A Blind OFDM Parameter Estimation Method Based on Cyclicprefix Analysis

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Abstract: The spectrum sensing problem has augmented new scenarios with cognitive radio and opportunistic spectrum access concepts. Further, it becomes one of the most challenging issues in cognitive radio systems when primary user signal characteristics at secondary level are unavailable. In this paper, we present a novel technique to sense, blindly infer signal features (FFT size, cyclic prefix (CP) length) and detect OFDM signal based on second order cyclostationarity analysis. First, we infer accurate FFT size and CP length from the sensed signal based on cross correlation through considering FFTs of different size (2^L) and CPs length. In our experimental study, we assume that CP length in the sensed OFDM signal could be 5% to 15% of the FFT size {64, 128, 256, 512, 1024, 2048 and 4096} used at primary user level. We successfully estimate accurate FFT size and CP length and carryout performance analysis of the proposed approach at various channel conditions and effect of increase in sample length (frames) of the sensed signal. In addition to this, we derive recursive procedure to calculate cross-correlation at sample (l+1) using cross-correlation value at sample (l) and few mathematical operations. We have also tested MAX values distribution for FFT size and CP whether inferred parameters are valid or not by finding confidence of estimation. Experimental results show that the proposed approach can be successfully used to measure unknown OFDM signal parameters and to detect OFDM signal blindly in cognitive radio at 0 % false alarm rate with detection rate 100%.
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1. Introduction

In the last few years, the growing success of wireless communication standards and the inefficient use of the licensed bands [1] have induced the regulation commissions to consider more flexible strategies for the wireless spectrum management. Further, given the limitations of the natural frequency spectrum, it becomes obvious that current static frequency allocation schemes cannot accommodate the requirements of an increasing number of higher data rate devices [2]. As a result, innovative techniques that can offer new ways of exploiting the available spectrum are needed. Cognitive radio arises to be an attracting solution to the spectral overcrowding problem by introducing opportunistic usage of the frequency bands that are not heavily occupied by licensed users [3], [4].

One of the most important components of the cognitive radio concept is the ability to measure, sense, learn, and be aware of the parameters related to the radio channel characteristics, availability of spectrum and power, radio's operating environment, user requirements and applications, available networks (infrastructures) and nodes, local policies and other operating restrictions. In cognitive radio terminology, primary users can be defined as the users who have higher priority or legacy rights on the usage of a specific part of the spectrum. On the other hand, secondary users, which have lower priority, exploit this spectrum in such a way that they do not cause interference to primary users. Therefore, secondary users need to have cognitive radio capabilities, such as sensing the spectrum reliably to check whether it is being used by a primary user and to change the radio parameters to exploit the unused part of the spectrum.

Different approaches can be applied in order to guarantee an adaptive opportunistic spectrum (OS) allocation for secondary users: one of the most promising strategies in this scenario is the cognitive radio. In such approach, the opportunistic spectrum is a common resource which has to be dynamically shared among the secondary users. One of the most suitable techniques to carry out an effective OS strategy is the Orthogonal Frequency Division Multiplexing (OFDM) [5] since its flexibility allows efficient spectrum utilization by guaranteeing a dynamic adaptation of the spectral occupancy of the transmitted signal [6]. In an OS model each secondary user has to verify the availability of the radio resource (i.e. primary user absent) before transmitting, and to know which transmission mode is to be used.

The determination of empty spectrum is typically done by spectrum sensing and is a critical challenge in cognitive radios. In particular, (i) spectrum sensing has to reliably determine the presence or absence of ongoing licensed transmissions, and (ii) sensing of multiple radio channels (possibly spanning several hundreds of MHz) has to be done as fast as possible.

In the communication spectrum, a number of primary users and as well as secondary users may exist. Further, each primary user may have its own communication characteristics for signal transmission like bandwidth, modulation type and transmitter power to achieve various transmission data rates. Spectrum sensing is traditionally understood as measuring the spectral content or measuring the radio frequency energy over the spectrum. Whereas, cognitive radio is considered as a more general term that involves obtaining the spectrum usage characteristics across multiple dimensions such as time, space, frequency, and code. It also involves determining what types of signals are occupying the spectrum including the modulation, waveform, bandwidth, carrier frequency, etc. However, this requires more powerful signal analysis techniques with additional computational complexity [2].

This paper makes the following contributions;

- Development and validation of FFT size and CP length inference method from OFDM signal in cognitive radio.
- Derivation of recursive procedure to calculate cross-correlation between two signals for a specified time range (CP length) to reduce computational cost.
- Finding confidence level for possibly used FFT size and CP length considering many different combinations of FFT size and CP length.
- Analysis of Max operator distribution for various FFT size and by varying CP length from 5-15% of considered FFT size.
- Validating theoretical and experimental results by varying alpha (ratio between frame length and sensed signal length).
- OFDM signal detection in cognitive radio by measuring 2nd order cyclostationarity properties.

The remaining paper is organized as follows; we present literature review about the OFDM signal detection techniques in cognitive radio in section II. Section III contains detail about the proposed OFDM signal detection technique. In section IV, we provide results and discussion. Section V concludes the carried out current research work.

2. OFDM Signal Detection Methods in Cognitive Radio

At present, spectrum sensing is still in its early stages of development. A number of different methods have been proposed for identifying the presence of signal transmissions which can be categorized based on energy detection, matched filter and cyclostationarity based methods. Since most of emerging and next-generation communications and broadcasting systems are orthogonal frequency division multiplexing (OFDM) based, detecting OFDM waveforms is of great importance [7]. Therefore, the detection method separating OFDM signal from other single carrier signal or random noise is very essential. Some of the most common spectrum sensing techniques used in cognitive radio include energy based filters, match filters, and cyclostationarity feature detection methods.

