Robust Multiband Spectrum Sensing in Cognitive Radio Networks via Exponentially Embedded Family Criterion

Haobo Qing[1], Yuanan Liu[1], Gang Xie[2], Kaiming Liu[1], and Fang Liu[1]
[1] Beijing Key Laboratory of Work Safety Intelligent Monitoring, School of Electronic Engineering, Beijing University of Posts and Telecommunications, Beijing 100876, China
[2] Beijing Key Laboratory of Network System Architecture and Convergence, School of Information and Communication Engineering, Beijing University of Posts and Telecommunications, Beijing 100876, China
Email: qinghaobo@gmail.com; {yuliu, xiegang, kmliu, lf}@bupt.edu.cn

Abstract—This paper proposes a robust spectrum sensing scheme for cognitive radio networks. The proposal performs spectrum sensing simultaneously over the total channels rather than a single channel at a time. It first estimates the number of occupied channels via the exponentially embedded family criterion, and then determines the occupancy status for each channel by sample power. The proposed method is robust to noise uncertainty since noise power estimation is avoided. Simulations demonstrate that our approach is robust to noise uncertainty and outperforms existing sensing methods.

Index Terms—Cognitive radio network, spectrum sensing, robust detection, exponentially embedded family, noise uncertainty

I. Introduction

Cognitive radio (CR) is a promising technique to deal with the spectrum scarcity problem in communication systems [1]-[3]. As a key component of CRs, spectrum sensing aims to find out the spectrum holes and its performance can get improved through a cooperative way [4], [5]. For spectrum efficiency improvement, secondary users (SUs) perform spectrum sensing over a wide range of frequency bands and then opportunistically access the spectrum holes without causing harmful interferences to primary users (PUs). In this case, the wideband spectrum can be divided into multiple nonoverlapping narrow subbands. Thus spectrum sensing can be carried out in each subband sequentially [6]. On the contrary, simultaneously detecting PU signals over multiple channels in a parallel manner [7], [8] is time-saving but at a high hardware implementation cost.

Among the numerous sensing algorithms, energy detector is most widely used due to its easy implementation as well as favorable performance [9]. However, energy detector is quite sensitive to noise uncertainty, which severely deteriorates its performance [10]. In order to resist the noise uncertainty, several approaches have emerged in the recent years [11], [12]. Exploiting the received signal samples for detection, these methods require no prior knowledge of noise power and thus are robust to noise uncertainty. In [11], based on the eigenvalues of covariance matrix under the random matrix theory, the maximum-minimum eigenvalue (MME) detector and energy with minimum eigenvalue (EME) detector are suggested. Multi-antenna assisted spectrum sensing algorithm using the generalized likelihood ratio test (GLRT) is raised in [12].

This paper investigates robust spectrum sensing from a novel perspective. The proposed method performs spectrum sensing simultaneously over the total frequency bands instead of a single subband each time. It first estimates the number of occupied channels, and then determines the accurate locations of occupied subbands as well as the vacant ones. The exploited characteristic in this letter is that sample power of the occupied subband is the superposition of noise and signal, whereas sample power of the vacant subband is only contributed by noise. Consequently, sample power of the occupied subband is larger than the vacant one. If there is a prior knowledge that the number of occupied subbands is K, those K subbands with the largest sample power are more likely to be the occupied ones. Thus the estimation of the number of occupied subbands becomes a critical issue which can refer to the subject of source number estimation. Akaike information criterion (AIC) and minimum description length (MDL) are the originally raised methods to address this problem by utilizing the information of eigenvalues of covariance matrix [13]. Recently, the exponentially embedded family (EEF) is proposed for model order estimation [14] and is applied to source enumeration [15], which can conduct spectrum sensing.

The remaining part of this paper is organized as follows. In Section II, system model for wideband spectrum sensing is formulated. In Section III, we put forward a robust sensing method. Simulations under different conditions are presented to demonstrate the performance in Section IV and the last section comes with the conclusions.

II. Problem Formulation

It is assumed that a multiband CR system operates over Q nonoverlapping narrowband subbands, among which K subbands are occupied by PUs. Fig. 1 depicts the

Manuscript received October 14, 2013; revised April 24, 2014.
Corresponding author email: qinghaobo@gmail.com.
doi:10.12720/jcm.9.4.357-363

structure of a wideband channel within a particular time interval and in a particular geographical region.

