AN EFFICIENT CYCLIC FEATURE DETECTION WITH SUB-NYQUIST SAMPLING FOR WIDE BAND SPECTRUM SENSING

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I ABSTRACT

A cognitive radio is an intelligent radio that can be programmed and configured dynamically. For cognitive radio networks, efficient and robust spectrum sensing is a crucial enabling step for dynamic spectrum access. Cyclic spectrum sensing techniques work well under noise uncertainty, but require high-rate sampling which is very costly in the wideband regime. The existing method develops robust and compressive wideband spectrum sensing techniques by exploiting the unique sparsity property of the two-dimensional cyclic spectra of communications signals. To do so, a new compressed sensing framework is proposed for extracting useful second-order statistics of wideband random signals from digital samples taken at sub-Nyquist rates. The time-varying cross-correlation functions of these compressive samples are formulated to reveal the cyclic spectrum, which is then used to simultaneously detect multiple signal sources over the entire wide band. But the disadvantage in this method is less spectrum sensing performance. So, in the proposed system a new technique is used which is called novel multi-rate sub-Nyquist spectrum sensing (MR-SNS) system that implements cooperative wideband spectrum sensing in a CR network. MS can detect the wideband spectrum using partial measurements without reconstructing the full frequency spectrum. An experimental result shows that the proposed method achieves high spectrum sensing performance in a fading scenario, with a relatively low implementation complexity and a low computational complexity.

Keywords – Cognitive radio,wide band spectrum,sub nyquist sampling,cylic spectrum,wireless spectrum,random signals,spectrum sensing.

II INTRODUCTION

A cognitive radio is an intelligent radio that can be programmed and configured dynamically. Its transceiver is designed to use the best wireless channels in its vicinity. Such a radio automatically detects available channels in wireless spectrum, then accordingly change its transmission or reception parameters to allow more concurrent wireless communications in a given spectrum band at one location. This process is a form of dynamic spectrum management.

Depending on transmission and reception parameters, there are two main types of cognitive radio

- Full Cognitive Radio , in which every possible parameter observable by a wireless node is considered
- Spectrum-Sensing Cognitive Radio, in which only the radio-frequency spectrum is considered.

Other types are dependent on parts of the spectrum available for cognitive radio:

- Licensed-Band Cognitive Radio, capable of using bands assigned to licensed users (except for unlicensed bands, such as the U-NII band or the ISM band.
- Unlicensed-Band Cognitive Radio, which can only utilize unlicensed parts of the radio frequency (RF) spectrum One such system is described in the IEEE 802.15Task Group 2 specifications.
- Spectrum mobility: Process by which a cognitive-radio user changes its frequency of operation. Cognitive-radio networks aim to use the spectrum in a dynamic manner by allowing radio terminals to operate in the best available frequency band.
- Spectrum sharing: Provides a fair spectrum-scheduling method; maintaining fairness is a major challenge to open-spectrum usage.

III SIGNAL MODEL

Let us consider a wide band of interest in the frequency range $[-f_{max}, f_{max}]$ where $f_{\max}$ is very large, e.g., over-GHz. There are I active PU signals emitting over this wide band, where the signal is denoted by $x_i(t), i \in \{1,2,..I\}$. There is no information regarding the waveform, bandwidth and carrier frequency of neither each signal, nor the number of signals present. A CR is equipped with an (ideal) wideband antenna that passes all signal components within $[-f_{max}, f_{max}]$. Hence, the received signal is given by,

