CP-OFDM Primary Users Sensing under Various Channels using Frequency Domain Autocorrelation

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Abstract : The Cyclic Prefix **-** Orthogonal Frequency Division Multiplexing (CP-OFDM) primary users is sensed using frequency domain autocorrelation under various channels with noise uncertainty. The spectrum sensing of Cognitive Radio systems plays crucial role to solve current spectrum scarcity. The spectrum sensing using energy detector is the most common method of sensing due to its low computational complexity and easy to implement but its detection performance degrades drastically for primary user signals under low SNR values and in the presence of noise uncertainty. The frequency domain autocorrelation method utilizes Fast Fourier Transform (FFT) and detects an active primary user through the cyclic prefix induced correlation peak estimated from the FFT samples. The performance of the frequency domain autocorrelation is estimated under channels such as AWGN channel, Rayleigh channel and Rician channel with noise uncertainty. It performs well in noise uncertainty contrasting traditional energy detection technique.

***IndexTerms* - Cognitive Radio, CP-OFDM Primary Users, Frequency Domain Autocorrelation, Spectrum Sensing**

I. INTRODUCTION

The spectrum measurements have shown in recent time that large portions of licensed spectrum are underutilized. The Cognitive Radio (CR) technology creates a way to access such unutilized spectrum. The CR detects its surrounding RF stimuli automatically and adapts its operating parameters intelligently to network infrastructure. Since the CRs are considered as Secondary Users (SUs) for using the licensed spectrum, a critical requirement is to exploit under-utilized spectrum efficiently without causing any harmful interference to the Primary Users (PUs). Hence, CRs should have ability to independently detect spectral opportunities without any assistance from PUs and that capability is known as Spectrum Sensing (SS). The spectrum sensing is one of the most critical components in CR. The spectrum sensing is carried out by the SUs to sense or detect a spectrum with the objective of detecting the presence of any PUs, identifying the spectrum opportunity for secondary access and preventing any interference to PUs. The spectrum sensing can be of coherent detection or non-coherent detection [1, 2]. In the coherent detection, the signal of interest is detected by the modulation parameters like the carrier frequency and phase, the order of the modulation, the shape and duration of pulses, etc. The matched filter is the optimal detector which provides solution in terms of the output Signal to Noise Ratio (SNR). The signal of interest is never perfectly known in practice, but some information about the signal is known as what kind of PUs that is to be detected and the transmitted signals are to some extent determined by standards and regulations. The non-coherent detection also known as blind detection does not require any prior knowledge of the PUs parameters. The Energy Detection (ED) is the most widely used blind detection technique [3]. Yet, the poor performance under low SNR regimes, the incapability of distinguishing between different types of signals and the vulnerability to uncertainty in noise variance estimation represent an important limitation in practice [4]. On the other hand, some features of the signal of interest are usually known. Such known features such as autocorrelation of the signal are exploited to improve performance and to avoid the problem of model uncertainties (imperfectly known noise variance). If the signal to sense contains redundancy, then the redundancy arises as non-zero average autocorrelation at some time lag.

The Orthogonal Frequency Division Multiplexing (OFDM) is widely used in present communication standards and thus OFDM based PUs sensing in CR receives much attention. An OFDM signal with a cyclic prefix of length N_{cp} and data or information symbols of length N_d is treated as primary user. Then, the average autocorrelation of the OFDM signal is non-zero at time lag N_d, due to the fact that some of the data symbols are repeated in the cyclic prefix of each OFDM symbol. This characteristic of CP-OFDM PUs can be used for sensing the spectrum [5]–[9]. The CP-OFDM is used as the PU waveform. In OFDM signals, CP introduces periodicity, which can be detected by the autocorrelation method. The autocorrelation of the received waveform is basically a time-domain operation. Usually, it is assumed that the spectrum sensing bandwidth matches the full bandwidth of the PU signal, and contains either noise only or noise plus PU signal. Considering wideband spectrum sensing in which PUs might be present and might be partly overlapped by other PUs transmissions with relatively narrow spectrum. This could be a case of a reappearing PU before the SU system has detected it. In this situation, time-domain autocorrelation based spectrum sensing is expected to fail [10]. This paper analyzes frequency domain autocorrelation based wideband spectrum sensing of CP-OFDM PUs under various channels with noise uncertainty.

