Spectrum Characterization for Opportunistic Cognitive Radio Systems

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***Abstract*— Spectrum sensing is one of the most challenging problems in cognitive radio systems. The spectrum of interest needs to be characterized and unused frequencies should be identified for possible exploitation. This process, however, should be computationally simple and fast in order to catch up with the changing transmission parameters. This paper proposes a sensing method for identifying the unused spectrum for opportunistic transmission by estimating the RF transmission parameters of primary users. The primary users are identified by matching the *a priory* information about their transmission characteristics to the features extracted from the received signal. The application of the proposed sensing method to WiMAX mobile stations for finding the active channels during initial network entry is also discussed as a case study.**

***Index Terms*— Cognitive radio, spectrum sensing, partial match filtering, bandwidth detection, WiMAX.**

I. Introduction

Cognitive radio is a new concept in wireless communication which aims to have more adaptive and aware communication devices which can make better use of available natural resources, *i.e.* the spectrum [1]. The two challenging tasks in cognitive radio are sensing the environment, and processing and making decisions based on the spectrum knowledge. Cognitive radios can be used as a secondary system on top of current allocation of users which are called primary (or licensed) users. In this case secondary (cognitive) users need to detect the unused spectrum in order to be able to exploit it.

One method proposed in the literature for exploiting the unused spectrum is spectrum pooling [2]. In this method, the frequency band is measured and unused part of the spectrum is utilized by transmitting OFDM signals whose subcarriers are nulled at the used subcarrier positions. The subcarriers where primary users transmit are set to zero in order to prevent interference. For reducing the leakage (so-called mutual interference), time domain windowing and nulling the neighboring subcarriers can be used [2], [3]. Another system similar to the spectrum pooling method is given in [4]. After the measurements, the empty frequencies in the spectrum are determined. The OFDM(A) sub-carriers are grouped into sub-bands and only the sub-bands that fall into the unused spectrum are employed.

One important task for realizing cognitive devices is characterization of the spectrum, or spectrum sensing. The cognitive radio devices should be able to identify the unused spectrum in a fast and efficient way. Conventional algorithms sense the spectrum without knowing the properties of the primary users. In this paper, the *a priory* information about the transmission properties of possible primary users, such as transmission bandwidths and center frequencies, are used to develop a *partial match-filtering* method. In this method, the parameters estimated from the received signal are matched to the possible transmission parameters for achieving a more robust and reliable sensing. This paper consists of two parts. In the first part, we present the proposed spectrum sensing algorithm for identifying the transmission opportunities by detecting the presence of primary users in a given frequency band. In the second part, we apply the algorithm developed in the first part to downlink channel detection problem for WiMAX mobile stations (MSs) performing initial network entry. It is shown that the two problems are identical and the same method can be used for solving these problems.

This paper is organized as following. The spectrum sensing problem is discussed in Section II, and proposed sensing algorithm is presented in Section III. We discuss the application to WiMAX in Section IV and present numerical results in Section V. Finally, the concluding remarks are given in Section VI.

II. Spectrum Sensing for Cognitive Radios

Although spectrum sensing is usually understood as measuring the spectral content of the environment, it is a more general term. In order to be able to realize a fully cognitive radio, the cognitive devices should be aware of not only spectral content but also temporal and spatial contents of the environment that they are operating in.

Matched filtering is the optimum method for detection of primary users. However, matched filtering requires the cognitive user/radio to demodulate the received signal hence it requires perfect knowledge of the primary users signaling features. Moreover, since the cognitive radio will need receivers for all signal types, it is practically difficult to implement [5]. The sensing might also be performed by correlating the received signal with a known copy of itself [6]. This method is only applicable to systems with known signal patterns such as wireless metropolitan area network (WMAN) signals [7], and it is termed as waveform-based sensing. Another method for detection of primary user transmission is cyclostationarity feature detection. This algorithm is proposed in [5], [8] and it exploits the cyclostationarity features of the received signal which is caused by the periodicity in the signal or in its statistics (mean, autocorrelation *etc*). Instead of power spectral density (PSD), cyclic correlation function is used for detecting the signals present in the given spectrum. This method can also differentiate the noise from the primary users which is a result of the fact that noise is a wide-sense stationary (WSS) signal with no correlation while modulated signals are cyclostationary with spectral correlation due to the redundancy of signal periodicities [8]. In [9], multitaper spectral estimation is proposed. The proposed algorithm is shown to be an approximation to maximum likelihood PSD estimator and for wideband signals it is nearly optimal. Although the complexity of this method is less then the maximum likelihood estimator, it is still large.

