Bayesian RVM based compressive sensing method for Spectrum Decision in Cognitive Radio Based IoT in 5G using Wavelet Transform

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Abstract—
This study details how a cognitive radio network and a wavelet transform can be used to build a compressive sensing technique for locating gaps in the spectrum. IoT deployments have limitations in areas such as resilience in hostile environments, bandwidth allocation and utilization, ease of use, and RF spectrum pricing. Effective use of the given RF spectrum is one of the greatest ways to integrate IoT in 5G, as this spectrum is typically underutilized due to consumption by the licensed users known as Primary Users (PUs). As a result, the Spectrum Decision by CR's unlicensed users is important for CR-based IoT in networks supporting 5G and beyond. Bayesian Compressive Sensing is utilized here to deal with the process's inherent complexity and uncertainty. Since the proposed Bayesian RVM-based compressive sensing technique, Bayesian Compressive Sensing requires less information about the measurement noise. Remarkably high accuracy and speed are maintained despite the fact that this technique requires fewer measurements to recover wideband signals. Even in transmissions from unlicensed users, who are subject to little regulation, the wavelet transform is used in this work to detect the primary user (PU). The method's value lies in the fact that it permits simultaneous evaluation of all viable hypotheses within the global optimization framework. Research is done using simulations to test how well the proposed method works in a cognitive radio setting. Recovery error, recovery time, and covariance are compared to the standard Bayesian approach to show the superiority of the proposed method.

Keywords-Internet of Things, Cognitive radio, Bayesian compressive sensing, Wavelet Transform, Relevance Vector Machine, fifth generation (5G).
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I. INTRODUCTION

Radio spectrum is becoming gradually scarce due to the swift improvement of wireless communication technology and the emergence of new technologies such as 5G and the Internet of Things (IoT) [1]. The spectrum allocation and occupancy campaign [2-4] found a wide range of total band utilization, ranging from 7% to 35%, demonstrating that spectrum resources are obviously not being exploited to their full potential. The IoT is the term given to the global network of electronic gadgets that are interconnected with one another. Products that is equipped for the Internet of Things will be networked via wireless communication technologies, which will provide a high-quality and easy lifestyle within the reach of customers who are away from home. Implementing the IoT can be difficult due to a number of factors, including variations in the climate and geography, as well as availability, bandwidth allocation, and the cost of radio frequency spectrum.

CRNs are becoming increasingly popular for Internet of Things (IoT) connections as a result of the scarcity of available radio frequency (RF) spectrum. Intelligent devices will have the ability to plan their use of the radio frequency (RF) spectrum in order to prevent interference and maximize the quality of service (QoS) for wireless communication. The advancement of wireless technology is picking up speed. We went from data speeds of 144 kbps on 2G packet switching and 2.5G circuit switching to data rates of 1 gigabit per second on 4G Long Term Evolution Advanced (LTE-A) in a little under a decade. Since current wireless communication places an emphasis on expanded capacity, higher data rates, lower end-to-end latency, enormous device connection, cheaper costs, and consistent Quality of Experience (QoE), 5G is gradually replacing 4G. Numerous wireless service providers and applications have already laid claim to the whole Radio Frequency (RF) frequency range, which they then proceed to use. On the other hand, when new wireless uses come into existence, there is a severe lack of frequency spectrum available to dedicate to the expansion of wireless services. Because the licensed users, also known as Primary Users (PUs), typically make normal use of the provided RF spectrum, the vast majority of it is left unused. Therefore, making good use of it is one of the best ways to integrate IoT in 5G networks.

The prior trade-off between available spectrum and the rate of technological advancement has been eliminated because to cognitive radio (CR). Over the course of the past decade, it has developed into a spectrum utilization technology that is at the cutting edge of the field. As the need for multimedia services continues to rise, one of the most significant challenges that has recently arisen is the proliferation of wireless devices that have high requirements for the transport of data. When there are only so many resources available, the only answer is to effectively allocate spectrum. Due to the sparse and non-uniform spectral requirements, it has been proved that the static spectrum allocation method is ineffective. CRoffers a solution to the problem of spectrum scarcity in the form of a dynamic spectrum allocation scheme. This scheme works by first sensing the radio spectrum to locate the spectrum that is not being used by the primary users, and then adjusting the transmission parameters of the cognitive radio system so that it can access the spectrum that is freely accessible and make it available to the secondary users (SU). CR holds the most promise for maximizing the utilization of the spectrum that is currently available because of its ability to observe and learn from its surrounding environment. [1]

Spectrum sensing, decision making, and action are the three pillars that make up the foundation of cognitive radio. Spectrum sensing is responsible for checking the PU channels to see if there are any open slots, and the decision-making process is in charge of allocating spectrum in accordance with the data gathered from spectrum sensing. During the phase where the selected technique for optimizing spectrum utilization is being implemented, the transmission parameters will be modified [1-3]. This will allow the approach to be put into action.

During the course of the last ten years, many researchers have concentrated their efforts on the problem of spectrum sensing that is both efficient and effective. Over the course of several decades, a number of different approaches, such as the cyclostationary process, energy detectors, and matching filters, have been put forward as possible solutions. However, there are a few issues with the techniques that you have proposed. Matching filters require prior knowledge of the signals used by the primary user (PU), cyclostationary detectors are extremely complex, and energy detectors have poor performance when the signal-to-noise ratio (SNR) varies. The detection capabilities of these methods are entirely reliant on the accuracy of the sensor due to the fact that they are predicated on certain signal-noise model assumptions and rely on thresholds to determine their effectiveness. Narrowband applications benefited tremendously from the use of these technologies; nonetheless, spectrum sensing calls for operation at frequencies ranging from several hundred megahertz to one gigahertz in order to achieve the requisite throughput and efficiency. According to Shannon's formula, [8-10], the maximum bit rate has a relationship that is proportionate to the spectral bandwidth. Consequently, the creation of a dependable and sensitive spectrum sensing system is one of the most sought-after aims among researchers working in the wireless industry.

