A Novel Spectrum Correlation Based Energy Detection for Wideband Spectrum Sensing

Bo Lan(✉), Tao Peng, PeiLiang Zuo, and Wenbo Wang

Wireless Signal Processing and Networks Laboratory (WSPN),
Key Laboratory of Universal Wireless Communications, Ministry of Education,
Beijing University of Posts and Telecommunications, Beijing, China
{lanboxianren,pengtao,zplzpl88,wbwang}@bupt.edu.cn

Abstract. With the rapid development of wireless communications technology, the problem of scarcity of spectrum resources is becoming serious. Cognitive radio (CR) which is an effective technology to improve the utilization of spectrum resources is getting more and more attention. Spectrum sensing is a key technology in cognitive radio. Wideband spectrum sensing (WBSS) can help secondary users (SUs) find more spectrum holes. However, for the traditional energy detection (ED) algorithm, when the signal-to-noise ratio (SNR) of the primary user (PU) is low, the detection performance is extremely poor owing to the single frequency point detection method. Therefore, the concept of spectrum correlation is proposed. Spectrum correlation algorithm uses the detection window to realize joint detection of multiple frequency points which can improve performance. This paper focuses on how to make the best of spectrum correlation to ensure the detection performance for low SNR signals. We propose an adaptive detection window (ADW) method, whose detection window is adaptively selected based on the estimated SNR of signal. The method can be directly used for wideband spectrum sensing when the approximate position of each signal and its estimated SNR are known. In this context, to show the robustness of the ADW method, a simulation of the sensitivity of the ADW method to the SNR estimation error is performed. Meanwhile, simulations of methods comparison demonstrate that the proposed ADW method outperforms the commonly used iterative energy detection method, frequency correlation methods and histogram-based segmentation method by far.

Keywords: Cognitive radio (CR) · Wideband spectrum sensing (WBSS) · Energy detection (ED) · Spectrum correlation · Detection window

---

This work is supported in part by the National Natural Science Foundation of China (No. 61631004) and the National Science and Technology Major Project of China under Grant 2016ZX03001017.

H. Gao et al. (Eds.): ChinaCom 2019, LNICST 312, pp. 220–234, 2020.
https://doi.org/10.1007/978-3-030-41114-5_17

1 Introduction

With the development of wireless communications technology, The fixed allocation of spectrum resources seems to be unable to meet the growing spectrum demand. However, many surveys indicate that most of the spectrum resources are not fully utilized [1]. Cognitive radio (CR) [2] is considered to be a promising technology to improve spectrum utilization. To ensure that secondary users (SUs) use shared spectrum without interfering with primary users (PUs), spectrum sensing is essential for CR [3]. Through spectrum sensing, SUs can seize the available opportunities of shared spectrum. Especially when the shared spectrum is idle, they can use spectrum resources for transmission. Once the PUs occupy the spectrum again, they can also give up the channel resources in time to avoid affecting the transmission quality of the PUs.

Many methods are proposed for the narrowband spectrum sensing (NBSS) [4], such as energy detection (ED) [5], matched filtering and cyclostationary feature detection. Although the latter two methods have better detection performance, ED is more widely used because it does not require any prior information of PU signals and has lower computational complexity. However, NBSS can only detect one channel at a time. Even though a larger spectrum sensing range can be obtained by a sequential sweep-tune fashion [6], it takes longer to perceive the wideband spectrum. Therefore, it is more appropriate to directly use wideband spectrum sensing (WBSS) for multi-channel detection. Due to the advantages of ED, it can also be used for WBSS. However, when the signal power is particularly low, its detection performance is poor.

In order to detect multiple signals with different bandwidths and SNRs in the spectrum, some ED-based WBSS method is proposed. In [7], a multi-band joint detection algorithm is proposed to optimize the decision thresholds of each subband. But the adopted detection method is also based on the single frequency point, the detection results for low SNR signals are still not satisfactory. In order to locate the boundary between sub-bands, [8] proposed a histogram-based segmentation method. However the distinction between noise and low SNR signal is not obvious. Detection window is a tool used by the spectrum correlation algorithm to detect signals, [9] first used the fixed detection window to detect the signal. The final performance improvement is limited due to the underutilization of spectrum correlation. In this paper, the histogram segmentation method, traditional iterative energy detection and spectrum correlation are used as the comparison methods.

