Bayesian Compressive Sampling Based Wideband Spectrum Sensing in Cognitive Radio Network using Wavelet Transform

Rohit Nigam, Santosh Pawar, Manish Sharma

Abstract*: *This paper deals with the implementation of sub Nyquist sampling for the efficient wideband spectrum sensing in cognitive radio network. Cognitive radio is a very promising technology in the field of wireless communication which has drastically changed the spectral dynamics through the opportunistic utilization of frequency band by the secondary users when it is not utilized by the primary users. The complexity of spectral detection strategy is reduced using the compressive sensing method. Bayesian technique is utilized in the compressive sampling to deal with uncertainty of the process and increase the speed of detection. This technique recovers the wideband signals even with few measurements via Laplace prior and Toeplitz matrix. Sparse signal recovery algorithm is used for the extraction of primary user frequency location. The condition of the detection of primary user even in the low regulated transmission from unlicensed user is been resolved in this paper through Wavelet transform. This approach enables the evaluation of all possible hypotheses simultaneously in the global optimization framework. Simulation analysis is performed to verify the effectiveness of the proposed technique over the cognitive radio network.

Keywords* : *Cognitive Radio, Bayesian Compressive Sensing, Sub-Nyquist Sampling, Spectrum Sensing, Wavelet Transform

I. INTRODUCTION

The rapid growth in the number of wireless devices with high data requirements has posed a severe challenge to the radio spectrum allocation. The static spectrum allocation policy is not a very efficient strategy to cope with this problem. Cognitive radio (CR) system is proved to be effective wireless technique to address the spectrum scarcity problem as it senses the radio spectrum, detect the unused spectrum hole and adjust its transmission parameters dynamically to access the freely available spectrum and providing it to the secondary users. CR has an ability to observe and learn adaptively from the environment so as to enable the secondary users to utilize the primary channel users channels. The cognitive cycle comprises of three processes: Spectrum sensing, Decision Making and acting. Spectrum sensing is about measuring the occupancy of the PU channels to detect the unused channel. However, the sensing results are analyzed and spectrum allocation decision is made in decision making process. The transmission parameters are adjusted on the basis of decision taken in the acting phase to efficiently utilize the spectrum [1-3].

The challenge of efficient and effective spectrum sensing has motivated many researchers over the last decades to work in this field. The spectrum sensing algorithms like energy detection, matched filter detection, cyclostationary feature detection, etc have been proposed by the researchers to deal with the problem of spectrum allocation in various scenarios [4-7]. Energy detection technique, though being simple, proved to be sensitive towards noise and interference. Cyclostationary feature detection algorithm has overcome the limitation of sensitivity towards noise and offered better performance than energy detection method. However, it is also suitable only for the narrow frequency range. Matched filter technique is based upon the a priori knowledge about the signals from primary users for the comparison and not found to be suitable for most of the practical situations. Also all these techniques failed to perform efficiently for a wider spectral range and so could not be applied to the practical applications of cognitive radio requiring wideband spectrum sensing. The range of spectrum sensing varies from some hundreds of megahertz to gigahertz for the desired performance in terms of throughput and efficiency as the maximum bit rate is directly proportional to the spectral bandwidth as per the Shannon's formula [8-10].

The wideband spectrum sensing has attracted many researchers working in the field of next generation communication technology due to the limitation of computational complexity, processing time and energy consumption. Owing to the conventional Nyquist criteria for the high sampling rate for wideband spectrum, the Analog-to-Digital Converter (ADC) requires a very high sampling rate and implementation complexity. Its implementation results in huge hardware cost and computation complexity. Several Nyquist based sensing techniques have been proposed for wideband spectrum sensing by the researchers [11-13] but do not find suitability for the applications requiring accuracy.

Quan et. al. [14] presented a Fast Fourier Transform (FFT) based algorithm to sense the primary signal over multiple frequency bands by converting the wideband signals to frequency domain. Optimized threshold detection has provided a better performance as compared to single band sensing in this work.