A method based on the Fast Fourier Transform (FFT) was proposed by Quan et al. [14] to identify the primary signal. This method was developed by transforming the wideband signals to the frequency domain across a variety of frequency bands. According to the findings of this research, spectrum conversion that is combined with enhanced threshold detection performs better than single band sensing. When analyzing the spectral characteristics of a wideband signal, Farhang-Boroujeny [15] recommends using a filter bank as the method of analysis. This method is ideal for the dynamic wideband spectrum with a low sampling rate since the baseband signals were generated by down-converting the wideband signals. However, due to the parallel architecture of the design, a large number of RF components were essential.

A spectrum sensing technique using Wavelet transform was published by Tian and Giannakis [16] to describe the power spectral density of wideband signals as a series of frequency sub-bands. This technique was developed by Tian and Giannakis. This approach makes use of the cyclostationary feature identification algorithm in order to improve both the data throughput and the noise robustness of the system. In order to create the spectral correlation function from the sparse samples, second-order statistics were applied as a data analysis method. The uncertainty that is brought about during measurement as a result of noise and other parasitic effects is one of the most significant challenges associated with wideband spectrum sensing. R. Hector and his colleagues [20] used a stochastic method that was based on a Bayesian model in order to estimate the spectrum's occupancy in real time. On the other hand, the processing of this method needed additional time and effort. M.R. Manesh [21] suggests a redesigned probabilistic framework as a way to combat uncertainty and improve mental performance. However, in order to apply this method effectively, the user needed to have prior knowledge of the measurement noise level, which necessitated more computational effort. The Bayesian Random Vector Model was introduced by Ji et al. [22] as an answer to the problem that the CS algorithm is dependent on the currently available mathematical model of noise. The Bayesian statistics methodology was established on the principle of optimizing the marginal likelihood (ML) of the Bayesian problem at each iteration. On the other hand, the availability of an accurate mathematical model of the noise was necessary for this strategy to be effective and quick in its recovery efforts.

Xie et al. (2020) put out the idea of data-driven detectors that automatically construct test statistics based on signal samples taken from the system. The researchers came to the conclusion that cutting-edge deep learning-based detectors need constant access to a sizable amount of labelled training data. This was one of the key findings of the study. The "unsupervised deep spectrum sensing technique" (also known as "UDSS") is a method that was developed by the author specifically for the purpose of addressing this problem. It bases itself on an unsupervised type of deep learning (DL), which is its primary methodology. It is not necessary to have the statistical covariance matrix or the signal-to-noise ratio in order to use this method [29]. In addition, when there are no PU signals present, the number of samples that must be collected is kept to a bare minimum [30]. However, in order for semi-automatic algorithms to learn, they need input that is both labelled and unlabeled. Because of this, adopting this strategy will cut down on automation while simultaneously lowering overall performance.

In this paper, a modified Bayesian RVM-based compressive sampling framework is used to the cognitive environment and a wavelet transform is utilized in order to efficiently and accurately detect spectrum holes. The goal of this endeavor is to locate spectrum holes. The simulation analysis reveals that the proposed technique outperforms the baseline in terms of resilience and complexity, as assessed by recovery time, recovery error, and correlation factors. This conclusion may be drawn from the fact that the suggested method beats the baseline.

The fundamental contribution of this paper is a unique modified Bayesian RVM model for compressive sensing. This model improves noise performance while coping with signal uncertainty and boosts accuracy in spectrum allocation in an Internet of Things (IoT) 5G network. This research combines the capabilities of the wavelet transform for extracting the spectrum's features with the advantages of using a Bayesian framework for addressing uncertainty. The amount of computer complexity required to complete this process is kept to a minimum. In this study, we implemented an integrated technique to improve noise robustness without sacrificing processing complexity in order to carry out wideband spectrum sensing within a cognitive radio environment. This allowed us to achieve our goals. The research component of the proposed project has been made easier to carry out because to the utilization of this Bayesian RVM-based stochastic technique for compressive sensing and wavelet transform-based edge detection. It has also been discovered that the framework that was proposed offers the additional benefit of expediting recovery and boosting the accuracy of reconstruction.

The remaining sections of the paper are organized as follows: In the IIsection, we will cover the principles of cognitive radio networks as well as spectrum sensing. In section III, Bayesian RVM and Bayesian Compressive Sensing are discussed. In Section IV, we suggest making use of a modified Bayesian Random Vector Model (RVM) in conjunction with the wavelet transform in order to perform spectral sensing. In Section V, the proposed method's usefulness by applying it to a CR environment through the use of simulation studies, and in Section VII, we bring the whole thing to a close.

II. System Preliminaries

A) 5G with Cognitive Radio NetworksCRN based IoT

The Internet of Things (IoT) envisions millions of low-powered devices with sensing, actuating, computing, and communication capabilities monitoring the world at a degree of detail never before possible. Cisco predicts that there will be more than 50 billion internet-connected devices by 2020 [9], with 20% coming from businesses. It will be required to study the data generated by these connected objects in order to gain insight into their behaviour. Communications in linked vehicles, smart buildings, and factories (industry 4.0) also commonly require high dependability, low latency, and scalability. For IoT applications that can't function with high latency, the fifth generation (5G)of networks promises not only faster data speeds but also low-latency data transfer. It will enable larger IoT devices to communicate across many networks and enable critical machine-type communications.Implementing processing close to the things ensures low, deterministic latency that underpins enforced security and real-time applications in IoT systems that support fog.

The IoT is a prototype for the future Internet and represents cutting-edge technological advancement. The primary objective of the Internet of Things is to connect everything that ever existed, living or dead, through the Internet. By designing items with built-in communication capabilities and a standard addressing scheme, a distributed and pervasive network of flawlessly connected, diversified electric and electronic gadgets can be created [11]. Recent technological developments and academic attention have focused on the IoT and CRNs. Spectrum allocation for the many devices and objects requiring IoT connectivity will have significant cost implications due to the policy's insistence on the acquisition of RF spectrum at a premium. As the Internet of Things grows, so do CRNs due to the peculiarities of the spectrum they employ. In order to boost system throughput and supply IoT-Us in CRN with high bandwidth transmission, [12] proposes shared-to-reserve (SR) and reserved-to-share (RS) techniques for CR-HetNets. Half-duplex mode (HD) operation is the default for the SU, allowing for simultaneous sensing and transmission [13]. It is possible for damaging interference to occur during the transmission of SU due to its HD functioning, especially if PU abruptly arrives and engages in activity at that time. As a result, sensing the spectrum should be an ongoing activity, and when a PU occurs, the SU should move from the licenced channel to one that is better suited to the current task at hand. Therefore, a good decision-making framework for the spectrum is essential. External storage systems offer virtually endless store space when combined with specialised signal processing to sift through information and identify signals, interactions, or events of interest. With today's crowded spectrum and innovative gadgets like cognitive radios, these high-bandwidth, long-duration solutions are ideal.

