Spectrum Sensing Using Adaptive Threshold based Energy Detection for OFDM Signals

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***Abstract*—Spectrum sensing is one of the key technologies to realize dynamic spectrum access in cognitive radio systems, especially for the next generation mobile systems. In this paper, the OFDM signal is sensed using a wide-band cognitive radio system. A new adaptive threshold algorithm is proposed for the Discrete Wavelet Packet Transform (DWPT) and Welch's energy detection methods to illustrate the trade-off between detection probability and false alarm probability. The proposed adaptive threshold algorithm in both DWPT and Welch's method demonstrates that the target performance requirements for the sensing algorithm equation for today can be achieved at -18dB, that is a very low signal level for sensing.**

I. Introduction

Cognitive radio (CR) is being viewed as a new intelligent wireless communication technology to solve the inefficiency of a fixed spectrum assignment policy [1]. Spectrum sensing is one of the most challenging tasks in CR systems as it requires high accuracy and low complexity for dynamic spectrum access [2].

In the spectrum sensing field, the spectrum sensing performance metric is usually measured as a trade-off between selectivity and sensitivity, and can be quantified by the levels of detection and false alarm probability. The higher the detection probability, the better primary users (PUs) can be protected. The lower the false alarm probability, the more chances a channel can be utilized by secondary users (SUs). A detection probability of 90% and a false alarm probability of 10% have been regarded as the target requirements for all the sensing algorithms [3].

Generally, the performance of spectrum sensing depends greatly on the setting of the detection threshold. Most conventional spectrum sensing methods adopt a fixed threshold to distinguish the primary user from noise. For example, an experimental value is set in [4] by the measurements of the noise power. However, it is difficult to guarantee the detection probability and false alarm probability with the fixed threshold setting method, especially when the noise power fluctuates [5]. Unlike the conventional fixed threshold based sensing algorithm, recent work considers an adaptive threshold. The adaptive threshold enables the SU to dynamically adjust its energy threshold according to the SNR [6], sensing time [7] or transmit power [8]. In [6], an adaptive threshold was studied according to the SNR for energy detection based spectrum sensing. In [7], the authors studied the design of sensing duration to maximise the energy efficiency for SUs with cooperative sensing in cognitive radio networks. In [8], a novel power control based threshold setting method was proposed for SU's coexistence with PU.

In addition to the requirements on the detection probability and false alarm probability, another major challenge for the spectrum sensing is the ability of detecting signals at low SNR levels. However, due to the noise uncertainty, the sensing performance at low SNR levels deteriorates rapidly for conventional spectrum sensing techniques, such as matched filters, energy detectors and even cyclostationary detectors. The sensing performance of Welch's energy detector was studied for detecting the OFDM signals used in LTE femtocell scenarios at SNR = -11dB in [9]. In [10], spectrum sensing using cyclostationaryity detector was studied for OFDM signals used in DVB-T signals. The minimum sensing level achieved in [10] was -14dB, which still has a big gap compared with the sensing requirement of DTV signals, e.g. -18dB [11]. Therefore, a very challenging task associated with each sensing technique is to detect signals at low SNR levels while optimizing the trade-off between the detection and the false alarm probability.

Therefore, in this paper, a new adaptive threshold algorithm is proposed for the discrete wavelet packet transform (DWPT) and Welch's energy detection methods with a varying influence ratio. The trade-off between detection probability P_d and false alarm probability P_f is also illustrated by the simulation results of proposed adaptive threshold algorithm to be demonstrated able to sense the LTE signal at a low SNR level while satisfy the sensing requirements required by the IEEE 802.22 standard.

The remainder of this paper is organized as follows: a generic CR system model is provided in Section II. The proposed adaptive threshold based DWPT and Welch's energy detection algorithms are described in Section III. In Section IV, simulation results are presented for both proposed adaptive threshold setting algorithms. The conclusions are drawn in Section V.