Energy detector based approaches (also called radiometry or periodogram) are the most common way of spectrum sensing because of their low computational complexity. Moreover, they are more generic as the receiver does not need any knowledge on the primary users' signal. The signal is detected by comparing the output of the energy detector with a threshold which depends on the noise floor. Some of the challenges include the selection of a threshold for detecting primary users, the inability for differentiating the interference from the primary users and from the noise, and poor performance under low SNR [6]. In this paper, energy detector based approach is used as an intermediate step for obtaining features about the transmissions in the frequencies of interest. These features, then, will be used for determining the presence of primary users.

A. Detection of Primary Users

One of the problems in spectrum sensing is the detection of a primary user in the band (and time) considered. There is a tradeoff between the false alarm rate and detection rate. In [10], FFT is applied to the received signal and using the output of FFT, the receiver tries to detect the existence of a primary user in the band. More than one FFT output (averaging in time) is used. However, averaging in time increases the delay or temporal overhead. For detection a likelihood function is used. In [11], the averaging size (number of FFTs) is adapted in order to increase the efficiency in a cooperative sensing environment.

The estimation of the traffic in a specific geographic area can be done locally (by one cognitive radio only) or the information from different cognitive radios can be combined [5], [11], [12]. Cooperative sensing decreases the probability of mis-detections and the probability of false alarms considerably. Moreover, the detection time might be reduced compared to local sensing. The signaling of detected information from cognitive devices, however, is an issue for research [13]. In this paper, we focus on local sensing. However, the developed method can be combined with different cooperation schemes among cognitive users for obtaining better results.

III. Details of the Proposed Algorithm

In this paper, we extend the algorithm proposed in [10] by exploiting the correlation of the power at neighboring frequencies in order to have a better detection. The proposed algorithm is based on FFT operation which is used to transform the time-domain signal into frequency domain. In [10], the FFT output samples are used for deciding whether an FFT frequency sample is occupied by a primary user or not. However, the primary users signal is usually spread over a group of FFT output samples as the bandwidth of primary user is expected to be larger than the considered bandwidth divided by the FFT size[1]. Using this fact, the FFT output is filtered for noise averaging in order to obtain a better performance,

The proposed algorithm is especially suitable for cognitive devices using OFDM as their transmission technique, such as systems similar to [2], [4]. The availability of FFT circuitry in these systems eases the requirements on the hardware. Moreover, the computational requirements of the spectrum sensing algorithm is reduced as the receiver already applies FFT to the received signal in order to transform the received signal into frequency domain for data detection.

The block diagram of the proposed algorithm is shown in Fig. 1. The signal that arrives to cognitive user $y(t)$ is first filtered with a band pass filter (BPF) to extract the signal in the frequencies of interest. This filter may be adjustable and controlled by a control unit in order to scan a wider range. The output of the filter is sampled at Nyquist rate and N-point FFT is applied to obtain the frequency domain samples. Each sample might be modeled as

$$Y(k) = \begin{cases} W(k) & \mathcal{H}_0, \\ S(k) + W(k) & \mathcal{H}_1, \end{cases} \qquad k = 1, \cdots, N \tag{1}$$