B) Cognitive Radio Networks

In the last decade, data usage in cutting-edge wireless technology has skyrocketed, making efficient management of radio spectrum resources an essential necessity. Spectrum regulatory authorities ensure that the limited quantity of frequency band is allocated fairly and efficiently between the numerous users for certain services and technologies. However, only 15%-85% of the available spectrum is used by the licensed users [1], according to research. This is due to the static spectrum allocation and the non-uniform channel usage. This has led to a recent uptick in academic interest in the concept of dynamic spectrum allocation. With the use of software-defined technologies, Mitola [1] has proposed a dynamic spectrum allocation scheme for licensed (Primary Users) and unlicensed (Secondary Users). By adjusting its transmission parameters, it shares its free channel with tertiary users when primary ones aren't using it. Detection, selection, and action are the three phases of cognitive radio, as shown in Figure 1.

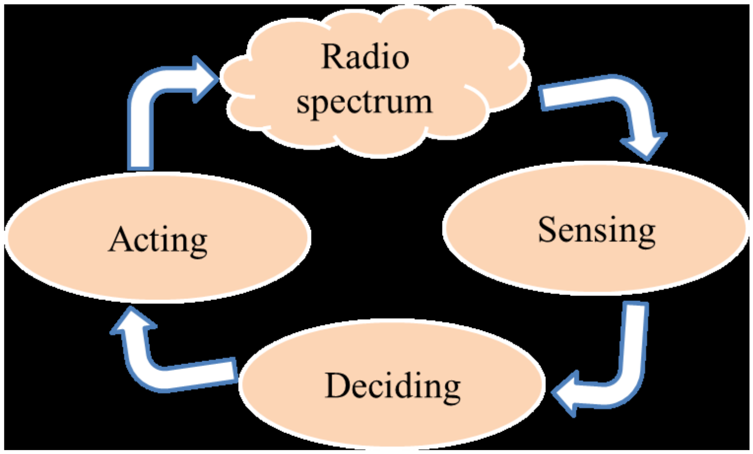

Figure 1. Cognitive radio cycle

The term "spectrum sensing" refers to the process of determining how much of the radio spectrum is being used by primary and secondary users. The data from these analyses is then used in the secondary step to determine how much spectrum should be allocated to those consumers. The final step is to implement the chosen course of action. Cognitive radio is severely hampered by parasitic effects such functional or parametric errors, channel state fluctuations, multi-path fading, etc. that manifest themselves during the measurement phase. Therefore, a robust approach for dealing with measurement mistakes and uncertainties is required.

C) Spectrum Sensing Model

The precision of the mathematical foundation is a prerequisite for the cognitive process's spectrum sensing, which is crucial to total spectral performance. The following is the model created to illustrate the spectrum sensing process:

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

where *w(n)* is the additive white Gaussian noise (AWGN) with zero mean and variance, *h(n)* is the channel gain, *y(n)* is the received signal at SU, *x(n)* is the PU signal, and *N* is the sample count. The hypotheses $H_0$and H_1 indicate, respectively, the lack and presence of the PU signal, which is what determines the sensing choice. As was covered in the prior part, numerous approaches of spectrum sensing have been proposed by researchers during the past ten years.

III. Bayesian Compressive Sensing

Spectrum sensing in CR works with a large amount of data that spans many frequencies, hence it faces issues in processing complexity and energy usage. The hardware requirements of sampling at the Nyquist rate also make it impracticable. Therefore, a framework is needed to deal with this mountain of data. Compressive sensing (CS) is a state-of-the-art method proposed in 2006 by David L. Donoho[9] to deal with this issue. It's a sparsity-based strategy that also allows for sub-Nyquist-rate signal reconstruction. The need to minimize signal loss during compression motivated the development of simultaneous sampling and compression. In 2008, Emmanuel J. Candes and Michael B. Wakin[25] developed the full mathematical framework to provide an efficient means of transmitting, receiving, and storing communication data. CS is based on the assumption that data can be adequately captured in sparse signals by sampling the incoherent part of the signal.

Numerous reconstruction models, such as the greedy method, combinatorial approach, threshold approach, convex optimization approach, non-convex approach, Bayesian approach, etc. [26-31], have been developed to estimate the signal from the sparse representation. Despite having the global optimization technique and noise-resistant, implementing the convex approach or non-convex approach for a massive data set was difficult due to complexity and processing time. On the other hand, the greedy algorithm relied on an iterative process based on correlations, making it a faster option. While simpler than the convex method, this methodology still hinged on how well it performed. More data points were needed than with the convex method to reach the desired level of convergence. Nonlinear thresholding criteria are used in the thresholding method to streamline the process but come at the cost of convergence speed. The adjustable step size improves convergence at the cost of complexity. The combinatorial approach worked well for noise-free samples following a prescribed pattern, but it proved ineffective for real-time signals. The Bayesian method strikes a good compromise between computational efficiency, complexity, and the use of prior knowledge. It is a stochastic technique that uses the probability density function of the incoming signal to recreate the original data.