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Boroujeny [15] proposed a filter bank approach for spectral detection. The filter banks have different shifted frequencies to process the wideband signal. The down converted wideband signals were used in this work to derive the base band signals, which were further been filtered through low pass filters. This technique was suitable for the dynamic wideband spectrum with low sampling rate but requires large number of RF components due to its parallel structure. Wavelet based spectrum sensing was proposed by Tian and Giannakis [16] which is based upon the modeling of power spectral density of the wideband spectrum as train of consecutive frequency subbands. Wavelet transform was used to locate the singularities of the PSD. Also, the application of subNyquist approach for wideband spectrum sensing to deal with the problem of high data rate and high computation complexity was addressed This work has improved the robustness against noise uncertainties and improved the performance by applying cyclostationary feature detection technique. The second order statistics were extracted and the wideband spectral correlation function was directly reconstructed from the sparse samples.

A distributed compressive sampling technique was used by Zeng et al. [17] for the wideband spectrum sensing in the multi-hop cognitive radio networks. The collaborative approach was implemented through the consensus optimization algorithm among the local estimates to nullify the effects of fading through spatial diversity. However compressive sensing was only confined to the discrete time signals in this work. Tropp et al. [18] extended this work to the analog domain through the analog to information converter (AIC).

The model mismatching is also a dominant challenge while the wideband spectrum allocation which was discussed by Mishali and Eldar [19]. They proposed a modified AIC model named as modulated wideband converter (MWC) model with a difference of multiple sampling channels and low pass filter in place of accumulator.

Uncertainty due to the noise and other parasitic effects in the measurement has also posed a severe challenge in the wideband spectrum sensing. Hector et al. [20] proposed a technique to deal with the uncertainty based on Bayesian model. They proposed to use this stochastic approach to estimate the spectral occupancy on real world scenario. However, this technique required high processing time and energy. This problem has been overcome by Manesh [21] through an improved probabilistic model to handle the uncertainty and improve the cognitive performance in terms of probability of detection.

Owing to the advantages of Bayesian compressive sampling to handle the practical uncertainty and that of wavelet based spectral detection to analyze local spectrum and identify characteristic and edges with low computational complexity, this work proposes combination of these techniques applied to the wideband spectrum sensing for cognitive radio. This work will improve the spectrum detection performance of the cognitive radio through the improved probability of detection and probability of failure parameters.

The main contribution of the paper lies in the implementation of Bayesian compressive sensing in CR network for the wideband spectrum sensing to deal with the signal uncertainty and providing accurate spectrum allocation with lesser complexity and hardware over a wide range of frequency. The combination of stochastic approach for compressive sensing and wavelet transform for spectrum sensing using edge detection has not been proposed so far in the existing literature to the best of the knowledge of the authors.

The paper is organized as follows: section II deals with the system preliminaries including the cognitive radio networks and spectrum sensing. Bayesian Compressive sensing is discussed in section III. Bayesian Compressive sensing based spectrum sensing with wavelet transform is proposed in section IV. Effectiveness of the proposed strategy is illustrated through the simulation analysis in CR environment in section V while section VI concludes the paper.

I. SYSTEM PRELIMINARIES

A) Cognitive Radio Networks

A rapid growth in the information traffic and the advancement in the wireless technologies over the last decade has resulted into unprecedented requirement of efficient radio resource management. The spectrum management is controlled by the regulation authorities like Telecom regulatory authority of India (TRAI) in India, federal communications commission (FCC) in the US, national agency for the legalization of communications (ANRT) in Morocco etc, which are responsible for efficient spectrum allocation from the limited available frequency band. The policy includes the optimized distribution of licences of available channels to various users for specific services and technologies. Studies have found that static spectrum distribution policy followed by these regulatory authorities have been very inefficient as only 15% to 85% of the available spectrum is utilized. It has also been revealed that the channel utilization is not uniform over the range. Some channels are heavily utilized while others are sparsely. This inefficient and scarce allocation has posed a serious requirement of some smart way of allotment of the spectrum to the other users also. Cognitive radio has emerged as revolutionary software defined technology to distribute the spectrum in the best possible manner among the licensed Users (Primary Users) and the unlicensed users (Secondary Users). According to Mitola [1], cognitive radio is an intelligent radio frequency transmitter/receiver which senses the availability of the channels and adjusts the transmission parameters to optimize the radio resources autonomously [22]. It allows the SUs to use the channels when not utilized by the primary users (PUs).

A cognitive radio system performs a 3-process cycle: sensing, deciding, and acting as shown in Fig. 1. Spectrum sensing is performed in the first process which measures the spectrum utilization from the environment. However, this process is very much affected by the parasitic effects like multipath fading, channel condition variation, uncertainties, etc. Hence it is the most important process

of the cycle. On the basis of these measurements, decision making is then performed to allocate the available spectrum to the secondary users.