where $S(k)$ is the transmitted signal by primary users at the output of FFT, $W(k)$ is the white noise sample at kth frequency sample, and N is the FFT size. $\mathcal{H}_0$ and $\mathcal{H}_1$ represent the null hypothesis and alternate hypothesis respectively. The white noise is modeled as a zero-mean Gaussian random variable with variance σ_0^2, *i.e.* $W(k) = \mathcal{N}(0, \sigma_0^2)$. The signal term is also modeled as a zero-mean Gaussian variable whose variance is a function of frequency, *i.e.* $S(k) = \mathcal{N}(0, \sigma_k^2)$, where σ_k is the local standard deviation. The variation of σ_k across frequency depends on the characteristics of primary users signals. The signal-to-noise ratio (SNR) is defined as the ratio of signal power to noise power during transmission, *i.e.* $SNR(k) = \sigma_k^2/\sigma_0^2$.

A. Frequency Domain Filtering

The magnitude square of FFT output $|Y(k)|^2$ might be compared with a threshold value λ for detection of presence of transmission at this frequency. In addition, the fact that a signal transmission will affect more than one frequency sample can be used to improve the detection performance. We achieve this by filtering the FFT output before applying the threshold detector. The optimum filter coefficients depend on the statistics of primary user's signal as well as the noise power. In [14], minimum mean-square error (MMSE) filtering is applied for estimating the noise plus interference ratio for orthogonal frequency division multiplexing (OFDM) systems.

[1]By using an analogy to OFDM systems, the primary users usually cover more than just one subcarrier.

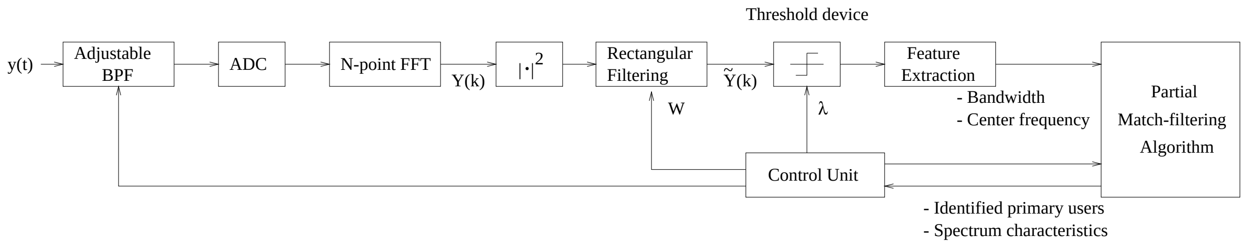

Fig. 1. Block diagram of the proposed algorithm.

The MMSE filter coefficients are derived as a function of the statistics of interference. As an approximation to MMSE filtering, a sliding rectangular window can also be applied for smoothing the spectrum estimates $Y(k)$. In this paper, we use rectangular filter for its simplicity and lower computational complexity. In this case, the estimates at different frequencies can be written as

$$\tilde{Y}(k) = \frac{1}{D} \sum_{w=k-D/2}^{k+D/2+1} |Y(w)|^2 \qquad (2)$$

where D is the width of the filter in frequency direction.

B. Threshold Detector

The output of the rectangular filter $\tilde{Y}(k)$ is fed to a threshold device to identify the frequencies occupied by the primary users. This is equivalent to distinguishing between the following two hypotheses:

$$\mathcal{H}_0 \quad : \quad Y(k) = W(k), \qquad (3)$$
$$\mathcal{H}_1 \quad : \quad Y(k) = S(k) + W(k). \qquad (4)$$

The performance of the detection algorithm can be summarized with two probabilities: probability of detection P_D and probability of false alarm P_F. P_D is the probability of detecting a signal on the considered frequency when it is truly present, thus large detection probability is desired. P_F is the probability that the test incorrectly decides that the considered frequency is occupied, when actually it is not, thus P_F should be kept as small as possible. In general, increasing P_D increases P_F and decreasing false alarms decreases P_D. Hence the threshold should be selected carefully for finding an optimum balance between P_D and P_F which depends on the application. The threshold value λ can be determined by pre-specified probability of false alarm P_F or probability of detection P_D. Moreover, the value of the threshold depends on the noise and received signal energies.

