World Academy of Science, Engineering and Technology
International Journal of Computer and Information Engineering
Vol:10, No:8, 2016

An Energy Detection-Based Algorithm for Cooperative Spectrum Sensing in Rayleigh Fading Channel

H. Bakhshi, E. Khayyamian

Abstract**—**Cognitive radios have been recognized as one of the most promising technologies dealing with the scarcity of the radio spectrum. In cognitive radio systems, secondary users are allowed to utilize the frequency bands of primary users when the bands are idle. Hence, how to accurately detect the idle frequency bands has attracted many researchers' interest. Detection performance is sensitive toward noise power and gain fluctuation. Since signal to noise ratio (SNR) between primary user and secondary users are not the same and change over the time, SNR and noise power estimation is essential. In this paper, we present a cooperative spectrum sensing algorithm using SNR estimation to improve detection performance in the real situation.

Keywords**—**Cognitive radio, cooperative spectrum sensing, energy detection, SNR estimation, spectrum sensing, Rayleigh fading channel.

I. Introduction

WITH the rapid growth of wireless communication technology and the emergence of new wireless applications, the wireless frequency spectrum has become a scarce resource. However, a large portion of the assigned spectrum is not yet utilized efficiently. Studies from the Federal Communication Commission (FCC) show that the utilization of licensed spectrum only ranges from 15% to 85% [1]. In order to reduce the spectrum scarcity, cognitive radio is identified as a technique which can improve spectrum underutilization [2]. This term "cognitive radio" was first coined by Joseph Mitola in his PhD thesis [3], [4]. Spectrum sensing is one of the most important cognitive radio's majorities which determine whether primary (licensed) user is present or not. It is often considered as a detection problem in which the aim is to detect the weak signal from a primary transmitter through the local observations of secondary users (SU). To improve the sensing accuracy, three different detection methods are investigated in [5], namely matched filter detection, energy detection and feature detection.

The energy detection approach is mostly used in the spectrum sensing since it has low computational and implementation complexities and prior knowledge of the primary users' (PU's) signal is not needed. However, a single SU cannot exactly detect the existence of PU due to the effects of hidden nodes, shadowing, and fading channels. In order to combat these effects, cooperative spectrum sensing has been proposed. Cooperative spectrum sensing (CSS), in which information from multiple SUs are incorporated for the detection of the PU, can improve the spectrum sensing performance [6]. There are various cooperative schemes to combine the sensing information from SUs. These schemes can be broadly categorized into decision based fusion [7] and data based fusion [8].

For decision based fusion schemes, each SU has to make a decision on the presence of PUs based on its sensing data and then sends its decision to a fusion center which will determine the final decision. For data based fusion schemes, SUs do not make any decision, instead, they send data, which are usually the test statistics of their sensing data, to the fusion center for it to make the final decision. This paper focuses on the decision based fusion scheme because it has low communication overhead.

A lot of work on spectrum sensing has been done nowadays but most of them assume the noise power is specified, while in practical sensing it is not a true assumption. Noise uncertainty and SNR fluctuations due to multipath effects complicate the spectrum sensing operation [9]. In this paper, we present an algorithm using SNR estimator in a desired manner to achieve acceptable performance of detection in the real situation. We assume that SNR between primary and SUs can vary from one sensing interval to another interval.

The rest of the paper is organized as follows. System model is described in Section II. In Section III, we describe SNR and noise power estimation. In Section IV, we present a CSS scheme using SNR estimation. Simulation results and analysis are given in Section V. Finally, we conclude the paper in Section VI.

II. System Model

Cognitive radios (CRs) utilize unused channel of PU's signal and spectrum sensing mechanism allows them to determine the presence of a PU. In energy detection method, the locations of the primary receivers are not known to the CRs, as there is no signaling between the PU and the CRs. To detect the PU signal, we have used the following hypothesis for the received signal [10]:

$$r(n) = \begin{cases} w(n), & H_0 \\ h.s(n) + w(n), & H_1 \end{cases} \tag{1}$$

H. Bakhshi is the Associate Professor of Electrical Engineering at Shahed University, Tehran, Iran(e-mail: bakhshi@shahed.ac.ir).