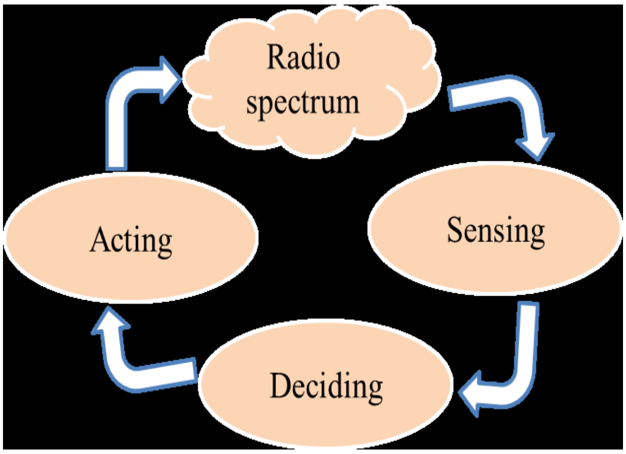

Figure 1: Cognitive radio cycle

Last process is to take action on the decision by allocation of the spectrum to the desired SU by suitable change in the transmission parameters. As the whole process is dominantly governed by the accurate spectrum sensing, the other processes of the cycle may also act wrongly if the uncertainty and other parameters have affected the measurements. So, there is always a need of an accurate spectrum sensing algorithm which should be robust enough to the uncertainties present in the process.

B) **S**pectrum Sensing Model

Spectrum sensing, being the most important aspect of cognitive cycle, requires a proper mathematical framework to provide an effective resource sharing. The model defining the spectrum sensing process is formulated as:

$$y(n) = \begin{cases} w(n) & H_0 \ :PU \ is \ absent \\ h * x(n) + w(n) & H_1 : PU \ is \ present \end{cases} \quad (1)$$

where N is the number of samples $y(n)$ represents the received signal at SU, $x(n)$ represents the PU signal, $w(n)$ is the additive white Gaussian noise (AWGN) with zero mean and variance, h is the channel gain and $n = 1, 2, \ldots, N$. H_0 and H_1 are the hypotheses denoting the absence and the presence of the PU signal respectively. The sensing decision is made on the basis of the hypothesis. There are many spectrum sensing methods proposed by various researchers over the last decade as discussed in the earlier section.

II. BAYESIAN COMPRESSIVE SENSING

The amount of data required to be processed during the spectrum sensing in cognitive radio over a large range of spectrum has posed a serious challenge to the researchers as the implementation of such any spectrum sensing technique would require very large number of ADCs which is not practicable. Sampling the data at Nyquist rate and then processing it over large bandwidth cost very huge in terms of power, size and computation complexity. This challenge has motivated a need of some algorithm to deal with such an enormous amount of data. Compressive sensing has emerged as an innovative technique to handle the issue of generation of large data after sampling. It allows the reconstruction of the signal again even if it is not sampled with the Nyquist rate using the concept of sparsity.

Compressive Sensing is a technique used for data acquisition that enables the sampling of a sparse signal from little number of measurements than its dimension. It was motivated by the desire of sampling and compression simultaneously, instead of spending too much effort on sampling than throwing away most of what is sampled in the compression stage. The technique was introduced by Donoho [9] in 2006 and has attracted attention ever since. In 2008 Emmanuel Candes and Wakin [25] fully introduced the developed method to the signal processing society as a scheme that offers more efficient transmission, reception, and storage of data. Compressed sensing is based on the idea that one can sufficiently capture all the information in a sparse signal by sampling only part of the signal using a sampling domain that is incoherent to the signal representation domain.

Researchers have proposed various reconstruction models for the sparse estimation from the input signal in compressive sensing algorithms like, convex optimization approach, Greedy Approach, Thresholding approach, combinatorial approach, non-convex approach, Bayesian approach etc [26-31]. Though convex approach is a global optimization method and is robust to noise, it is difficult to implement this method for a larger size problem. This method is complex also and consumes more time to process. Greedy algorithm, on the other hand, is a correlation based iterative method and faster than convex approach. Its parallel architecture reduces the complexity of the algorithm also by discarding the wrong entries selected in the previous iteration. It makes this method more robust to the noise. However, it has some limitations too in terms of more measurements than convex algorithm, degree of convergence and dependence on the prior knowledge of signal sparsity. Thresholding method also has low complexity and speedy processing, but it has poor convergence performance as it uses the nonlinear thresholding criteria to select atoms. Convergence can be improved using adaptive step size of iteration, but it increases the complexity of the algorithm. Combinatorial approach is suitable only for the noiseless samples and specific patterns of measurements, which is not possible for real time signals. Non-convex method also has the limitations of complexity and speed of processing like convex approach. Considering the constraints associated with these approached about the complexity, speed of processing and dependence on the prior knowledge of the signals, Bayesian approach is found to be the most suitable tradeoff. This method is based upon the probability distribution function of the input signal and proved to be more practical approach for the real time signals.