C. Feature Extraction

In this stage, features like bandwidth and center frequencies of primary users are extracted by using the threshold detector output. In order to achieve this, we define two parameters B_{min} and G_{max}. B_{min} is the minimum assumed bandwidth for the primary users and G_{max} is the maximum gap allowed between two frequency samples. The feature extraction algorithm searches for continuous frequencies which are marked by threshold detector as having signal, not G_{max} samples away and with more adjacent frequency samples then B_{min}. Hence, using these two parameters, the occupied frequency band can be identified. It is then straightforward to estimate the bandwidth and the center frequency of transmission. One drawback of this method, however, is that the cognitive radio may not differentiate between two (or more) superimposed primary user transmissions and threat them as a single transmission with a larger bandwidth. However, this might be tolerated as our goal is to identify the unused bands.

D. Partial Match-filtering

In the final step, the primary users are further identified by using the *a priory* information about their transmission parameters. The set of possible systems and their transmission parameters might be broadcasted by a central unit for cognitive devices for assisted identification. These parameters include the center frequencies, bandwidths, signal types, duplexing and multiple accessing methods of the potential users. For example, IEEE 802.11a signal has a bandwidth of 20MHz and operates at ISM or U-NII bands in the US. The knowledge about the center frequencies and bandwidth of this type of a signal can be used in order to identify the presence of an 802.11a transmission and in order to improve the spectrum sensing. We match the parameters estimated by the feature detection block to the *a priory* sets of known parameters. By finding the transmissions by primary users, possible estimation errors due to the sensing algorithm and noise is removed. We refer to this process as *partial match-filtering* as we are matching to the parameters of the primary user's signal instead of the signal itself. Once the primary users (or the occupied frequencies) are detected, the unused portion of the spectrum can be identified for opportunistic exploitation.

Two transmission parameters are used in [15] as features for identification of among bluetooth and wireless local area network (WLAN) signals: maximum duration of a signal and instantaneous power of each frequency bin. Some other parameters that can be used for partial matching include the center frequencies, transmission bandwidths, signal types, duplexing, multiple accessing methods and prior probabilities of the potential users in the band considered. These parameters can be collected by the cognitive device (blind) or they can be provided by a central unit (assisted).

The partial match-filtering algorithm can be realized in three main steps:

1) Extraction of a predefined set of parameters/features from the received signal,

2) Using the extracted features for making decisions on the presence of an anticipated transmission,
3) Exploring the gained knowledge about the active primary users for multi-dimensional spectrum characterization.

In the following, we explain these steps in more detail.

1) Feature Extraction: Primary users can be identified by using the *a priori* information about their transmission parameters. These parameters need to be extracted from the received data using signal processing techniques. The set of possible primary user classes and their transmission parameters can be collected by cognitive devices using previous decisions/measurements (blind) or they can be broadcasted by a central unit (assisted). Alternatively, these parameters can be preconfigured to the cognitive radio during hardware design[2]. In this paper, we use energy detector based feature detection. The features used are bandwidths and center frequencies of the candidate transmissions.

Let us represent the feature set as a vector X. Then this vector can be used for classifying the detected transmission into one of K candidate transmissions using a classification algorithm that will be discussed in the next section.

2) Decision Making (Classification): In this step, the measured signal is associated with a primary radio class. This process can be regarded as a classification problem. For this purpose, various classification methods can be used such as pattern recognition, neural networks or statistical classification [15]. Bayesian classifier is the optimum method from the statistical viewpoint and it will be considered as an example in this paper. By using the Bayesian decision rule, we classify the feature set obtained using measurements in the previous section (step 1) to the systems or devices that has the highest *a posteriori* probability. The classifier can be represented in terms of a set of discriminant functions $g_i(X)$, $i = 1, \ldots, K$ where K is the total number of systems[3]. The classifier is said to assign a feature vector X to a system w_i if $g_i(X) > g_j(X)$ for all $j \neq i$.