$$x(t) = \sum_{i=1}^{I} x_i(t) + w(t)$$

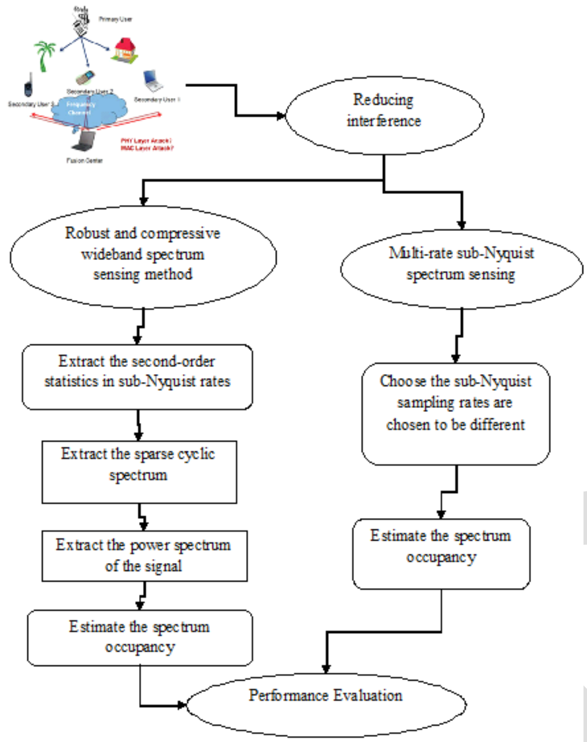
Where w (t) is the additive ambient noise. Suppose that primary user signals $x_i(t)$ are non-overlapping in frequency, since they could represent emitters from different services. The goal is to estimate the spectrum occupancy of the composite signal $x(t)$ over the entire wide band, whose nonzero support regions reveal the frequency locations and bandwidths of individual signal components $x_i(t)$. This is different from most existing work on cyclostationary signal processing, in which only one signal or signal mixture occupies the frequency band of interest. To motivate to investigate the cyclic spectrum $S(\alpha, f)$ of $x(t)$ where f is the frequency and α is the cyclic frequency. Defining the cyclic autocorrelation function, $R_{\downarrow}x\ (\alpha, \tau) = (\int [\![x(t+\tau]\!])/2\ x^{\uparrow} *\ (t-\tau/2) e^{\uparrow}(-j2\pi\alpha t)\, dt$ the cyclic spectrum, also termed the spectral correlation function (SCF), is the Fourier transform of $R_x(\alpha, \tau)$ with respect to the time-delay τ .

$$S_x(\alpha, f) = \int R_x(\alpha, \tau) e^{-j2\pi f \tau} d\tau$$

It essentially indicates the correlation of spectral components that are separated by α in frequency, and exhibits nonzero values only at a discrete set of cyclic frequencies that reveals the inherent second-order periodicity of x(t). It is known that $S(\alpha, f)$ can be nonzero only for $|f| + \frac{|\alpha|}{2} \le f_{\max}$ which suggests a diamond-shaped region around the origin of the bifrequency plane.The cyclic spectrum of the digital samples contains folded replicas of the original cyclic spectrum, with folding intervals being integer multiples of f_s on both (α, f) directions. To avoid any aliasing in the cyclic spectrum, the minimum sampling rate should be $2f_{\max}$ that is

$$f_s = \frac{1}{T_s} \ge 2f_{\max}.$$

Because $f_{\max}$ is very large in the CR sensing task, the required sampling rate f_s has to be very high, causing large energy consumption and high hardware costs in ADC.



IV ESTIMATION OF SPECTRUM OCCUPANCY

After recovering the sparse 2-D cyclic spectrum $S(\alpha, f)$ in its vectorized form $\hat{s}_x^{(c)}$ now want to simultaneously estimate the spectrum occupancy of all frequency sub-bands within the monitored wide band. The two spectrum detection algorithms are developed: one adopts a band-by-band multi-cycle generalized likelihood ratio test (GLRT) framework that works for all types of modulation and waveform patterns, and the other is tailored to known modulation types for simple and fast estimation, for which take BPSK signals as an example.

Band-by-Band Approach Based on Multi-Cycle GLRT: The goal of spectrum occupancy estimation is to decide whether a specific frequency location $f^{(n)}$ is occupied or not. To set $f^{(n)} = \left(\frac{n}{N}\right) f_s, \forall n \in \left[0, \frac{N}{2}\right]$ according to the frequency resolution of the discrete cyclic spectrum $s_x^{(c)}(a, b)$. The sensing task amounts to a band-by-band inspection of the spectrum occupancy over the entire frequency range

$$|f| \leq \frac{f_s}{2}, with \frac{f_s}{2} > f_{max}$$

It is important to note that such a band-by-band inspection is a computational approach for processing the data collected simultaneously from a wideband antenna, which is fundamentally different from a narrowband approach in which narrowband antennas scan the wide spectrum one by one along with frequency shifters and narrowband filters/processors. Now focus on the occupancy decision on a single band $f^{(n)}$. An active signal on this band would occupy a region $I^{(n)}$ of the 2-D cyclic spectrum map defined by the cyclic-frequency and frequency pairs (α, f) satisfying $f + \frac{\alpha}{2} = f^{(n)}$ and $|f| + \frac{|\alpha|}{2} \leq f_{max}, \forall(\alpha, f) \in I^{(n)}$.
In the discrete-time domain, this region is represented by discrete Points

$$(\alpha_i, f_i) \in I^{(n)}$$

which correspond to a set of integer- valued indices (a_i, b_i) that is $S(\alpha_i, f_i) = s_x^{(c)}(a_i, b_i), \forall i \in I_d^{(n)}$. Because $\alpha_i \in \left(\frac{a_i}{N}\right) f_s$ and $f_i = \left(\frac{b_i}{N}\right) f_s$ by definition, the index set $I_d^{(n)}$ can be deduced,