Bayesian compressive sensing approach treats all unknowns as stochastic quantities with assigned probability distributions. Considering a general compressive sensing system as

$$y = \phi x + n \tag{2}$$

where x is the original signal, $\phi = [\phi_1, \phi_2, \ldots, \phi_N]$ is the measurement matrix,

n is the acquisition noise and y is the linear measurements of the original signal x.

The reconstruction process is formulated by exploiting the sparsity of x and regularizing the inverse problem by l_p norm of x as

$$\hat{w} = \arg\min_{w} \left\{ \|y - \phi x\|_2^2 + \tau \|x\|_p \right\} \tag{3}$$

All the parameters in this mathematical framework are considered as stochastic quantities with the respective probability distributions. The input signal and the observed signals are considered to be random with the distribution of p(x|γ) and p(y|w, β) respectively, where γ and β are the model parameters known as hyperparameters. The acquisition noise is also assumed to be Gaussian with zero mean and β^{-1} variance. Maximum likelihood approach is then utilized for the Bayesian inference is performed on the basis of the following decomposition

$$p(x,\gamma,\lambda,\beta|y) = p(x|y,\gamma,\lambda,\beta)p(\gamma,\beta,\lambda|y) \tag{4}$$

$p(x|y,\gamma,\lambda,\beta)$ is found to be a multivariate Gaussian distribution with $N(x|\mu,\zeta)$ as

$p(x,\gamma,\lambda,\beta|y) = p(x,y,\gamma,\lambda,\beta)$.

Here

$$\zeta = \left[\beta\phi^T\phi + \Lambda\right] \text{ with } \Lambda = diag(1/\gamma_i). \qquad \mu = \zeta\beta\phi^T y \tag{5}$$

Hyperparameters can be estimated by the maxima of joint probability distribution, $p(y,\gamma,\beta,\lambda)$. The value of c is updated only once in each iteration instead of whole γ vector to reduce the complexity of the algorithm. The effectiveness of this method lies in its ability to delete the basis function after been determined irrelevant. It also enables to fix the errors generated in the beginning stage in the later stages by discarding the irrelevant basis vectors. These irrelevant basis vector deviate the algorithm output away from the optimum results.

III. PROPOSED METHODOLOGY

The method proposed in this work is the implementation of Bayesian compressive sampling for the wideband sensing in cognitive radio network using wavelet transform based spectrum hole detection technique. The robustness towards noise of the sensing process will be provided by the Bayesian compressive sampling, which will capture very few samples to recover the signal. Wavelet transform is then used to detect the spectral characteristics through edge detection to identify the spectrum holes and offers an effective cognitive scheme. The overall mathematical framework for the proposed methodology is presented here. Considering the received signal $y(t)$ received at the secondary user as:

$$y(t) = \sum_{i=1}^{N} x_i(t) * h_i(t) + w(t) \tag{6}$$

where N represents the signal number of sub-bands of the wideband signal. $x_i(t)$ is the signal of the i[th] primary user, $h_i(t)$ represents the channel response to the i[th] primary user, and $w(t)$ represents the additive white Gaussian noise. As all the users are not expected to transmit simultaneously, only few channels will be occupied at any time instance t. The corresponding received signal having only few transmitted signals is represented by

$$y(t) = \sum_{j \in U} x_i(t) * h_i(t) + w(t) \tag{7}$$

where j is the number of occupied channels and S is the set of all channels. The frequency domain representation of received signal is given as

$$Y = \sum_{j \in S} X_i * G + W \tag{8}$$

with G representing the channel gain matrix. The sparse nature of Y in frequency domain draws the importance of using compressive sampling in this case. In the noiseless case, $w(t) = 0$, which means that the received signal only contains the transmitted PU signal $x_i(t)$. As only few PUs are active at a given time, the spectrum is not efficiently utilized. To improve this spectral utilization, opportunistic transmission by SU under compressive sampling model finds its suitability. The sampling process in this framework can be represented as

