Cognitive Radio wideband spectrum sensing using Sub-Nyquist sampling

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Abstract - ***Wireless communication systems are demanding for more and more spectrum but since the spectrum is limited resource, there is a need for sensing the sparsely used spectrum which can be used by other users through Cognitive Radio network. Here the first and foremost challenging task is spectrum sensing. Cognitive radio networks need spectrum sensing over a wideband frequency range from hundreds of MHz to few GHz, so that it can have many opportunistic white spaces. The biggest bottleneck for this is the need of ADC with very high sampling rates which follows the traditional requirement of data samples at Nyquist rate. Hence here we have proposed a method for wideband spectrum sensing at Sub-Nyquist rate. This is done using multi-coset sampling which is a periodic non uniform sampling. Correlation matrix consisting of finite number of samples is computed. Subspace estimator uses this matrix to detect if the channels are active or vacant. We simulate the model using MATLAB reconstructing the spectrum showing the active and vacant channels.***

Key Words: *Cognitive Radio, Wideband Spectrum sensing, Sub-Nyquist sampling, Correlation matrix, Subspace analysis.*

I. INTRODUCTION

Day by day wireless communication applications are increasing; hence demand for the spectrum is also increasing. But the spectrum is a limited resource and spectrum presently is distributed using fixed spectrum allocation, which uses the spectrum inefficiently and hence spectrum is underutilized. Thus in several applications like TV broadcasting, aeronautical telemetry the frequencies are used sparsely and most of the time such frequency bands are free and not being used.

To overcome this, a new concept of Cognitive Radio is tossed by Gerald Maguire and Joseph Mittola [1]. Cognitive radio is a technology that enables to access the unoccupied frequencies and hence promoting better utilization of the spectrum. Primary users (PU) are the licensed users and the unlicensed users are called the secondary users (SU) or Cognitive Radio users (CR users). The cognitive Radio users sense the RF environment to know the presence of Primary users and thus detects if the frequency band is being used or not. This process is called spectrum sensing.

The received analog signal from the Cognitive Radio has to be sampled and then has to be sensed to detect for the active and vacant channels. The received analog signal is sampled by multi-coset sampler at a sampling rate which is lower than the Nyquist rate called sub-nyquist rate. The outputs from the multi-coset sampler are sent into the sample correlation matrix block which contains interpolation, delaying and down sampler stages. This block shifts the outputs from multi-coset sampler partially and a matrix of sample correlation is computed from the data received. Finally the matrix is checked to find the active and vacant channels using subspace analysis method.

II. BACKGROUND

Quan, Sayed and Poor in [5] proposed a method called multi-band-joint-detection. The wideband signal is first sampled at high rate using ADC whose serial output is then converted into parallel data using serial to parallel converter. Then FFT(Fast Fourier Transform) converts this to frequency domain. This wideband frequency spectrum is then divided into narrow band spectrums, for which hypothesis test is used to find the available white spaces. This hypothesis test senses the white spaces, where the 'Ho' denotes that the primary users are absent and the 'H1' denotes that the primary users are present. This method would give a better performance than sensing the single band. In [6] Tian along with Giannakis in 2006 proposed another method called wavelet-based-spectrum sensing method. The power spectral density (PSD) of the spectrum which is wideband is viewed as the train of narrow frequency bands which are sub-bands, whose PSD is uniform within the sub-band and shows some irregularity near the edges of adjacent frequency sub-bands. Thus the wideband spectrum sensing is made using wavelet transform. Sampling used in these methods has to sample the wideband signal with at least twice the rate of the maximum frequency of the signal i.e. Nyquist rate in order to avoid aliasing. For example if the highest frequency of the signal is 5GHz then the sampling should be done at the rate of 2*5GHz i.e. 10GHz. But to implement practically these high rate ADCs is very difficult and if implemented this sampling would be very expensive. Another approach is shown in [7] given by Farhang-Boroujeny in 2008 which is known as filter-bank method. A group of filters with different centre frequencies are used to process the wide-band signal. Each narrow/sub-band here is down converted to base band and then filtered using low pass filter. Hence the sampling rate in this method is low. But parallel filters used this way require huge number of RF circuits. Compressive sensing of the wideband spectrum helps to operate at a rate lesser than Nyquist rate i.e. Sub-Nyquist rate. Tian with Giannakis first introduced this method of compressive sensing in 2007 which used the samples less than Nyquist rate nearing to the rate of information [8]. Thus formed wideband spectrum then uses wavelet-based-edge- detection to find the available white spaces. This method showed some uncertainties due to noise. In [9] Zen, Li and Tian tossed a distributed compressive sensing method. This was done with the idea that spatially apart cognitive radios can contribute for local approximation of the spectrum to alleviate the fading effect. This also aimed at distributed computing and sensing with reduced computational cost. But these compressive sensing methods are confined to discrete signals. In [10] J.A.Tropp and group has hence introduced Analog to Information conversion method which extended the compressive sensing to the continuous signals. It consisted of pseudo-random-number generator which produces the discrete sequence, which then passed through mixer and accumulator which demodulates the signal. A sparse signal which is discrete and formed by low rate sampling is formed out of this AIC which can be reconstructed to find the available white spaces. But this method is found to be easily affected by the imperfections present in the design and also by any mismatches in the model. This model mismatch problem was overcome by modifying Analog to Information conversion method by Mishali and Elder in [11]. This method is called Modulated-wideband converter method which now has multiple parallel sampling channels with low pass filter. The best advantage of this method is that it provides robustness against model mismatch and noise. In [12], Multi-Coset sampling is applied with sampling rate 'fs/m' among 'v' sampling channels are chosen with different offsets of time. The sampling rate is thus reduced by 'm' times than Nyquist rate but the channels should be synchronized for proper reconstruction of the spectrum. This synchronization problem was overcome by Multi-Rate wideband sensing method in [13] which uses different sub-nyquist sampling rate in different channels improving the performance of wideband sensing. Hence it is easy to implement as it requires only magnitude of spectra and do not need exact synchronization among these multiple channels.