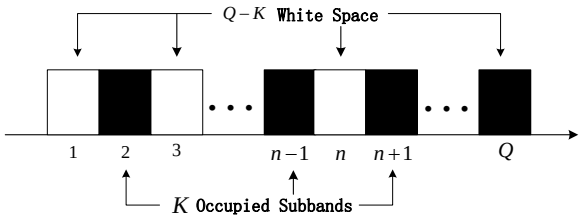

Fig. 1. Schematic illustration of a wideband channel.

We model the detection problem as one of choosing between a hypothesis H_0 and an alternative hypothesis H_1, which represent the absence and presence of PU signals, respectively. The binary hypotheses at subband $i\left(1 \le i \le Q\right)$ can be expressed as

$$H_0: x_i\left(n\right) = \varepsilon_i\left(n\right) \tag{1}$$

$$H_1: x_i\left(n\right) = h_i s_i\left(n\right) + \varepsilon_i\left(n\right) \tag{2}$$

where $x_i\left(n\right)$ is the received signal sample, $\varepsilon_i\left(n\right)$ is the background noise and $s_i\left(n\right)$ denotes the transmitted PU signal. h_i reflects the channel gain including the effects of multipath fading, path loss as well as time dispersion.

M $\left(K < M\right)$ uniform linear arrays are assumed to be placed in the cognitive receiver. The received signals can be given as

$$\mathbf{r}\left(n\right) = \sum_{i=1}^{K} \tilde{s}_i\left(n\right)\mathbf{a}_i + \boldsymbol{\varepsilon}\left(n\right) = \mathbf{A}\tilde{\mathbf{s}}\left(n\right) + \boldsymbol{\varepsilon}\left(n\right) \tag{3}$$

in which $\mathbf{A} = \left[\mathbf{a}_1, \mathbf{a}_2, \cdots, \mathbf{a}_K\right]$ denotes the direction matrix with

$$\mathbf{a}_i = \left[1, \exp\left(j\frac{2\pi}{c}df_i \sin\left(\theta_i\right)\right), \cdots, \exp\left(j\frac{2\pi}{c}\left(M-1\right)df_i \sin\left(\theta_i\right)\right)\right]^T \tag{4}$$

$\left(\cdot\right)^T$ stands for the transpose and θ_i represents the incident angles. f_i denotes the central frequency of each PU signal, c represents the wave speed and d is the distance between adjacent arrays. $\tilde{\mathbf{s}}\left(n\right) = \left[\tilde{s}_1\left(n\right), \tilde{s}_2\left(n\right), \cdots, \tilde{s}_K\left(n\right)\right]^T$ represents the received PU signals including the effects of channel response, namely $\tilde{s}_i\left(n\right) = h_i s_i\left(n\right)$. The noise vector is expressed as $\boldsymbol{\varepsilon}\left(n\right) = \left[\varepsilon_1\left(n\right), \varepsilon_2\left(n\right), \cdots, \varepsilon_M\left(n\right)\right]^T$.

The covariance matrix of received signals can be denoted as

$$\mathbf{C}_r = E\left[\mathbf{r}\left(n\right)\mathbf{r}^H\left(n\right)\right] = \mathbf{A}\mathbf{C}_s\mathbf{A}^H + \sigma^2\mathbf{I} \tag{5}$$

with $\mathbf{C}_s = E\left[\tilde{\mathbf{s}}\left(n\right)\tilde{\mathbf{s}}^H\left(n\right)\right]$. $E\left[\cdot\right]$ and $\left(\cdot\right)^H$ stand for the expectation operator and Hermitian transpose, respectively.

However, in practical applications, the covariance matrix can only be estimated by a finite number of samples, namely

$$\hat{\mathbf{C}}_r = \frac{1}{N}\sum_{n=1}^{N}\mathbf{r}\left(n\right)\mathbf{r}^H\left(n\right) \tag{6}$$

in which N represents the number of samples.

Throughout this paper, we make the following assumptions on signals and noises:

a) The PU signals obey independent Gaussian distribution with mean-zero.

b) The noise is modeled as an independent additive white Gaussian noise (AWGN) with mean-zero and variance σ^2. In addition, the noises are uncorrelated with the PU signals.

III. Robust Spectrum Sensing Via EEF Criterion

A. Principle Analysis

For the wideband spectrum sensing problem, multiple channels need to be detected and we must detect the presence or absence of PU in each channel. In other words, wideband sensing is to find out the exact locations of the channels occupied by PUs so that CRs can make use of the idle channels after spectrum sensing. Besides, sample power of the busy channel is the superposition of noise and signal while idle channel only corresponds to noise; hence received signal with larger sample power is more likely not to be pure noise. Consequently, sample powers of the idle channels are approximately identical and lower than those of the busy channels. Exploiting this characteristic, if we sort the sample powers of each channel in descending order, the first coming $\hat{K}$ channels correspond to the busy channels while the rest Q-$\hat{K}$ channels correspond to the idle ones. That is to say, the knowledge of $\hat{K}$ is the essential issue needs to be settled. So the multiband spectrum sensing problem is transformed into estimation of the number of occupied channels, which in fact belongs to the source number estimation problem.