E. Khayyamian is the M.Sc. student in Electrical Engineering Department of Shahed University, Tehran, Iran (e-mail: ehsan.khayyamian@gmail.com).

where $r(n)$ shows the signal received by CR user. The transmitted signal of the PU, denoted $s(n)$, is a complex signal and $w(n) = w_r(n) + jw_i(n)$ is additive white Gaussian noise with zero mean and variance $2\sigma_w^2$. Further $w_r(n)$, $w_i(n)$are real-valued Gaussian random variables with mean zero and variance σ_w^2. Here h denotes the quasi-static Rayleigh flat-fading channel gain between the PU and the CR user. Note that the channel is assumed to remain constant over the duration of the N observed samples. H_0 is the null hypothesis, which indicates the absence of PU, and H_1 isthe alternative hypothesis, which indicates that PU is present.

For the detection of unknown deterministic signals corrupted by the additive white Gaussian noise, an energy detector (ED) is derived in [11], which is called conventional ED. This is an easily implemented detector for the detection of unknown signals in spectrum sensing. It collects the test statistic and compares it with a threshold (λ) to decide whether the PUsignal is present or absent. The test statistic is given by [10]:

$$Y = \sum_{n=1}^{N} \left| r(n) \right|^2 \tag{2}$$

where N is the number of samples which is equal to $2\text{u} = 2TW$, and Y denotes the energy of the received input signal, which is compared with threshold to make the final decision.

According to energy detection theory [11], energy observed (Y) by the cognitive user has the following distribution:

$$Y \sim \begin{cases} \chi_{2u}^2 & H_0 \\ \chi_{2u}^2(2u\gamma) & H_1 \end{cases} \tag{3}$$

where $\gamma = \frac{|h|^2 2\sigma_s^2}{2\sigma_w^2}$ denotes the instantaneous SNR, χ_{2u}^2 and $\chi_{2u}^2(2u\gamma)$ are central and non-central chi-square distribution respectively, each with $2u$ degrees of freedom and a non-centrality parameter of $2u\gamma$ for the latter one.

Threshold value is set to meet the target probability of false alarm P_f according to the noise power. The probabilityof detection P_d can be also identified. If only additive white Gaussian noise (AWGN) is considered, the expression for P_f and P_d for AWGN channel can be defined according to (3) [12]:

$$P_f = P_r(Y > \lambda \mid H_0) = \frac{\Gamma\left(u, \frac{\lambda}{2\sigma_w^2}\right)}{\Gamma(u)} \tag{4}$$

$$P_d = P_r(Y > \lambda \mid H_1) = Q_u\left(\sqrt{2u\gamma}, \frac{\sqrt{\lambda}}{\sigma_w}\right) \tag{5}$$

where $\Gamma(n, x) = \int_x^\infty t^{n-1} e^{-t} dt$ is the incomplete gamma function and $\text{Q}_N(a, b) = \int_b^\infty x \left(\frac{x}{a}\right)^{N-1} e^{\frac{-x^2+a^2}{2}} I_{N-1}(ax) dt$ is the generalized Marcum-Q function. If the signal amplitude follows a Rayleigh distribution, then the SNR follows an exponential PDF given by [13]:

$$f(\gamma) = \frac{1}{\bar{\gamma}} \exp\left(-\frac{\gamma}{\bar{\gamma}}\right), \quad \gamma \geq 0, \tag{6}$$

In this case, the average probability of detection may be derived by averaging (5) over fading statistics [13]:

$$\begin{aligned} \overline{P}_{d,ray} &= e^{-\frac{\lambda}{2\sigma_w^2}} \sum_{i=0}^{u-2} \frac{1}{i!} \left(\frac{\lambda}{2\sigma_w^2} \right)^i + \left(\frac{1+u\bar{\gamma}}{u\bar{\gamma}} \right)^{u-1} \\ &\times \left[e^{-\frac{\lambda}{2\sigma_w^2(1+u\bar{\gamma})}} - e^{-\frac{\lambda}{2\sigma_w^2}} \sum_{i=0}^{u-2} \frac{1}{i!} \left(\frac{\lambda u \bar{\gamma}}{2\sigma_w^2 (1+u\bar{\gamma})} \right)^i \right] \end{aligned} \tag{7}$$