III. PROPOSED MODEL

The received analog signal is sampled by multi-coset sampler at a sampling rate which is lower than the Nyquist rate called sub-nyquist rate. The outputs from the multi-coset sampler are sent into the sample correlation matrix block which contains interpolation, delaying and down sampler stages. This block shifts the outputs from multi-coset sampler partially and a matrix of sample correlation is computed from the data received. Finally the matrix is checked to find the active and vacant channels using subspace analysis method. For the project scenario, the wideband spectrum is divided into 32 numbers of channels each with a bandwidth of B=10MHz and for evaluation purpose 3 active channels are considered.

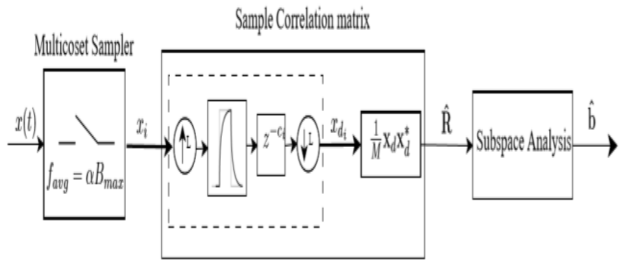

Figure 3.1: Proposed model for spectrum sensing

The wideband signal received by cognitive radio is passed through the proposed block for spectrum sensing as follows:

3.1 Multi-Coset sampler

Multi-Coset sampling is said to be a periodic and non-uniform sampling method which samples the given signal at a rate lesser than Nyquist rate, capturing the amount of information that is sufficient for accurate signal reconstruction. This process starts with selecting an appropriate sampling period which is less than Nyquist period. Let $x(t)$ represent the analog wideband signal which will be sampled using multi-coset sampler scheme. A sequence of data received from sampler for $i = [1, \ldots\ldots p]$ can be given as,

$$x_i(m) = x\left[\frac{mL+C_i}{B_{max}}\right], m \in z \tag{1}$$

Where, $\{C_i\}$ Contains distinct integer from the set $L = \{0,1, \ldots\ldots L-1\}$. The average sampling rate used in this scheme is $f_{avg} = \propto B_{max}$, where $\propto$ is sub Nyquist factor. Where, $\propto = \frac{p}{L}$ and the 'p' i.e. the number of data sequences selected should be more than the maximum active channels.

3.2 Sample Correlation matrix

In this stage a correlation matrix of the sampled data is generated which relates parameter estimation to spectrum sensing. The output of multi-coset sampler $x_i(m)$ is Over-sampled by a sampling factor L, so that

$$x_{u_i}[n] = \begin{cases} x_i\left(\frac{n}{L}\right), n = mL, m\epsilon z \\ 0, \ otherwise \end{cases} \tag{2}$$

Then $x_{u_i}[n]$ is sent to next stage which is Interpolation filter in order to obtain

$$x_{h_i}[n] = x_{u_i}[n] * h[n] \tag{3}$$

Where, Parameter $h[n]$ of interpolation filter has its response given by,

$$H(f) = \begin{cases} 1, & f\epsilon[0,B] \\ 0, & otherwise \end{cases} \quad (4)$$