A general compressive sensing system can be represented as [32]

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

where $\phi = [\phi_1, \phi_2, \ldots, \phi_N]$ is the measurement matrix, *n* denotes acquisition noise, and *x* denotes the original signal. *y* denotes the linear measurements of the original signal. The reconstruction procedure is defined in terms of the regularized inverse problem by the l_p norm of the original signal x as

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

The distributions of the input signal x and the observed signals are assumed to be p(x|γ) and p(y|w, β), respectively, where γ and β are the hyperparameters of the model. The acquisition noise is similarly presumed to be Gaussian, with a standard deviation of one and an average of zero and β^{-1}variance. Following this decomposition, the maximum likelihood method can be utilized to carry out the Bayesian inference.[33]

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

Here $p(x | y, \gamma, \lambda, \beta)$ is a multivariate Gaussian distribution with $N(x | \mu, \zeta)$ as $p(x, \gamma, \lambda, \beta | y) = p(x, y, \gamma, \lambda, \beta)$. Also

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

Rather of modifying the full vector γ at each iteration, the complexity of the algorithm is reduced by modifying the weights only once. Maximum joint PDF $p(y, \gamma, \beta, \lambda)$ is also utilized for estimating the hyperparameters' worth. Since the output of the algorithm deviates from the ideal value when the basis function is irrelevant, it plays an important role in this process. The approach decreases the number of first-pass errors by doing away with these unused fundamental functions. However, prior knowledge of the noise level in the measured data is necessary for successful application of Bayesian compressive sensing to a noisy system. [34-36]

IV. Modified Compressive Sensing Algorithm

Regularized Variable Modelling using Bayes

The compressive sensing algorithm is a

technique that makes use of Bayesian statistics. The probabilistic sparse model (RVM) is a Bayesian variant of the standard Support Vector Machine (SVM) model in the linear domain. The performance may be generalized with less measurements than with SVM, which is an advantage. To achieve sparsity, it disregards the posterior distribution weights, which sharply peak at zero, in accordance with the Automatic Relevance Determination (ARD) concept.[37] The RVM method iteratively maximizes the marginal likelihood (ML) of the Bayesian problem at each stage. The sparse matrix generated via Sub-Nyquist sampling is then divided into two groups, internal to the model and external to the model, based on the indices. When starting with a blank slate, the index and its corresponding basis function are incorporated into the model during the sequential evaluation of the support. However, if it becomes apparent during the process that this index is not necessary, it can be modified. The resulting shift in ML value is compared across all indices to determine which course of action corresponds to the highest ML value. When the stopping requirement is met, the iteration process ends. In this case, the required precision of the sub-Nyquist reconstruction can be achieved with a simple variance-based estimation of the noise.[38]

The value of the MLs from the previous two iterations are used to determine the stopping condition. Stopping the process and accepting the associated solution as stable and the best one can come up with if the change is negligible. This stopping criterion, however, may generate an unwanted noise component due to the later-created support. This problem can be solved if the operation terminates immediately after producing 2S supports, where S is analogous to a sparse matrix with only S non-zero components. This modification to the technique has resulted in better performance in terms of both computation time and noise. The following are brief descriptions of each stage of the process.:[39]

1. Set the noise variance's initial value.
2. Utilize the Bayesian inference approach to assess the hyperparameter values λ and β.
3. Assess the basis function and each Bayesian parameter.
4. Calculate the value of ML and update the hyperparameters appropriately for each iteration if the Bayesian parameters are positive and the hyperparameters are finite.
5. Determine ΔML to check whether to update the hyperparameters and the basis function.
6. If there are more than 2S supports (Ns), stop iterating and carry out the chosen action that corresponds to the lowest ΔML.
7. Update every Bayesian parameter before finishing the computation.

Since it must be both large enough to cover the entire measurement range and small enough to reduce the noisy components, estimating the measurement's sparsity level S is a crucial challenge.

V. Proposed Methodology

Combining wavelet-based spectrum hole detection with modified Bayesian RVM-based compressive sensing is the approach proposed in this study for wideband spectral sensing. The proposed RVM is more resistant to noise because it only needs an approximate estimate of the noise variance of the sampled measurement to function. Fig. 2 is a schematic representation of the entire approach proposal. The linear measurements of the original signal, i.e., are input to the RVM-based compressive sensing module, which then uses those measurements to generate sparse samples and reconstruct the signal. A wavelet transform-based spectral detection method that provides temporal frequency localisation while also accounting for the sparseness of the signal improves the detection accuracy of the spectrum.

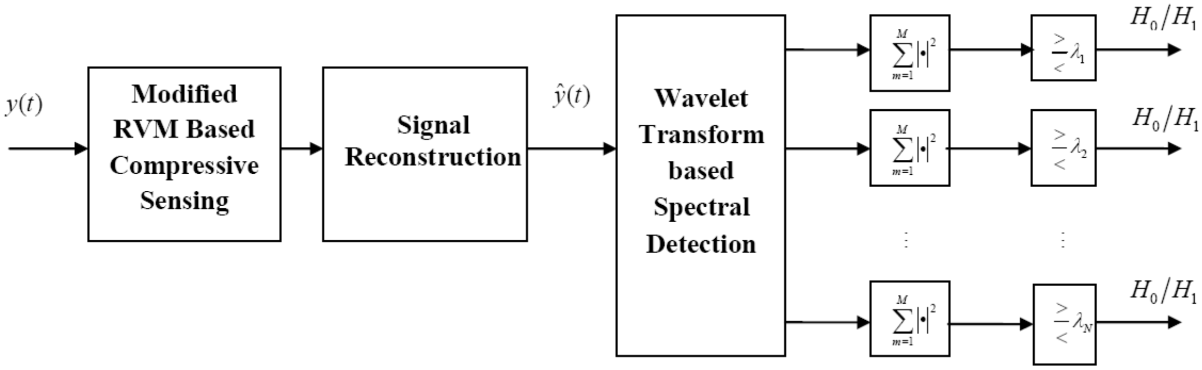

Figure 2. Proposed RVM based Wideband Spectrum Sensing

The wavelet transform is then used to estimate the spectral properties in order to pinpoint the spectrum gaps in the cognitive radio network. Taking into account the signal that was received by the secondary user is given as:

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

where $x_i(t)$ 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 noiseand The wideband signal's N stands for the number of its subbands. Assuming that there are never more than a few channels in use at once, we obtain the received signal represented by

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

where *j* is the number of used channels and *S* is the whole set of channels. In the frequency domain, we can write down equation (7) as

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

In this case, *G* stands for the channel gain matrix. In this approach, the sampling procedure may be described as

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

where V is the signal with decreased dimension and ϕ is the measurement matrix, which may have a different dimension for each channel. In terms of a convex optimization problem, the process of reconstructing the received signal from compressed samples is described as

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

In this work, Modified Bayesian RVM is employed, which is based on the joint pdf of the hierarchical model $f(Y, \gamma, \beta, V)$ and takes into account the computation complexity of the optimization framework and its dependence on the a priori knowledge of noise such that

$f(Y, \gamma, \beta, V) = f(V / Y, \beta)\, f(Y / \gamma)\, p(\beta)$ and $\beta = \sigma^2 / 2$.