II. System Model

SUs with the energy detection technique is used to detect the presence of PU signals. The energy detector firstly measures the power of the input PU signals over a time interval T, then the received power is compared with a predefined fixed

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threshold to decide whether the frequency band is occupied or not. The sensing decision can be formulated into a binary hypothesis by

$$\begin{aligned} H_0 &: y(n) = w(n) \qquad\qquad (signal\ absent) \\ H_1 &: y(n) = h(n)s(n) + w(n)\ (signal\ present) \end{aligned} \tag{1}$$

where H_0 and H_1 denote the hypothesis PU absent and present, respectively. After bandpass filtering over a bandwidth W, the received signal is denoted as *y(n) (n = 0,1,...,N-1)*. *w(n)* represents the additive white Gaussian noise, assumed to be independent and identically distributed (iid) with zero mean and variance of σ_n^2. *s(n)* is the PU signal, also assumed to be an iid random process with zero mean and variance of σ_s^2. *h(n)* is the channel gain. With the signal and noise variance, the signal to noise ratio (SNR) can be defined as $SNR = \sigma_s^2/\sigma_n^2$.

The performance metric of spectrum sensing can be measured by the detection probability P_d and the false alarm probability P_f. When there are sufficient sample points N, the decision threshold can be derived for a target P_d or P_f. Under hypothesis H_1, the threshold λ_{P_d} can be set for a constant detection rate (CDR) as [12]

$$\lambda_{P_d} = (\sigma_n^2 + \sigma_s^2)\left(1 + \frac{Q^{-1}(P_d)}{\sqrt{N/2}}\right) \tag{2}$$

Similarly, under hypothesis H_0, the threshold λ_{P_f} can be set for a constant false alarm rate (CFAR) as

$$\lambda_{P_f} = \sigma_n^2\left(1 + \frac{Q^{-1}(P_f)}{\sqrt{N/2}}\right) \tag{3}$$

It was shown in (2) and (3) that the threshold derivation results are similar for both CDR and CFAR. The threshold based on CFAR is commonly applied in conventional energy detection algorithms.

III. Proposed Threshold Setting Algorithm

A. *Adaptive Threshold based DWPT Energy Detection*

The procedure of the proposed algorithm for the DWPT based energy detection algorithm is shown in Fig. 1 and described in Algorithm 1:

For $(i+1)^{th}$ level DWPT decomposition $(i = 1, 2, 3...RI - 1)$, the adaptive threshold $\lambda_{i+1,j}$ of channel $j (j = 1, 2, 3...2^i)$ can be written as

$$\lambda_{i+1,2j} = \frac{\lambda_{i,j} + \alpha \cdot E_{i+1,2j}}{2} \tag{4}$$

$$\lambda_{i+1,2j-1} = \frac{\lambda_{i,j} + \alpha \cdot E_{i+1,2j-1}}{2} \tag{5}$$

where $E_{i+1,2j}$ and $E_{i+1,2j-1}$ are the energy contributions for the computation of the adaptive threshold of channels *2j* and *2j-1* respectively. Channel *j* is one of the sub-bands when doing i^{th} level DWPT decomposition to the spectrum of interest. Channels $2j - 1$ and $2j$ are the channels further divided of channel *j* at the $(i+1)^{th}$ level. $\lambda_{i,j}$, $\lambda_{i,2j-1}$ and $\lambda_{i,2j}$ are thresholds for channel *j*, channel *2j-1* and channel *2j* respectively. $\alpha (0 < \alpha < 1)$ is the influence ratio mainly affected by the energy of the received signal to determine the adaptive threshold.