Source number estimation with no prior knowledge of the signals has been widely investigated in radar array processing. AIC and MDL, two common information theoretic criteria, are put forward to estimate the number of signal sources [13]. In the recent years, a novel information theoretic criterion called EEF is proposed for model order estimation [14] and is applied to source enumeration [15]. Inspired by source number estimation, we can estimate the number of occupied channels utilizing the EEF criterion. Details are given below.

B. EEF Criterion

The EEF criterion is put forward for model order estimation [14] and its consistency has been proved [15]. The i th model under EEF criterion is formulated as

$$EEF_i = \left\{ l_i(\mathbf{r}) - \phi_i \left[\ln\left(\frac{l_i(\mathbf{r})}{\phi_i} \right) + 1 \right] \right\} u\left(\frac{l_i(\mathbf{r})}{\phi_i} - 1 \right) \quad (7)$$

where ϕ_i is the number of free adjustable parameters and $u(\cdot)$ stands for the unit step function. $l_i(\mathbf{r})$ is the likelihood ratio defined as

$$l_i(\mathbf{r}) = 2\ln \frac{f\left(\mathbf{r}|\hat{\mathbf{C}}_r^{(i)}\right)}{f\left(\mathbf{r}|\hat{\mathbf{C}}_r^{(0)}\right)} \quad (8)$$

in which $\mathbf{r} = [\mathbf{r}(1), \mathbf{r}(2), \cdots, \mathbf{r}(N)]$ is the received data vector, $\hat{\mathbf{C}}_r^{(i)}$ is the maximum-likelihood (ML) estimation of the covariance matrix under the i th model and $\hat{\mathbf{C}}_r^{(0)}$ is the ML estimation under the reference model. $f(\cdot)$ represents the conditional probability density function. Note that EEF extends the GLRT to multiple alternative hypotheses, especially when the alternatives have different numbers of unknown parameters. The EEF criterion estimates the model order by the maximum value of (7), namely

$$\hat{K} = \underset{i=1,2,\cdots,M-1}{\arg\max}\ EEF_i \quad (9)$$

C. Spectrum Sensing via EEF Criterion

Since we only know the number of total channels but do not know the number of busy channels, Q hypotheses can be generated. Using the spectral representation theorem, the covariance matrix $\mathbf{C}_r$ under the i th hypothesis is given as

$$\mathbf{C}_r^{(i)} = E\left[\mathbf{r}(n)\mathbf{r}^H(n)\right] = \sum_{j=1}^{i}\left(\lambda_j - \sigma^2\right)\mathbf{q}_j\mathbf{q}_j^H + \sigma^2\mathbf{I} \quad (10)$$

where λ_j and $\mathbf{q}_j$ are the eigenvalues and eigenvectors of $\mathbf{C}_r^{(i)}$, respectively.

According to [13], the ML estimation of $\mathbf{C}_r^{(i)}$ is

$$\hat{\mathbf{C}}_r^{(i)} = \sum_{j=1}^{i}\left(\hat{\lambda}_j - \hat{\sigma}^2\right)\hat{\mathbf{q}}_j\hat{\mathbf{q}}_j^H + \hat{\sigma}^2\mathbf{I} \quad (11)$$

in which

$$\hat{\lambda}_j = \rho_j \quad (12)$$

$$\hat{\sigma}^2 = \frac{1}{M-i}\sum_{j=i+1}^{M}\rho_j \quad (13)$$

$$\hat{\mathbf{q}}_j = \mathbf{u}_j \quad (14)$$

ρ_j are the eigenvalues in descending order of the sample covariance matrix $\hat{\mathbf{C}}_r$ and $\mathbf{u}_j$ are the corresponding eigenvectors. It is readily shown that the number of free adjustable parameters under the i th hypothesis is

$$\phi_i = i(2M - i) + 1 \quad (15)$$

Since the observation data is regarded as independent Gaussian random variable with mean-zero, its joint probability density function is given by

$$\begin{aligned} f\left(\mathbf{r}\,|\,\hat{\mathbf{C}}_r^{(i)}\right) &= f\left(\mathbf{r}(1), \mathbf{r}(2), \cdots, \mathbf{r}(N)\,|\,\hat{\mathbf{C}}_r^{(i)}\right) \\ &= \prod_{n=1}^{N} f\left(\mathbf{r}(n)\,|\,\hat{\mathbf{C}}_r^{(i)}\right) \\ &= \prod_{n=1}^{N} \frac{1}{\pi^Q \det \hat{\mathbf{C}}_r^{(i)}} \exp\left\{-\mathbf{r}^H(n)\left[\hat{\mathbf{C}}_r^{(i)}\right]^{-1}\mathbf{r}(n)\right\} \end{aligned} \quad (16)$$