$$V = \phi * Y \tag{9}$$

where $V(\omega)$ is the reduced dimension signal obtained by multiplying the received signal $Y(\omega)$ by the measurement matrix ϕ. The dimension of ϕ may be different for each channel. The reconstruction of the received signal through the compressed samples is a convex optimization problem

$$\hat{Y}_i = \arg\min \|Y_i\|, \quad s.t. \; AY_i = V_i \tag{10}$$

However the implementation of this optimization framework is complex in computation. The speed of processing and dependence on the prior knowledge of the signals are also the consequent limitations associated with this method. Bayesian compressive sensing is therefore used in the proposed work to overcome the limitations. In this method, Bayesian inference strategy is used on the sparse signal to reconstruct the original signal. The model is based upon the joint probability distribution function (pdf) of the hierarchical model

$f(Y,\gamma,\beta,V)$ with pdf as $f(Y,\gamma,\beta,V)=f(V/Y,\beta).f(Y/\gamma).p(\beta)$. Here, γ and β are the hyperparameters with $\beta=\sigma^2/2$ representing the inverse of noise variance. β also follows the gamma pdf given by

$$f(\beta/a^\beta,b^\beta)=\Gamma(\beta/a^\beta,b^\beta). \quad (11)$$

Considering the signal model equivalent to Laplace prior on Y, the pdf can be written as

$$f(Y|\gamma)=(\gamma/2)^N \exp(-\gamma/2\|Y\|)$$

This implies that the Bayesian implication may be framed as:

$$f(X,\gamma,\beta,\lambda/V)=f(Y/V,\gamma,\beta,\lambda).f(\gamma,\beta,\lambda/V) \quad (12)$$

$f(Y/V,\gamma,\beta,\lambda)$ is a multivariate Gaussian distribution

$$N(Y/\mu,\xi)$$

$$where\ \ \mu=\xi\phi^T y,\ \ \xi=\left[\beta\phi^T\phi+\Lambda\right]\ and\ \Lambda=diag(1/\gamma_i)$$

The hyperparameters are evaluated using the proportional relationship between $f(\gamma,\beta,\lambda/V)$ and $f(\gamma,\beta,\lambda,V)$ through the established expression given by:

$$l=\log(f(\gamma,\beta,\lambda,y))=-\frac{1}{2}\log|C|-\frac{1}{2}y^TC^{-1}y+N\log(\lambda)-\frac{1}{2}\sum\lambda_i+\frac{\theta}{2}\log\left(\frac{\theta}{2}\right)-\log\left(\frac{\theta}{2}\right)$$
$$+\left(\frac{\theta}{2}-1\right)\log(\lambda)-\frac{\theta}{2}\lambda+\left(a^\beta-1\right)\log(\beta)-b^\beta\beta \quad (13)$$

Gradient descent method is applied for l with respect to λ and β to estimate the update rule for the parameters. The hyperparameters are estimated as

$$\beta=\frac{\frac{N}{2}+a^\beta}{\frac{\left\langle\|y-\phi x\|^2\right\rangle}{2}+b^\beta},$$

$$\lambda=\frac{N-1+\frac{\theta}{2}}{\sum_i\frac{\gamma_i}{2}+\frac{\theta}{2}} \quad (14)$$

The values of hyperparameters can now be used to evaluate the joint pdf $f(Y,\gamma,\beta,V)$ and the reconstruction could be obtained as per equation (10).

After the complete wideband signal reconstruction framework, the next task is to derive a sensing mechanism for the cognitive decision making. Owing to the advantages of wavelet based spectral detection to analyze local spectrum and identify spectral characteristics and edges with low computational complexity, we have used this method for the spectral sensing in this paper. The objective of spectral sensing is to detect and identify the frequency positions and their respective PSD levels of the N spectrum bands of the signal received at the CR system. These spectrum bands are distributed between over the range between f_0 and f_N. The PSD of the nth band is defined as

$$B_n:\{f\in B_n: f_{n-1}\le f\le fn\},\qquad n=1,2,\ldots,N.$$

Considering that the PSD S(f) of a signal is the Fourier transform of its autocorrelation function, we may write the PSD of the received signal in cognitive radio network as:

$$S_r(f)=\sum_{n=1}^{N}\alpha_n^2 S_n(f)+S_w(f),\quad f\in[f_0,f_N] \quad (15)$$

where $S_n(f)$ is the nth signal PSD, $S_r(f)$ is the PSD of received signal, $S_w(f)$ is the PSD of the AWGN and α_n^2 is the signal power density within the nth band. The problem of spectrum sensing is solely dependent on the estimation of the wideband spectral parameters, f_n and α_n^2. Wavelet Transform is used in this method to evaluate these spectral parameters. The continuous wavelet transform (CWT) of $S_r(f)$ is represented as

$$W_s(S_r(f))=S_r(f)\otimes\phi_s(f) \quad (16)$$

Where $\otimes$ denotes the convolution operation and $\phi_s(f)$ is the wavelet smoothing function with dilation factor s i.e. $\phi_s(f)=\frac{1}{s}\phi\left(\frac{f}{s}\right)$. Interestingly, $W_s(S_r(f))$ can also be computed as

$$W_s(S_r(f))=F\{W_s(S_r(\tau))\} \quad (17)$$

With $W_s(S_r(\tau))=R_r(\tau).\phi(s\tau)$ we can write the wavelet transform of $S_r(f)$ as

$$W_s(S_r(f))=F\{R_r(\tau).\phi(s\tau)\}. \quad (18)$$

The boundaries of f_n are identified by evaluating the local maxima of the first derivatives as:

$$\hat{f}_n=\max_f\{|W_s(S_r'(f))|\},\qquad f\in(f_0,f_N) \quad (19)$$

As,

$$W_s(S_r'(f)) = s\frac{d}{df}\left(S_r(f)\otimes\phi_s(f)\right)$$
$$= S_r(f)\otimes\left(s\frac{d}{df}\phi_s(f)\right)$$
$$= \text{-}sF\left\{\tau R_\tau(\tau)\phi_s(s\tau)\right\} \quad (20)$$

We can rewrite $\hat{f}_n$ as

$$\hat{f}_n = \max_f\left\{\text{-}sF\left\{\tau R_\tau(\tau)\phi_s(s\tau)\right\}\right\} \quad (21)$$

The other spectrum parameter α_n^2 can be evaluated as

$$\alpha_n^2 = \beta_n^2 - \min_{n'} \hat{\beta}_n \quad (22)$$

where

$$\hat{\beta}_n = \frac{1}{\hat{f}_n - \hat{f}_{n-1}}\int_{\hat{f}_{n-1}}^{\hat{f}_n} S_r(f)df\ .$$

The estimation of these two parameters f_n *and* α_n^2 is used to identify the frequency boundary and detect the occupied and unoccupied bands. The capability of wavelet transform and Bayesian compressive sensing is used in the wideband spectral sensing for the cognitive radio network.

IV. SIMULATION STUDY

The effectiveness of the implementation of Bayesian compressive sensing on cognitive radio with wavelet transform method for wideband spectral detection is evaluated using the simulation analysis. The model depicting the received signal in the cognitive radio for the numerical simulation is given by

$$x[n] = \sum_{i=1}^{N}(r_i[n]*u[n])e^{(j2\pi f_i n/B\max)} + \delta[n] \quad (23)$$

where $r_i[n]$ is the transmitted signal, f_i is the carrier frequency, $\delta[n]$ is the AWGN disturbance and $u[n]$ is the interpolation filter with frequency response given as

$$U[f] = \begin{cases} 1, & f\in[0B] \\ 0, & otherwise \end{cases}.$$

(24)

The wideband considered here is containing 32 channels with equal bandwidth of B=10MHz with a range of [0,320] MHz. The objective is to find the positions of occupied and vacant channels at sub-Nyquist rate. Gaussian wavelet has been used in this simulation along with four dyadic scales s = 2^j , j = 1, 2, 3, 4 to detect the spectrum holes. The simulation results are shown in the figures. The effectiveness of the proposed technique using wavelet transform to estimate the vacant spectrum hole is shown in figures 2-4. Figure 2 reflects the location of the active channels over the whole spectrum. As seen from the figure 2, channel 4, 5, 11, 16 and 17 are active during the communication span. This estimation of the active channel is performed using the wavelet transform with db1 wavelet as mother wavelet. Figure 3 shows the spectral distribution of the channel utilization. The transmitted and the received signals are shown in figure 4 to show the superiority of the radio performance.

