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Energy Detection Based Sensing and Primary User Traffic Classification for Cognitive Radio

Urvee B. Trivedi, U. D. Dalal

***Abstract*—**As wireless communication services grow quickly; the seriousness of spectrum utilization has been on the rise gradually. An emerging technology, cognitive radio has come out to solve today's spectrum scarcity problem. To support the spectrum reuse functionality, secondary users are required to sense the radio frequency environment, and once the primary users are found to be active, the secondary users are required to vacate the channel within a certain amount of time. Therefore, spectrum sensing is of significant importance. Once sensing is done, different prediction rules apply to classify the traffic pattern of primary user. Primary user follows two types of traffic patterns: periodic and stochastic ON-OFF patterns. A cognitive radio can learn the patterns in different channels over time. Two types of classification methods are discussed in this paper, by considering edge detection and by using autocorrelation function. Edge detection method has a high accuracy but it cannot tolerate sensing errors. Autocorrelation-based classification is applicable in the real environment as it can tolerate some amount of sensing errors.

***Keywords*—**Cognitive radio (CR), probability of detection (P_D), probability of false alarm (P_F), primary User (PU), secondary user (SU), Fast Fourier transform (FFT), signal to noise ratio (SNR).

I. INTRODUCTION

IN the last few years, the demand for digital wireless communication has increased dramatically. Due to the flexible protocols and standards in wireless communication network new and valuable applications such as mobile internet access, electronic healthcare monitoring service and many others have emerged. Due to this trend there is a great demand on premium radio resources especially the radio spectrum. So, the spectrum scarcity comes into an emerging problem nowadays, in fact the spectrum scarcity is not by limitation of the spectrum resource but by inefficiency of the spectrum usage [1]. To utilize the wasted radio resources more efficiently, cognitive radio (CR) technology, which uses unused spectrum bands not interfering licensed users, has emerged [3]. A spectrum sensing technique for searching the unused spectrum in CR system is a key function and it requires high precision and fast speed processing. Spectrum sensing methods are divided into two categories; an energy detector and a feature detector [5], [6].

The main aim for CR techniques is to sense the spectrum with much lower complexity so many precise spectrum sensing techniques had been developed for signal identification in the field such as Radar engineering are unsuitable for CR techniques because of their high complexity [5]. To search the unused spectrum faster and more correctly, the two-stage sensing architecture was proposed by IEEE 802.22 working group (WG) [2], [4]. At the first stage fast sensing is done by an energy detector that searches spectrum bands of relatively high power, which are determined as occupied channels. Then a feature detector senses only filtered spectrum bands accurately at the second stage. Therefore, the main role of the energy detector at the first stage is to send the unassured channels to the second stage quickly.

Various methods are used for energy detection such as cyclostationary feature detector, matched filter, Fast Fourier Transform (FFT) and Discrete Wavelet Packet Transform (DWPT). Spectrum sensing techniques based on the FFT are easy to implement and conventional technique for cognitive radio but have a drawback of low accuracy [7]-[9].

Classification of traffic pattern of primary channels allows a more accurate prediction of future idle times. The classification algorithm uses binary information collected by spectrum sensing. Two types of classification algorithm are proposed, one calculates the average separation of peaks of sensed binary data by detecting the edges and other uses discrete autocorrelation function to check periodicity of traffic from the sensed binary pattern [10], [11].

In this paper, Section II describes a brief introduction to Fast Fourier transform based Energy Detector, Section III gives the performance analysis of FFT based Energy detector, Section IV introduces traffic classification techniques for cognitive radio, Section V gives performance analysis of traffic classification techniques and finally Section VI concludes the paper.