where $\bar{\gamma}$ is the average SNR. On the other hand, detection and false alarm probabilities over AWGN channel can be derived approximately by using the central limit theorem (CLT). The CLT suggests that the sum of N i.i.d random variables with finite mean and variance approaches a Normal distribution when N is large enough. Using this theorem, the distribution of the test statistic can be accurately approximated with a Normal distribution for a sufficiently large number of samples as [12]:

$$Y \sim \begin{cases} \mathcal{N}\left(N(2\sigma_w^2)(1+\gamma), N(2\sigma_w^2)^2(1+2\gamma)\right) ; & H_1 \\ \mathcal{N}(N(2\sigma_w^2), N(2\sigma_w^2)^2); & H_0 \end{cases} \tag{8}$$

so we have:

$$P_f = P_r(Y > \lambda \mid H_0) = Q\left(\frac{\lambda - N(2\sigma_w^2)}{\sqrt{N(2\sigma_w^2)^2}} \right) \tag{9}$$

$$P_d = P_r(Y > \lambda \mid H_1) = Q\left(\frac{\lambda - N(2\sigma_w^2)(1+\gamma)}{\sqrt{N(1+2\gamma)}(2\sigma_w^2)} \right) \tag{10}$$

where Q(.) denotes Gaussian probability Q-function.

In order to achieve the desired sensing performance, two approaches, the constant detection rate (CDR) and the constant false-alarm rate (CFAR), have been considered [10]. The use of a CDR detector minimizes the false alarm probability when the detection probability is fixed at a desired level. On the other hand, the use of a CFAR detector maximizes the detection probability while guaranteeing that the false alarm probability remains at a desired level. As there is no information about the PU's signal (actually, we even do not know whether the signal of PU exists), the use of a CFAR detector is usually considered [10].

III. SNR Estimation

A good SNR estimation is critical in many digital communication systems as it is a key parameter in many receiver application such as decoding, spectrum sensing and power control in multiple-access systems [14]. Hence, various algorithms were proposed to compute an accurate estimation of this parameter. In general, these algorithms can be divided into two main categories: data-aided (DA) and non-data aided

(NDA) estimation. A DA estimator, such as Maximum Likelihood (ML) and Squared Signal-to-Noise Variance (SNV), would require the transmitted data to be perfectly known to the receiver, or at least the first few samples [14]. As for the NDA estimators, such as second and fourth moment (M2M4) and Signal-to-Variation Ratio (SVR), they assume the transmitted signal to be unknown to the receiver. Even though the DA estimation would give a better and more accurate estimation, the advantage of the NDA is that it does not need the transmitted data to be previously known at the receiver; hence, it is more bandwidth efficient than DA [15]. Since there is not any signaling between primary and SU, we need an NDA estimator in this paper. We choose sixth order statistics-based estimator from [16], because it can be employed and tuned for non-constant modulus constellation in order to extend the usable range of SNR values in quasi-static flat-fading channel. The SNR estimation of the received signal can be expressed:

$$\gamma = \frac{|h|^2 .2\sigma_s^2}{2\sigma_w^2} . \tag{11}$$

From sixth order statistics-based SNR estimation method, found [16], we have:

$$\gamma = \frac{\hat{z}}{1-\hat{z}} \quad , \quad \hat{z}^{(n+1)} = \sqrt{\frac{\hat{D}/\hat{M}_2^3}{\alpha \hat{z}^{(n)} + \beta}} \tag{12}$$

where

$$D = \hat{M}_6 - 2(3-b)\hat{M}_2^3 - b\hat{M}_2\hat{M}_4 , \tag{13}$$

$$\alpha = c_6 - 9c_4 + 12 \quad , \quad \beta = (9-b)(c_4 - 2), \tag{14}$$

$\hat{M}_p$ and C_p are the sample moment and constellation moment that can be expressed, respectively, as:

$$\hat{M}_p = \frac{1}{N}\sum_{n=1}^{N} |r(n)|^p \tag{15}$$

$$c_p = E\left\{ |s_k|^p \right\}. \tag{16}$$

Either $\hat{z}^{(0)} = 0$ or 1 can be used as starting point and the choice of the free parameter b should be tailored to the particular constellation [16]. From received energy of PU signal, we know:

$$P_r = |h|^2 . P_s + P_n \tag{17}$$

where $P_s = 2\sigma_s^2, P_n = 2\sigma_w^2$. So after SNR estimation from (12), using (11) and (17) noise power can be expressed as:

$$P_n = \frac{P_r}{\gamma + 1} \tag{18}$$

IV. Presented CSS Algorithm

In energy detection method, we compare received energy with a specified threshold. Threshold specification is one of the most important ED's task on characterizing detection performance so that appropriate threshold selection can increase probability of detection and reduce false alarm probability that is our purpose. From (9), for given target false alarm probability $(\bar{P}_f)$, the threshold λ can be determined as:

$$\lambda = \left(Q^{-1}(\bar{P}_f) + \sqrt{N}\right)\sqrt{N}2\sigma_w^2 \tag{19}$$

So for threshold determining, noise power estimation is inevitable. As mentioned before, most researches assume noise power is known, while it is not a correct assumption in practical systems. So, we intend to use SNR estimator in order to specify noise power. It is notable that when PU is absent, SNR estimation would be invalid because there is not any signal sample basically and ideally it must be equal to zero. So when PU is not present or does not detect yet, we compare received energy with a fixed threshold (λ_{cte}). The defined threshold is (19) with:

$$P_n \triangleq \tfrac{1}{2}\left(P_{n,max} + P_{n,min}\right) \tag{20}$$

where$P_{n,max}, P_{n,min}$are the maximum and minimum noise power experienced respectively.

When licensed user come back to the band and detector does not decide PU presence yet, we perform fixed threshold comparison which lead to detection latency because fix threshold has low performance. So, in the presented method for this stage, we perform SNR estimation every L sensing interval to mitigate problem of detection latency. This operation improves detection performance while sensing duration will increase. So, there is a tradeoff between performance and sensing time.

The proposed CSS method has shown in Fig. 1 and it has three steps as follow:

1) When we decide PU is absent, each radio measure receives energy and compares it with fixed predetermined threshold. In addition, SNR estimation process is performed every L sensing interval and therefore received energy will compare with dynamic threshold that calculated from estimated noise power in this interval. We perform estimation in this phase because we want to detect PU's signal quickly when it comes back to the band. Then SU's get a local binary decision and relay it to the fusion center. Fusion center use K-out-of-N rule [17] (where N is the total number of reported local decisions, while K is the number of local decisions that identify the spectrum as used) to get global decision and relay result to SU.
2) When PU is detected, SNR estimation process is performed in all sensing interval and threshold is calculated using estimated noise power. In this phase, SNR estimation is reliable. So, after making decision,

each SU transmit estimated SNR and local binary decision to the fusion center. Fusion center chooses most reliable user's decision as a global decision (user with maximum SNR).

3) If PU does not detect, we return to step one.