This paper focuses on the full-utiliazation of spectrum correlation in wideband spectrum sensing. Specifically, the theoretical relationship between detection window and detection performance is acquired. The corresponding detection window can be selected according to the estimated SNR of the signal to guarantee performance rather than fixed. We propose an adaptive detection window (ADW) method, the detection window can be adaptively utilized for detecting the signals in wideband provided that the approximate position of the signals and the estimated SNR are known. The method has a theoretical minimum detectable bandwidth at each SNR. For signals with a certain SNR, the method can detect the signal having a bandwidth greater than the corresponding minimum detectable bandwidth.

The structure of the paper is as follows. We first briefly introduce the wideband sampling model and the single frequency point detection mode in Sect. 2. Then we detail the frequency correlation in Sect. 3. In Sect. 4, the performance of the proposed method is simulated and compared with the previously mentioned method. Finally, conclusions are given in Sect. 5.

2 Preliminary

2.1 Wideband Sampling Model

The sampling frequency of the signal in the time domain is f which is higher than the Nyquist rate. N represents the number of points per sampling, and N_t denotes the total number of sampling times. As shown in Fig. 1, N sampled signal is converted into the signal in frequency domain by Fast Fourier Transform (NFFT). $Y(k)$ is the kth frequency value of the sampled signal after FFT, then

$$\begin{aligned} Y(k) &= \frac{1}{\sqrt{N}} \sum_{n=0}^{N-1} y(n) \cdot e^{-j\frac{2\pi}{N} \cdot kn} \\ &= \frac{1}{\sqrt{N}} \sum_{n=0}^{N-1} y(n) \cdot \cos(\frac{2\pi kn}{N}) - j\frac{1}{\sqrt{N}} \sum_{n=0}^{N-1} y(n) \cdot \sin(\frac{2\pi kn}{N}) \\ &= Y_{real} + jY_{imag} \end{aligned} \quad (1)$$

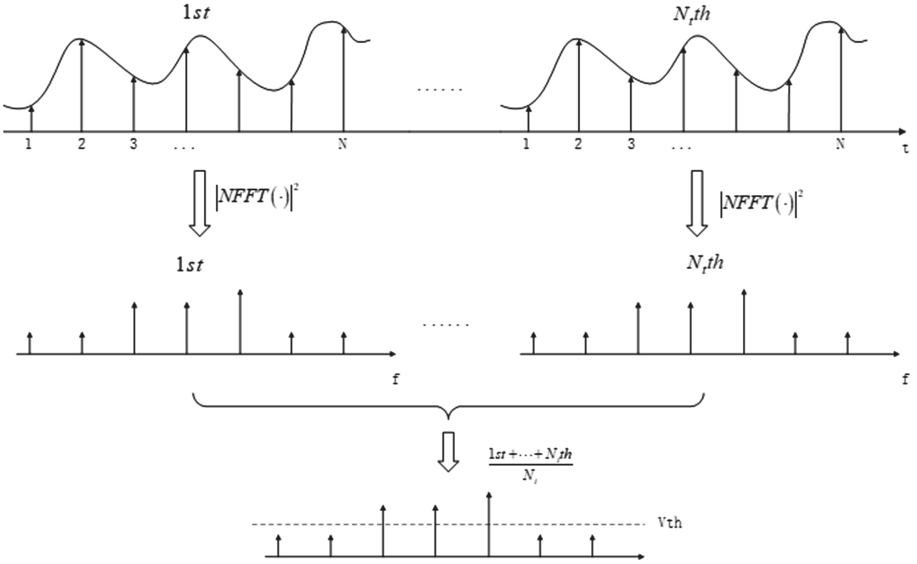

Fig. 1. The sampling process of the signal in the time domain

The energy of the signal in frequency domain obtained by each sampling is averaged to obtain the average power of each frequency point. The average statistic is T, which is obtained according to the signal sampling model:

$$T = \frac{1}{N_t} \cdot \sum_{N_t} |Y(k)|^2 \tag{2}$$

According to the sampled signal model, the sampling result can be defined as a binary hypothesis model: H_0 means that the frequency point is idle, and H_1 means that the frequency point is occupied. $\sigma_{s,i}^2$ represents the power of i-th signal frequency point and σ_w^2 represents the power of white Gaussian noise.