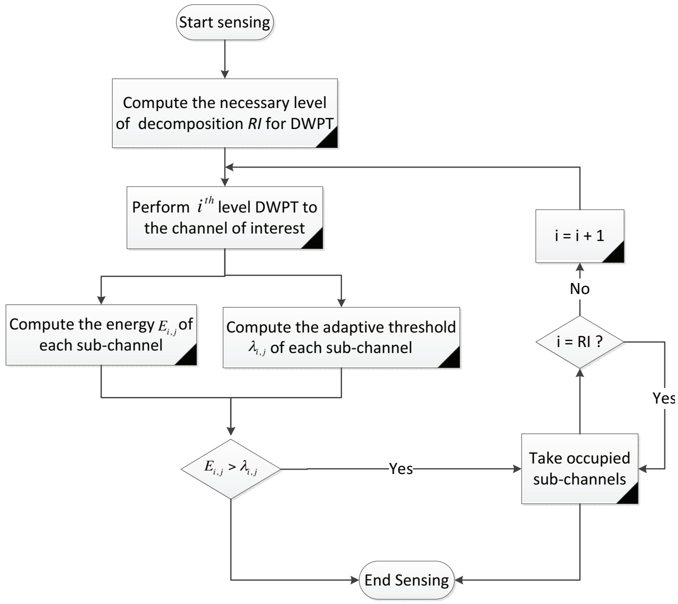

Fig. 1: A graphical structure of the flow Chart for adaptive DWPT based energy detection

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Algorithm 1 Adaptive DWPT based Energy Detection

Require:

1: Compute the necessary level of decomposition *RI* for DWPT as $RI = \log_2(B_s/B_d)$. B_s refers to the spectrum of interest and B_d refers to the bandwidth of each sub-channel.

2: Perform i^{th}-level DWPT decomposition.

3: Compute the energy of each sub-channel, and compare it to the threshold. If the energy of a specific sub-channel is lower than the threshold, it will be determined as unoccupied and will not be processed in the next level DWPT decomposition. Otherwise, it will be processed in the next level DWPT decomposition. In the first level DWPT decomposition, the fixed threshold is applied and computed by (3). The adaptive threshold will be used for the further level DWPT decomposition.

Ensure:

Steps 2 and 3 are repeated until the input signal is completely decomposed with *RI* times.

Fig. 2 shows the process of how to determine the energy component in the proposed adaptive threshold algorithm. Assume $E_{i+1,2j}$ is the current energy of channel *2j*, $E^*_{i+1,2j}$ is the energy of channel *2j* when only one primary user exists. $E_{i+1,2j}$ should be first compared with $E^*_{i+1,2j}$. If $E_{i+1,2j}$ is greater than $E^*_{i+1,2j}$, this means that there are multiple primary users in the spectrum of interest. Then, $E_{i+1,2j}$ should be replaced by $E^*_{i+1,2j}$. This is because if $E^*_{i+1,2j}$ is used

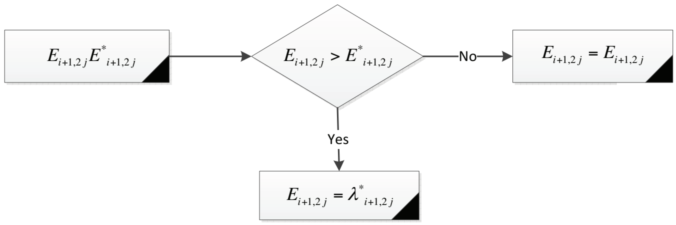

Fig. 2: A graphical structure of the energy component computation process for proposed adaptive threshold algorithm

in any case, the adaptive threshold will contain the practical energy component, which will be used as part of the adaptive threshold in the next level. This extra energy would make the adaptive threshold become too high according to (4) and (5). By adopting the process of judging the energy component for the adaptive threshold, the proposed adaptive threshold will avoid being too high to cause all the sub-bands being falsely determined as vacant even though primary users actually exist.

According to (4) and (5), when α tends to *1*, the adaptive threshold will be mainly affected by the energy of the received signals. When *a* tends to *0*, the threshold for each sub-band of $(i+1)^{th}$ level tends to be half of the threshold of i^{th} level. In this case, it will be close to the fixed threshold of the sub-band of the $(i+1)^{th}$ level. However, the initial detection performance of the proposed adaptive threshold based DWPT algorithm cannot reach a very low SNR level for some wide band signal like DVB-T. This is because the noise always spreads over a broadband signal. The amount of noise, or noise power, reaching the detector in the receiver is directly proportional to the overall bandwidth. The wider the bandwidth, the more noise power reaches the detector. In order to make the proposed adaptive threshold based DWPT algorithm suitable for the DVB-T signal at low SNR level, a modified method that can normalise the received signal is adopted. The threshold adapter is also modified to improve the performance of spectrum sensing for DVB-T signals.