Energy detector based spectrum sensing approach is the most common used because of its low computational and implementation complexities including OFDM signal [8]-[12]. Further, it is more advantageous as receivers do not need any knowledge on the primary users' signal. The primary signal is detected by comparing the output of the energy detector with a threshold which depends on the noise present in the signal [13]. Some of the challenges with energy detector based sensing include selection of the threshold for detecting primary users. Further, its performance is not robust to noise and is known to be poor at low SNRs [14]. Moreover, energy detectors do not work efficiently for detecting spread spectrum signals [15].

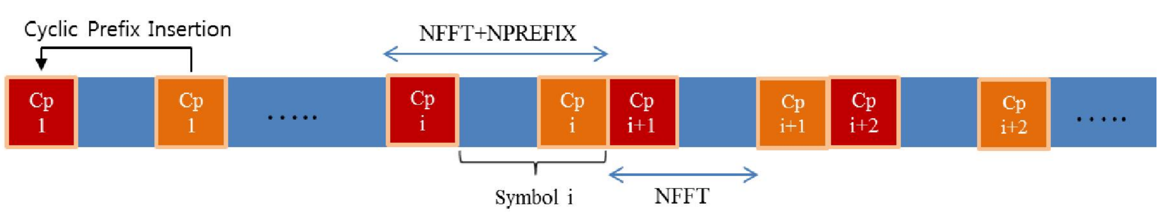


Figure 1. Representative of OFDM signal with cyclic prefix.

Matched filter based techniques detect the signal more reliably and outperform any detection method at hand. But, these methods are applicable to systems with known signal patterns and their main advantage is to achieve a certain probability of false alarm in short time [16]-[17]. In the presence of a known pattern, sensing can be performed by correlating the received signal with a known copy of itself [10], [16]. In practical spectrum sensing scenarios, however, we seldom have full knowledge of the primary transmitter's signal at the detecting receiver. In an OFDM system, one can use the pilots embedded in the symbols and attempt to detect the signal using a filter matched to these pilot tones. The limitation of this strategy in real systems is that pilot tone values are usually pseudo randomly coded and hence not known to the receiver. Thus, simply adding the output of the matched filter from consecutive symbols will not necessarily improve performance. In fact, it could have a negative impact on the detection performance of the system. A similar detection strategy proposed in [18] auto-correlates consecutive OFDM symbols to exploit identical pilot sequences that are embedded within each symbol. This method is also not practical as deployed systems seldom repeat identical pilot sequences from one OFDM symbol to the next.

Cyclostationarity feature detection method exploits the cyclic stationary features of the received signals for detecting primary user transmissions [19]-[20]. Periodicity in the signal or in its statistics like mean and autocorrelation results in cyclostationarity features [21]. Further, cyclic features can be induced deliberately to assist spectrum sensing like the cyclic prefix inserted in the OFDM signal and detection reliability increases as the cyclic prefix length of the signal increases [22]. However, many OFDM systems do not add a cyclic prefix or a sufficiently long one due to spectral flatness and throughput considerations [23].

Some researchers in [24]-[25] tries to extract the cyclic frequency corresponding to the sampling rate for the OFDM systems. These both OFDM signal detection techniques are based on the cyclostationarity of the signal. They treat the OFDM signal like a pulse-amplitude-modulated waveform which degrades the performance of these methods upto 5 dB in some cases [26]. In contrast, authors of [27] and [28] aim to exploit the cyclostationary signatures of an OFDM symbol realized from its embedded pilots. However, they assume that the pilot signal is unchanged over consecutive OFDM symbols.

Cyclostationarity feature based OFDM signal detection methods work well but primary user transmission characteristics are essentially needed at secondary user receiver. Currently, many standards are being used in OFDM signal transmission systems and to keep knowledge/information of system characteristics for all standards in use is very difficult at secondary level. Further, it would increase the computational complexity as well as cost of the secondary user spectrum sensing and signal transmission system.

In this paper, we focus ourselves to first infer accurate FFT size and CP length from sensed signal and then detect primary user OFDM signal in cognitive radio based on cyclostationarity features with more confidence in presence of various channel conditions. In our experimental study, we assume that the primary user is employing OFDM based communication system for signal transmission. Further, it is supposed that no information is available at secondary receiver about primary user OFDM signal characteristics including synchronization, sampling rate, symbol size (FFT size and cyclic prefix length). Our aim in this paper is to sense the spectrum for detection of an OFDM signal based on cyclic features by employing periodic correlation function. Based on cyclic features analysis, first we determine accurate size of FFTs and CP length from the sensed signal which is essentially required to divide the sensed signal in frames of correct symbol size (FFT + CP). Further, we also estimate confidence level for each possible combination of used FFT size and CP length from the sensed OFDM signal in cognitive radio. Based on identified accurate FFT size and CP length, we predict the presence or absence of primary user OFDM signal with more confidence by considering adverse channel conditions.

In our experimental study, we intend to detect WIBRO OFDM signal and assume that primary user is employing the following OFDM transmission characteristics; IEEE 802.16e, frequency bandwidth 2.3 GHz, max mobility 60 km/hr, cell coverage ~ 1 Km, data rate about 25 Mbps and modulation scheme QAM. Further, cyclic prefix is inserted in OFDM symbols to avoid inter symbol interference. We also study the performance of the proposed approach in various adverse channel conditions.