The next stage in sample correlation matrix is delayer, which introduces a delay in filter output's sampled sequence, given as

$$x_{c_i}[n] = x_{h_i}[n - C_i] \quad (5)$$

Then DFT is applied on the $x_{c_i}[n]$ delayed filter output sequence, in order to generate $X_i[f]$ which is the key factor for generation of signal spectrum parameters given as

$$y(f) = \left[X_1[f], X_2[f], \ldots X_p[f]\right]^T \quad (6)$$

Where,

$$X(f) = \begin{pmatrix} X(f+b_1B) \\ X(f+b_2B) \\ \vdots \\ X(f+b_NB) \end{pmatrix} \quad (7)$$

Where, $X(f + b_iB)$, are elements representing the elements in active channel and finally a Fourier transform is applied on both sides of above equation and the results are rearranged in the form of matrix

$$y(f) = A(b)X(f) + n(f) \quad (8)$$

Where, $A(b)$ is modulation matrix given by

$$A(b)(i,k) = B\ exp\left(\frac{j2\pi C_i b_k}{L}\right) \quad (9)$$

$n(f)$ Represents noise and it is considered to be Gaussian complex noise in order to make analysis less complex. The correlation matrix of vector is given as

$$R = E[y(f)y^*(f)] = A(b)PA^*(b) + \sigma^2 I \quad (10)$$

Where, *() denotes Hermitian transpose and

$$P = E[X(f)X^*(f)] \quad (11)$$

The above equation is the correlation of the signal vector. The sequence is finally down sampled by L the reduced factor of bandwidth is given as

$$x_{d_i}(m) = x_{c_i}[mL] \quad (12)$$

The sequence of steps of oversampling, filtering, delaying and down sampling to get $x_{d_i}(m)$ from $x_i(m)$ is nothing but shifting of the sequence $x_i(n)$ by a fraction, and the final vector $x_d(m)$ as

$$X_d(m) = \begin{bmatrix} x_{d_1}(m) \\ x_{d_2}(m) \\ \cdot \\ \cdot \\ \cdot \\ x_{d_p}(m) \end{bmatrix} \quad (13)$$

The sample correlation matrix is computed using the formula.

$$\hat{R} = \frac{1}{M}\sum_{m=1}^{M} X_d(m) X_d^*(m), where\ M \rightarrow \infty \quad (14)$$

3.3 Subspace Analysis

The signals in the spectral band are assumed to be uncorrelated to each other thus vector representing correlation matrix of signal is full class of subspace methods are applicable for analysis.

Estimation of number of active channels

The R is decomposed into signal and noise as given follows

$$R = E_s \wedge_s E_s^* + E_n \wedge_n E^*_n \quad (15)$$

Where, $\wedge_s$ and $\wedge_n$ are diagonal matrices representing signal and noise respectively, E_s and E_n are Eigen vector matrices of signal and noise respectively. The order of Eigen values of $\hat{R}$ can be denoted as $\lambda_1, \lambda_2, \lambda_3, \ldots \lambda_p$. This can be done as in geometrical point of view any orthogonal vector to A(b) is nothing but a Eigen vector of R, having Eigen vector σ^2. In real scenarios it is necessary to make sure that the sensing period is small, however it depends upon number of samples. It is necessary to set a threshold level the value above which is considered as active channel and remaining are noise signals and the threshold should be dynamic in nature such as minimum description length [MDL].

The estimation of number of active channels can be done using MDL criteria for $0 \le r \le A_{max}$ given by

$$\hat{N} = \arg min - M(p-r)log\frac{g(r)}{a(r)} + \frac{1}{2}r(2p-r)logM \quad (16)$$

Where, M represents number of samples, $g(r)$ and $a(r)$ are the geometric and arithmetic mean respectively, (p-r) is Eigen values of correlation.

Active channel set recovery

In the previous step the active channels number is estimated, in the present step noise Eigen values are specified as $(P-N)$ smallest Eigen values with $\hat{E}_n$ as a $p*(p-\hat{N})$ matrix.

Now the task is to locate active channels which can be done using MUSIC like algorithms.

$$P_{MU}(k) = \frac{1}{\|a_k \hat{E}_n\|^2}, 0 \le k \le L-1 \quad (17)$$

Where, $\|.\|$ denotes the 2-norm, k is channel index and a_k is column of $A(b)$ given by

$$a_k = \left[exp\left(\frac{j2\pi k c_1}{L}\right), exp\left(\frac{j2\pi k c_2}{L}\right), \ldots exp\left(\frac{j2\pi k c_p}{L}\right)\right] \quad (18)$$

The algorithm generates L values corresponding to the L channels. If the index of an active channel is k, "$P_{MU}(k)$ is significant in that point, otherwise it will be small value which is insignificant".