The energy of sub-band *j* at level *i* is:

$$E_{i,j} = |w_{i,j}|^2 \tag{6}$$

Then, the total energy of the spectrum of interest at level *i* is:

$$E^i_{total} = \sum_1^{2^i} \left|w^i_j\right|^2 \tag{7}$$

Thus, the average energy in each sub-band at level *i* is:

$$E^i_{avg} = \frac{E^i_{total}}{2^i} \tag{8}$$

Finally, the decision parameter can be defined as:

$$d_{i,j} = \frac{E_{i,j}}{E^i_{avg}} \tag{9}$$

where $d_{i,j}$ is the normalised energy of the sub-band *j* at level *i*, which will be compared to the adaptive threshold given by (10) to determine whether the sub-band is occupied or not.

$$\lambda_{i,j} = \lambda^*_i \pm \alpha \cdot d_{i,j} \tag{10}$$

where $\lambda_{i,j}$ is the adaptive threshold for sub-band *j* at level *i*, and λ^*_i is the normalised fixed threshold for level *i* given by

$$\lambda^* = \frac{Q^{-1}(P_f)\sqrt{2N} + N}{N} \tag{11}$$

where *a* is the key parameter to adjust the adaptive threshold. An optimal value can be found through intensive simulations.

B. Adaptive Threshold based Welch's Energy Detection

Welch's algorithm is a modified periodogram. The principle of the Welch algorithm is to divide the data sequence into segments in order to reduce the large fluctuations of the periodogram [13]. For instance, a signal *s(n)* is segmented into M segments in the time domain with length L for each segment. L is the number of frequency bins to be averaged around the zero frequency. Therefore, an input signal *s(n)* can be defined as a matrix with $L \times M$ elements

$$s(m,l) = s(l + (m-1) \cdot (L-1)) \tag{12}$$

where *m* = 1,...*M* and *l* = 1,...*L*. After partitioning the input signal *s(n)* into *M* segments, FFT is first applied to each segment, and averaging is then performed over the squared outputs of the FFT. At this point, the average signal energy of *s(n)* in the frequency domain can be presented by:

$$P(l) = \frac{1}{M} \sum_{m=1}^{M} \left[|FFT(s(m,l))|\right]^2 \tag{13}$$

Then, averaging over *L* samples in the frequency domain, the average energy over the entire frequency band *Y* can be obtained as:

$$Y = \frac{1}{L} \sum_{l=-L/2}^{L/2} P(l) \tag{14}$$

Finally, the decision parameter can be defined as

$$d_i(l) = \frac{P(l)}{Y} \tag{15}$$

where $d_i(l)$ $\{d_1(l), d_2(l), ...\}$ represents the normalised Welch's energy vector of the i^{th} primary user. As $d_i(l)$ covers the entire frequency band of signal, each sub-signal represents the probability distribution of each primary user. This normalised Welch's energy detector would make its decision based on the associated adaptive threshold λ_i.

$$\lambda_i = \lambda^* \pm \alpha \cdot d_i(l) \tag{16}$$

where λ_i is the adaptive threshold for the i^{th} primary user, $a(0 < a < 1)$ is an influence ratio mainly affected by the energy of the received signal, namely the number of primary users, λ^* is the normalised fixed threshold determined by the false alarm probability P_f and the number of sample points N_s.

$$\lambda^* = \frac{Q^{-1}(P_f)\sqrt{2N_s} + N_s}{N_s} \tag{17}$$

TABLE I: Simulation parameter settings for LTE down-link signals [14]

Duplex	Frequency Division Duplex (FDD)
LTE channel	4.5
Number of LTE channels	16
Subcarrier spacing	15 KHz
Number of useful carriers	300
Number of resource blocks	25
Number of carriers per RB	12
FFT size	2048
Sampling frequency	80 MHz
Primary users	Channel 3,7,11,15

When α tends to 1, the adaptive threshold is affected largely by the energy of the received signals. When α tends to 0, the proposed threshold tends to be affected by the Gaussian noise, which is similar to the fixed threshold. By adjusting the value of α, a trade-off between false alarm rate P_f and detection probability P_d can be obtained. An optimal α value can be found through intensive simulations. s