When H_0 is true, $|Y(k)|^2$ obeys the exponential distribution of the parameter $1/\sigma_w^2$. When H_1 is true, $|Y(k)|^2$ obeys the exponential distribution of the parameter $1/\left(\sigma_s^2 + \sigma_w^2\right)$, According to the central limit theorem, when N_t is large, T obeys the following Gaussian distribution [9]:

$$\begin{aligned} H_0 &: \ T - Normal(\sigma_w^2,\ \sigma_w^4/N_t) \\ H_1 &: \ T - Normal((\sigma_s^2 + \sigma_w^2),\ (\sigma_s^2 + \sigma_w^2)^2 \Big/ N_t) \end{aligned} \tag{3}$$

2.2 Single Frequency Point Detection Model

In the traditional energy detection algorithm, after the statistic T is obtained, a power threshold V_{th} needs to be designed [10]. The frequency point above the threshold is the signal frequency point, and lower than the threshold is the noise frequency point. The selection of the threshold value will directly affect the detection performance of the energy detection algorithm. If the threshold value is too high, some signal frequency points will be missed and the detection ratio will be reduced. If the threshold is too low, some noise frequency points will be misjudged as signal frequency points, which will increase the false alarm ratio. In practical applications, two decision criteria are obtained according to the energy detection performance index: constant detection rate criterion (CDR) and constant false-alarm rate criterion (CFAR) [11]. [12] proposed a double-threshold based energy detection (DTED) for the cooperative spectrum sensing (CSS). A common feature of these methods is that the judgment of a single frequency point depends only on its own power.

In the single frequency point detection model, $P_{d,single}$ indicates the probability that the signal frequency point is judged correctly (i.e the probability that the frequency point power exceeds the threshold V_{th} when H_1 is true). Where $Q(x) = \int_x^\infty \frac{1}{\sqrt{2\pi}} e^{\frac{t^2}{2}} dt$

$$P_{d,single} = \{T > V_{th} | H_1\} = Q\left(\frac{V_{th} - \left(\sigma_s^2 + \sigma_w^2\right)}{(\sigma_s^2 + \sigma_w^2)/\sqrt{N_t}}\right) \tag{4}$$

$P_{f,single}$ denotes the probability that the noise frequency point is judged wrong (i.e the probability that the frequency point is below V_{th} the threshold when H_0 is true).

$$P_{f,\text{single}} = \{T > V_{th} | H_0\} = Q\left(\frac{V_{th} - \sigma_w^2}{\sigma_w^2/\sqrt{N_t}}\right) \tag{5}$$

Suppose the threshold V_{th} is noise power (i.e. $V_{th} = \sigma_w^2$), the theoretical value of P_d will be given in the following table.

As can be seen from Table 1, the value of $P_{d,single}$ has been on a steady decline with the decreasing SNR. The results can explain the reason why the traditional energy detection algorithm using single frequency point detection has the poor detection performance for low SNR signals.

Table 1. The theoretical value of $P_{d,single}$

SNR (dB)	$P_{d,single}$
−19	56.98%
−18	58.73%
−17	60.90%
−16	63.55%
−15	66.77%
−14	70.59%
−13	75.01%
−12	79.94%
−11	85.10%
−10	90.07%
−9	94.31%
−8	97.35%

3 Research on Spectrum Correlation

This section first introduces the concept of spectrum correlation, and then gives the theoretical relationship between detection window and detection performance, finally puts forward the ADW method which adopts adaptive detection window according to the SNRs to detect signal.

3.1 Spectrum Correlation

The spectrum correlation algorithm mainly uses the correlation between adjacent signal frequency points for joint detection. If there is a signal in the spectrum, since the signal has the certain bandwidth, the frequency point near the signal point is also a signal point, then the probability that the adjacent frequency point is higher than the noise power will exceed 50%. The noise frequency points are independent and identically distributed. Thus, there is no correlation between adjacent noise points.