II. SYSTEM MODEL

Let an OFDM system with N_s subcarriers has the N_d length of the useful data symbol and N_{cp} length of cyclic prefix where $N_s = N_d + N_{cp}$. The N_d data samples are obtained from the IFFT of the sequence of complex data symbols. Now an OFDM signal is constructed by feeding N_d complex QAM or PSK data symbols $D(0), D(1), D(2),\ldots,D(N_d\text{-}1)$ to an Inverse Fast Fourier Transform (IFFT) through serial to parallel conversion. The outputs of the IFFT are

$$d(n) = \frac{1}{\sqrt{N_d}} \sum_{f=0}^{N_d-1} D(f) e^{\frac{j2\pi f}{N_d}}, n = 0,1,2,..., N_d - 1 \tag{1}$$

where n and f are discrete time and frequency indices respectively. The N_d denotes the number of symbols in an OFDM data block. Let N_{cp} be the number of symbols in the cyclic prefix which are replication of last N_{cp} samples of N_d useful data symbols, added in front of the OFDM data block to form an OFDM block. The advantage of replicating useful data sequence as cyclic prefix is to maintain orthogonality of the useful data symbols at the receiver by converting the Toeplitz convolution structure of the channel into circulant structure [9]. An OFDM frame may contain any number such blocks. They are converted to a serial stream by parallel to serial conversion which are then transmitted. Let us denote the symbols of the transmitted OFDM frame by $s(n)$ for convenience. Such OFDM signal exhibits non-zero autocorrelation property, the autocorrelation coefficient in such systems can be written as [11, 12].

$$\mu = \frac{N_{cp}}{N_d + N_{cp}} \tag{2}$$

where μ is the autocorrelation coefficient. This can also be calculated from the time interval for useful data N_d and time interval for cyclic prefix N_{cp}. The received signal is

$$y(n) = \underbrace{s(n) * h(n)}_{x(n)} + w(n) \tag{3}$$

A wideband can be viewed as collection of number of subbands. A wide spectrum band ranging from 0 to W Hz can be equally divided into M subbands each with the bandwidth of W/M Hz. The wideband of interest can have different and varying occupancy states depending on the activities of different PUs. One way to learn the usage conditions of a wide spectrum band is to directly apply the traditional narrow channel detection methods to sense the sub-bands one by one. There are many existing studies to decide how to sense the candidate channels. For example, an algorithm proposed [13] determines the optimal channel sensing order. For a wideband with a fairly large number of subbands, sensing of subbands one by one leads to unacceptable overhead and sensing delay. For example, for a 0 to 1 GHz wideband with each subband occupying 1 kHz, the number of subbands is 106. Another way to facilitate wideband spectrum sensing is to equip CRs with essential components such as wideband antenna, wideband RF front-end and high speed ADC to perform sensing over the wideband directly. For wideband sensing, a big challenge is that the required Nyqusit sampling rate can be excessively high. For example, a 0 to 500 MHz wideband would result in a Nyquist sampling rate of 1 GHz, which would incur high ADC element costs and processing overhead. This motivates to use compressive sensing for significantly reducing the required sampling rate for wideband sensing [14-16]. In this work, it is assumed the wideband spectrum samples are obtained using compressive sensing technique and all PUs within the wideband can be regarded to occupy part of the subbands in the wideband.