II. ENERGY DETECTION ALGORITHM BY USING FAST FOURIER TRANSFORM

Energy Detection is the most common way of spectrum sensing because of its low computational and implementation complexities. In this method the receivers do not need any knowledge on the primary user's signal. Therefore, this is the most generic method of signal detection. The signal is detected by comparing the output of the energy detector with a threshold which depends on the noise floor. The fundamental challenge with the energy detector based sensing is the selection of the threshold for detecting primary users. The other challenges include its ability to differentiate interference from primary users and noise and poor performance under low signal-to-noise

Urvee B. Trivedi, Lecturer, is with the EC Department, Government Polytechnic, Dahod (e-mail: trivedi_urvi@yahoo.co.in).
U. D. Dalal is Head of Electronics Department, SVNIT, Surat (e-mail: udd@eced.svnit.ac.in).

ratio values [5]-[7]. Two probabilities are of interest for spectrum sensing: *Probability of detection* (P_D), i.e. the probability of the algorithm correctly detecting the presence of primary user; and *Probability of false alarm* (P_F), i.e. the probability of the algorithm falsely declaring the presence of primary user when primary user is not present [5], [6].

A. FFT-Based Energy Detector

It is a non-coherent detection method that detects the primary signal based on the sensed energy. This architecture also provides the flexibility to process wider bandwidths and sense multiple signals simultaneously [6].

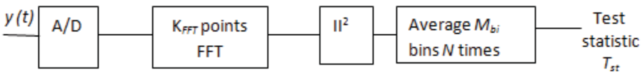

Fig. 1 FFT based energy detector

In order to measure signal energy, the received signal is first sampled, then converted to frequency domain by taking FFT followed by squaring the coefficients and then taking the average. The detector computes the energy of received signal and compares it to certain threshold to decide whether the desired signal is present or not. Here the K_{FFT} indicates the no. of FFT points with respect to power of 2. It depends on the total no. of time samples which is to be considered. More no. of time samples better the detection probability [6], [11]. The sampling frequency determines the frequency range or bandwidth of the spectrum and that for a given sampling frequency, the number of points acquired in the time-domain signal record determine the resolution frequency. To increase the frequency resolution for a given frequency range, increase the number of points acquired at the same sampling frequency. The no. of FFT bins in N point FFT is equal to N/2, where N is the number of points in the acquired time-domain signal. The first frequency bin is at 0 Hz, that is, DC. The last frequency bin is at Fs/2 – Fs/N. where Fs is the frequency at which the acquired time-domain signal was sampled. The frequency bins occur at Δf intervals where Δf = Fs/N. The total interval of frequency bin is from DC to Fs/2 – Fs/N with an increment of Δf. Thus, the detector computes the energy of the received signal after taking average of M bins and compares it with the threshold value (the noise floor) to decide whether the primary signal is present or not [5]. As shown in Fig. 1, the energy of the received signal, also termed as the decision value of energy detector, is given by (1) [8]

$$T = \sum_{n=1}^{N} |x(n)|^2 \tag{1}$$

where$x(n)$ is the received signal and N is the number of its samples in the band of concern [6], [8].

The decision value is subjected to the test of two hypotheses $H_0$and H_1. $H_0$is the null hypothesis meaning that the received signal comprises of noise only. If the decision value given by (1) is less than threshold, H_0 is true as shown in (2). On the other hand, if the decision value is larger than the threshold, i.e. the receivedsignal comprises of both signal and noise, H_1 is true as shown in (3).

$$H_0 : x(n) = w(n); signalabsent \tag{2}$$

$$H_1 : x(n) = s(n) + w(n); signalpresent \tag{3}$$

where n = 1, 2, ...,N is the sample index, $w(n)$ is the noise and $s(n)$ is the primary signal required to detect with zero mean and variance of σ_s^2, $w(n)$ is additive white Gaussian noise (AWGN) with zero mean and variance of σ_w^2. Two probabilities are of interest for spectrum sensing: *probability of detection*, which is defined, under hypothesis H_1 i.e. the probability of the algorithm correctly detecting the presence of primary user [8]; and *probability of false alarm*, which is defined, under hypothesis H_0 [8] i.e. the probability of the algorithm falsely declaring the presence of primary user. The lower the probability of false alarm, there are more chances for which the secondary users can use the frequency bands when they are available [6]. For a good detection algorithm, the probability of detection should be as high as possible while the probability of false alarm should be as low as possible.