For a single frequency point, the probability that the point is higher than the estimated noise is $P_{s,T>\hat{\sigma}_w^2}$ [13], and the noise frequency point higher than the estimated noise is $P_{w,T>\hat{\sigma}_w^2}$.

$$\begin{aligned} P_{s,T>\hat{\sigma}_w^2} = H_1 : P(T > \hat{\sigma}_w^2) &= Q(\frac{\hat{\sigma}_w^2 - (\sigma_s^2 + \sigma_w^2)}{(\sigma_s^2 + \sigma_w^2)/\sqrt{Nt}}) \\ &= Q((\frac{\mu}{1+r} - 1) * \sqrt{Nt}) \end{aligned} \tag{6}$$

$$\begin{aligned} P_{\mathrm{w},T>\hat{\sigma}_w^2} = H_0 : P(T > \hat{\sigma}_w^2) &= Q(\frac{\hat{\sigma}_w^2 - \sigma_w^2}{\sigma_w^2/\sqrt{Nt}}) \\ &= Q((\mu - 1) * \sqrt{Nt}) \end{aligned} \tag{7}$$

$\hat{\sigma}_w^2$ is the estimated noise power, $\gamma = \sigma_s^2/\sigma_w^2$ is the SNR of the signal, $\mu = \hat{\sigma}_w^2/\sigma_w^2$ is the ratio of the estimated noise power value to the actual noise value.

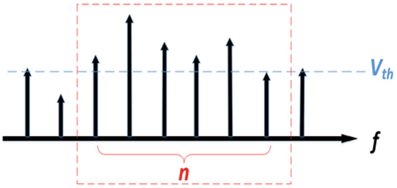

Fig. 2. Multi frequency point joint detection model (Color figure online)

In the spectrum correlation algorithm, we will refer to the window containing multiple frequency points as the detection window (the red dotted line area of Fig. 2), assuming the window size is n (i.e there are n frequency points in the detection window). If at least n_1 frequency points of the n frequency points are higher than the noise power, then we think that the frequency points in the window are the signal frequency points, otherwise they are noise frequency points. $\rho = n_1/n$ is the correlation rate. n and ρ are the most important factors in the subsequent process. P_d is the probability that the signal frequency points are determined as signal points and P_f is the probability that noise frequency points are determined as a signal point. $P_{s,T>\hat{\sigma}_w^2}$, $P_{w,T>\hat{\sigma}_w^2}$ can be simply expressed as P_s, P_w.

$$P_d = \sum_{k=n\cdot\rho}^{n} C_n^k \cdot {p_s}^k \cdot (1-p_s)^{n-k} \tag{8}$$

$$P_f = \sum_{k=n\cdot\rho}^{n} C_n^k \cdot {p_w}^k \cdot (1-p_w)^{n-k} = (\sum_{k=n_1}^{n} C_n^k) \cdot 0.5^n \tag{9}$$

Assume the noise estimation is accurate (i.e. $\mu = 1$), and the sampling times N_t is 200, $n = 200$, $\rho = 0.65$. Table 2 gives the theoretical value of P_d.

Table 2. The theoretical value of P_d and $P_{d,single}$

SNR (dB)	P_d	$P_{d,single}$
−19	1.26%	56.98%
−18	4.10%	58.73%
−17	13.18%	60.90%
−16	36.47%	63.55%
−15	72.94%	66.77%
−14	93.64%	70.59%
−13	99.94%	75.01%
−12	100.00%	79.94%
−11	100.00%	85.10%
−10	100.00%	90.07%
−9	100.00%	94.31%
−8	100.00%	97.35%

It can be concluded from the results that the joint detection P_d outperforms the single frequency point detection $P_{d,single}$ when SNR is above −14dB. If single frequency point detection gets into trouble, joint detection using the correlation of signal frequency points is the method that can effectively improve performance.

From the above description of spectrum correlation, the detection window is the most important parameter to reflect the correlation. The window size n represents the number of signal frequencies participating in the joint detection, and the correlation ratio ρ indicates the decision threshold. Although the existing method using detection window utilizes the spectrum correlation of the signal, the research on the spectrum correlation is insufficient. The selection of window parameters lacks theoretical basis and the window parameters are fixed at different SNRs. As shown in Table 2, once the SNR is too low, the detection performance will drop dramatically. The theoretical lowest detectable SNR and minimum detectable bandwidth of the signal cannot be calculated by theoretical formula. In order to further improve the detection performance, it's necessary to study the effect of the detection window on performance. The next section will discuss how to choose the best detection window and give the specific detection process.