3. The Proposed OFDM Signal Detection Technique

Cyclostationarity based methods offer superior performance as compared to other techniques to detect OFDM signal in the presence of high channel degradations. But, these cyclostationarity based techniques also require OFDM signal transmission system information at secondary user receiver (sampling rate, symbol length, FFT size, CP length, symbol level synchronization). Nowadays, many practical OFDM signal transmission systems exist and are employing different standards. Further, because of dynamic spectrum access policy, a primary user may exist in sub-spectrum of interest with dynamic transmission characteristics and secondary user may not be aware of this change. Resultantly, secondary user may not be able to detect the OFDM primary user signal in the sensed spectrum and may declare empty. This act of secondary user may increase false alarm rate (FAR) which may not be allowed in cognitive radio. Further, it is very difficult and expensive to keep knowledge of all OFDM transmission standards at secondary level. Considering the above mentioned facts, the key point is that if primary user OFDM signal characteristics can be measured from the sensed signal at secondary level then using these characteristics, sensed primary OFDM signal can be detected with more confidence. This is one of the important objectives in this research work. To tackle this problem, we propose an intelligent inference method to first estimate accurate FFT size and CP length from sensed primary signal to divide the signal into frames of appropriate length. Figure 1 shows a structure of captured OFDM signals. Based on these measured essential features, we perform OFDM signal detection in cognitive radio based on cyclostationarity properties. The schematic flow chart of the proposed technique to estimate appropriate size of FFTs and CP is shown in Figure 2.

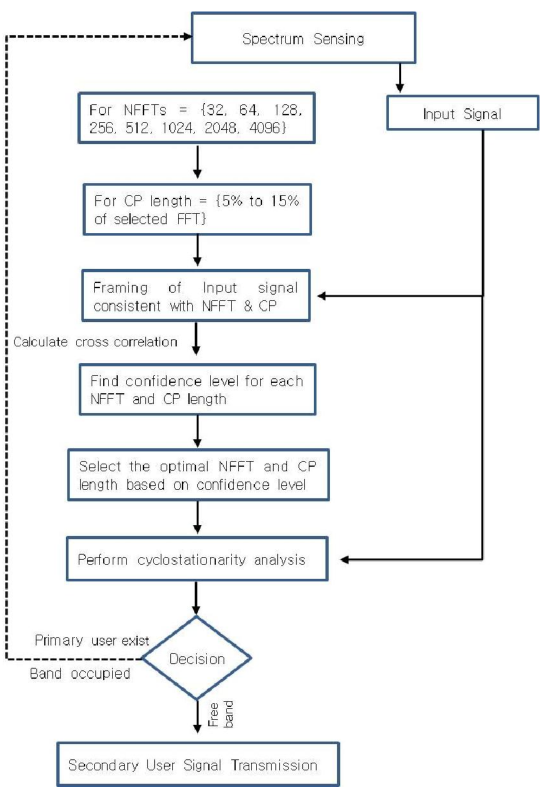


Figure 2. Flowchart of the proposed procedure to estimate.

Since, OFDM communication signal has a cyclic prefix means copying last samples of the symbol into the beginning of each OFDM symbol. Further, number of FFTs in OFDM signal can be expressed by 2^L (L is length of data in a symbol). According to the properties of OFDM signal mentioned above, OFDM characteristic parameters inference method can be achieved as follows;

- Loop: for FFT size {32, 64, 256, 512, 1024, 2048, 4096}
- Choose input signal within the range of 2^L from the sensed signal
- If there is CP in the chosen FFTs, estimate the CP length and confirm its existence through cross correlation
- Loop: for CP length {5-15%} of chosen FFT size
  - Calculate cross-correlation of the sensed signal for the considered CP length in each frame by shifting it through k symbols
  - Calculate confidence value for each possible CP length at selected FFT size
- End
- Maximum of measured confidence for all considered CP lengths at a fixed FFT size
- End
- Determination of FFTs and CP length at which confidence is maximum
- Perform cyclostationarity analysis on the sensed signal by employing estimated FFT size and CP length to detect OFDM signal

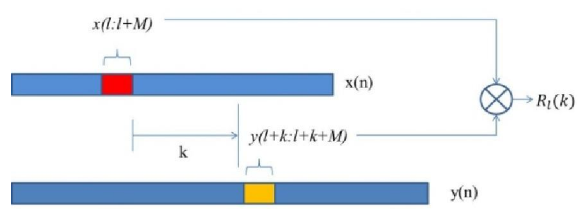


Figure.3 Schematic procedure to calculate cross-correlation.

Similarly, for the existence of the prefix, number of FFTs can be estimated. Further, it can be assumed that CP can exist within 5% to 15% range of FFT. Let's assume X (n) and Y (n) are two OFDM signals shifted through length k (Y (n) is a copy of shifted signal X (n) by length k). FFT size used in OFDM signal transmission by primary user can be estimated by calculating cross-correlation between these two signals by varying '*l*' and '*k*' using equation (2).

$$R_l(k) = \sum_{n=0}^{M} x(l+n)\,y(l+n+k) \tag{2}$$

To estimate cross-correlation for time L, window range M is specified, k represents specified time interval as shown in Figure 3. In accordance with time characteristics considered in Figure. 3, cross-correlation is calculated through M+1 samples by fixing time lag 'k' between two signals (x (n), y (n)). Mathematical derivation is given below to calculate cross-correlation, recursively.