IV. Results and Analysis

A. Experiment Setup

Simulation of the cognitive radio network under spectrum sensing environments with multiple PUs is conducted to determine the impact of threshold setting and varying influence ratio α on the performance of spectrum sensing. The target sensing signal is an OFDM signal for both DVB-T and LTE networks. Taking the LTE down-link signals as the study, 1000 Mote-Carlo simulations are performed and the simulation parameters of an OFDM based cognitive radio system are shown in Table I: An example of power spectral density (PSD) for 4 out of 16 LTE channels occupied at SNR = 10dB is shown in Fig. 3. In this simulation, it is assumed that there are 16 LTE channels for a spectrum of interest from 0MHz to 80MHz with each channel occupying 4.5MHz. Channel 3 (10MHz - 14.5MHz), Channel 7 (30MHz - 34.5MHz), Channel 11 (50MHz - 54.5MHz), Channel 15 (70MHz - 74.5MHz) are assumed to be occupied by four primary users. The remaining 12 channels are empty, but with the additive white Gaussian noise. Therefore, the primary users' initial spectrum utilisation is set to $a = 0.25$. The desired probability of false alarm for the fixed threshold is set as $P_f = 0.1$. Based on the OFDM signal parameters described in Table I, the performance of the proposed adaptive threshold based wavelet and Welch's algorithm is analysed and compared with the conventional fixed one.

B. Results and Analysis

Fig. 4 and Fig. 5 show the simulation results obtained by adaptive DWPT and Welch based energy detection in terms of P_d and P_f respectively. It is shown that the results obtained from both adaptive DWPT and Welch based energy detection algorithms matched well with each other and could keep the same changing trend.

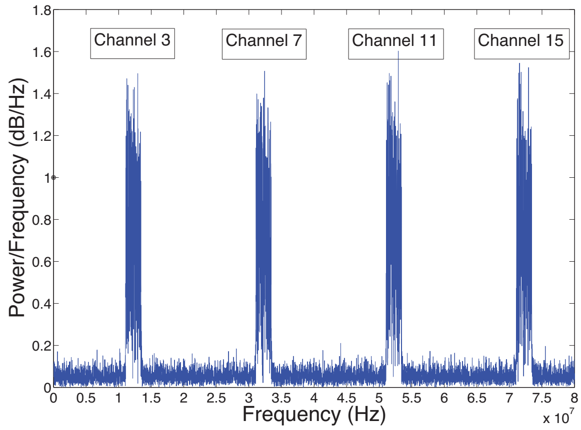

Fig. 3: A graphical illustration of the PSD for 16 LTE channels where channel 3,7,11 and 15 are occupied (SNR=10dB).

Fig. 4 shows the comparison between the fixed and adaptive DWPT/Welch based sensing algorithms in terms of probability of detection P_d. The performance of P_d with a changing threshold influence ratio α is presented Fig. 4 in as well. Here, the PUs' spectrum utilisation is set to *a = 0.25*. It is seen that the proposed adaptive threshold based DWPT/Welch algorithms always achieves a higher detection probability P_d than the conventional fixed DWPT/Welch algorithms when the threshold influence ratio α is negative. Further, the detection probability P_d will be increased with a decreasing in the influence ratio *a* from *-0.002* to *-0.008*. Particularly, for $\alpha = -0.008$, the proposed adaptive threshold based DWPT/Welch energy detection has improved the detection probability P_d by about *30%* at *SNR = -20dB* compared with the conventional fixed threshold based energy detection. This is because the new thresholds obtained from(10) and (16) are smaller than that of the conventional fixed one when the influence ratio α is negative. Therefore, more channels will then be judged as occupied due to this lower threshold.

On the other hand, it can be found that the proposed adaptive threshold based DWPT/Welch algorithms will always achieve a lower detection probability P_d than the conventional fixed DWPT/Welch algorithms when the threshold influence ratio α is positive. This is because the new thresholds obtained from(10) and (16) are always higher than that of the conventional fixed one when the influence ratio α is positive. Therefore, more channels will be judged as empty due to the higher threshold. Further, the detection probability P_d will be decreased as the increasing of influence ratio α from *0.002* to *0.008* as shown in Fig. 4.