β also follows the gamma pdf given by

$$f(\beta / a^{\beta}, b^{\beta}) = \Gamma(\beta / a^{\beta}, b^{\beta}). \tag{11}$$

Over Y, the Laplace prior can be utilized to offer the greatest amount of sparsity while being log-concave, the pdf can be written as $f(Y|\gamma) = (\gamma / 2)^N \exp(-\gamma / 2\|Y\|)$.

The Bayesian implication could be stated as follows:

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

where $f(Y/V,\gamma,\beta,\lambda)$ is a multivariate Gaussian distribution $N(Y/\mu,\xi)$, $\mu = \xi\phi^T y,\ \ \xi = \left[\beta\phi^T\phi + \Lambda\right]$ and $\Lambda = diag(1/\gamma_i)$.

Using equations (13) and (14) as a starting point, the hyperparameters can be calculated as

$$\beta = \frac{\frac{N}{2} + a^{\beta}}{\frac{\left\langle \left\| y - \phi x \right\|^2 \right\rangle}{2} + b^{\beta}}, \tag{13}$$

$$\lambda = \frac{N - 1 + \frac{\theta}{2}}{\sum_i \frac{\gamma_i}{2} + \frac{\theta}{2}}$$

$$l = \log(f(\gamma,\beta,\lambda,y)) = -\frac{1}{2}\log\left|C\right| - \frac{1}{2}y^T C^{-1} y + N\log(\lambda) - \frac{1}{2}\sum\lambda_i + \frac{\theta}{2}\log\left(\frac{\theta}{2}\right) - \log\left(\frac{\theta}{2}\right)$$
$$+\left(\frac{\theta}{2} - 1\right)\log(\lambda) - \frac{\theta}{2}\lambda + \left(a^{\beta} - 1\right)\log(\beta) - b^{\beta}\beta \tag{14}$$

Marginal Liklihood (ML), $p(\theta|Y,M)$ of a model M resembling to the joint pdf $f(Y,\gamma,\beta,V)$ is denoted by

$$p(\theta|Y,M) = \frac{p(Y|\theta,M)\,p(\theta|M)}{p(Y|M)} \tag{15}$$

θ is a random variable that, according to Bayesian statistics, must be minimized (integrated out of the process).

The updated Bayesian RVM algorithm described in Section IV relies heavily on the parameter θ to decide whether or not the basis function is important. The hyperparameters and the basis function are adjusted based on ΔML. The value and range of θ decide whether or not the basis vector is used in the model. After calculating the ML values at each iteration, the sparsity level S is calculated and the change in ML, ΔML is assessed using the stopping criterion described in the previous section. All of the Bayesian parameters are adjusted to reflect the most recent iteration of the model in order to evaluate its robustness.

The next step in the decision-making process is locating the available gap in the spectrum, after which a channel allocation decision can be made. In this work, we utilize the wavelet transform to analyze the spectral features of the wideband frequency band, look at the local spectrum, and locate the band's boundaries based on the peak-to-average power ratio (PSR). The nth band of the overall range from f_0 to f_N is given by $B_n : \{ f \in B_n : f_{n-1} \le f \le fn \},\quad n = 1,2,\ldots,N$. The PSD $S_r(f)$ of the received signal maybe written in terms of the Fourier transform of autocorrelation function as

$$S_r(f) = \sum_{n=1}^{N} \alpha_n^2 S_n(f) + S_w(f), \quad f \in [f_0, f_N] \tag{16}$$

where α_n^2 is the signal power density within the nth band, $S_w(f)$ is the PSD of the AWGN, and $S_n(f)$ is the nth signal PSD. The effectiveness of the spectrum sensing method is governed by the estimation of the wideband spectral parameters f_n *and* α_n^2., and wavelet transform is employed in this paper to estimate their values.

As shown, the continuous wavelet transform (CWT) of $S_r(f)$ is

$$W_s(S_r(f)) = S_r(f) \otimes \phi_s(f) \tag{17}$$

where $\otimes$ stands for the convolution operation and $\phi_s(f)$ is the wavelet smoothing function with the dilation factor s, i.e. $\phi_s(f) = \frac{1}{s}\phi\left(\frac{f}{s}\right)$. $W_s(S_r(f))$ may also be expressed as

$$W_s(S_r(f)) = F\{W_s(S_r(\tau))\} \tag{18}$$

As $W_s(S_r(\tau)) = R_r(\tau).\phi(s\tau)$,wavelet transform of $S_r(f)$ may be written as

$$W_s(S_r(f)) = F\{R_r(\tau).\phi(s\tau)\}. \tag{19}$$

By calculating the local maxima of the first derivatives as follows, the bounds of f_n are determined as:

$$\hat{f}_n = \max_f \{|W_s(S_r'(f))|\}, \qquad f \in (f_0, f_N) \tag{20}$$

$$W_s(S_r'(f)) = s\frac{d}{df}(S_r(f) \otimes \phi_s(f))$$

As,

$$= S_r(f) \otimes \left(s\frac{d}{df}\phi_s(f)\right) \tag{21}$$

$$= \text{-}sF\{\tau R_\tau(\tau)\phi_s(s\tau)\}$$

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

$$\hat{f}_n = \max_f \{\text{-}sF\{\tau R_\tau(\tau)\phi_s(s\tau)\}\} \tag{22}$$

The other spectrum parameter α_n^2 can be evaluated as

$$\alpha_n^2 = \beta_n^2 - \min_{n'} \hat{\beta}_n \tag{23}$$

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

In the cognitive radio setting, the frequency ceiling and spectrum gaps are identified using estimations of f_n *and* α_n^2. Finally, the cognitive cycle adjusts the transmission settings so that the SU may use the available channels in the spectrum. In a condensed piece of work, we leverage the enhanced capabilities of the wavelet transform and Modified Bayesian RVM-based compressive sensing to perform wideband spectral sensing for the cognitive radio network.

