} > V_{\text{th2}} \mid H_0\} + P\{Y_{2,\text{aed}} < Y_{1,\text{aed}} < V_{\text{th2}} \mid H_0\} \cdot \\ &\quad \left[ P\{Y_{2,\text{aed}} > V_{\text{th2}} \mid H_0\} + (1 - P\{Y_{2,\text{aed}} > V_{\text{th2}} \mid H_0\}) \cdot \right. \\ &\quad \left. P\left\{\frac{Y_{1,\text{aed}} + Y_{2,\text{aed}}}{2} > V_{\text{th1}} \mid H_0\right\} \right] \end{aligned} \quad (6)$$

$$\begin{aligned} P_{\text{d,aed}} &= P\{Y_{1,\text{aed}} > V_{\text{th2}} \mid H_1\} + P\{Y_{2,\text{aed}} < Y_{1,\text{aed}} < V_{\text{th2}} \mid H_1\} \cdot \\ &\quad \left[ P\{Y_{2,\text{aed}} > V_{\text{th2}} \mid H_1\} + (1 - P\{Y_{2,\text{aed}} > V_{\text{th2}} \mid H_1\}) \cdot \right. \\ &\quad \left. P\left\{\frac{Y_{1,\text{aed}} + Y_{2,\text{aed}}}{2} > V_{\text{th1}} \mid H_1\right\} \right] \end{aligned} \quad (7)$$

Since  $Y_{1,\text{aed}}$  and  $Y_{2,\text{aed}}$  follow identical distributions,

$$P\{Y_{1,\text{aed}} > V_{\text{th2}} \mid H_0\} = P\{Y_{2,\text{aed}} > V_{\text{th2}} \mid H_0\} = P_{\text{fa,ed}} \mid \bar{V}_{\text{a}} = \bar{V}_{\text{a2}} \quad (8)$$

$$P\{Y_{1,\text{aed}} > V_{\text{th2}} \mid H_1\} = P\{Y_{2,\text{aed}} > V_{\text{th2}} \mid H_1\} = P_{\text{d,ed}} \mid \bar{V}_{\text{a}} = \bar{V}_{\text{a2}} \quad (9)$$

where  $\bar{V}_{\text{th1}} = V_{\text{th1}}/\sigma_w^2$  and  $\bar{V}_{\text{th2}} = V_{\text{th2}}/\sigma_w^2$  denote the double thresholds.

Let

$$P_0 = P\left\{\frac{Y_{1,\text{aed}} + Y_{2,\text{aed}}}{2} > V_{\text{th1}} \mid H_0\right\} = Q(\sqrt{N}(\bar{V}_{\text{th1}} - 1)) \quad (10)$$

$$P_1 = P\left\{\frac{Y_{1,\text{aed}} + Y_{2,\text{aed}}}{2} > V_{\text{th1}} \mid H_1\right\} = Q\left(\sqrt{N} \frac{\bar{V}_{\text{th1}} - (1 + \gamma)}{1 + \gamma}\right) \quad (11)$$

Then

$$\begin{aligned} P_{\text{fa,aed}} &= P_{\text{fa,ed}} \mid \bar{V}_{\text{a}} = \bar{V}_{\text{a2}} + (P_{\text{fa,ed}} \mid \bar{V}_{\text{a}} = \bar{V}_{\text{a2}} - P_{\text{fa,ed}} \mid \bar{V}_{\text{a}} = \bar{V}_{\text{a2}}) \cdot \\ &\quad [P_{\text{fa,ed}} \mid \bar{V}_{\text{a}} = \bar{V}_{\text{a2}} - (1 - P_{\text{fa,ed}} \mid \bar{V}_{\text{a}} = \bar{V}_{\text{a2}})P_0] \end{aligned} \quad (12)$$

$$\begin{aligned} P_{\text{d,aed}} &= P_{\text{d,ed}} \mid \bar{V}_{\text{a}} = \bar{V}_{\text{a2}} + (P_{\text{d,ed}} \mid \bar{V}_{\text{a}} = \bar{V}_{\text{a2}} - P_{\text{d,ed}} \mid \bar{V}_{\text{a}} = \bar{V}_{\text{a2}}) \cdot \\ &\quad [P_{\text{d,ed}} \mid \bar{V}_{\text{a}} = \bar{V}_{\text{a2}} - (1 - P_{\text{d,ed}} \mid \bar{V}_{\text{a}} = \bar{V}_{\text{a2}})P_0] \end{aligned} \quad (13)$$