Taking the logarithm, substituting (11)-(14) into (16) and after some straightforward algebra, it follows that

$$\begin{aligned} \ln f\left(\mathbf{r}\,|\,\hat{\mathbf{C}}_r^{(i)}\right) = -N\Bigg[& M\ln\pi + \ln\prod_{j=1}^{i}\rho_j + \\ & (M-i)\ln\left(\frac{1}{M-i}\sum_{j=i+1}^{M}\rho_j\right) + M \Bigg] \end{aligned} \quad (17)$$

$$\ln f\left(\mathbf{r}\,|\,\hat{\mathbf{C}}_r^{(0)}\right) = -N\left[M\ln\pi + M\ln\frac{tr\left(\hat{\mathbf{C}}_r\right)}{M} + M \right] \quad (18)$$

Substituting (17) and (18) into (8), we have

$$\begin{aligned} l_i(\mathbf{r}) = -2N\Bigg[& \ln\prod_{j=1}^{i}\rho_j + (M-i)\ln\left(\frac{1}{M-i}\sum_{j=i+1}^{M}\rho_j\right) \\ & -M\ln\left(\frac{1}{M}tr\left(\hat{\mathbf{C}}_r\right)\right)\Bigg] \end{aligned} \quad (19)$$

Until now, we are able to estimate the number of occupied channels using the EEF criterion by (7), (9), (15) and (19). Next we turn to find out the occupancy status of each subband.

Firstly we compute sample power of each sub-channel. Similar to energy detector, it is formulated as

$$\varphi_i = \frac{1}{N}\sum_{n=1}^{N}\left|x_i(n)\right|^2 \quad i = 1, 2, \cdots, Q \quad (20)$$

We have pointed out that sample power of the occupied subband is larger than the vacant one. Consequently, after getting the number of occupied channels via the EEF criterion, we can conclude that channels with the largest $\hat{K}$ sample power would be occupied by PU signals and the rest can be opportunistic accessed by SUs.

In summary, the steps of the proposed scheme are shown below.

Step I: Estimate the sample covariance matrix (6).

Step II: Compute the EEF criterion by (7), (15) and (19).

Step III: Estimate the number of occupied channels using the EEF criterion (9).

Step IV: Select channels with the highest $\hat{K}$ sample power as the occupied ones and the rest are the idle ones.

D. Remarks on the Proposed Algorithm

Remark A: In our approach, several modeling

functions are constructed under different hypotheses by the EEF criterion to depict the number of busy channels. The judgment of the true hypothesis is equivalent to finding the variable that maximizes these modeling functions, and thus the number of occupied channels is determined. Afterwards, PU signals are considered to be present in channels with the maximum sample power.

Remark B: Distinct from the classical sensing methods, our scheme is robust to noise uncertainty since it does not involve the estimation of noise variance. Thus the impact induced by an inaccurate estimation would be totally eliminated. In addition, subjective decision threshold is not required, either.

Remark C: The major computational burden of the proposed schemes mainly involves two parts: the calculation of sample covariance matrix $\hat{\mathbf{C}}_r$ and its eigenvalue decomposition. The former needs $O\left(M^2N\right)$ multiplications and additions while the latter demands $O\left(M^3\right)$ operations. By contrast, the calculation of EEF criterion and sorting of sample power can be neglected. Therefore, the computational complexity in total is approximately $O\left(M^2N\right)+O\left(M^3\right)$.

IV. Numerical Results

In this section, simulations are presented to evaluate our approach's performance. Detection probability P_d and false alarm probability P_f are used to scale the performance. In IEEE 802.22, $P_d \geq 0.9$ is the generally required detection probability with $P_f \leq 0.1$ the generally required false alarm probability for ideal CR networks [16].