VI. Experimental Study

The proposed method, based on modified Bayesian RVM and wavelet transform, is validated through simulation analysis in MATLAB to ensure its efficacy in spectrum detection in cognitive radio settings. The proposed method is shown to be superior to the conventional Bayesian sparse recovery algorithms by comparing the results of the modified Bayesian RVM-based compressive sampling method. A CRN operating in spectrum band 'S' between 54 MHz and 50 GHz is under consideration since it is capable of supporting the vast majority of the wireless applications shown in Table 5. Uplink and downlink frequencies, transmission modulation schemes, and bandwidth are only some of the other factors that must be considered; the full list may be found in [37]. The term "channel bandwidth" refers to the range of frequencies that can be used by a transceiver on an IoT-U to send and receive signals in a carrier radio network. An IoT-U can use narrow, broad, or ultra-wide band (UWB) transmissions depending on the RF environment and wireless applications. A base station (BTS) or other centralized network operator handles "serve to provide" functions for the CRN. Figure 5 displays a region with five base transceiver stations (BTSs), an infinite number of mobile devices, and full wireless service coverage in all neighbouring buildings. The 3GPP channel model was used because it possesses the common properties for wireless systems, especially the ability to reflect important propagation channel parameters. Furthermore, wireless network optimization occurs in the domain of system modelling. In this CRN, we propose having 'J' SUs (with ED for SS) equipped with their own Software Defined Radio (SDR) so that they can exploit many frequency bands across large geographic areas simply by changing their operational frequency with a few clicks of a mouse. The BTSs have authority over all J IoT-Us within their broadcast range. Each of the N processing cores can use the same number of shared spectrum slots. IoT-Us is targeting these windows of opportunity for its broadcast. The air interface in wireless services is a hybrid of FDMA and TDMA.The number of BTS and PUs are taken as 5 and the RF spectrum range is considered as 890-915 MHz. The wireless channel model is taken as 3GPP and the bandwidth is taken as 200 KHz.

The simulation's model of communication is based on work by

$$y[n]=\sum_{i=1}^{N}(x_i[n]*u[n])e^{(j2\pi f_i n/B\max)}+\delta[n] \tag{24}$$

where $y[n]$ is the received signal with $x_i[n]$ as 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

$$U[f]=\begin{cases}1, & f\in[0.B]\\ 0, & otherwise\end{cases}. \tag{25}$$

In this investigation, we assume a wideband spectrum with 32 equally-broadband channels. The mother wavelet used to locate voids in a spectrum is a four-dyadic-scale Gaussian wavelet (s = 2j, j = 1, 2, 3, and 4). The modified Bayesian RVM discussed in the first section is used in compressive sensing. Figures 3 and 4 illustrate how the proposed method may be used to effectively identify spectral gaps. Channels 4, 5, 11, 16, and 17 are shown in their respective active places over the wideband spectrum in Figure 3. Figure 4 provides complementary time- and frequency-domain spectrum distributions of channel usage to that seen in Figure 3. For a user of a cognitive radio network, the spectral index k corresponds to the channel number.