The test statistic is a random variable whose probability density function (PDF) is chi-square distributed. When N is sufficiently large, we can approximate the PDF using Gaussian distribution according to the central limitation theorem.

$$\mathcal{H}_0 \sim \mathcal{N}(N\sigma_w^2, 2N\sigma_w^4) \tag{4}$$

$$\mathcal{H}_1 \sim \mathcal{N}(N(\sigma_s^2 + \sigma_w^2), 2N(\sigma_s^2 + \sigma_w^2)^2) \tag{5}$$

Referred to constant false alarm rate (CFAR) principle, we have probability of false alarm P_F as [8];

$$P_F = P(X > \gamma | H_0) \tag{6}$$

$$P_F = Q\left(\frac{\gamma - N\sigma_w^2}{\sigma_w^2\sqrt{2N}}\right) \tag{7}$$

$$P_D = P(X > \gamma | H_1) \tag{8}$$

$$P_D = Q\left(\frac{\gamma - N(\sigma_s^2 + \sigma_w^2)}{(\sigma_s^2 + \sigma_w^2)\sqrt{2N}}\right) \tag{9}$$

where $Q(a) = {}^1\!/_2\, erfc(a/\sqrt{2})$, $erfc(.)$ is complementary error function, and γ is the decision threshold.

If Statistics > γ, we can make a decision that the channel is occupied by one PU or more. Otherwise, the channel is vacant, and SUs could make use of the channel at this moment.

III. Simulation Environment

In the simulation environment a TV signal is detected. And the algorithm applies to detect the probability of detection vs. SNR.

The steps, result of the test and analysis are given below.

Step 1: ATV signal is detected.
Step 2: Additive White Gaussian noise is added with signal.
Step 3: FFT of final signal is calculated.
Step 4: The level of threshold is decided and variance is calculated.

Step 5: Probability of detection is calculated at various SNR using FFT.

Fig. 2 shows the result of probability of detection vs. SNR. From the result it is clear that as SNR increases, probability of detection also increases.

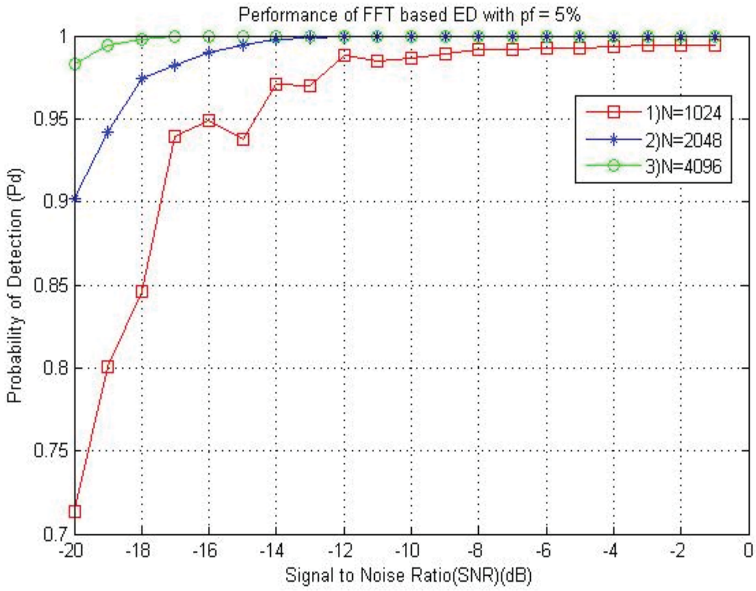

Fig. 2 Pd vs. SNR for FFT based energy detector

When no. of FFT points (N) is large enough, the probability of detection is close to 1. In fact, the larger the N, the more information about the primary signal. But by increasing N, system complexity is increased and performance will be slower.