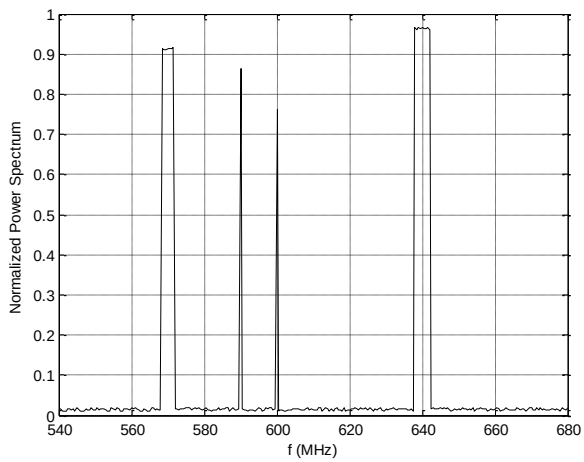

Fig. 2. Normalized power spectrum of the PU signals for occupied channels.

Considering a multiband CR system with $M=8$ antenna arrays, PU signals are present in $K=4$ subbands among the total $Q=25$ subbands. Four PU signals with central frequencies $\{570,590,600,640\,(MHz)\}$ impinge on the antenna arrays from distinct directions $\{4^\circ,9^\circ,12^\circ,18^\circ\}$, respectively. The distance between adjacent arrays is $d=0.25m$. Note that the aforementioned central frequencies of PU signals might be the frequencies of narrowband carriers, and they could represent the central frequencies of wideband signals as well, e.g., IEEE 802.22 signals with bandwidth 6MHz or 8MHz. Fig. 2 illustrates the normalized power spectrum of the PU signals for occupied channels. In the following simulations, five hundred Monte Carlo trials have been carried out respectively.

Noise uncertainty is also taken into account. The estimated noise power is uniformly distributed in an interval $\left[\sigma^2/A, A\sigma^2\right]$, where A is a positive number not smaller than 1. Thus, the noise uncertainty is $\delta=10\log_{10}A\ dB$. As a result, energy detector with noise uncertainty has to set the threshold by using the estimated noise variance to meet the given P_f. In the simulations, P_f of the ideal energy detector is set to be 0.1.

We provide a set of simulations to verify the performance of our approach under Rayleigh fading in comparison with energy detector. Fig. 3 illustrates the probability of detection and false alarm versus SNR when $N=1000$, where ED $(\delta=1)$ indicates energy detector with 1 dB noise uncertainty. Note that P_f performance of energy detector with noise uncertainty is too poor to meet the requirements of CR networks. Therefore energy detector is quite unreliable due to the inevitability of noise uncertainty. Besides, we can observe that the proposed method outperforms energy detector with noise uncertainty whether P_d or P_f is concerned. Thus we can conclude that the proposed method is superior to energy detector with noise uncertainty.

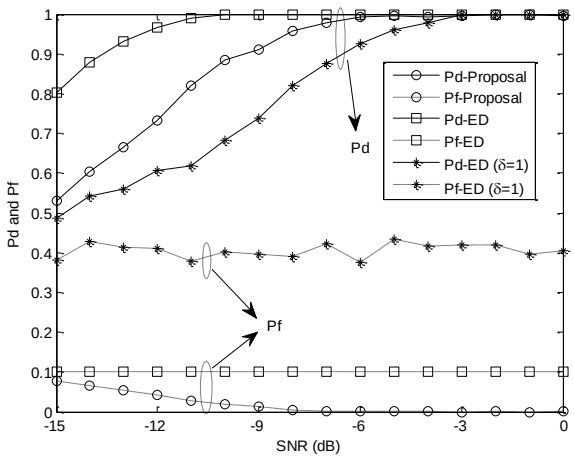

Fig. 3. Probability of detection and false alarm versus SNR under Rayleigh fading compared to energy detector (N=1000).

Now we focus on the impact of the number of samples. The performance against the number of samples is plotted in Fig. 4 when SNR is fixed at -10 dB. The figure suggests that when the number of samples exceeds a certain value, P_d of energy detector with noise uncertainty is no longer enhanced due to SNR wall. However, the other two methods are still further improved. This finding implies

that even though the proposed scheme achieves a worse P_d performance at low samples, it will surpass energy detector with noise uncertainty as the number of samples increases. We can draw that noise uncertainty greatly deteriorates the performance of energy detector.

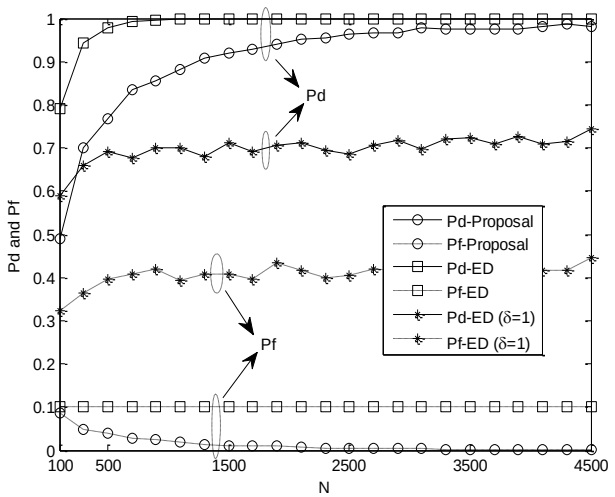

Fig. 4. Probability of detection and false alarm versus the number of samples under Rayleigh fading compared to energy detector (SNR=-10 dB).