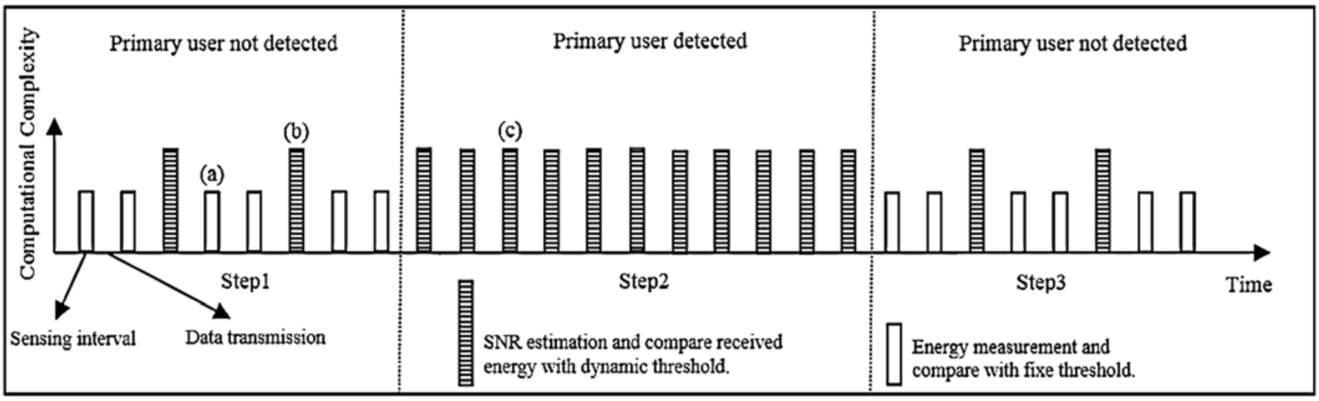

Fig. 1 Operation of the proposed CSS method: L is equal to 3

As our sensing procedure when PU is present, is different from when it is absent, we evaluate false alarm and detection probabilities for every interval separately. According to Fig. 1, (9), (10) and (20) when we are in intervals like (a):

$$P_f = Q\left(\frac{2\lambda_{Cte} - N\left(P_{n,\max} + P_{n,\min}\right)}{\sqrt{N\left(P_{n,\max} + P_{n,\min}\right)^2}}\right) \tag{21}$$

for intervals like (b) we have:

$$P_f = Q\left(\frac{\lambda_{Dyn} - NP_{n,est}}{\sqrt{NP_{n,est}^2}}\right) \tag{22}$$

where $P_{n,est}$ is the estimated noise power. Cooperative false alarm probability Q_f at fusion center in these intervals (a), (b) is:

$$Q_f = \sum_{K=l}^{M} \binom{M}{K} P_f^K \left(1 - P_f\right)^{M-K} \tag{23}$$

and when we are in intervals like (c):

$$Q_d = P_d = Q\left(\frac{\lambda_{Dyn} - NP_{n,\max snr}(1+\gamma_{\max})}{\sqrt{N(1+2\gamma)}P_{n,\max snr}}\right) \tag{24}$$

where λ_{Dyn} is obtained from (19) by substituting noise power estimation and $P_{n,max\,snr}$ is the estimated noise power of SU with maximum SNR.

V. Simulation Result

In this section, we present simulation results to demonstrate the performance of the presented detection method. We assume that the cognitive area has only one licensed user, and M SUs that participate in CSS. There is also only one data fusion center in the cognitive area and does not participate in sensing. All of the simulation results are obtained by averaging 10000 experiments. We assume that the transmitted PU signal is QPSK over Rayleigh fading channel. Channel is assumed to remain constant over the duration of the N observed samples. SNR estimation and received energy measurements are obtained by using a total of 500 and 50 samples, respectively and $P(H_1) = P(H_0) = 0.5$.

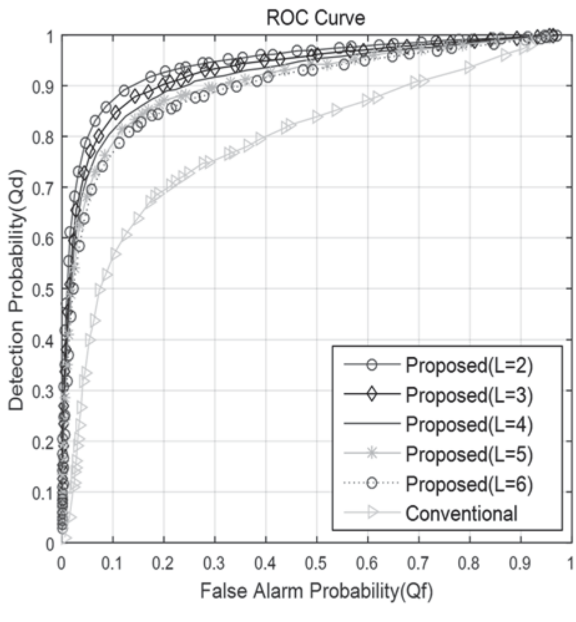

Fig. 2 ROC curves of proposed algorithm for different $\boldsymbol{L}$ and comparison with conventional method

Fig. 2 depicts the receiver operating characteristic (ROC) curve of the presented scheme for different L. We assume that received SNR between SU's and PU vary uniformly between $-10dB$ and $0dB$, depending on the distance from PU. As shown in this figure, when L increase, detection performance will improve. So, we select a reasonable L in order to satisfy our desired sensing time and accuracy.