III. FREQUENCY DOMAIN AUTOCORRELATION ANALYSIS

The frequency domain autocorrelation calculation is performed over subband samples obtained at the output of the FFT process represented as

$$y_{k,m} = FFT[y(m,K),..., y((m+1),(K-1))$$

where $y_{k,m}$ is FFT output of received signal $y(t)$, $k = 1,..,K$ is the subband index based on IFFT size of the primary user and $m = 1,\ldots,M$ is the subband sample index [17,18]. In the context of spectrum sensing from the FFT of subband signals can be expressed as

$$\begin{aligned} H_0 &: y_{k,m} = w_{k,m} \\ H_1 &: y(n) = x_{k,m} + w_{k,m} \end{aligned} \tag{4}$$

where $x_{k,m} = H_k s_{k,m}$ is the primary user signal at m^{th} FFT of subband k, H_k channel gain of subband k and $w_{k,m}$ noise sample. The distribution of noise and signal in sample domain

$$\begin{aligned} w_{k,m} &\sim N_c(0, \sigma^2_{w,k}) \\ x_{k,m} &\sim N_c(0, \sigma^2_{x,k}) \end{aligned} \tag{5}$$

$\sigma^2_{x,k}$ denotes the primary user signal variance in subband k and the subband noise variances can be assumed as

$$\sigma^2_w / K \cong \sigma^2_{w,k} \ldots\ldots \tag{6}$$

The autocorrelation function can be implemented effectively from the subband samples in FFT domain for a specific time lag τ

$$C_y(\tau) = \frac{1}{M} \sum_{k=\Omega} \left(\sum_{m=1}^{M} y^*_{k,m} y_{k,m+m_\Delta} \right) e^{-j2\pi\tau k} \tag{7}$$

where Ω is the set of K_c used subcarriers and M is the integration length in FFT subband samples. K_c can be chosen as different values to reach the required sensing performance with minimum complexity while avoiding the use of interfered subbands. The basic autocorrelation calculation with the spacing of m_Δ helps to maximize the correlation observation for different combinations of the primary user OFDM symbol duration and FFT based subband sample interval. Actually, the lag can be expressed in high-rate samples as

$$N_d = (m_\Delta + \tau)M \text{ where } m_\Delta = round(N_d / M) \tag{8}$$

The distribution of frequency domain autocorrelation based on Gaussian approximation under hypothesis H0 and H1 are

$$H_0 : C_Y(\tau) \sim N_c\left(0, \frac{1}{MK_c}\right) \qquad H_1 : C_Y(\tau) \sim N_c\left(\mu\sigma_x^2, \frac{(\sigma_x^2+\sigma_w^2)+2\mu_1^2}{MK_c}\right) \tag{9}$$

The test statistics based on the magnitude of complex autocorrelation of $y(n)$ at the lag N_d given by

$$T_s = \frac{\frac{1}{N}\left|\sum_{n=1}^{N} y(n)y^*(n+N_d)\right|}{\frac{1}{N+N_d}\sum_{n=1}^{N+N_d}|y(n)|^2} \tag{10}$$

The test statistics based on the real part of complex autocorrelation of $y(n)$ at the lag N_d given by

$$T_s = \frac{\frac{1}{N}\sum_{n=1}^{N}\Re\{y(n)y^*(n+N_d)\}}{\frac{1}{N+N_d}\sum_{n=1}^{N+N_d}|y(n)|^2} \tag{11}$$

Due to Gaussian statistics, T_s has a probability of exceeding threshold $\gamma_{s,c}$ which is given by

$$P(T_s > \gamma_{s,c}) = \frac{1}{2} erfc\left(\frac{\gamma_{s,c}}{\sqrt{2\sigma_c}}\right) \tag{12}$$

where *erfc* represents complementary error function and σ_c standard deviation of the complex signal. Then, the $P(T_s > \gamma_{s,c} \mid H_0)$ can be obtained as a probability of false alarm P_{FA}, in the context of detecting noise samples under H_0 hypothesis.

$$P(T_s > \gamma_{s,c} \mid H_0) = \frac{1}{2} erfc(\sqrt{N\gamma_{s,c}}) \tag{13}$$