According to the Neyman-Pearson criterion<sup>[18]</sup>, for a given probability of false alarm  $\beta$ , the aim is to find the optimal thresholds,  $\bar{V}_{\text{th1}}$  and  $\bar{V}_{\text{th2}}$ , such that those thresholds jointly maximize the probability of detection,  $P_{\text{d,aed}}$ . The corresponding problem can be described as

$$\begin{aligned} &\max_{\bar{V}_{\text{th1}}, \bar{V}_{\text{th2}}} P_{\text{d,aed}}(\bar{V}_{\text{th1}}, \bar{V}_{\text{th2}}) \\ &\text{s. t. } P_{\text{fa,aed}} = \beta \end{aligned} \quad (14)$$

From Eqs. (10) to (13), the relationship between the thresholds,  $\bar{V}_{\text{th1}}$  and  $\bar{V}_{\text{th2}}$ , can be written as

$$\bar{V}_{th2} = f(\bar{V}_{th1}) \quad (15)$$

Furthermore, the problem in Eq. (14) can be rewritten as

$$\max_{\bar{V}_{th1}} P_{d, aed}(\bar{V}_{th1}, f(\bar{V}_{th1})) \quad (16)$$

which is an unconstrained problem. The optimal  $\bar{V}_{th1}$  can be found from Eq. (16). Then, the optimal  $\bar{V}_{th2}$  can be obtained by substituting the optimal  $\bar{V}_{th1}$  into Eq. (15).

## 2.2 Sensing Time

In cognitive radio networks, the SUs have to vacate the channel as fast as possible if a primary user appears in this channel. Therefore, fast sensing can make a SU have enough time to transmit with other SUs and can improve spectral efficiency. Next, we analyze the average sensing time of the proposed scheme.

In the proposed scheme, the sensing time includes two parts as follows:

$$\bar{T}_{aed} = \bar{T}_{ed} + K\bar{T}_{ed} \quad (17)$$

where  $\bar{T}_{ed} = N_{ed}/f_s$  denotes the sensing time of the AED in the first step as well as the sensing time of the ED. The probability of requiring the second step  $K$  is given as

$$K = P(H_0)(P_{fa, ed} | \bar{V}_{th} = \bar{V}_{th1} - P_{fa, ed} | \bar{V}_{th} = \bar{V}_{th2}) + P(H_1)(P_{d, ed} | \bar{V}_{th} = \bar{V}_{th1} - P_{d, ed} | \bar{V}_{th} = \bar{V}_{th2}) \quad (18)$$

where  $P(H_0)$  is the probability that the PU does not exist and  $P(H_1)$  is the probability that the PU appears in the sub-channel. Substituting Eq. (18) into Eq. (17) and after some manipulations, the average sensing time is derived as

$$\bar{T}_{aed} = N_{ed} [1 + P(H_0)(P_{fa, ed} | \bar{V}_{th} = \bar{V}_{th1} - P_{fa, ed} | \bar{V}_{th} = \bar{V}_{th2}) + P(H_1)(P_{d, ed} | \bar{V}_{th} = \bar{V}_{th1} - P_{d, ed} | \bar{V}_{th} = \bar{V}_{th2})] / f_s \quad (19)$$

As we mentioned before,  $P_{fa, ed}$  is independent of  $\gamma$ , and  $P_{d, ed}$  is a function of  $\gamma$  for given  $\bar{V}_{th}$  and  $N_{ed}$ ; so  $\bar{T}_{aed}$  is a function of  $\gamma$  for given  $\bar{V}_{th1}$ ,  $\bar{V}_{th2}$ ,  $f_s$  and  $N_{ed}$ . Either if  $\gamma$  is high enough or low enough, there will be only one round of sensing, which means that the values of sensing time for the ED and the EAD will be close. However, there must be an increase in sensing time caused by the second round sensing when the value of  $\gamma$  is in a specific area.

## 2.3 Computer simulations

In this section, the simulations are provided to compare the performance of the proposed scheme with that of the scheme that employs only energy detection. The parameters of the simulation are shown in Tab. 1.