Similarly, Fig. 5 shows the corresponding false alarm probability P_f comparison between the fixed and proposed adaptive DWPT/Welch based sensing algorithm. As the desired P_f for the conventional fixed threshold is set as $P_f = 0.1$, the P_f obtained from simulation could almost keep the same trend of *0.1*. Unlike the better sensing performance in terms of P_d when α is negative, the proposed adaptive DWPT/Welch algorithm

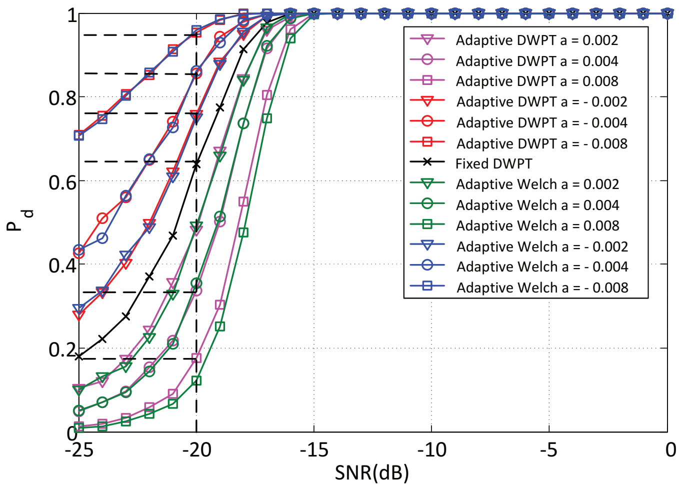

Fig. 4: P_d versus SNR for fixed/adaptive DWPT and Welch algorithms with different influence ratio α

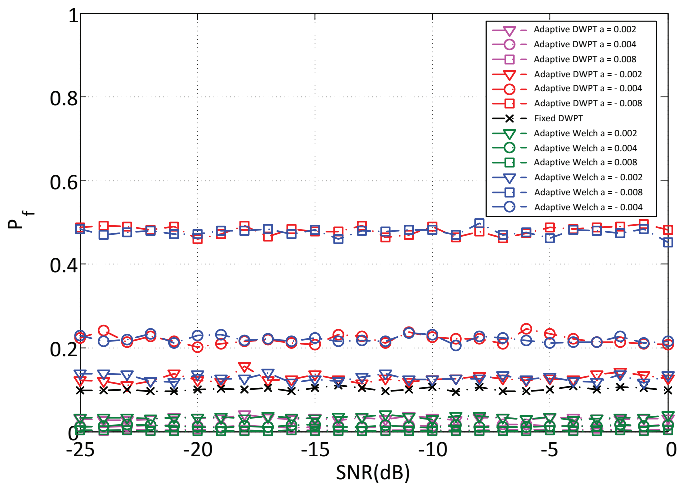

Fig. 5: P_f versus SNR for fixed/adaptive DWPT and Welch algorithms with different influence ratio α

keeps a higher P_f value than the conventional fixed threshold based energy detection when the influence ratio α ranges from *-0.002* to *-0.008*. This is because the lower adaptive threshold obtained from (10) and (16) when α is negative will result in more original empty channels being falsely judged as occupied. Thus, a higher false alarm probability P_f will be obtained as the decreasing of α from *-0.002* to *-0.008*.

In Fig. 5, compared with the poor sensing performance of P_d when α is positive, the proposed adaptive DWPT/Welch algorithm keeps a lower P_f value than the conventional fixed threshold based energy detection when the influence ratio *a* ranges from *0.002* to *0.008*. This is because the higher the threshold influence ratio α, the higher the proposed adaptive thresholds obtained from (10) and (16), thus a lower false alarm probability P_f is obtained.

By observing Fig. 4 and 5 together, the target sensing requirement ($P_d \geq 90\%$, $P_f \leq 10\%$) can be achieved around SNR = -18dB, which is a very low sensing level. These unified results further proved the benefit of our research on the effect of the adaptive threshold in different ways.