Hence, given the desired P_{FA}, the threshold, $\gamma_{s,c}$ can be expressed as

$$\gamma_{s,c} = \frac{1}{\sqrt{N}} erfc^{-1}(2P_{FA}) \tag{14}$$

The probability of detection under H1 can be

$$P(T_s > \gamma_{s,c} \mid H_1) = \frac{1}{2} erfc\left(\sqrt{N}\frac{\gamma_{s,c}-\rho}{1-\rho^2}\right) \tag{15}$$

where $\rho = \frac{N_{cp}}{N_d+N_{cp}} \frac{\sigma_s^2}{\sigma_s^2+\sigma_w^2}$

IV. SIMULATION RESULTS

The CP-OFDM based PUs for the spectrum sensing of cognitive radio with N_d=64 and N_{cp}=8. The simulation parameters for frequency domain spectrum sensing are 1024 FFT size in frequency domain, 100 FFT average correlation, 16QAM modulation and 1.9 frequency offset. In this study for AWGN channel with users SNR of -10dB, the receiver performance of frequency domain autocorrelation is quantified by Receiver Operating Characteristics (ROC) curve shown in Fig.1. The figure 1 reveals efficacy of autocorrelation based sensing that for probability of false alarm of 0.15 achieves the probability of detection greater than 0.9.

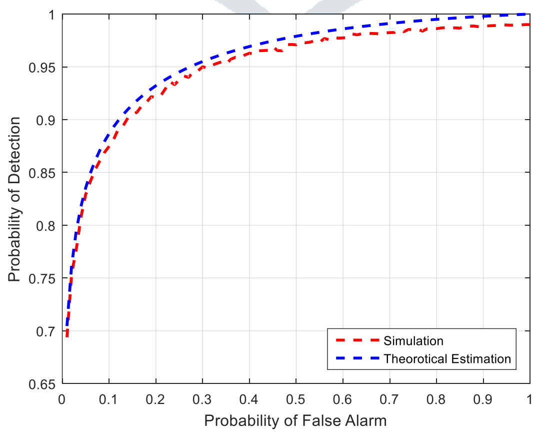

Fig.1 ROC Curve for Frequency Domain Autocorrelation Sensing

The frequency domain autocorrelation sensing performance also detected over various channels interms of reconstruction error. The Bit Error Rate (BER) reconstruction error versus user SNR is plotted in Fig. 2 under uncertainty of 0.5dB. Note that the impact of noise uncertainty in all the channels is negligible for frequency domain autocorrelation sensing. Also note that this is the best performance one can get by using an autocorrelation coefficient based local detector for detecting a CP-OFDM based system. Hence frequency domain autocorrelation serves as an upper performance of the practical detectors of CP-OFDM PUs.

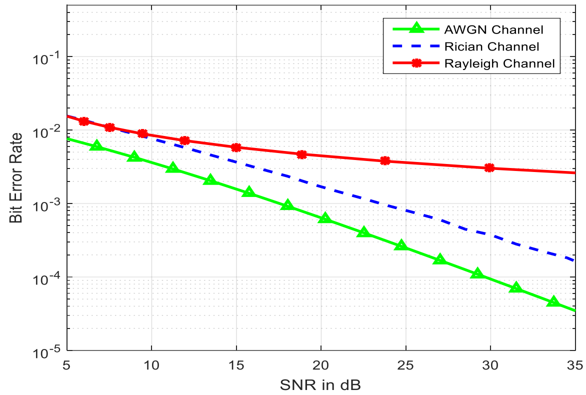

Fig. 2 BER Reconstruction Error versus User SNR under various Channels

V. CONCLUSION

The frequency domain autocorrelation based spectrum sensing performance was evaluated for the detection of CP-OFDM primary users in noise uncertainty. It was observed that the frequency domain autocorrelation spectrum sensing able to overcome the problem of noise uncertainty under both AWGN and frequency selective channels contrasting traditional energy detection.

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