IV. Classification of Primary User Traffic

The sensing of primary channels is a periodic sampling process to determine the state (ON or OFF) of the channels at every sampling instant. The outcome of sensing is a binary sequence for each channel. When a sufficiently long history of traffic patterns of channels is stored in the database, the patterns can be classified and appropriate prediction performed [12]-[14]. A couple of traffic periods are enough for periodic traffic but to classify random traffic more no. of traffic periods needs to consider. Traffic classification helps for ‘intelligent channel selection’ in cognitive radio. By adding limited ‘‘intelligence’’ to secondary users, they can take advantage of inherent patterns of primary users’ spectrum usage; observe, model and make predictions about future changes in spectrum availability. Secondary users then use these predictions, along with current observations, to determine spectrum usage patterns to achieve reliable communication while minimizing disruption to primary users [16]. In order to achieve high resource utilization, one would prefer precise prediction. Unfortunately, prediction accuracy deteriorates quickly as the prediction interval increases. Clearly there is a tradeoff between a large prediction interval and a small prediction error [15]. Two types of classification algorithm are proposed in this paper one is based on edge detection and the other is autocorrelation based classification.

In edge detection based classification it is assumed that all channels are sensed perfectly. From the channel data, separation of peaks is calculated. The idle time of channel can be calculated from peak separation. For periodic or deterministic data, separation of peak always remains constant. From the calculated data it is determined that weather the data in particular channel is periodic or not. For periodic data the peak separation is constant and for stochastic data the peak separation varies.

A. Channel Usage Pattern for Stochastic Traffic

Channels are modeled as ON/OFF model or 0/1 state, 0 for free channel and 1 for occupied channel by either licensed or other unlicensed user under the assumption that there are no priority considerations among the unlicensed users. This 0/1 alternating model is referred to as channel usage pattern where unlicensed users can utilize only portions of the OFF periods to communicate with other nodes. Simulation is done on 10 different channels. Channel usage pattern of single channel consists of stochastic traffic is demonstrated in Fig. 3.

From the traffic pattern it is clear that ON/OFF time are not constant. It changes in random manner.

B. Calculation of Peak Separation for Stochastic Traffic

Fig. 4 shows the peak separation of stochastic traffic of channel ‘d’.

It is clear from the Fig. 4 that for stochastic traffic peak separation is not constant. It varies with Pus appearance.

C. Calculation of Peak Separation for Periodic Traffic

Fig. 5 shows the periodic channel generation with fixed ON and OFF times.