$b_i + \frac{a_i}{2} = n \; and \; |b_i| + \frac{|a_i|}{2} \leq \frac{f_{\max N}}{f_s} \leq \frac{N}{2}, \forall i \in I_d^{(n)}$

To stack the estimated $\{s_x^{(c)}(a_i, b_i)\}_{i \in I_d^{(n)}}$ into a vector $\hat{c}^{(n)}$ of length $|I_d^{(n)}|$ which is formed by selected entries of the vectorized cyclic spectrum, $s_x^{(c)}$ that is $\hat{c}^{(n)}[i] = \hat{s}_x^{(c)}(a_i, b_i), \forall i \in I_d^{(n)}$. The roe selection can be expressed as,

$\hat{c}^{(n)} = J_n \hat{s}_x^{(c)}$

Where the binary-valued selection matrix $J_n \in \{0,1\}^{|I_d^{(n)}| \times N^2}$ is obtained from the $N^2 \times N^2$ identity matrix by retaining its rows with indices $\forall i \in I_d^{(n)}$ only. Apparently $J_n^T J_n = I_{|I_d^{(n)}|}$. To est for the presence of a PU signal at the frequency $f^{(n)}$ the following binary hypothesis test is formulated:

$H_1: \hat{c}^{(n)} = c^{(n)} + \epsilon$

$H_0: \hat{c}^{(n)} + \epsilon$

Where $c^{(n)}$ is the nonrandom true vector of cyclic spectrum, values and ϵ is asymptotically Gaussian distributed, i.e., $lim_{LN \to \infty} \sqrt{LN}\epsilon \sim N(0, \Sigma^{(n)})$ where $\Sigma^{(n)}$ is the asymptotic covariance matrix. Because $\Sigma^{(n)}$ is not readily available, to derive a blind estimator for $\hat{\Sigma}_{\square}\ (n)$ using the available reduced-rate measurements $\{z_t(l)\}_{l=0}^{L}$. Replacing $\Sigma^{(n)}$ by $\hat{\Sigma}_{\square}\ (n)$ results in a data-adaptive GLRT detector. Treating $c^{(n)}$ as an unknown nuisance parameter, the adaptive Form the cyclic spectrum matrix $\hat{S}_x^c$ from $\hat{s}_x^c = vec\{\hat{S}_x^c\}$.

1) Let $f^{(n)} = \left(\frac{n}{N}\right) f_s$. Find the cyclic spectrum values of interest from (32), and calculate $\hat{c}^{(n)}$.
2) Calculate the test statistic using $\hat{\Sigma}^{(n)}$ is computed. If it is larger than a predetermined threshold $\eta^{(n)}$ then a PU is declared present at frequency $f^{(n)}$ otherwise PU absence is declared.
3) If $n < \frac{N}{2}$ increase n by 1 and go to Step 2).

Fast Algorithm for Known Modulation Types: When the modulation type of the signal sources are known, their cyclic features on the bi-frequency plane can be utilized to quickly identify the key signal parameters. For example, consider that x(t) consists of multiple BPSK signals, each with carrier frequency f_c symbol rate $\frac{1}{T^0}$ and a full-width rectangular pulse shaper. The number of signal components and their modulation parameters are unknown, but the modulation type is known. Ignoring the weak sidelobes in the frequency domain, the major cyclic feature is a main lobe at $\alpha = 2f_c$ spanning Over $f = -\frac{1}{T_0 to} f = \frac{1}{T_0}$.

The idea is to identify the modulation-dependent parameters T_0 and f_c by finding the lobe locations on the estimated 2-D cyclic spectrum. First, can simply search over the cyclic frequency α along the axis $f = 0$. If $|\hat{S}(\alpha, 0)| > \gamma$ then claim that there is a BPSK signal with estimated carrier frequency $\hat{f}_c = \frac{\alpha}{2}$. Next, let $\mathcal{A} = \{\alpha \dashv ||S(\alpha,)| > \gamma\}$. For each $\bar{\alpha} \in \mathcal{A}$ search along the line $\alpha = \hat{\alpha}$ to find the double –sided width of the lobe, denoted by 2ω, such that all the points in the lobe have absolute values equal to or greater than γ. The bandwidth of the corresponding BPSK signal is also 2ω, and hence can claim that the frequency band $\left[\frac{\hat{\alpha}}{2} - w, \frac{\hat{\alpha}}{2} + w\right]$ is occupied and be estimated symbol period is $\hat{T}_0 = \frac{1}{\square}$. By now, identified not only the carrier frequency f_c but also the bandwidth $\frac{1}{T_0}$ of a BPSK signal. The procedure is applicable to the entire wide band to identify all BPSK signals. Combining all the occupied frequency bands, which is able to draw the spectrum occupancy map.