$$R_{l+1}(k) = \sum_{n=0}^{M} x(l+1+n)y(l+1+n+k)$$

$$= \sum_{n=0}^{M-1} x(l+1+n)y(l+1+n+k) + x(l+1+M)y(l+1+M+k) + x(l)y(l+k) - x(l)y(l+k)$$

$$= \sum_{n=1}^{M} x(l+n)y(l+n+k) + x(l+1+M)y(l+1+M+k) + x(l)y(l+k) - x(l)y(l+k)$$

$$= \sum_{n=0}^{M} x(l+n)y(l+n+k) + x(l+1+M)y(l+1+M+k) - x(l)y(l+k)$$

$$= R_l(k) + x(l+1+M)y(l+1+M+k) - x(l)y(l+k)$$

$$R_{l+1}(k) = R_l(k) + x(l+1+M)y(l+1+M+k) - x(l)y(l+k) \quad (3)$$

This recursive step in equation (3) to find cross-correlation for sensed signal time L plays a crucial role to estimate FFT size and CP length in a very short time which makes it feasible to blindly detect OFDM signal in cognitive radio using the proposed technique. If $R_l(k)$ is known, only two multiplication operations are needed to estimate $R_{l+1}(k)$. Considering both OFDM signals same (y (n) = x (n)), the cross-correlation converts to auto-correlation. In equation (3), k means FFT size selected in experiment because prefix length will be based on selected FFT and here M is 15% of FFT size.

In the following section, we infer various parameters from sensed signal and make analysis of the OFDM signal corrupted through AGWN at various SNRs based on these estimated features. We calculate confidence measure for each considered FFT size and CP length in experiment and choose the best one based on confidence. We also investigate the effect of number of frames in estimating FFT size and CP length in severe channel conditions.

4. Results and Discussion

In this section, we perform analysis of the infer method on a simulated signal to estimate FFT size and CP length by increasing number of frames and at various SNRs. In our experimental study, we do not need any information about the primary user OFDM signal communication system (FFT size, CP length, synchronization, etc.). This aspect of the proposed method to infer accurate estimate of FFTs and CP length from the sensed signal differentiates it from other well-known techniques in cognitive radio which assume both primary user transmitter and secondary user receiver are synchronized at symbol level.

4.1 Cross-Correlation based Signal Analysis

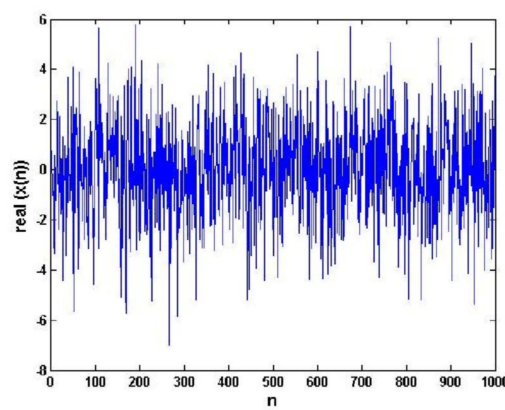


Figure 4. Plot of real coefficients of simulated Wibro OFDM signal corrupted through -5dB AWGN.

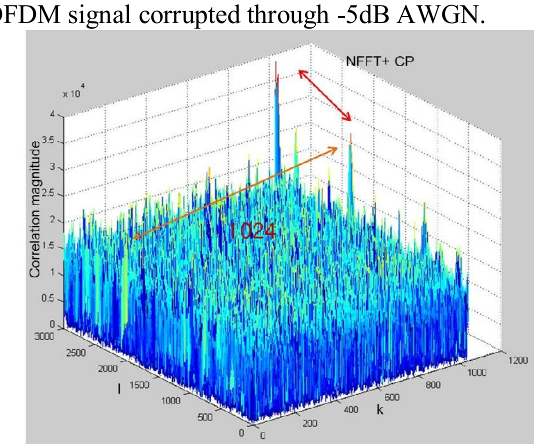


Figure 5. Plot of cross-correlation $R_l(k)$ of Wibro OFDM signal (FFT size 1024 and CP 128) corrupted through 0dB AWGN.

A typical example of WIBRO OFDM signal generated through FFT size 1024 and CP length 128, and corrupted through 0dB AGWN is shown in Figure 4. We find cross-correlation by considering various FFTs size and CP length to perform analysis of the sensed signal. At each considered FFT size (‘k’), M is 15% of used FFT size, and by varying ‘l’ cross-correlation of two signals x (n) and y (n) is calculated. Signal y (n) is a shifted version of the sensed signal x (n) by ‘k’. Obtained cross-correlation results using equation (2) and the procedure depicted in Figure 3 by varying ‘l’ and ‘k’ are plotted in Figure 5. From results shown in Fig. 4, if the sensed signal owns OFDM characteristics and comprises CP in each symbol then a big peak can be observed from the cross-correlation plot at time axis L. This $R_l(k)$ peak occurs (at FFT + CP) when the actual number of FFTs used to generate OFDM signal and FFT size used in experiment are same. We estimate FFT size by exploiting the coordinates of the obtained big peak along k-axis which represents number of FFTs used in OFDM signal communication system.

4.2 Cyclic Prefix (CP) Length Estimation

In this section, we find accurate length of cyclic prefix used in the OFDM signal by estimating cross-correlation through fixing FFT size and varying CP length. Cross-correlation is estimated by setting M equals to 15% of the FFT size in equation (2).