The discriminant function can be defined as

$$g_i(X) \equiv \log P(X|w_i) + \log P(w_i)\ . \quad (5)$$

In this work, the distribution of the feature vector X within the ith class is assumed to be a multivariate normal distribution with mean vector μ_i and covariance matrix Σ_i. Under such an assumption, the discriminant functions can be obtained as

$$g_i(X) = -\frac{1}{2}(X-\mu_i)^T\Sigma_i^{-1}(X-\mu_i) - \frac{1}{2}\log|\Sigma_i| + \log P(w_i)\ . \quad (6)$$

The mean vector μ_i can be obtained by using the expected values of features. In practice, the covariance matrix Σ_i is unknown and it needs to be estimated using some sort of training data as

$$\Sigma_i = \frac{1}{N-1}\sum_{j=1}^{N}(X_j - \mu_i)(X_j - \mu_i)^T\ . \quad (7)$$

[2]Some example databases can be FCC Licensing and ITU frequency allocation rules.

[3]Note that the systems operating at different bands are regarded as different systems for the sake of classification. The transmission band of a system needs to be known for identifying the frequencies occupied by primary users.

The covariance matrix can be assumed to be the same for all classes using the same transmission technique. For example, all the classes using WLAN are expected to have the same covariance matrix as only center frequency is changed.

When the estimated features are not correlated to each other, the correlation matrix becomes a diagonal matrix. Different features will have different units and hence proper normalization of this features needs to be established. Moreover, the values of diagonal elements give the weights for each feature and we can assign different weights on different features.

3) Multi-dimensional Spectrum Characterization: In this step, the output of the partial matched-filtering method is used for obtaining a complete multi-dimensional spectrum awareness in cognitive radio. The knowledge of primary users can help identify the transmission opportunities across different dimensions. For example if the identified signal is a cordless phone, the range is expected to be around 100 meters and for Bluetooth signals it is around 10 meters. This type of knowledge can be used in a cooperative sensing environment for gaining knowledge in the space direction. The characterization in time, frequency, and code dimensions is straightforward once primary users are associated with a particular transmission technique/class.

In the next section, we investigate the application of proposed partial match-filtering approach to automatic bandwidth detection for mobile WiMAX systems.

IV. Application to Mobile WiMAX

Cognitive radio based devices should support different transmission bandwidths and center frequencies. Similar concept is also true for the devices operating according to the recent WMAN standard known as mobile WiMAX [7]. These devices should support different profiles that the base station (BS) might be using. Hence, they should be capable of operating in more than one bandwidth or FFT size. The detection of the downlink signal parameters (bandwidth, FFT size, CP size, center frequency) is MS's responsibility. In this section, we apply the algorithm proposed in the previous section to detect the downlink transmissions in WiMAX. The proposed method identifies the center frequencies and bandwidths of used channels. We specifically consider 802.16e MSs and searching for channels with active transmission.

A. Overview of Mobile WiMAX

The recently approved 802.16e standard [7] (known as mobile WiMAX) uses scalable OFDMA as physical layer transmission technique. By changing the FFT size as a function of the transmission bandwidth, the subcarrier spacing is kept constant for all bandwidths aiming to reduce the inter-carrier interference (ICI), due to mobility and frequency offsets, to a negligible level [16]. The available FFT sizes and system bandwidths are given in Table I. Moreover, the fixed standard supports FFT sizes of 256 and 2048 with different bandwidths (multiple of 250 kHz and no less than 1.25 MHz). Hence the MSs should have support for various channel bandwidths. This requires dynamic detection of the FFT size and the channel bandwidth which is a similar problem to detection the primary

TABLE I

AVAILABLE BANDWIDTHS AND FFT SIZES FOR 802.16E

System bandwidth (MHz)	1.25	NA	5	10	20
Sampling frequency (MHz)	1.429	NA	5.714	11.429	22.857
FFT size	128	256	512	1024	2048

users in a given frequency band and the algorithm proposed in the previous section might be used for this purpose. In both cases, some *a priori* information about the center frequencies and bandwidths of the expected signals is assumed to be available.