IV. PERFORMANCE ANALYSIS

The spectrum of wideband signal at the sensing end of the radio is having 32 numbers of channels and each having a bandwidth of 10MHz; few channels are made active for representation sake three channels are considered active. The signals in the spectral band are assumed to be uncorrelated to each other thus vector representing correlation matrix of signal is full class of subspace methods. The spectrum is sensed and sampled at a rate lower than Nyquist rate and a correlation matrix is calculated corresponding to the signal in the sub bands. This correlation matrix is used to calculate Eigen values of both noise and the signal. Then these values are compared to the threshold value which is dynamic and calculated using minimum description length [MDL]. The plot based on this comparison is plotted wherein we can detect the active and vacant channels. The Eigen vectors of signal and noise are shown in fig 4.1 which is calculated using the estimation of number of active channels technique discussed in the previous chapter i.e., based on minimum description length [MDL] and these are classified using the threshold.

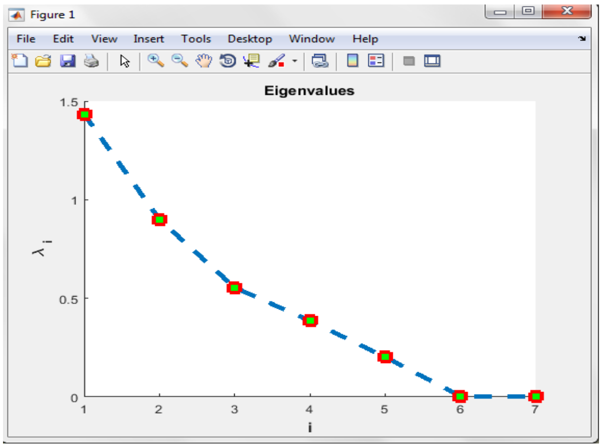

Figure 4.1: Eigen values of Signal and Noise

The number of Eigen values greater than threshold depends on the number of active channels. After the grouping of Eigen values into signal and noise respectively it is plotted as shown in fig 4.2.

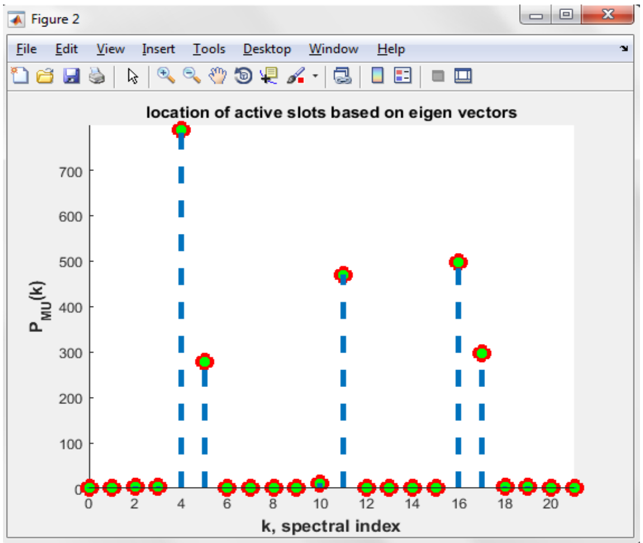

Figure 4.2: Active Channel detection using P_{MU}

MUSIC algorithm is used to find the active channels based on the P_{MU} values. Fig 4.3 shows frequency and time domain representation of received signal at CR.

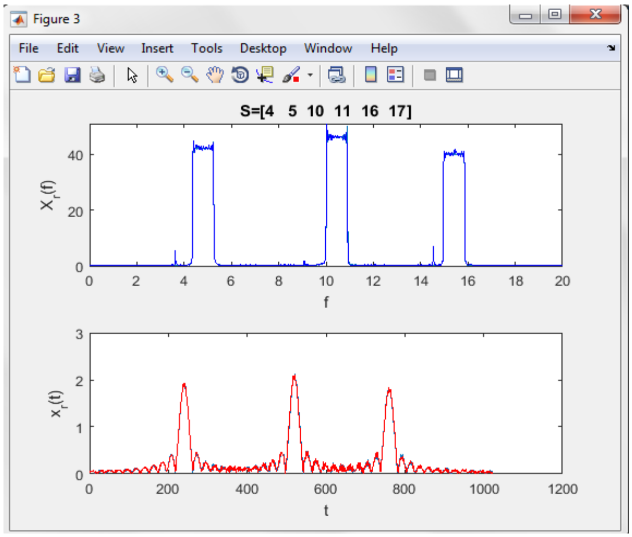

Figure 4.3: Frequency and time domain representation of received signal

Fig 4.4 represents the frequency representation of received signal and P_{MU} values of typical wideband system.