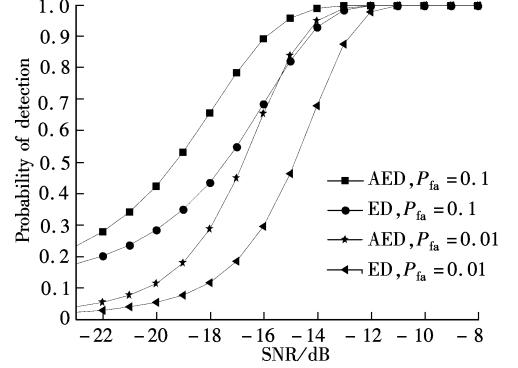
**Tab. 1** Simulation parameters

Parameter	Value
$N$	$10^6$
$P(H_0)$	0.2, 0.8
$P_{fa, aed}$	0.1, 0.01

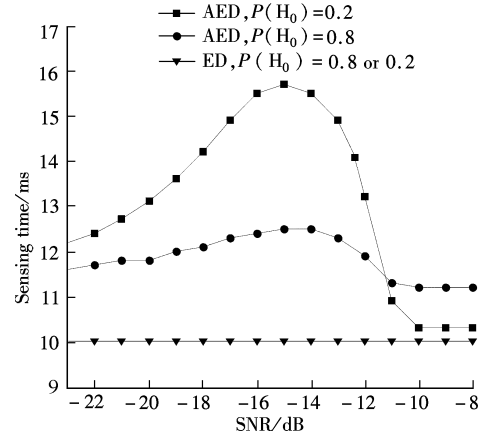
Fig. 2 shows the probabilities of detection of the ED algorithm and the AED algorithm for given false alarm probabilities 0.1 and 0.01. The average SNR of the sensing channel is assumed to vary from  $-23$  to  $-8$  dB. It can be observed that the proposed scheme obtains better performance than the

ED. For example, at  $\text{SNR} = -15$  dB, the probability of detection for the AED is at least 0.8 for a given  $P_{fa, aed} = 0.01$ , while the probability of detection for the ED is 0.45.

Fig. 3 gives the simulations of sensing time vs. SNR for the fixed  $P(H_0) = 0.2$  and  $P(H_0) = 0.8$ . We can see that the sensing time of the AED is slightly greater than that of the ED, which is caused by the second step sensing. Moreover, the AED can perform better when the value of  $P(H_0)$  is higher.



**Fig. 2** Simulation of the probability of detection vs. SNR



**Fig. 3** Simulation of sensing time vs. SNR

## 3 Experimental Platform

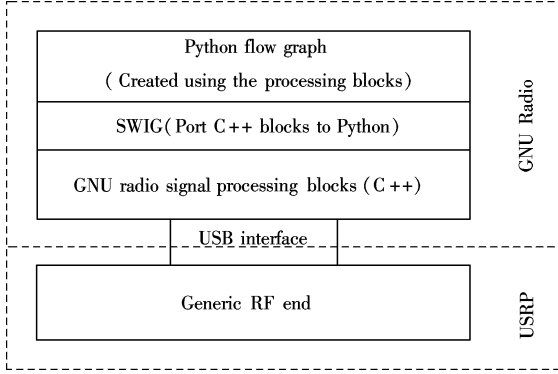
Software-defined radio (SDR) is a system where the main part of the radio is implemented in software. Typical components such as amplifiers, filters, mixers, modulators/demodulators and detectors that are usually implemented in hardware, can now be implemented in software. This system is characterized by its flexibility and reconfigurability, due to the fact that changing its behavior only requires modifying or replacing the software.

Since SDR is a radio where its components are implemented in software, there is a need for a standard set of tools to process the signal received on the antenna. The GNU Radio is a toolbox to implement such a SDR. It is a free software development toolkit that provides the signal processing runtime and processing blocks to implement software radios using readily-available, low-cost external RF hardware and commodity processors. It contains large numbers of libraries written in C/C++ programming language, while GNU Radio applications are mainly written and developed by using Python programming language which provides a friendly front-end environment to the developer to write routines in a

rapid way.

The universal software radio peripheral (USRP)<sup>[9]</sup> is the hardware which receives the RF signal and downconverts it to the baseband for digital processing. It consists of an RF front end and IF blocks. Since its design is open and schematics and drivers are freely available, at an affordable cost, it is a worthwhile choice for those who work with SDR.