B. Proposed Algorithm

The center frequencies and bandwidths of possible transmission channels are already known by the mobile station. These parameters are defined in the standard as profiles and depends on which profiles the MS is supporting. The possible transmission channels can be calculated as

$$F_c = F_{start} + n \cdot \Delta F_c \qquad \forall n \in 1, \ldots, N_{range} \qquad (8)$$

where F_{start} is the start frequency for the specific band, ΔF_c is the center frequency step and N_{range} is the range of values for the parameter n [7]. The MS should be able to estimate transmission frequency F_c and transmission bandwidth B for successful entry to the system.

One method is the excessive search method where the MS tests the presence of transmission at each possible channel. In other words, the MS calculates all possible F_c values for the profiles it has support for, and tests the presence of transmission in these channels. The specifically designed downlink preambles can be used for testing of the existence of a frame in a channel as well [17]. This method, however, might be inefficient especially if MS supports a large number of profiles. Time delay introduced by serial testing is also not desired during handoff where the receiver switches between different BSs operating at different profiles and/or different frequencies.

The algorithm proposed in Section III can be updated for detecting the DL transmission effectively and quickly. The proposed algorithm can be summarized as following:

1) Apply Fourier transform to the received signal with the maximum available FFT size[4].
2) Smooth the FFT output by using a moving window [14].
3) Compare the output of moving window with a threshold and mark the subcarriers with power larger than the threshold.
4) Estimate the bandwidth and center frequencies of DL transmission by using the marked subcarriers as described before.
5) If there is no active channels, shift the center frequency to next channel (with largest possible bandwidth) and go to step 1.

The performance of the bandwidth estimation algorithm can also be summarized with two probabilities P_D and P_F as primary user detection in cognitive radios. In this application, we can select the detection threshold such that we have a high P_D as false alarms can be tolerated. For subsequent network entries, the MS can remember the last entered network channel widths and FFT sizes and optimize its search to quickly reacquire the same channel.

[4]The maximum FFT size that the MS is capable of depends on the profiles supported by the MS, and the maximum available value is 2048.

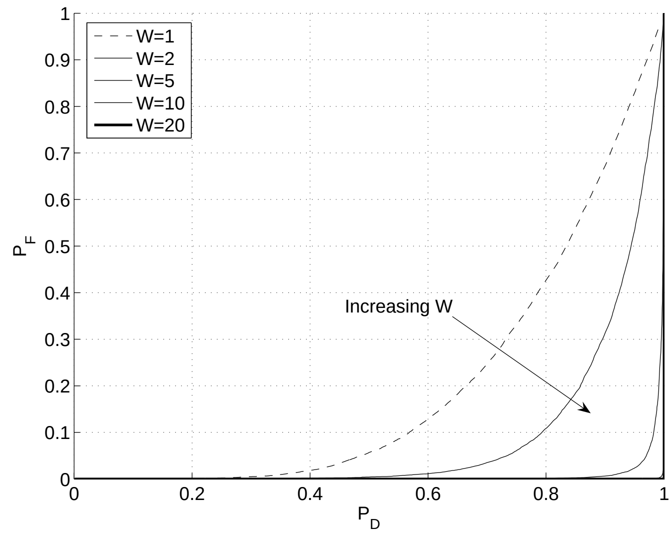

Fig. 2. ROC curves for different rectangular window sizes. The SNR is set to 5dB.

V. NUMERICAL RESULTS

The developed algorithms are tested with computer simulations. The considered frequency band is divided into subbands of 20MHz and proposed algorithm is applied for each subband. The FFT size is chosen as 1024.

Figs. 2 and 3 show the receiver operating characteristics (ROCs) for a single frequency sample at the output of threshold device (see Fig. 1). In Fig. 2, the ROC curves for different smoothing window sizes are presented when no averaging in time is performed, *i.e.* only one FFT output is considered. The signal's power is assumed to be 5dB higher than the noise level. It is easy to see the performance improvement obtained by using the smoothing filter compared to [10]. The performance is enhanced as the window size increases.