Thus far, a few robust sensing algorithms have existed in the literature. To further validate the performance of our approach, the MME and EME detectors in [11] are adopted for comparison. These algorithms aim to combat noise uncertainty as well and can be applied to wideband case in each subband sequentially. PU signals transmit through an AWGN channel. Fig. 5 depicts the probability of detection and false alarm with different SNR when $N = 100$. It follows from the figure that while these methods own a satisfactory P_f performance, our approach outperforms MME and EME methods in terms of P_d.

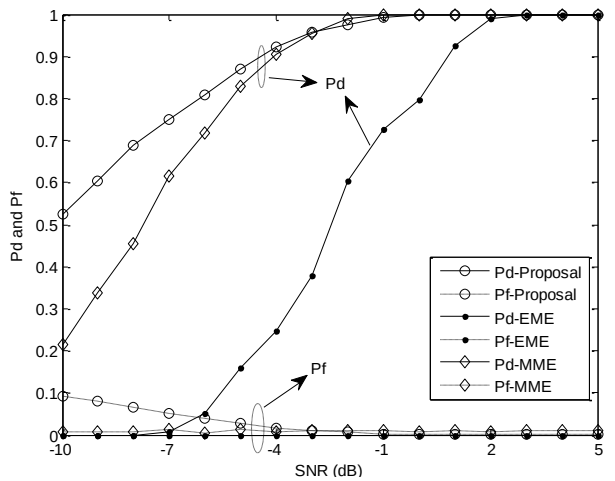

Fig. 5. Probability of detection and false alarm with different SNR under AWGN channel compared to existing algorithms (N=100).

To study the effect induced by the number of receiver antennas, 16 uniform linear arrays in the cognitive receiver are adopted for performance comparison. Fig. 6 illustrates P_d and P_f versus SNR under different number of antenna arrays when the number of samples is fixed at 500. The figure indicates that a better performance can be achieved with larger arrays due to higher array gain. Nevertheless, the number of arrays cannot be arbitrarily increased in order to acquire high array gain due to the limitations of antenna size. In practical situations, the number of antenna arrays is generally selected as 4, 8, 16 or 32.

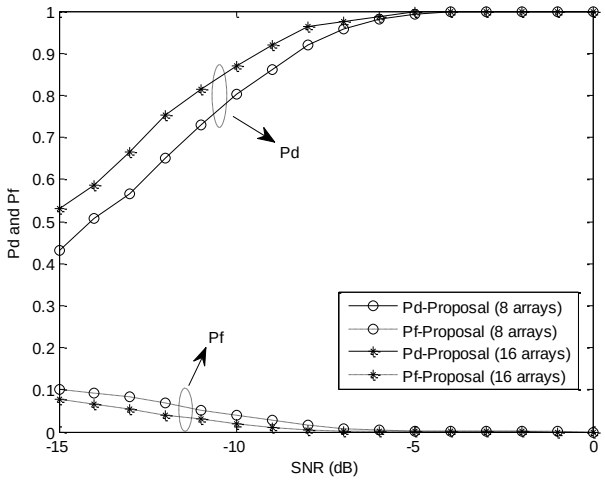

Fig. 6. Probability of detection and false alarm against SNR with various number of antenna arrays (N=500).

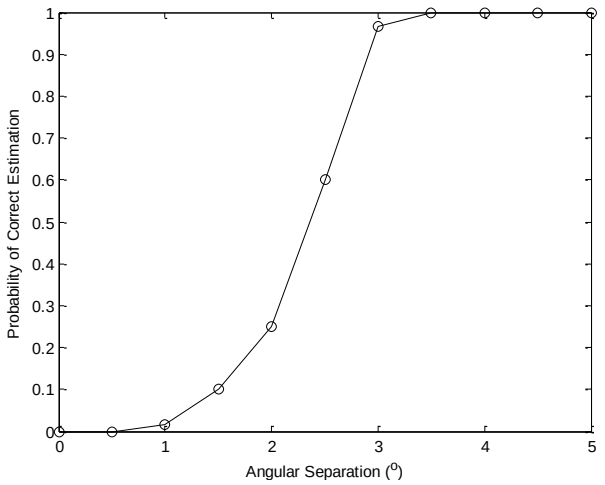

Fig. 7. Probability of correctly estimating the number of occupied channels versus angular separation (SNR=0 dB, N=100).