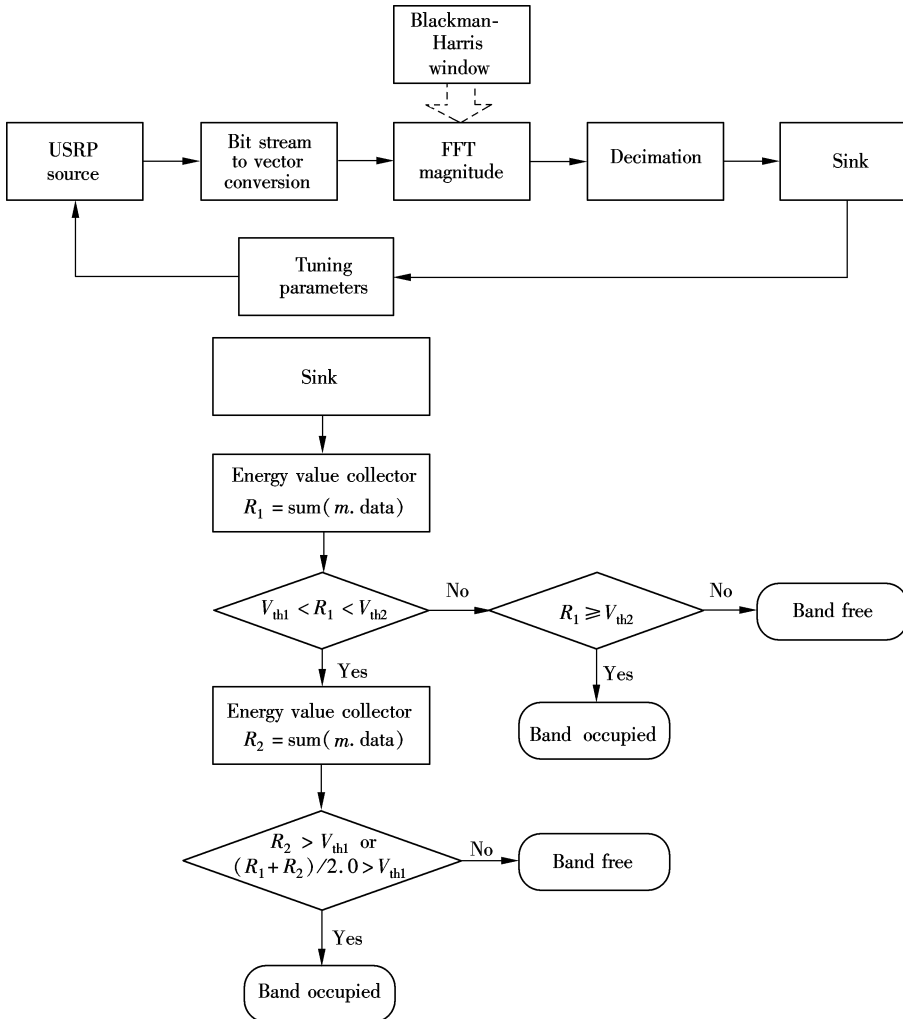
Fig. 4 shows the structure of GNU Radio and USRP SDR. The signal is detected by the USRP and digitized, then passed to GNU Radio through the USB interface.



**Fig. 4** Experimental platform architecture

## 4 Experimental Results

The implementation of the AED algorithm is presented in Fig. 5, where  $m$ . data is the magnitude-squared of the FFT output. Fig. 5 shows the flow of data from USRP to the sink which is a Linux command line interface in our scenario. USRP fetches the signal of the desired frequency from the sink as a tuning parameter. After passing through the USRP, the raw data bit streams are converted to vectors or arrays of data. The FFT is performed on the received raw data with the help of signal processing blocks, and the Blackman-Harris window is used to overcome the spectral leakage effect. When the FFT routine is implemented on non-periodic data, it results in spectral leakage; i. e., the energy of the signal spreads out to a larger band of frequencies. Window functions help out in reducing the effect of spectral leakage. After performing the FFT magnitude module, decimation of the data is performed. Decimation is the inverse of interpolation. Decimation reduces the sample rate of data by performing downsampling to the desired rate and sends the desired rate to the USRP as a tuning parameter. After performing decimation, the obtained data is appended into a file or plotted by a GUI tool. The collected data is in the form of FFT magnitude bins.



**Fig. 5** Flow chart of the AED algorithm

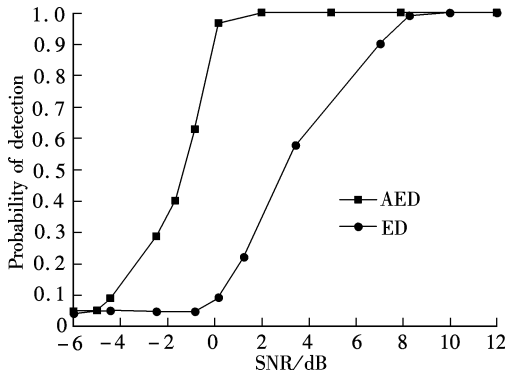
The AED algorithm steps across the sub-channels and takes the measurement in terms of FFT magnitude bins. The number of FFT bins, gain, decimation, time delay, dual delay and frequency range are forwarded to the USRP as tuning parameters.