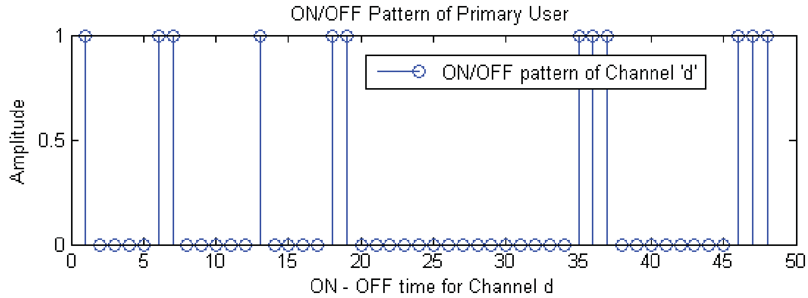

Fig. 3 ON/OFF traffic pattern of channel ‘d’ with stochastic traffic

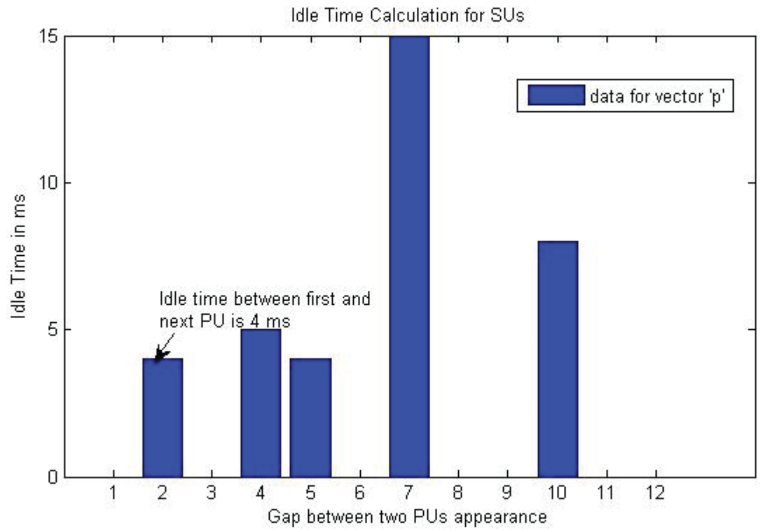

Fig. 4 Peak separation of primary user traffic

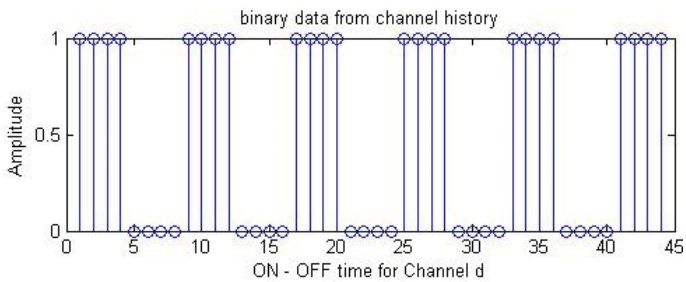

Fig. 5 ON/OFF traffic pattern of periodic traffic for channel ‘d’

As shown in Fig. 6, for periodic traffic the peak separation is always constant. Edge detection based algorithm works perfectly for any no. of primary users.

For autocorrelation based classification first the autocorrelation of input sequence is calculated. Then calculate average separation between consecutive local max values, τ_{av}. Then calculate standard deviation of separations, *std.* If deviation is zero, traffic is periodic. If the deviation is higher than average separation of peaks traffic is considered as stochastic [12], [13]. Same channels which are used for edge detection are used for autocorrelation based classification.

Edge detection method always classified correct. While in autocorrelation based classification some percentage of error may occur. The reason for error is if the ON/OFF times are too short or too long the outcomes sometimes are not as expected. Sometimes due to fake maxima the outputs are not appropriate.

Simulations are performed on 12 different channels for 10 times. Among those 10 channels are classified perfectly and 2 channels are wrongly classified.

Fig. 7 shows the histogram of error percentage of autocorrelation based classification. From simulation, it is also known that which channels are wrongly classified. Following Fig. 8 shows the channels which are wrongly classified.