3.2 Adaptive Detection Window

To ensure the optimal detection performance, we define the following formula, P_{dset} and P_{fset} are the preset performance requirements.

$$Target : P_d > P_{dset}\, and\, P_{fset} < P_f \tag{10}$$

Since P_s is related to γ and P_d is affected by P_s, the higher the SNR of the signal, the value of P_s is larger. When the window parameters (i.e. n and ρ), and other conditions (e.g. bandwidth) are the same under signals with different SNRs, the detection performance of the high SNR will be better than the performance of low SNR. When the fixed detection window are used, there is a certain threshold, if the SNR is higher than the threshold, the performance can achieve (10), but if the SNR is lower than the threshold, the performance cannot meet (10). In order to make different SNR signals satisfy (10), different detection window can be set at different SNRs. Since n indicates that n frequency points are participated in the detection process, if the number of frequency points of the signal itself is less than n, the detection performance will decrease, so we will try to make n small enough to make more signals meet the requirements of bandwidth.

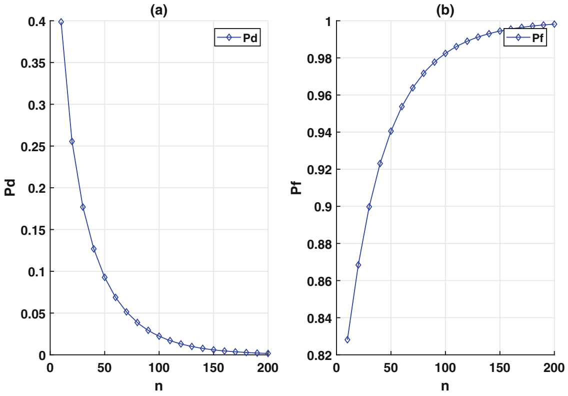

Fig. 3. The relationship between window size and detection ratio (a) $\rho > P_s$ (b)$\rho < P_d$

When the SNR is fixed, if $\rho > P_s$, as shown in Fig. 3(a), P_d is inversely related to n and the maximum value does not exceed 0.5. If $\rho < P_w$, as shown in Fig. 3(b), P_f is positively correlated with n and the minimum value is not less than 0.5. Therefore the correlation ratio should satisfy $P_w < \rho < P_s$.

When $P_w < \rho < P_s$, as shown in Fig. 4, n is positively correlated with P_d and negatively correlated with P_f. So the larger n is, the more values of ρ can satisfied (10). The selection process of the minimum detection window at a specific SNR can be divided into the following five steps:

- *Step 1*, Initialize n and n_1 to 1;
- *Step 2*, By gradually increasing n_1, the corresponding p_d and p_f can be obtained. when the formula (10) is satisfied, it will jump to step 5. If (10) is not reached until $n_1 > n$, step 3 will be executed;
- *Step 3*, Let $n = n + 1$, $n_1 = 1$;
- *Step 4*, Gradually increase n_1. when (10) is met, skip to step 5. If (10) is not reached until $n_1 > n$, it will return to step 3;
- *Step 5*, The current n and $\rho = n_1/n$ are the parameters of the detection window under the SNR.

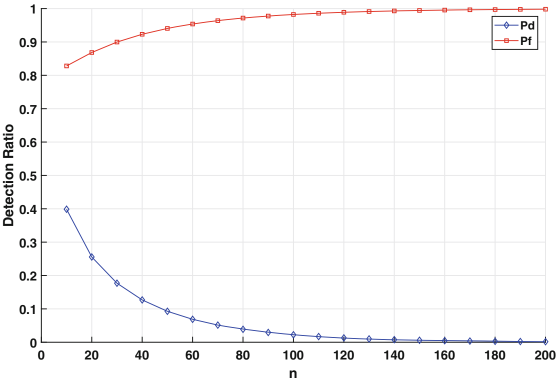

Fig. 4. The relationship between window size and detection ratio

Let $N = 5000$, $N_t = 200$, $P_{dset} = 99.5\%$, $P_{f\text{set}} = 0.1\%$ and assume that the estimated noise power value is accurate. The size of window and correlation ratio are given in Table 1, SNR from −19 dB to −8 dB.