V. Conclusion

In this chapter, a new adaptive threshold algorithm is proposed for the energy detection based sensing algorithm with varying influence ratio. The proposed adaptive threshold is then implemented with both DWPT and Welch's energy detection methods to illustrate the trade-off between P_d and P_f. The simulation results show the proposed adaptive threshold based energy detection could obtain a higher detection probability P_d with a negative threshold influence ratio α and a lower false alarm probability P_f with a positive threshold influence ratio α. Furthermore, the proposed adaptive threshold algorithm could achieve a sensing level of -18dB.

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] M. Nekovee, "Impact of cognitive radio on future management of spectrum," *3rd International Conference on Cognitive Radio Oriented Wireless Networks and Communications (CrownCom)*, pp. 1–6, May. 2008.

[3] P. Van Wesemael, S. Pollin, E. Lopez, and A. Dejonghe, "Performance evaluation of sensing solutions for lte and dvb-t," *New Frontiers in Dynamic Spectrum Access Networks (DySPAN), 2011 IEEE Symposium on*, pp. 531–537, May. 2011.

[4] D. Cabric, A. Tkachenko, and R. W. Brodersen, "Experimental study of spectrum sensing based on energy detection and network cooperation," *Proc. of First Int. Workshop on Technology and Policy for Accessing Spectrum (TAPAS)*, Aug. 2006.

[5] E. Axell, G. Leus, E. Larsson, and H. Poor, "Spectrum sensing for cognitive radio : State-of-the-art and recent advances," *IEEE Signal Process. Mag.*, vol. 29, no. 3, pp. 101–116, May. 2012.

[6] X. Ling, B. Wu, H. Wen, P.-H. Ho, Z. Bao, and L. Pan, "Adaptive threshold control for energy detection based spectrum sensing in cognitive radios," *in Proc. IEEE Wireless Commun Lett.*, vol. 1, no. 5, pp. 448–451, Jul. 2012.

[7] Y. Gao, W. Xu, K. Yang, K. Niu, and J. Lin, "Energy-efficient transmission with cooperative spectrum sensing in cognitive radio networks," *in Proc. IEEE Wireless Commun. Netw. Conf. (WCNC'13)*, pp. 7–12, Apr. 2013.

[8] H.-H. Choi, K. Jang, and Y. Cheong, "Adaptive sensing threshold control based on transmission power in cognitive radio systems," *in Proc. Third Intl Conf. Cognitive Radio Oriented Wireless Networks and Comm. (Crowncom)*, pp. 1–6, May. 2008.

[9] J. Lotze, S. A. Fahmy, J. Noguera, B. Ozgul, and L. E. Doyle, "Spectrum sensing on lte femtocells for gsm spectrum refarming using xilinx fpgas," in *Software-Defined Radio Forum Technical Conference (SDR Forum)*, Washington DC, USA, Dec 2009.

[10] M. Kim, P. Kimtho, and J.-i. Takada, "Performance enhancement of cyclostationarity detector by utilizing multiple cyclic frequencies of ofdm signals," in *New Frontiers in Dynamic Spectrum, 2010 IEEE Symposium on*, April, pp. 1–8.

[11] Y. Zeng and Y.-C. Liang, "Maximum-minimum eigenvalue detection for cognitive radio," in *Personal, Indoor and Mobile Radio Communications, 2007. PIMRC 2007. IEEE 18th International Symposium on*, Sept., pp. 1–5.

[12] E. Peh and Y.-C. Liang, "Optimization for cooperative sensing in cognitive radio networks," *Proc. IEEE Wireless Commun. Netw. Conf. (WCNC'07)*, pp. 27–32, Mar. 2007.

[13] D. Martinez and A. Andrade, "Performance evaluation of welch's periodogram-based energy detection for spectrum sensing," *IET Commun*, vol. 7, no. 11, pp. 1117–1125, Jul. 2013.

[14] 3GPP, "Evolved Universal Terrestrial Radio Access (E-UTRA); Physical channels and modulation," 3rd Generation Partnership Project (3GPP), TS 36.211, Sep. 2008.