In Fig. 3, we show detection performance for different average SNR for $M = 4,6,8$ SUs. It can be seen that increasing SUs is gainful when average SNR is in the middle range.

As mentioned before, when we are in stage two, fusion center selects decision of user with maximum SNR as final decision.

If we assign a weight to each SU according to SNR ($w_i = \frac{\gamma_i}{\frac{1}{M}\sum_{i=1}^{M}\gamma_i}, \sum_{i=1}^{M} w_i = M$ [18]), instead of choosing most reliable decision as final decision, results has been in Fig. 4. So it can be concluded that in this scenario choosing most reliable decision as final decision is more reasonable.

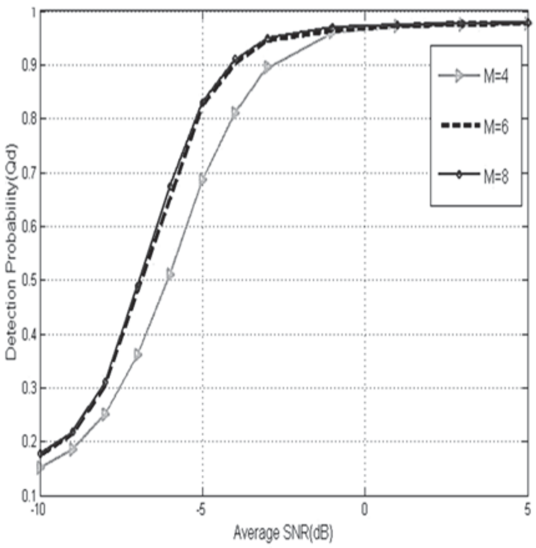

Fig. 3 Probability of detection versus SNR at $P_f = 0.1$ for different numbers of SUs, L=3

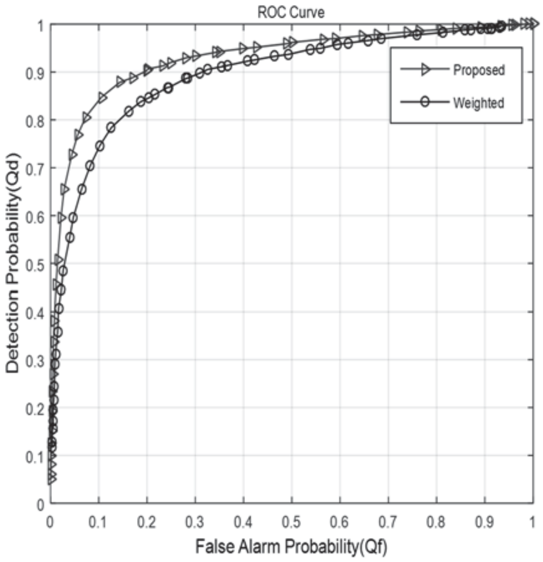

Fig. 4 Comparison between proposed and weighted method, L=3

VI. Conclusion

In this paper, a CSS algorithm in CR networks has been presented. We describe a practical scenario which noise power is unknown and should be estimated. SNR estimation is a time and processing-intensive procedure so we employ estimator in some interval to establish a tradeoff between performance, time cost and complexity. Simulation result shows performance of the proposed method and reveals that estimation in specific interval when PU is absent can mitigate detection latency.