The minimum detectable bandwidth is defined as the bandwidth of the signal when its passband width is equal to the size of detection window. In other words, the minimum detectable bandwidth is different under different SNR. Therefore, in this improved method we can know the lowest detectable SNR and the minimum detectable bandwidth, and for low SNR signals, the detection performance can also satisfy (10).

The specific process of the ADW method is as follows.

Table 3. Selected detection window parameters

SNR (dB)	n	ρ	SNR (dB)	n	ρ
−19	1647	53.8%	*−18.5*	1309	54.3%
−18	1045	54.8%	*−17.5*	839	55.4%
−17	667	56.0%	*−16.5*	537	56.7%
−16	427	57.5%	*−15.5*	347	58.3%
−15	279	59.3%	*−14.5*	221	60.2%
−14	181	61.5%	*−13.5*	144	62.6%
−13	119	64.2%	*−12.5*	95	65.3%
−12	81	66.7%	*−11.5*	66	68.2%
−11	54	70.4%	*−10.5*	43	72.1%
−10	38	73.7%	*−9.5*	33	75.8%
−9	27	77.8%	*−8.5*	24	79.2%
−8	21	81.0%	*−7.5*	18	83.4%

- Obtain the estimated noise power, the approximate position and the estimated SNR of the signal by using methods such as edge judgement;
- Adopt corresponding detection window parameters based on estimated SNR;
- Slide the detection window from left to right at the approximate position of the signal. When the ratio of the frequency points above the estimated noise power to the total points in the detection window is higher than ρ, the frequency points in the window are determined as the signal frequency points.

4 Simulation and Discussion

In the end of Sect. 3.1, the theoretical probability that a single signal frequency point power exceed the noise power $P_{d,single}$ is lower than the probability of joint detection P_d. The following simulations are used to verify whether the above theory is accurate. Use the detection window parameters obtained in Method 1 to obtain P_d (Tables 4 and 5).

Table 4. Simulation parameters

Parameter	Value
Total bandwidth	50 MHz
Sampling duration d_t	0.01 s
Sampling times N_t	200
Sampling points per time N	5000
Frequency resolution	10 KHz
Preset signal detection ratio P_{dset}	99.5%
Preset false alarm ratio P_{fset}	0.1%

Table 5. Detection methods

Methods	Detailed description
Method 1	Adaptive detection window in Sect. 3.2 in this paper
Method 2	The detection window is fixed of the frequency correlation method in [9]
Method 3	The iterative detection algorithm given in [7]
Method 4	The histogram-based segmentation method proposed in [8]

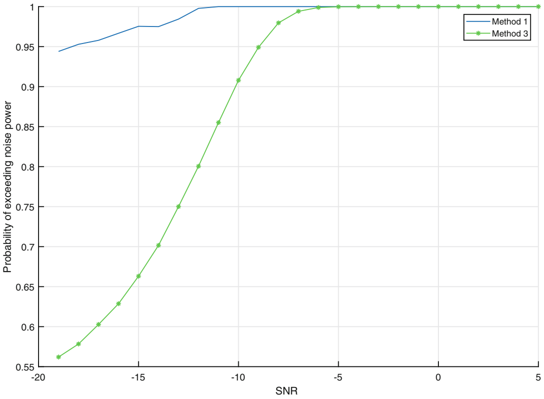

Fig. 5. Probability of exceeding noise power

The simulation result (Fig. 5) confirms that the probability that the frequency point is higher than the noise power can be greatly improved when the correlation of the signal is utilized. Then, we will detect the entire signal. The bandwidth of the signal to be detected is 25 MHz, the modulation method is Direct Sequence Spread Spectrum (DSSS), and the root raised cosine filter with a roll-off factor of 0.22 is used. Other parameters related to adaptive detection window(ADW) are given in Table 2. Comparison algorithms are common detection methods in simulation, and their detailed introduction is shown in Table 3. Use these methods to detect the passband of the signal.