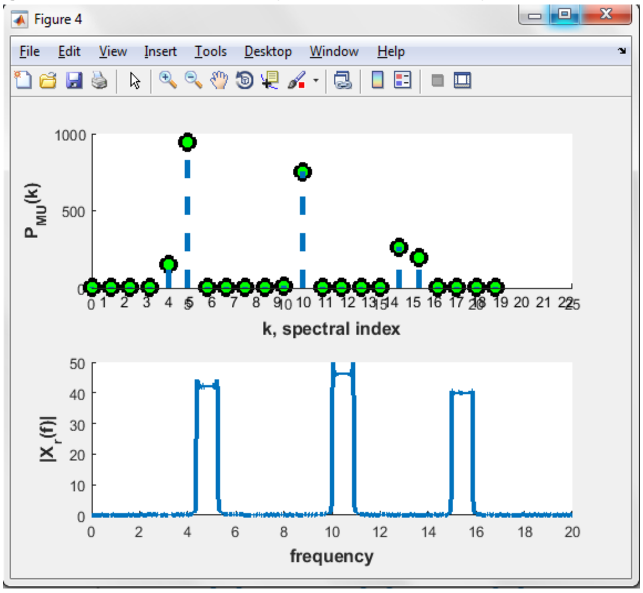

Figure 4.4: Frequency representation of received signal along with P_{MU} values

The fig 4.5 brings out the comparison between input signal and the output signal in spectrum sensing in both time and frequency domain respectively.

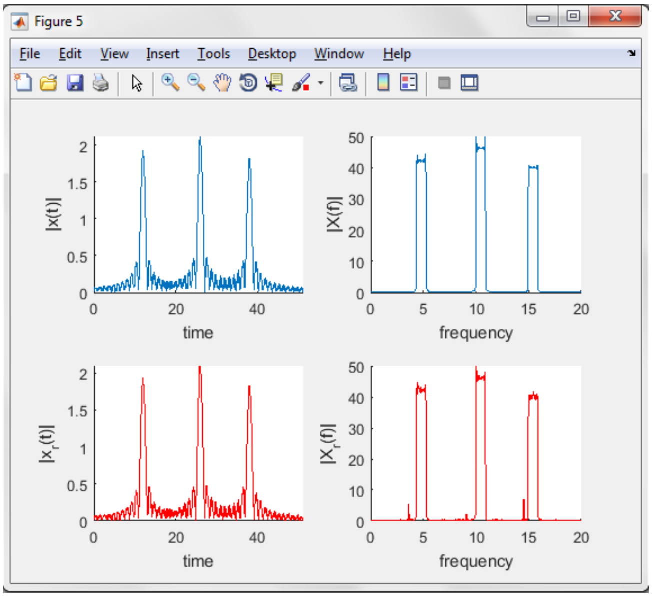

Figure 4.5: Comparison of Input and Output Signals

Where, $|x(t)|$ is the input at the sensing is end of the radio and $|X(f)|$is the convolution of the same representing in frequency domain and $|x_r(t)|$ is the output from the spectrum sensing end of the radio and $|X_r(f)|$is the convolution of the same representing in frequency domain. The fig 4.5 illustrates the signal values which significantly show active channels and the remaining channels are interpreted as vacant channel, and can be used by cognitive radio system networks.

V. CONCLUSION

The proposed method can sense the wideband spectrum effectively which uses the multi-coset sampling achieved by sampling rate lesser than the Nyquist rate. This is done by selecting the proper sampling parameter. The model for sampling and reconstruction is given in this project. The spectrum is reconstructed using the sampled data by spectral estimation. The result of this proposed model depends on the sampled data, SNR and the sampling parameters selected. This method is reliable for even low SNR and also for the smaller number of sampled data. Hence with sampling rate lesser than Nyquist rate called Sub-Nyquist rate and recovery of spectrum from fewer samples, leads to better spectrum sensing by the Cognitive Radios which is efficient wideband spectrum sensing method with periodic non-uniform sampling. This method reduces the limitation of high sampling rate and noise uncertainty and also reduces the cost of computation as the data is linear in nature.

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