We estimate CP at each possible prefix by taking the mean of the reshaped cross-correlation and then applying max operation. Matlab function ‘reshape’ is employed to reshape the cross-correlated signal as given in equation (4).

$$CP(Nprefix) = reshape(R_l(NFFT), (NFFT + Nprefix), J) \qquad (4)$$

where $J = fix\left(\frac{L}{NFFT + Nprefix}\right)$ and ‘L’ represent total signal length.

Location of maximum value in CP (Nprefix) vector represents the CP length used in OFDM signal and the value itself signifies confidence about the estimated CP. Reshaped cross-correlated signals for CP (128) and CP (140) are shown in Figure 6 and 7.

A CP (Nprefix) vector is generated against each fixed FFT based on reshaped cross-correlation as shown in Figure 8. From Figure 8, a big peak may be observed at Nprefix 128 with FFT size 1024. This is because in our experimental study, we have generated an OFDM signal employing FFT 1024 and CP length 128. So, Nprefix from the experimental results can be defined through the following relation;

$$CP_{estimated} = ArgMax_{Nprefix} CP(Nprefix) \qquad (5)$$

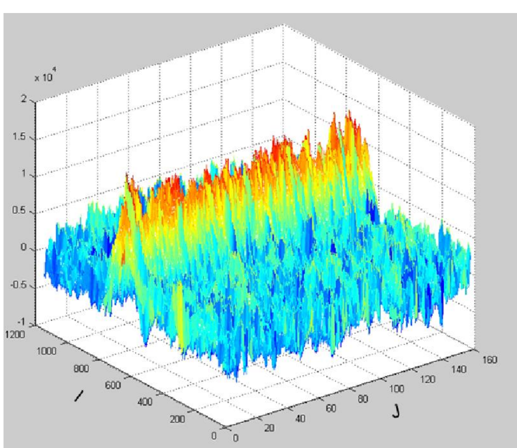


Figure 6. Reshaped correlated signal CP (128) at Nprefix = 128.

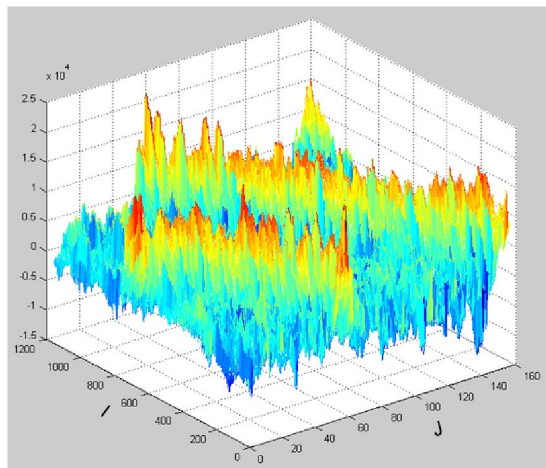


Figure 7. Reshaped correlated signal CP (140) at Nprefix = 140.

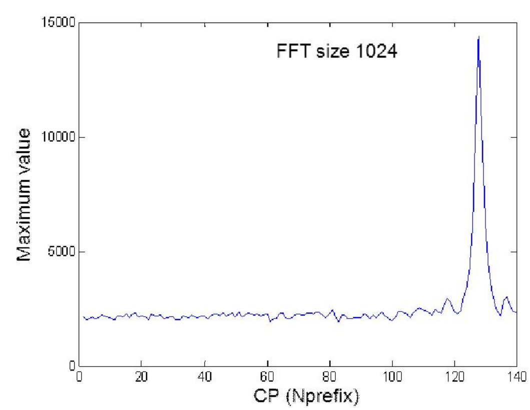


Figure 8. Plot of estimated CP vector for FFT size 1024.

Calculating the mean and standard deviation from CP (Nprefix) vector for a fixed FFT size, we can evaluate the worth of the inferred CP length by finding its confidence. Confidence regarding estimated CP length can be calculated using the following formula;

$$Confidence = \frac{\max(\overline{CP}) - mean(\overline{CP})}{std(\overline{CP})} \quad (6)$$

We find confidence for inferred CP length against each possible FFT size used in OFDM signal communication system using equation (6) and the obtained results are presented in table 1.

Table 1. Confidence of inferred FFTs and CP length.

FFT Size	CP length	Confidence
64	13	1.2
128	19	3.1
256	9	2.2
512	59	3.0
1024	**128**	**16.8**
2048	151	3.1

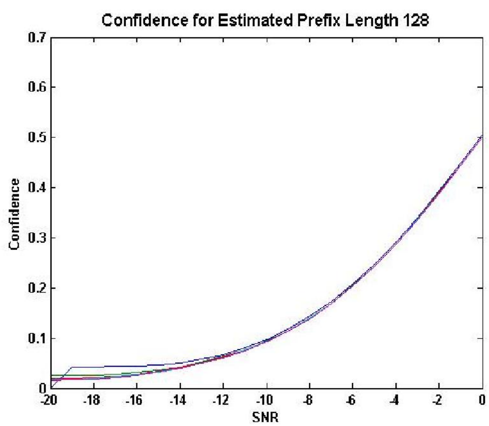


Figure 9. Confidence of estimated FFT size (1024) verses channel noise (dB) by varying number of frames.

From Table 1, we may detect the credibility of inferred CP length when FFT is 1024. Large value of confidence against inferred FFTs and CP length shows the possible parameters used in OFDM signal communication by the primary user. Based on these estimated parameters, we detect the primary user OFDM signal in cognitive radio by exploiting 2nd order cyclostationarity properties measured from the sensed signal.