The detection ratio indicates the proportion of the signal frequency points determined as signal points by the detection methods to the total signal frequency points. As can be seen from Fig. 6, Method 1 has the highest ratio of signal detection for different SNR signals, and the detection ratio is both above 96%. The signal detection ratio of Method 4 fluctuates with the change of

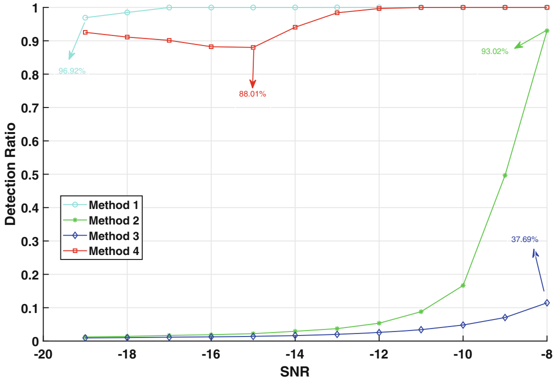

Fig. 6. Detection ratio of the signal passband

SNR, but in general, the performance of Method 4 is only worse than Method 1 and obviously better than Method 2 and 3. When the SNR of the signal is $-19\,\mathrm{dB}$ $-10\,\mathrm{dB}$, the detection ratios of Method 2 and 3 are basically close to 0. As the SNR of signals increases, the detection ratio becomes larger, and the improvement of Method 2 is larger than that of Method 3. When the SNR ratio of the signal is -8 dB, the detection ratio of the Method 2 has reached 93%, which is close to the detection performance of the Method 1 and 4.

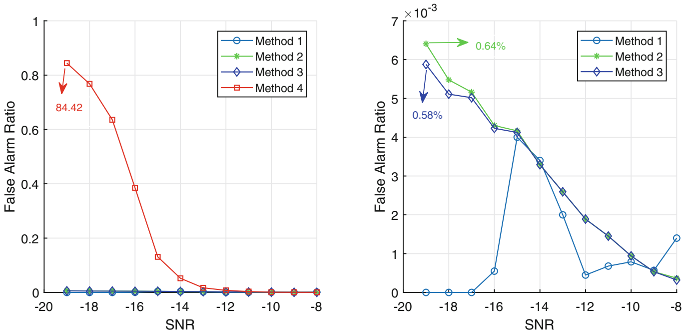

Fig. 7. False alarm ratio of the noise stopband

Then use these methods to detect the stopband, and the results are shown in Fig. 7. The false alarm ratio denotes the proportion of the frequency points in the stopband are determined as signal frequency points by the detection methods to the total noise signal frequency points. It can be seen that the false alarm ratio of Method 4 gradually increases with the decrease of SNR, and the highest is 84.4%. The false alarm ratio of the other three methods has been very low, basically less than 1%. The false alarm ratio of Method 1 fluctuates with the change of SNR, reaching a maximum of 0.4%, but it has been the lowest of the four methods. The false alarm ratio of Method 2 and Method 3 is positively correlated with the SNR.

Since the choice of detection window parameters is related to the SNR, when there is an error in the SNR estimation of the signal, the detection ratio of the signal using the detection window is as follows:

The coordinate axis SNR in Fig. 8 represents the actual SNR of the signal. The SNR Error is the estimated SNR of the signal minus the actual SNR. We can conclude that as the SNR error value becomes smaller, the detection ratio of the signal gradually increases. The simulation results are consistent with the conclusions mentioned at the beginning of 3.2. Even if the estimated error of SNR reaches 1.5 dB, the detection ratio of most signals is higher than 95%, and the worst can also be higher than 90%. The reason why the detection ratio with SNR error of −1.5 dB is much higher than that with +1.5 dB, and even higher than that with no error (0 dB) is that the detection window parameters used are for the lower SNR When the SNR error becomes lower.

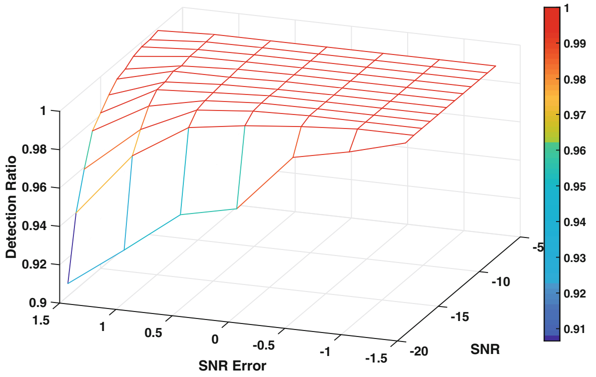

Fig. 8. The influence of the SNR estimation error on the detection ratio of signal passband

The detection ratio of Method 2 and 3 is positively correlated with the SNR. The false alarm ratio is negatively correlated with the SNR. Although the detection performance (comprehensive consideration of detection ratio and false alarm ratio) improved with the increase of the SNR, it is still not well. Even though the detection ratio of Method 4 has been relatively high, the false alarm ratio is very high at low SNR, reaching 84%. The detection ratio of method 1 is always above 95%, and the false alarm ratio is the lowest among the four methods. The detection performance is the best of the four methods.