The parameters of the simulation are shown in Tab.2. The results are averaged over 5 000 Monte Carlo simulations.

**Tab.2** Experimental parameters

Parameter	Value
$N$ (receiver)	256
Frequency range(receiver)/GHz	2.500 to 2.503
Modulation(PU)	QPSK
Centre frequency(PU)/GHz	2.501 5
Symbol rate(PU)/( $10^6$ signal $\cdot$ s $^{-1}$ )	1
$P_{fa, cad}/\%$	0.5
$P(H_0)$	0

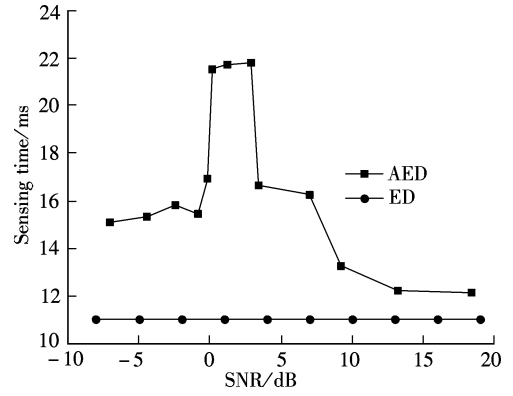
Fig.6 shows the probabilities of the detection of the ED algorithm and the AED algorithm for a given false alarm probability of 0.5. It can be observed that the proposed scheme obtains better performance than the ED when SNR is between  $-4$  and  $8$  dB.



**Fig.6** Experiment of the probability of detection vs. SNR

Fig.7 shows the sensing time differences between the two algorithms under different SNR conditions. We can find that the sensing time for the AED is greatly increased when the SNR is between  $-4$  and  $8$  dB, and at its peak, it is two times higher than the sensing time for the ED. The phenomenon can be explained as follows. In a low SNR environment, most of the observations satisfy  $R_1 < V_{th1}$ . The algorithm finds out the sub-channel to be unoccupied immediately, thus resulting in a rather short sensing time. With the increase in the SNR, most of the observations will be situated in the zone between  $V_{th1}$  and  $V_{th2}$ . It triggers the second-round, causing a sharp increase in the sensing time. When the SNR continues to increase, most of the observations will be located in the “occupied area”, thus satisfying  $R_1 > V_{th2}$  and the sensing time will decrease and finally become stable, which is comparable to that of the ED. It should be noticed that here we have  $P(H_0) = 0$ . Based on the analysis in Section 3, it is the worst condition of the sensing time. In other words, with the increase in  $P(H_0)$ , the sensing time will decrease gradually.

Simulation results in Fig.2 and Fig.3, and experimental results in Fig.6 and Fig.7 show that compared with the conventional energy detection algorithm, the proposed scheme can achieve a higher probability of detection within a rea-



**Fig.7** Experiment of sensing time vs. SNR

sonable sensing time.

## 5 Conclusion

In this paper, we propose an adaptive double-threshold energy detection algorithm for cognitive radio. The algorithm can adaptively switch between one-round sensing and two-round sensing by comparing its observations with two pre-fixed thresholds. Mathematical expressions for the probability of detection, the probability of false alarm, and the sensing time are derived in this paper. The performance of the proposed scheme is then investigated by the data obtained from a real-time experiment based on GNU Radio and the USRP, as well as the Monte Carlo simulation. Numerical results show that compared with the conventional energy detection, the proposed scheme can achieve a higher probability of detection at the expense of a little performance loss of sensing time.

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# 一种认知无线电自适应双门限能量检测算法

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**摘要:**针对传统频谱感知方法易受噪声波动影响的缺点,提出了一种认知无线电自适应双门限能量检测算法.该算法基于双门限能量检测,通过比较认知用户接收的能量值和预定义的门限值,判断当前信道状态并自适应地选择一轮感知或两轮感知.推导了所提算法的检测概率、虚检概率和感知时间的性能表达式,并采用蒙特卡洛仿真得到信噪比与检测概率、感知时间的关系,最后利用 GUN Radio 和 USRP 搭建软件无线电系统平台,在实际的无线电环境中对所提算法进行验证.仿真结果与实际验证结果均表明,与传统频谱感知方法相比,所提算法在合理的感知时间范围内,能达到更高的检测概率.

**关键词:**能量检测;软件无线电;检测概率;感知时间

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