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Extensions of the fast approach to other types of modulated signals are possible, using the features of the modulation types. For instance, for an SQPSK signal with carrier frequency f_c and symbol rate $\frac{1}{T}$ two peaks with similar heights will appear $\alpha = 2f_c - \frac{1}{T}$ and $\alpha = 2f_c + \frac{1}{T}$ and this feature can be used for fast detection.

VI MULTI-RATE SUB-NYQUIST SPECTRUM SENSING METHOD

To improve the detection performance of sub-Nyquist sampling system in the preceding subsection, the influence of sampling rates is analyzed. Firstly, consider the case of spectral sparsity level s=1 which means that only one frequency bin $k_1 \in \Omega$ is occupied by the PU. If the numbers of samples in multiple CRs, i.e., $M_1, M_2, \ldots M_v$ are different primes, and meet the requirement of

$$M_i M_j > N, \qquad \forall i \neq j \in [1, v]$$

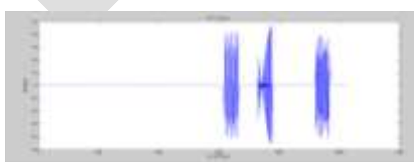
then two or more CRs cannot have mirrored frequencies in the same frequency bin. Secondly, considering the spectral sparsity level $s \geq 2$ find that, if the conditions in Lemma 1 are satisfied, the parameter p is bounded by s. It is because only one CR can map the original frequency bin $k_j \in \Omega_i$ to the aliased frequency in Ω_A and the cardinality of the spectral support Ω_i s. Therefore, to obtain the detection performance. If the numbers of samples in multiple CRs $M_1, M_2, \ldots M_v$ are different consecutive primes, and meet the requirement of $M_i M_j > N, \forall i \neq j \in [1, v]$ using the decision rule of the probabilities of false alarm and detection have the following bounds:

$$\frac{\Gamma\left(J_v, \frac{\lambda_k}{2}\right)}{\Gamma(J_v)} \leq P_{f,k} \leq Q_{Jv}\left(\sqrt{\frac{2}{N}\sum_{i \in \gamma}^{|\gamma|=s} M_i \gamma_i [k]}, \sqrt{\lambda_k}\right)$$

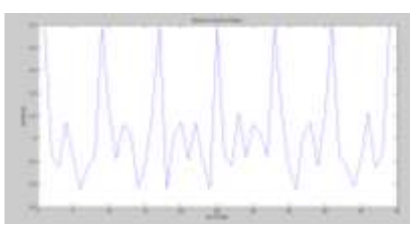
$$P_{d,k} \geq Q_{Jv}\left(\sqrt{\frac{2}{N}\sum_{i=1}^{v} M_i \gamma_i [k]}, \sqrt{\lambda_k}\right)$$

Further more, when the energy of one spectral component in Ω maps to another spectral component in Ω the probability of detection will increase.

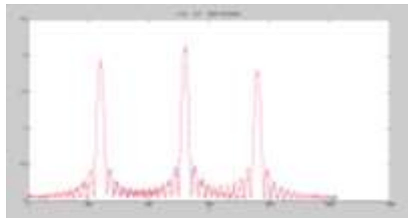
(a) Input signal generation



(b) FFT output



(c) Spectrum sensed output



(d)Minimum Square Error

VII CONCLUSION

In the existing method, a new method is used for recovering the sparse 2-D cyclic spectrum from a reduced number of compressive samples. The vectorized cyclic spectrum is reformulated to take a linear relationship with the covariance function of the compressive samples, which is a key step in enabling effective recovery of the 2-D cyclic spectrum via convex $\mathbf{l_1 - norm}$ minimization. As a special case of the compressive cyclic spectrum estimator, a new power spectrum estimator for stationary signals is also developed, which allows sub-Nyquist rate sampling even for non-sparse signals. From the recovered cyclic spectrum, two techniques have been developed to estimate the spectrum occupancy of a wide band hosting an unknown number of active sources: a band-by-band multi-cycle GLRT detector and a fast thresholding technique for signals with known modulation types such as BPSK signals. The proposed spectrum occupancy estimation techniques demonstrate salient robustness to sampling rate reduction and noise uncertainty. But the disadvantage in this method is less spectrum sensing performance. So, in the proposed system a new technique is used which is called novel multi-rate sub-Nyquist spectrum sensing (MR-SNS) system that implements cooperative wideband spectrum sensing in a CR network. MS can detect the wideband spectrum using partial measurements without reconstructing the full frequency spectrum.

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