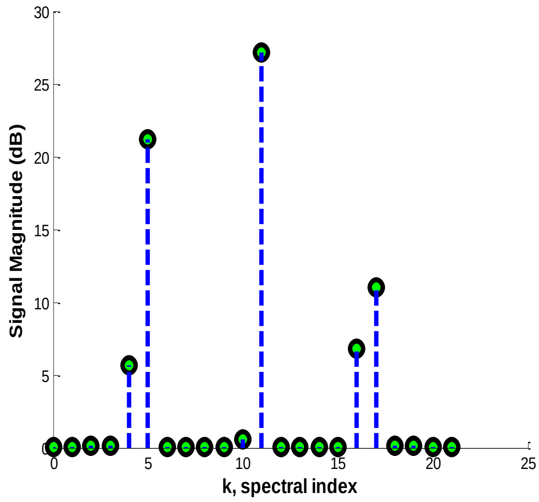

Figure 2: Location of active channels.

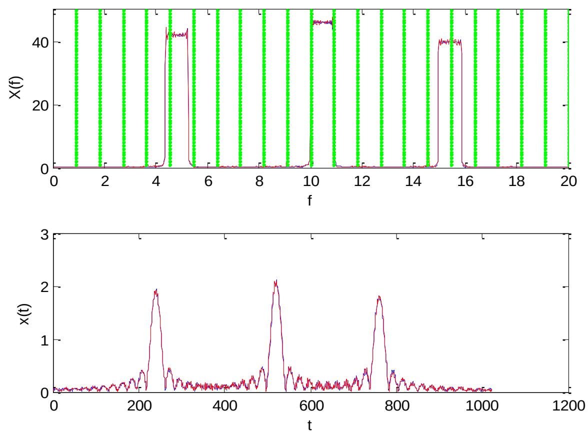

Figure 3: Frequency spectrum and respective time domain representation.

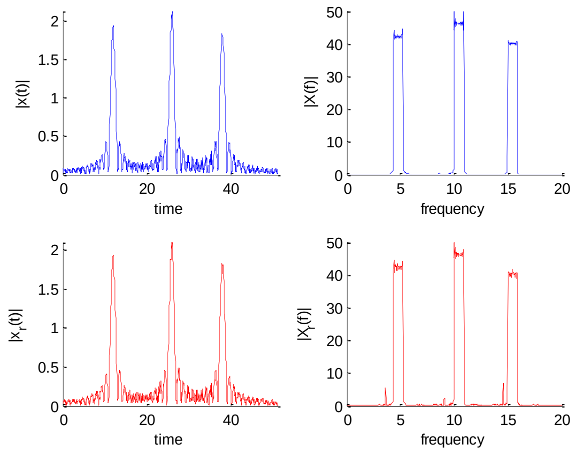

Figure 4: Transmitted and received signals

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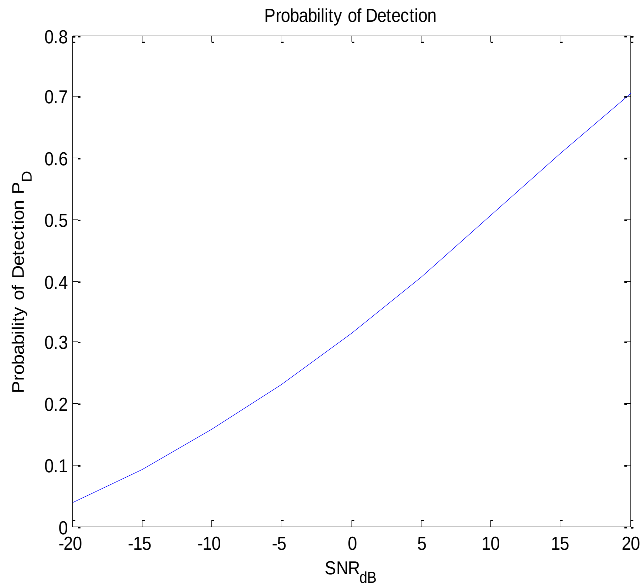