4.3 Effect of Number of Frames on Confidence for Estimated FFT Size and CP Length

We also perform experimental analysis to see the effect of number of frames on FFT size and CP length estimation by varying channel conditions (0dB to -20db). Further, we run the simulations for 1000 times and average out the results. Obtained results for FFTs and CP length by increasing number of frames and at various Signal-to-Noise Ratios (SNR)) channel conditions are plotted in Figure 9 and 10, respectively. From Figure 9 and 10, it may be observed that confidence level improves by increasing number of frames to compute signal parameters. On the other hand, confidence level regarding estimated FFT and CP length reduces in adverse channel conditions.

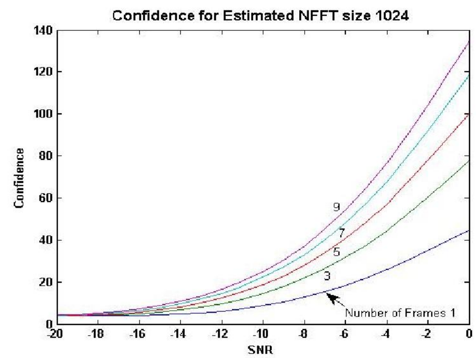


Figure 10. Plot of normalized confidence value of Estimated CP length (128) verses channel noise (dB) by varying number of frames.

4.4 Effect of Number of Frames on ROC curve for Estimated FFT Size and CP Length

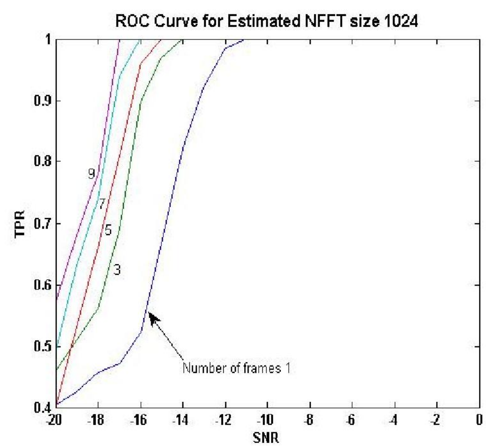


Figure 11. ROC curve for estimated correct FFT size (1024) verses channel noise (dB) by varying number of frames.

In this subsection, we perform experimental analysis to see the effect of number of frames on true positive rate (TPR) for correctly estimated FFT size 1024 and CP length 128 at various channel conditions by plotting receiving operating characteristic (ROC) curve. Obtained results for correctly inferred FFTs 1024 and CP length 128 from unknown sensed signal in cognitive radio are plotted in Figure 11 and 12, respectively. From Figure 11 and 12, it may be observed that TPR at estimated FFTs size and CP length increases by increasing number of frames of sensed signal to compute signal parameters. Further, from our experimental results, the proposed approach at 0% FAR can successfully estimate FFT size and CP length in very severe channel conditions (snr = -17dB) by increasing number of frames of sensed signal which proves the efficacy of the method.

4.5 Mathematical Verification of the Proposed Signal Detection Method

The inference algorithm to estimate FFT size and CP length can be summarized as;

- Calculate correlation function $R_l(k)$
- Generate transformation matrix for correlation function $R_l(k)$ and average out $CP_{Nprefix}$
- Determine the location of maximum in $CP_{Nprefix}$ vector (i.e. CP length)

According to central limit theorem, $CP_{Nprefix}$ results have characteristics of Gaussian distribution. Max function calculus of a Gaussian random sequence can determine the credibility of inferred CP length.

Let $\mathbf{X_1}$, $\mathbf{X_2}$,……., $\mathbf{X_n}$ be random sequence vectors. So, in order to get the maximum of Gaussian random variable, probability distribution of $\mathbf{Y} = \{\mathbf{X_1}, \mathbf{X_2}, ……., \mathbf{X_n}\}$ should be known. Whereas, $\{\mathbf{X_1}, \mathbf{X_2}, ……., \mathbf{X_n}\}$ has identical probability distribution (Gaussian distribution) and each $\mathbf{X_k}$ distribution can be represented through the following formula;

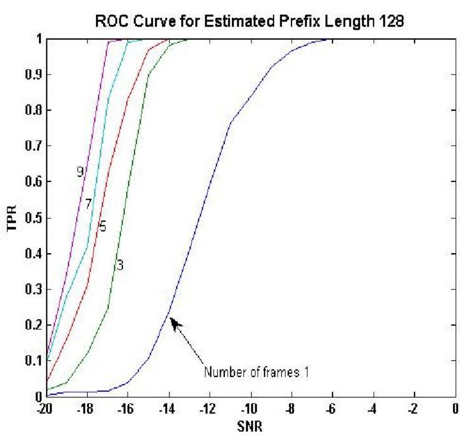


Figure 12. ROC curve for accurately estimated CP length (128) verses channel noise (dB) by varying number of frames.

$$p_X(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \quad (7)$$

Cumulative distribution function (CDF) of maximum **Y's** can be denoted using the mathematical expression given in equation (8).

$$F_n(y) = p\left[(X_1 \le y) \cap (X_2 \le y) \cap .... \cap (X_n \le y)\right]$$

$$F_n(y) = \{F_x(y)\}^n \quad (8)$$

$F_x(X)$ in the above equation (8) is CDF of irregular variable x. CDF of this type of variable in Gaussian distribution can be shown as follows;

$$P_X(x) = \frac{1}{2}\left[1 + erf\left(\frac{x-\mu}{\sqrt{2\sigma^2}}\right)\right] \quad (9)$$

So, using equation (9), CDF of maximum **Y's** can be written as;

$$P_Y(y) = \left\{\frac{1}{2}\left[1 + erf\left(\frac{x-\mu}{\sqrt{2\sigma^2}}\right)\right]\right\}^n \quad (10)$$

By taking derivative of equation (10), we can get probability distribution function (PDF) of **Y's**.