Since the antenna arrays are rather sensitive to the incident angles, errors of estimating the number of occupied channels appear when the impinging angles of PUs get close. To ease exposition, we only take the case of two occupied channels into account. The directions of the PUs are given as $[\theta_1, \theta_2] = [9°, 9° + \Delta\theta]$, where $\Delta\theta = \theta_2 - \theta_1$ denotes the angular separation. Fig. 7 investigates the angular separation between PUs needed for reliable detection, in which SNR is 0 dB, the number of samples equals to 100 and the angular separation varies from 0° to 5°. It is observed from the figure that the minimum angular separation required to reach a desired

performance is $3°$. The algorithm fails to reliably estimate the number of occupied channels for a tiny angular separation. This is due to the fact that when the PUs are nearby and their signals impinge from almost the same direction, the spatial resolution of multi-antennas is destroyed.

V. Conclusions

This paper proposes a robust spectrum sensing scheme for CR networks through the EEF criterion. Our approach operates simultaneously over multiple channels in a parallel manner instead of one channel each time. Unlike the conventional methods, the proposed method does not require the estimation of noise power, which is severely deteriorated by noise uncertainty. This paper presents simulations under various conditions to validate the proposal's performance and the results show that our approach is robust and outperforms existing sensing algorithms.

Acknowledgment

The authors wish to thank the anonymous reviewers for their insightful and constructive comments that significant improved the quality of this paper. This work was supported in part by the National Natural Science Foundation of China (Grant Nos. 61327806 and 61302083), Important National Science and Technology Specific Projects of China (Grant No. 2012ZX03003001-004), Beijing Higher Education Young Elite Teacher Project.

References

[1] S. Haykin, "Cognitive radio: Brain-empowered wireless communications," *IEEE J. Sel. Areas Commun.*, vol. 23, no. 2, pp. 201-220, Feb. 2005.

[2] Y. Zhao and M. T. Lizdabel, "Cognitive radio: Forging ahead from concept, testbed to large-scale deployment," *Journal of Communications*, vol. 7, no. 7, pp. 514-523, July 2012.

[3] R. C. Qiu, C. Zhang, Z. H, and M. Wicks, "Towards a large-scale cognitive radio, network testbed: Spectrum sensing, system architecture, and distributed sensing," *Journal of Communications*, vol. 7, no. 7, pp. 552-566, July 2012.

[4] G. Ganesan and Y. G. Li, "Cooperative spectrum sensing in cognitive radio, part I: two user networks," *IEEE Trans. Wireless Commun.*, vol. 6, no. 6, pp. 2204-2213, June 2007.

[5] S. Zhang and L. Guo, "Performance analysis of multi-hop relay cooperative spectrum sensing," *Journal of Communications*, vol. 7, no. 12, pp. 921-927, Dec. 2012.

[6] A. Taherpour, S. Gazor, and M. N. Kenari, "Invariant wideband spectrum sensing under unknown variances," *IEEE Trans. Wireless Commun.*, vol. 8, no. 5, pp. 2182-2186, May 2009.

[7] Z. Quan, S. G. Cui, A. H. Sayed, and H. V. Poor, "Optimal multiband joint detection for spectrum sensing in cognitive radio networks," *IEEE Trans. Signal Process.*, vol. 57, no. 3, pp. 1128-1140, Mar. 2009.

[8] H. Qing, Y. Liu, and G. Xie, "Robust spectrum sensing for blind multiband detection in cognitive radio systems: A Gerschgorin likelihood approach," *KSII Trans. Internet and Information Systems*, vol. 7, no. 5, pp. 1131-1145, May 2013.

[9] T. Yucek and H. Arslan, "A survey of spectrum sensing algorithms for cognitive radio applications," *IEEE Commun. Surveys & Tutorials*, vol. 11, no. 1, pp. 116-130, First Quarter 2009.

[10] R. Tandra and A. Sahai, "SNR walls for signal detection," *IEEE J. Sel. Topics Signal Process.*, vol. 2, no. 1, pp. 4-17, Feb. 2008.

[11] Y. Zeng and Y. C. Liang, "Eigenvalue-based spectrum sensing algorithms for cognitive radio," *IEEE Trans. Commun.*, vol. 57, no. 6, pp. 1784-1793, June 2009.