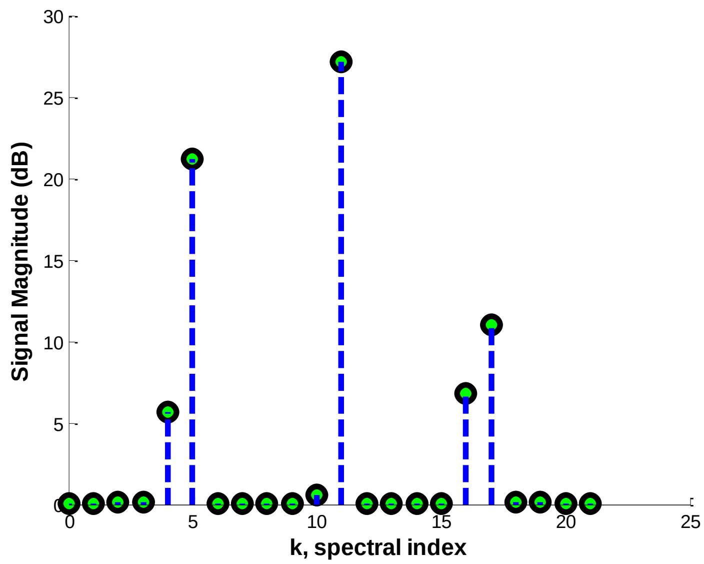

Figure 3. Location of active channels

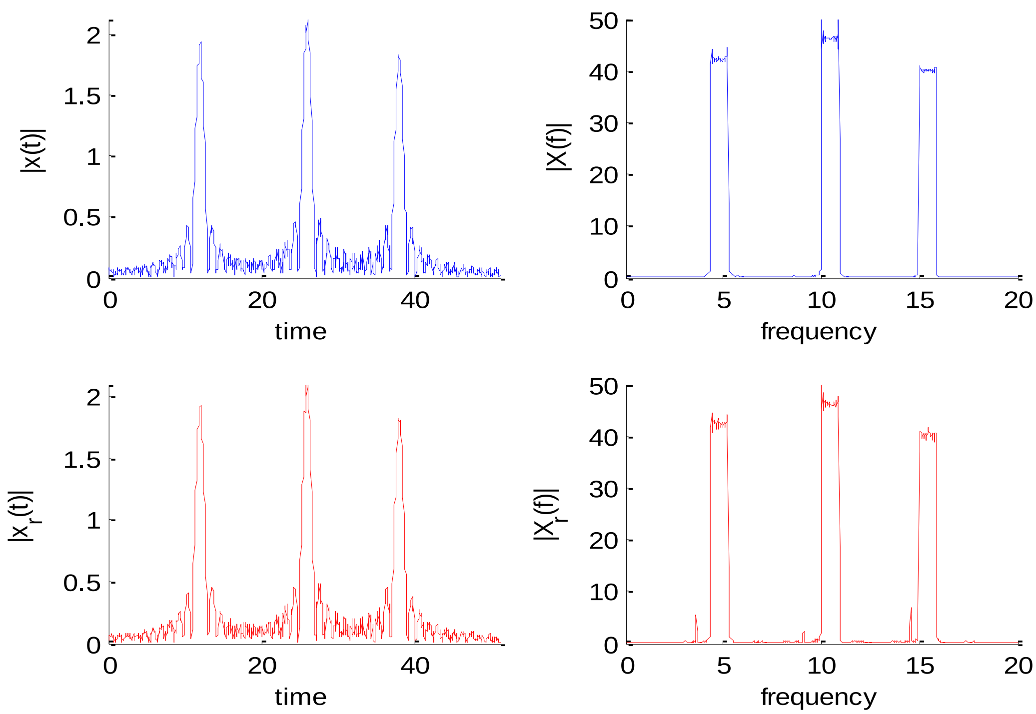

Figure 4. Transmitted and received signals

While using the PU activity time to pinpoint the available spectrum slot, two types of mistakes are possible. One is a false positive while the other is a failure to detect something. Mistaking an active spectrum slot for a vacant one is what causes the delay between now and the next available one. Here, the efficacy of the proposed spectrum choosing framework is measured using ROC curves between the false alarm and miss detection probabilities. The proposed decision-making process involves an interaction between these two factors. Since they are intertwined, it is impossible to acquire the low-probability estimates of PU(s) activity time and occupancy status that are required for trustworthy data collection.That's why finding the sweet spot in your range is crucial. For the PU's active time and spectrum slot occupancy, the ROC curves change depending on the transmission SNR value.

The results of the proposed strategy on the cognitive cycle's detection probability, false alarm probability, miss detection probability, and total mistake rate in the face of SNR fluctuation are depicted in Figures 5-9. These results demonstrate conclusively that employing a modified Bayesian RVM and wavelet transform-based spectrum hole detection has no impact on cognitive function, while employing compressive sensing simplifies the process overall. In addition, the estimation procedure is significantly more resilient than before, even with only a partial understanding of the noise involved.