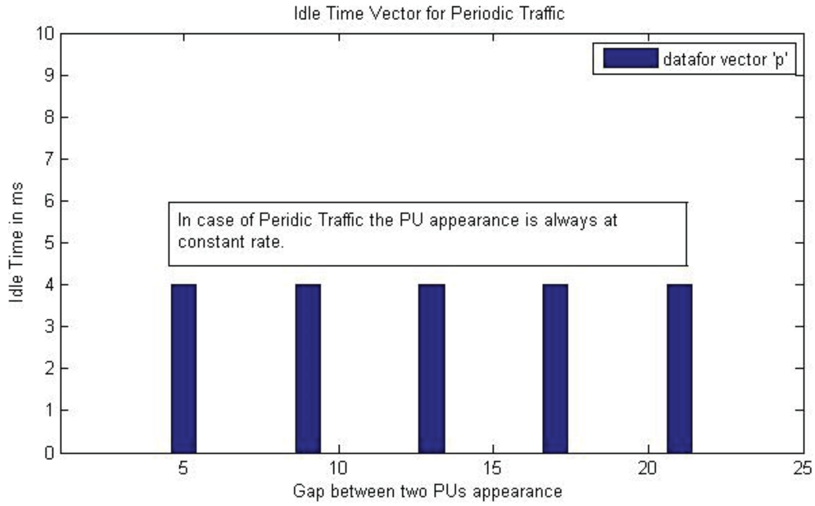

Fig. 6 Peak separation of primary user traffic

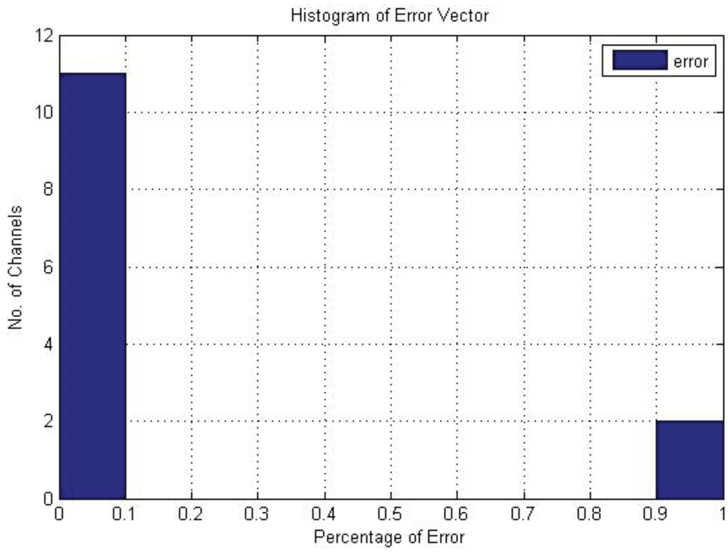

Fig. 7 Percentage of error in autocorrelation based classification

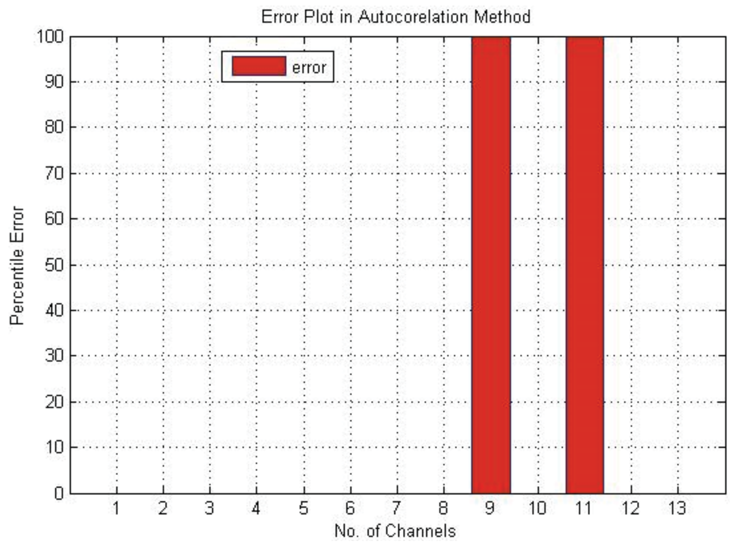

Fig. 8 Channels classified wrongly by autocorrelation method

Fig. 8 shows that from 12 channels channel no. 9 and 11 are wrongly classified.

Edge detection based classification works perfectly for any no. of channels if sensing is perfect. It cannot tolerate any misdetection or false alarm. Whereas autocorrelation based classification can tolerate some percentage of error in detection. But when the ON/OFF times are too long or too short the outcomes sometimes are not as expected.

Further improvement in classification is proposed which is based on multihypothesis sequential probability ratio test (MSPRT). A modified MSPRT classifier is based on the average likelihood function considering partial knowledge of the PU traffic parameters. Using the sequential algorithm, this method can achieve higher classification performance compared to the traditional maximum likelihood classifier using constant number of samples [17].

V. CONCLUSION

Energy detection is the conventional technique for spectrum sensing in cognitive radio. The key challenge for the Energy Detector is the detection of the weak signal in real environment corrupted by noise and suffering from interference. Energy detector using FFT is one of the simplest detection mechanisms among those proposed so far. In this paper probability of detection is calculated for different values of SNR. It is observed that as the value of SNR increases P_d also increases for different sample numbers. It is also observed that as no. of samples increased, the P_d is increased but then system performance becomes slower. Classification helps to identify primary user traffic pattern. In this paper two types of classification algorithm are discussed. Classification method is proposed that divides traffic patterns into stochastic and deterministic ones. Edge detection based classification is accurate but it cannot tolerate sensing errors which limits its applicability in real environment. Autocorrelation based classification method is simple to implement but some amount of error may occur due to fake maxima generation. From practical point of view, the method based on autocorrelation function can be used in real-time applications. The method can be used by CR systems to allow more accurate predictive channel selection. Furthermore, traffic classification can enable a good resource management tool for optimization of the network.

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