[12] R. Zhang, T. J. Lim, Y. C. Liang, and Y. Zeng, "Multi-antenna based spectrum sensing for cognitive radios: A GLRT approach," *IEEE Trans. Commun.*, vol. 58, no. 1, pp. 84-88, Jan. 2010.

[13] M. Wax and T. Kailath, "Detection of signals by information theoretic criteria," *IEEE Trans. Acoust., Speech, Signal Process.*, vol. 33, no. 2, pp. 387-392, Apr. 1985.

[14] S. Kay, "Exponentially embedded families-new approaches to model order estimation," *IEEE Trans. Aerosp. Electron. Syst.*, vol. 41, no. 1, pp. 333-344, Jan. 2005.

[15] C. Xu and S. Kay, "Source enumeration via the EEF criterion," *IEEE Signal Process. Lett.*, vol. 15, pp. 569-572, Oct. 2008.

[16] Spectrum Sensing Requirements Summary, IEEE 802.22 Working Group Doc. Num. 22-06-0089-04-0000.

Haobo Qing was born in Sichuan, China, in 1988. He received his B.S. degree (with distinction) in Electronic and Information Engineering from Sichuan University (SCU), Chengdu, China, in June 2010. He participates in the successive postgraduate and doctoral program and is pursuing the Ph.D degree in Electronic Science and Technology from Beijing University of Posts and Telecommunications (BUPT), Beijing, China.

During his Ph.D. study, he has taken part in the International Scientific and Technological Cooperation Programs with Carleton University, Canada, Linköping University, Sweden and the University of Electro-Communications, Japan. He was a recipient of the Honorable Student Award of SCU in 2010 and the Best Performance Award for 2010 Triangle ICT International Forum. His research interests include spectrum sensing in cognitive radios, MIMO-OFDM channel estimation, cooperative communication and the next generation wireless communication systems.

Yuanan Liu received the B.E., M.Eng., and Ph.D. degrees in electrical engineering from the University of Electronic Science and Technology of China (UESTC), Chengdu, China, in 1984, 1989, and 1992, respectively.

In 1984, he joined the 26th Institute of the Electronic Ministry of China to develop the inertia navigating system. In 1992, he began his first postdoctoral position with the EMC Laboratory, Beijing University of Posts and Telecommunications (BUPT), Beijing, China. In 1995, he started his second postdoctoral position with the Broadband Mobile Laboratory, Department of System and Computer Engineering, Carleton University, Ottawa, ON, Canada. Since July 1997, he has been with the Wireless Communication Center, School of Telecommunication Engineering, BUPT, as a Professor, where he is involved in the development of next-generation cellular systems, wireless LANs, Bluetooth applications for data transmission, EMC design strategies for high-speed digital systems, and low-cost, high-performance EMI and EMS measuring sites. His research interests include smart antennas for high-capacity mobiles, signal processing techniques in fading environments, EMC for high-speed digital systems, ISI suppression, OFDM, and multicarrier system design.

Prof. Liu is a fellow of the Institution of Engineering and Technology (IET), U.K.; the Vice Chairman of Electromagnetic Environment and Safety of the China Communication Standards Association; the Vice Director of the Wireless and Mobile Communication Committee, Communication Institute of China; and a Senior Member of the Electronic Institute of China.

Gang Xie received the Ph.D. degree at the Beijing University of Posts and Telecommunications (BUPT) in 2007. Currently he is an assistant professor in Beijing Key Laboratory of Network System Architecture and Convergence, of Beijing University of Posts and Telecommunications. Dr. Xie is a member of IEEE and IEICE. His research fields include wireless communications and signal processing, especially HARQ, MIMO transmission and cognitive radios.

Kaiming Liu received the Ph.D degree from Beijing University of Posts and Telecommunications (BUPT) in 2006. Now he is an associated professor of School of Electronic Engineering, BUPT. His research interests include wireless communication technologies, wireless mesh networks, and convergence of heterogeneous networks. And he is now the director of Wireless Smart Transmission & Networking Laboratory of School of Electronic Engineering, BUPT.

Fang Liu received the M.S and Ph.D degrees in Electronic Engineering from Shandong University, Ji Nan, China in 2002 and Beijing University of Posts and Telecommunications Beijing, China in 2005 respectively. From 2005 to 2010, she worked in department of advanced wireless system Lab as a research fellow in DOCOMO Beijing Communications Laboratories Co., Ltd. Since May 2010, she has been with the School of Electronic Engineering at Beijing University of Posts and Telecommunications, Beijing, China. Her research interests include MIMO systems, LTE wireless systems, resource allocation and cross-layer design of wireless networks.