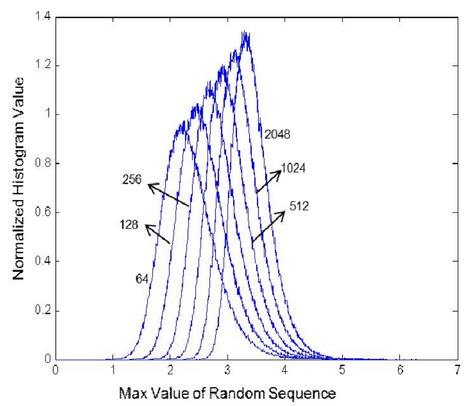
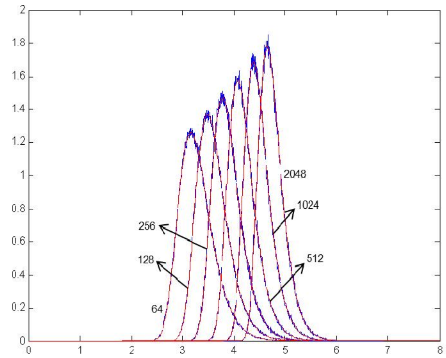


Figure 13. Max value probability distribution histogram for random sequence of length 'N' based on 800,000 simulations.

$$p_Y(y) = \frac{d}{dy} P_Y(y) \quad (11)$$

The above PDF can be obtained by applying MAX function on random sequences $\{\mathbf{X_1}, \mathbf{X_2}, ……., \mathbf{X_n}\}$ containing various numbers of coefficients (N). In current research, this distribution histogram can be realized by performing each experiment for 800,000 times as shown in Figure 13.

From histogram data plotted in Figure 13, obtained mean and standard deviation of Max probability distribution for N = 64 , 128, 256, 512, 1024, 2048 is presented in Table 2. From results presented in Table 2, it may be observed that mean increases and standard deviation decreases by increasing random sequence length, i.e. sharp distribution is obtained. Further, we compare the experimental results of Max probability distribution and theoretical probability distribution. The graphical representation of both experimental and theoretical distributions is shown in Figure 14.



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Experimental standard deviation result shown in figure 14 can be modeled by a linear equation

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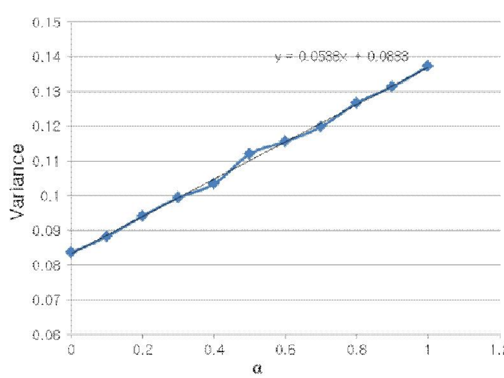

Figure 15. Variance of correlation function 'r' with respect to alpha.

Table 3. Mean and standard deviation of $CP_{Nprefix}$ function for empty (H_0) and occupied (H_1) sensed spectrum.

Sensed Signal	Features	H_0 (empty)	H_1 (occupied)
Ideal Channel	μ_r	0	$\alpha\sigma_s^2$
Noisy Channel	σ_r^2	$\frac{(\sigma_n^2)^2}{L}$	$\frac{(\sigma_s^2+\sigma_n^2)^2}{L}+\alpha\frac{\sigma_s^4}{L}$

Similarly, for noise signal only (i.e. $\sigma_s^2 = 0$), we can estimate $\mu_r = 0$ and $\sigma_r^2 = \frac{(\sigma_n^2)^2}{L}$ using equation (13) and equation (14), respectively. From the above discussion, we may conclude that mean and standard deviation of function $CP_{Nprefix}$ can be calculated using equation (13) and equation (14) in both scenarios i.e. sensed spectrum empty or occupied. Further, based on measured mean and standard values, we can classify the sensed spectrum as occupied or empty. For only noise signal (AWGN), the measured mean value will be zero and variance =1. And for OFDM signal case, mean and variance values will be high. Second order cyclostationarity properties calculated from sensed signal based on the proposed method to decide the fate of sensed spectrum are summarized in Table 3.

5. Conclusions

An intelligent novel technique to infer accurate FFT size, cyclic prefix (CP) length with 100% accuracy is analyzed. Based on estimated FFTs and CP, the sensed OFDM primary user signal is blindly detected in cognitive radio using 2nd order cyclostationarity properties. A recursive procedure to calculate cross-correlation at sample (l+1) using cross-correlation value at previous sample has been derived to reduce the computational cost of the proposed method. MAX values distribution of the conducted experiments has been tested whether inferred parameters are valid or not by finding confidence. Further, performance analysis of the proposed approach is carried out at various channel conditions and by increasing sample length (frames) of the sensed signal. From experimental results, it may be observed that detector performance (at 0% FAR) increases with increase in sample length (frames) of the sensed signal to estimate the signal parameters blindly and successfully detect the primary user OFDM signal. Promising detection results for OFDM signal shows the efficacy of the proposed approach. In future, we intend to extend our approach to further study validation of NFFT and CP statistics from the unknown sensed signal in cognitive radio.