Fig. 3 presents the ROC curves for different SNR values. In this figure, the width of the rectangular window is set to 5 samples. The detection performance improves with increasing SNR as expected.

The histogram of the estimated bandwidth using the feature extraction method given in Section III is presented in Fig. 4 for 5dB average SNR and a window size of 5. The parameters used are $G_{max} = 10$ and $W_{min} = 40$. The threshold λ is chosen by assuming the signal and noise power levels are known to the cognitive radio, and by using a 90% detection probability P_D for each frequency sample. The primary user is assumed to have a bandwidth of 2MHz. The estimated bandwidths are close to the actual bandwidth. It is also observed that the presence of a primary user could be detected for 99.5% of the time using these parameters.

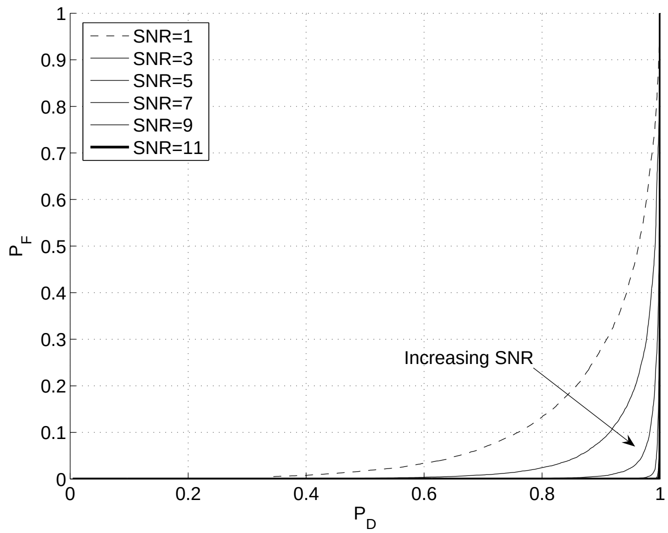

Fig. 3. ROC curves for different SNR values when the rectangular window size is 5, *i.e.* $W = 5$.

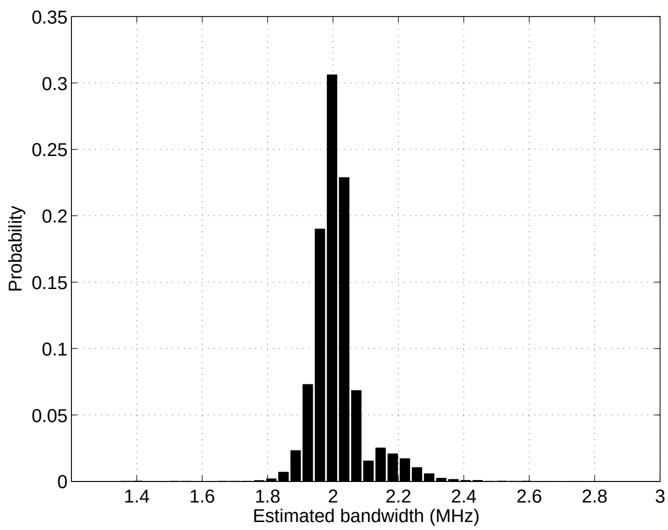

Fig. 4. The histogram of the estimated bandwidth of primary user at 5dB SNR and window size of 5.

VI. Conclusions

Spectrum sensing algorithms for cognitive radio devices are proposed in this paper. Frequency correlation is exploited for obtaining better detection performance in energy detector based algorithms. A simple feature extraction method is proposed for finding the transmission parameters using the energy detector output. Moreover, partial match-filtering is used to detect the active primary users by matching to the extracted features. The application of the proposed algorithm to WMAN devices for finding the transmission parameters effectively during initial network entry is also presented. By applying the partial match-filtering algorithm, the spectrum estimation can be improved significantly.