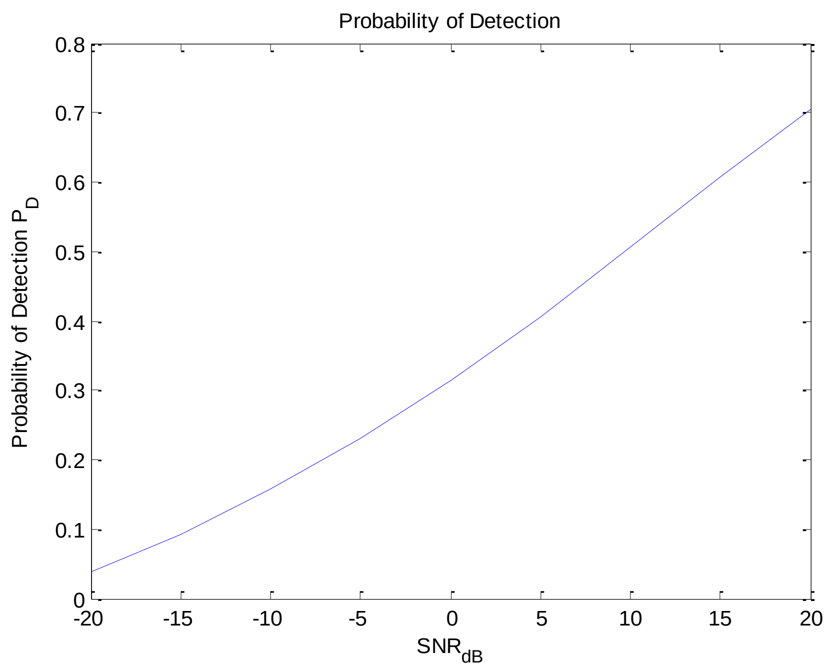

Figure 5. Probability of detection v/s SNR

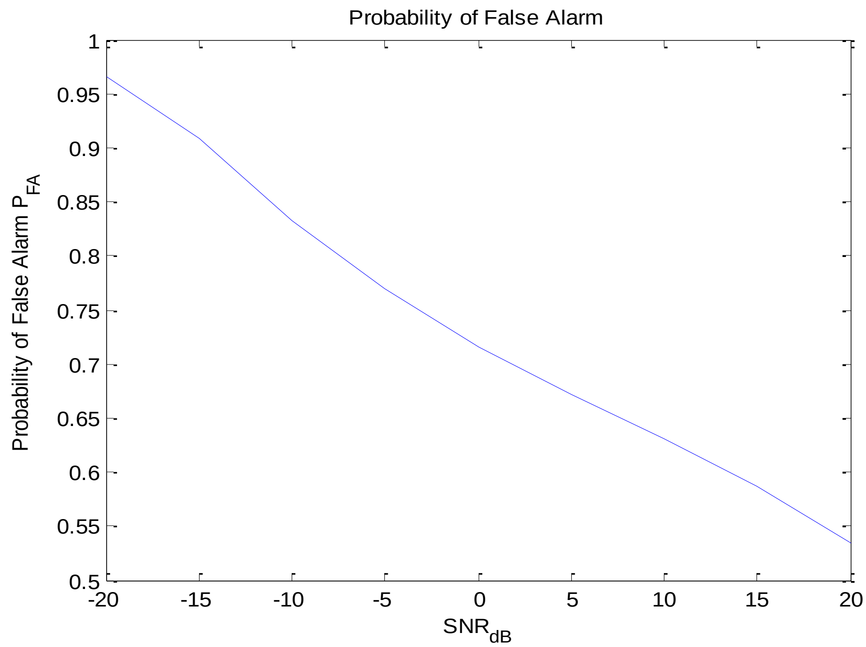

Figure 6. Probability of false alarm v/s SNR

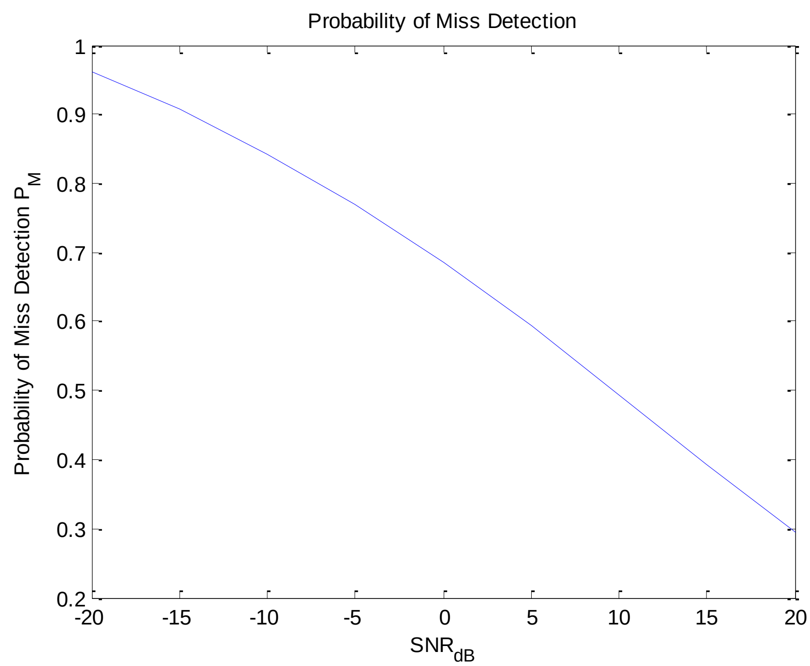

Figure 7. Probability of Miss detection v/s SNR

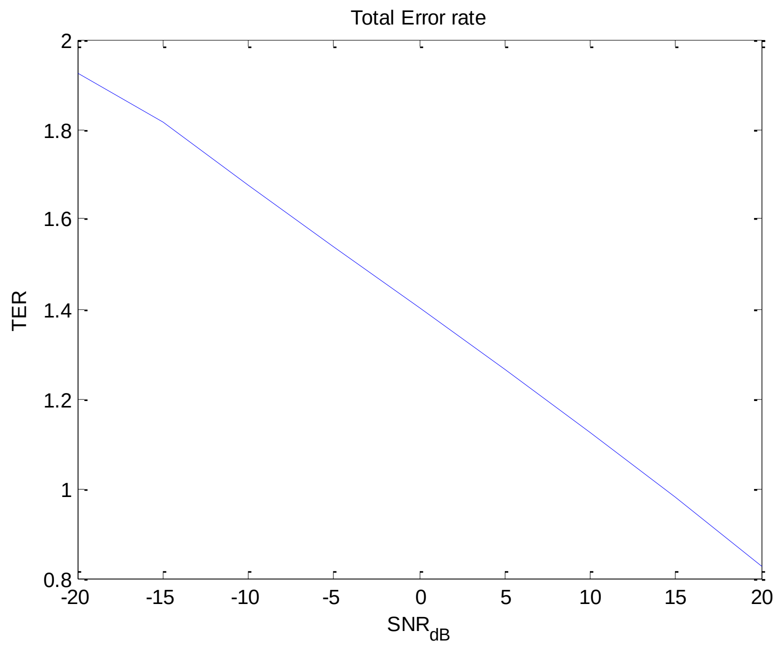

Figure 8. Total Error Rate (TER)

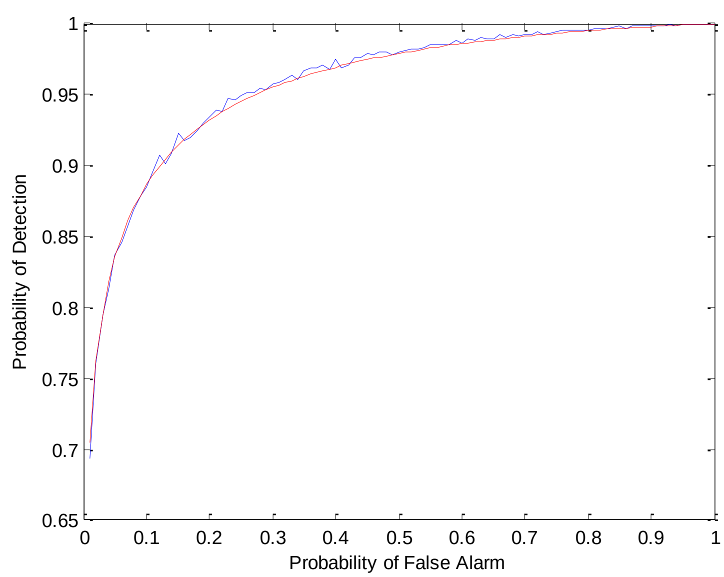

Figure 9. Receiver operating characteristics (ROC) Curve (Desired(red) and actual(blue))

The cognition's variability is depicted in Figure 5-9 in terms of detection probability, false alarm probability, misdetection probability, and the Receiver operating curve. The impact of noise on performance is depicted graphically through a range of graphs that show how different attributes shift in proportion to SNR.

VII. Conclusion

This research suggests Bayesian RVM with Variation using wavelet transform-based spectrum hole detection and compressive-sampling-based wideband spectrum sensing For the cognitive radio network. Here, opportunistic spectrum distribution between PU and SU over the wideband is executed, with enhanced noise robustness. RVM Compressive Sampling significantly reduced the sample size, which improved computational complexity performance, because the signals were sparse. Compressive sensing has leveraged the Bayesian foundation to speed up detection while simultaneously dealing with uncertainty. Compressive sensing's dependence on previous knowledge has also been minimized thanks to the Bayesian method. In terms of TER, ROC curve of cognitive radio, covariance, recovery error, and recovery time, the simulation analysis demonstrates the effective performance of the proposed technique.

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