References

[1] Federal Communications Commission, "Spectrum policy task force," Rep. ET Docket no. 02-135, Nov. 2002.
[2] Federal Communications Commission, "Notice of proposed rulemaking and order, Facilitating opportunities for flexible, efficient and reliable spectrum use employing cognitive radio technologies", FCC 03-322, Dec. 2003.
[3] J. Mitola and G. Q. Maguire, "Cognitive Radio: Making software radios more personal," *IEEE PersCommun.,* vol. 6, no.4, pp 13-18, Aug. 1999.
[4] J. Mitola, "Cognitive radio: An integrated architecture for software defined radio," PhD. Diss., Royal Institute of Technology, Stockholm, Sewden, 2000.
[5] D. Cabric, S. Mishra, R. Brodersen, "Implementation issues in spectrum sensing for cognitive radio". *Asilomar Conf. on Signals, Systems and Computers*, November 2004, vol. 1, pp. 772–776.
[6] T. Yucek, H. Arslan, "A survey of spectrum sensing algorithms for cognitive radio applications", *IEEE Commun. Surv. Tutor*, 2009, 11, pp. 116–130.
[7] Z. Chair and P. K. Varshney, "Optimal data fusion in multiple sensor detection systems," *IEEE Trans. Aerosp. Electron. Syst*., vol. 22, no. 1, pp. 98–101, Jan. 1986.
[8] Z. Quan, S. Cui, and A. H. Sayed, "Optimal linear cooperation for spectrum sensing in cognitive radio networks," *IEEE J. Sel. Topics Signal Process*. vol. 2, no. 1, pp. 28–40, Feb. 2008.
[9] H. Sun, A. Nallanathan, C. X. Wang and Y. Chen, "Widband Spectrum Sensing for Cognitive Radio Networks: A Survey," *Wireless Communications, IEEE*, vol. 20, no. 2, pp. 74–81, 2013.
[10] Y.-C. Liang, Y. Zeng, E. C. Y. Peh, and A. T. Hoang, "Sensing throughput tradeoff for cognitive radio networks," *IEEE Trans. Wireless Commun.*, vol. 7, no. 4, pp. 1326–1337, Apr. 2008.
[11] H. Urkowitz, "Energy detection of unknown deterministic signals," *Proc. IEEE*, vol. 55, no. 4, pp. 523–531, Apr. 1967.
[12] S. Atapattu, C. Tellambura, and H. Jiang, *Energy Detection for Spectrum Sensing in Cognitive Radio*. Springer, 2014.
[13] F. F. Digham, M. S. Alouini, and M. K. Simon, "On the energy detection of unknown signals over fading channels," *IEEE Trans on Communication.,* vol. 55, no. 1, pp. 21–24, Jan. 2007.
[14] T. Salman, A. Badawy, T.M. Elfouly, T. Khattab, A. Mohamed, "Non-data-aided SNR estimation for QPSK modulation in AWGN channel." *Wireless and Mobile Computing, Networking and Communications (WiMob), IEEE 10th International Conference on.* Oct. 2014 pp. 611-616.
[15] A. Wiesel, J. Goldberg, and H. Messer, "Non-data-aided signal to noise-ratio estimation," in *Communications, ICC 2002. IEEE International Conference on,*vol. 1, pp. 197–201.
[16] R. Lopez-Valcarce and C. Mosquera, "Sixth-order statistics-based nondata aided SNR estimation," *IEEE Communications Letters*, vol. 11, no.
4, pp. 351–353, April 2007.
[17] W. Zhang, R. K. Mallik, and K. B. Letaief, "Optimization of cooperative spectrum sensing with energy detection in cognitive radio networks," *IEEE Trans. on Wireless Comm.*, vol. 8, no. 8, pp. 5761-5766, December 2009.
[18] Su-wen, W.J. kang, Z. Ling, Q. Ming, "SNR-based weighted cooperative spectrum sensing in cognitive radio networks," *ELSEVIER, The Journal of China Universities of Posts and Telecommunications,* Vol. 17, Issue 2, pp. 1-7, April 2010.

Hamidreza Bakhshi was born in Tehran, Iran on April 25, 1971. He received the B.Sc. degree in Electrical Engineering from Tehran University, Iran in 1992, and his M.Sc. and Ph.D. degree in Electrical Engineering from Tarbiat Modarres University, Iran in 1995 and 2001, respectively. Since 2010, he has been an Associate Professor of Electrical Engineering at Shahed University, Tehran, Iran. His research interests include wireless communications, multiuser detection, and smart antennas.

Ehsan Khayyamian received the B.Sc. degree in Electrical and Electronic engineering from Azad University- Najaf Abad branch, Iran in 2012. He is currently pursuing his M.Sc. in Communication Engineering at Shahed University, Tehran, Iran. His research interests are in the areas of wireless communications, with current emphasis on cooperative spectrum sensing in cognitive radio networks.