5 Conclusion

Since the traditional energy detection adopts the single frequency point detection mode, the detection performance of the low SNR signal is poor. Spectrum correlation algorithm using multi frequency point joint detection is a promising improvement scheme. However, the detection window parameters used in the existing methods are fixed and have no theoretical support. This paper fully considers the influence of the detection window on the performance, and then proposes the ADW method. The commonly used wideband spectrum detection method is used to compare the detection performance with the proposed method. Simulation results in several aspects show that the performance of the method is better than the comparison method when the approximate position and the estimated SNR of the signal are known. The method can detect the signals with low SNR in the spectrum with high probability at a low false alarm ratio.

References

1. Facilitating Opportunities for Flexible, Efficient, and Reliable Spe ctrum Use Employing Cognitive Radio Technologies, FCC 03–322. Federal Commun. Commission, Washington, DC, USA, December 2003
2. Haykin, S.: Cognitive radio: brain-empowered wireless communications. IEEE J. Sel. Areas Commun. **23**(2), 201–220 (2005)
3. Mitola, J., Maguire, G.Q.: Cognitive radio: making software radios more personal. IEEE Pers. Commun. **6**(4), 13–18 (1999)
4. Yucek, T., Arslan, H.: A survey of spectrum sensing algorithms for cognitive radio applications. IEEE Commun. Surv. Tutor. **11**(1), 116–130 (2009)
5. Mariani, A., Giorgetti, A., Chiani, M.: Effects of noise power estimation on energy detection for cognitive radio applications. IEEE Trans. Commun. **59**(12), 3410–3420 (2011)
6. Hwang, J., Chang, W., Hu, P.: A sub-nyquist wideband spectrum sensing scheme using aliased spectral edge detection and database matching. In: 2015 International Conference on Wireless Communications and Signal Processing (WCSP), Nanjing, pp. 1–5 (2015)
7. Quan, Z., Cui, S., Sayed, A.H., Poor, H.V.: Optimal multiband joint detection for spectrum sensing in cognitive radio networks. IEEE Trans. Signal Process. **57**(3), 1128–1140 (2009)
8. Bao, D., De Vito, L., Rapuano, S.: A histogram-based segmentation method for wideband spectrum sensing in cognitive radios. IEEE Trans. Instrum. Meas. **62**(7), 1900–1908 (2013)
9. Yuan, L., Ren, F., Xing, L., Peng, T., Wang, W.: Wideband spectrum sensing algorithm based on frequency correlation. In: 2013 15th IEEE International Conference on Communication Technology, Guilin, pp. 211–217 (2013)
10. Gahane, L., Sharma, P.K., Varshney, N., Tsiftsis, T.A., Kumar, P.: An improved energy detector for mobile cognitive users over generalized fading channels. IEEE Trans. Commun. **66**(2), 534–545 (2018)
11. Ziyang, L., Tao, P.: Energy detection about broadband signal without priori information of interference system. J. Beijing Univ. Posts Telecommun. **35**(5), 31–35 (2012)

12. Bhowmick, A., Chandra, A., Roy, S.D., Kundu, S.: Double threshold-based cooperative spectrum sensing for a cognitive radio network with improved energy detectors. IET Commun. **9**(18), 2216–2226 (2015)
13. Wang, X., Peng, T., Wang, W.: Low-SNR energy detection based on relevance in power density spectrum. In: Liang, Q., Mu, J., Wang, W., Zhang, B. (eds.) Proceedings of the 2015 International Conference on Communications, Signal Processing, and Systems. LNEE, vol. 386, pp. 283–291. Springer, Heidelberg (2016). https://doi.org/10.1007/978-3-662-49831-6_29