Figure 5: Probability of detection v/s SNR

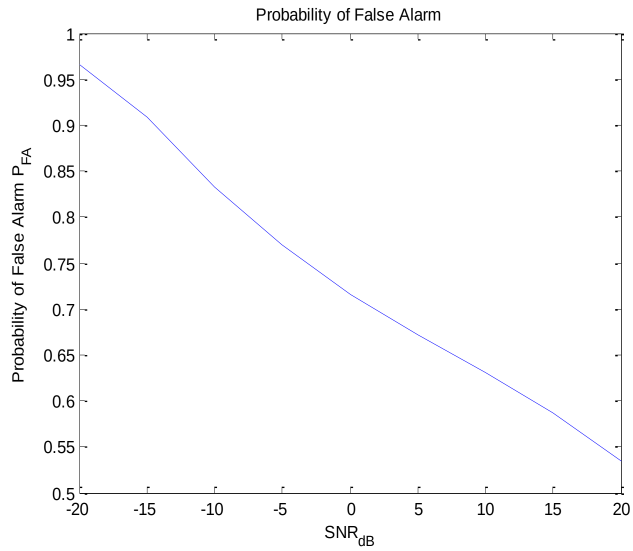

Figure 6: Probability of false alarm v/s SNR

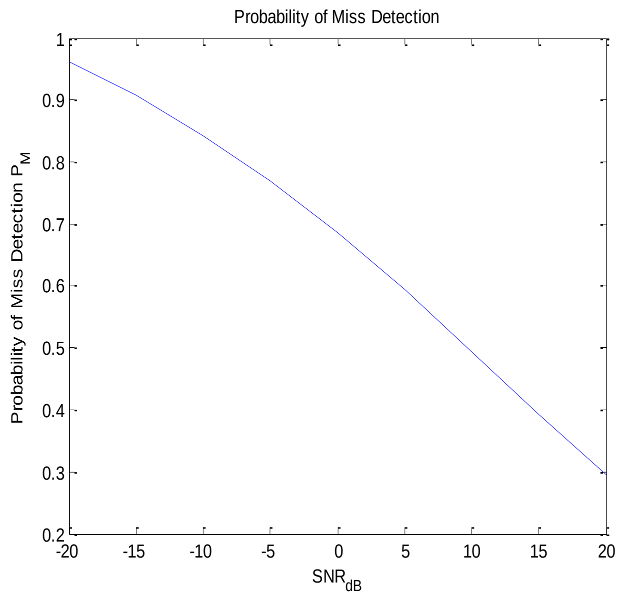

Figure 7: Probability of Miss detection v/s SNR

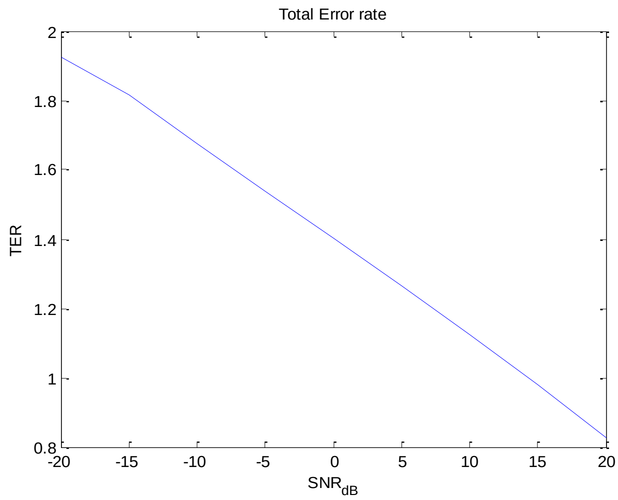

Figure 8: Total Error Rate.

Figures 5-8 reflect the performance of the cognitive radio in terms of probability of detection, probability of false alarm, probability of miss detection and total error rate with respect to the SNR variation.

V. CONCLUSION

Bayesian Compressive sampling based wideband spectrum sensing is proposed in this work for the cognitive radio network. The frequency band has been utilized very efficiently through the opportunistic distribution of spectrum among the primary users and secondary users. Compressive sampling has improved the algorithmic performance in terms of computational complexity by reducing the sample size drastically on the basis of sparseness of the signals. The uncertainty has been dealt by using the Bayesian basis in the compressive sensing which increases the speed of detection also. The dependency of the compressive sensing on prior information has also been mitigated using the Bayesian method. Laplave prior and Toeplitz matrix are used in this work to recover the wideband signals from few measurements. The spectrum hole detection has been performed through wavelet transform method. The performance of the proposed technique is reflected through the simulation study.

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