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References

1. Luca Bixio, Giacomo Oliveri, Marina Ottonello and Carlo S. Regazzoni. OFDM recognition based on cyclostationary analysis in an Open Spectrum scenario. Proceeding of the 69th IEEE VTC 2009; 1-5.
2. Tevfik Yucek and Huseyin Arslan. A Survey of Spectrum Sensing Algorithms for Cognitive Radio Applications. IEEE Communications Surveys & Tutorials 2009; 11(1).
3. Mitola, J. and J. Maguire, G. Q. Cognitive radio: making software radios more personal. IEEE Personal Commun. Mag. 1999; (6)4: 13–18.
4. Federal Communications Commission. Notice of proposed rule-making and order: Facilitating opportunities for flexible, efficient, and reliable spectrum use employing cognitive radio technologies. ET Docket 2005; 03-108.
5. R. van Nee and R. Prasad. OFDM for Wireless Multimedia Communications, Artech House Publishers, 2000.
6. M. Oner and F. Jondral. On the extraction of the channel allocation information in spectrum pooling systems. IEEE Journal on Selected Areas in Communications 2007; 25: 558–565.
7. Arash Z. G, Alireza T. and Babak D. Spectrum Sensing of OFDM Waveforms Using Embedded Pilots in the Presence of Impairments. IEEE Trans. On Vehicular Tech. 2012; 61(3): 1208-1221.
8. D. Datla, R. Rajbanshi, A. M. Wyglinski and G. J. Minden. Parametric adaptive spectrum sensing framework for dynamic spectrum access networks. Proceeding of IEEE Int. Symposium on New Frontiers in Dynamic Spectrum Access Networks 2007; pp. 482–485.
9. F. Digham, M. Alouini, and M. Simon. On the energy detection of unknown signals over fading channels. Proceeding of IEEE Int. Conf. Comm.

2003; 5: 3575–3579.
10. H. Tang. Some physical layer issues of wide-band cognitive radio systems. Proceeding of IEEE Int. Symposium on New Frontiers in Dynamic Spectrum Access Networks 2005; 151–159.
11. M. Wylie-Green. Dynamic spectrum sensing by multiband OFDM radio for interference mitigation. Proceeding of IEEE Int. Symposium on New Frontiers in Dynamic Spectrum Access Networks 2005; 619–625.
12. J. Lehtom¨aki, M. Juntti, H. Saarnisaari, and S. Koivu. Threshold setting strategies for a quantized total power radiometer. IEEE Signal Processing Letter 2005; 12(11): 796–799.
13. H. Urkowitz. Energy detection of unknown deterministic signals. Proceeding of IEEE 1967; 55: 523–531.
14. Sina Maleki, Ashish Pandharipande and Geert Leus. Two-Stage Spectrum Sensing for Cognitive Radios. Proceeding of IEEE ICASSP 2010; 2946-2949.
15. T. Yucek and H. Arslan. Spectrum characterization for opportunistic cognitive radio systems. Proceeding of IEEE Military Comm. Conf. 2006; 1–6.
16. J. G. Proakis. Digital Communications 4th ed., McGraw-Hill, 2001.
17. Z. Quan, S. Cui, H. V. Poor, and A. H. Sayed, Collaborative wideband sensing for cognitive radios. IEEE Signal Process. Mag. 2008; 25(6): 60–73.
18. H. Chen, W. Gao, and D. Daut. Spectrum sensing for OFDM systems employing pilot tones and application to DVB-T OFDM. Proceeding of ICC 2008; 3421–3426.
19. N. Han, S. H. Shon, J. H. Chung, and J. M. Kim. Spectral correlation based signal detection method for spectrum sensing in IEEE 802.22 WRAN systems. Proceeding of IEEE Int. Conf. Advanced Communication Technology 2006; 3.
20. K. Kim, I. A. Akbar, K. K. Bae, J. S. Um, C. M. Spooner, and J. H. Reed. Cyclostationary approaches to signal detection and classification in cognitive radio. Proceeding of IEEE Int. Symposium on New Frontiers in Dynamic Spectrum Access Networks 2007; 212–215.
21. U. Gardner. Exploitation of spectral redundancy in cyclostationary signals. IEEE Signal Processing Mag. 1991; 8(2): 14–36.
22. S. Y. Tu, K. C. Chen, and R. Prasad. Spectrum sensing of OFDMA systems for cognitive radios. Proceeding of Int. Symp. PIRMC 2007; 1–5.
23. Online. Available: http://www.wimedia.org
24. M. Oner and F. Jondral. Air interface identification for software radio systems. Int. J. Electron. Comm. 2007; 61(2): 104–117.
25. J. Lunden, S. Kassam, and V. Koivunen. Nonparametric cyclic correlation based detection for cognitive radio systems. Proceeding of CrownCom 2008; 1–6.
26. Zahedi-Ghasabeh, A. Tarighat, and B. Daneshrad. Spectrum sensing of OFDM waveforms using embedded pilots. Proceeding of ICC 2010; 1–6.
27. S. H. Sohn, N. Han, J. M. Kim, and J. W. Kim. OFDM signal sensing method based on cyclostationary detection. Proceeding of CrownCom 2007; 63–68.
28. P. D. Sutton, K. E. Nolan, and L. E. Doyle. Cyclostationary signitures in practical cognitive radio applications. IEEE J. Sel. Areas Comm. 2008; 26(1): 13–24.

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