References

[1] F. K. Jondral, “Software-defined radio–basics and evolution to cognitive radio,” *Eurasip Journal on Wireless Comm. and Networking*, vol. 3, pp. 275–283, 2005.

[2] T. Weiss and F. Jondral, “Spectrum pooling: an innovative strategy for the enhancement of spectrum efficiency,” *IEEE Commun. Mag.*, vol. 42, no. 3, pp. 8–14, May 2004.

[3] T. Weiss, J. Hillenbrand, A. Krohn, and F. Jondral, “Mutual interference in OFDM-based spectrum pooling systems,” in *Proc. IEEE Veh. Technol. Conf.*, vol. 4, May 2004, pp. 1873–1877.

[4] D. Falconer and M. Muck, “Feasibility of multi-bandwidth transmission in future broadband wireless systems,” in *Proc. IST Mobile & Wireless Commun.*, Dresden, Germany, 2005.

[5] D. Cabric, S. Mishra, and R. Brodersen, “Implementation issues in spectrum sensing for cognitive radios,” in *Proc. Asilomar Conf. on Signals, Systems and Computers*, vol. 1, Nov. 2004, pp. 772–776.

[6] H. Tang, “Some physical layer issues of wide-band cognitive radio systems,” in *Proc. IEEE Int. Symposium on New Frontiers in Dynamic Spectrum Access Networks*, Nov. 2005, pp. 151–159.

[7] *IEEE Standard for Local and Metropolitan area networks Part 16*, The Institute of Electrical and Electronics Engineering, Inc. Std. IEEE 802.16E-2005, 2005.

[8] D. Cabric and R. W. Brodersen, “Physical layer design issues unique to cognitive radio systems,” in *Proc. IEEE Int. Symposium on Personal, Indoor and Mobile Radio Commun.*, Sept. 2005.

[9] S. Haykin, “Cognitive radio: brain-empowered wireless communications,” *IEEE J. Select. Areas Commun.*, vol. 3, no. 2, pp. 201–220, Feb. 2005.

[10] T.Weiss, J. Hillenbrand, and F. Jondral, “A diversity approach for the detection of idle spectral resources in spectrum pooling systems,” in *Proc. of the 48th Int. Scientific Colloquium*, Ilmenau, Germany, Sept. 2003.

[11] J. Hillenbrand, T. Weiss, and F. Jondral, “Calculation of detection and false alarm probabilities in spectrum pooling systems,” *IEEE Commun. Lett.*, vol. 9, no. 4, pp. 349–351, Apr. 2005.

[12] G. Ganesan and Y. Li, “Agility improvement through cooperative diversity in cognitive radio,” in *Proc. IEEE Global Telecommunications Conf. (Globecom)*, vol. 5, Nov./Dec. 2005, pp. 2505–2509.

[13] T. Weiss, J. Hillenbrand, A. Krohn, and F. Jondral, “Efficient signaling of spectral resources in spectrum pooling systems,” in *Proc. IEEE Symposium on Commun. and Veh. Technol.*, Nov. 2003.

[14] T. Yücek and H. Arslan, “MMSE noise power and snr estimation for ofdm systems,” in *Proc. IEEE Sarnoff Symposium*, Princeton, NJ, Mar. 2006.

[15] M. Gandetto, M. Guainazzo, and C. S. Regazzoni, “Use of time-frequency analysis and neural networks for mode identification in a wireless software-defined radio approach,” *EURASIP Journal on Applied Signal Processing*, vol. 2004, pp. 1778–1790, 2004.

[16] H. Yaghoobi, “Scalable OFDMA physical layer in IEEE 802.16 WirelessMAN,” *Intel Technology Journal*, vol. 8, no. 3, pp. 201–212, Aug. 2004.

[17] T. Schmidl and D. Cox, “Low-overhead, low-complexity [burst] synchronization for OFDM,” in *Proc. IEEE Int. Conf. Commun.*, vol. 3, Dallas, TX, June 1996, pp. 1301–1306.