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A Novel Technique for Bayesian Compressive Sensing in Cognitive Radio Networks

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ABSTRACT: Compressive sensing has been proposed in spectrum sensing to velocity up the radio spectrum scanning and limit the hardware cost. Existing compressive sensing methods go through from uncertainty due to random measurements as nicely as low effectivity in convalescing signals. In this Paper, we advise a technique, particularly Bayesian compressive sensing with Circulant matrix sampling for quick and environment friendly compressive sensing. In addition, our model requires less measurements, much less sampling time, much less healing time, and much less processing time. It additionally allows estimating the unique sign with low sparsity level, excessive correlation, minimizes the mean square error, and handles the uncertainty in the course of the encoding and decoding processes.

KEYWORDS: Compressive Sensing, Cognitive Radio, CS reconstruction, CS Application, Nyquist sampling rate etc.

I. INTRODUCTION

Wireless networks and data site visitors have grown exponentially over the final decade, which resulted in an immoderate demand for the radio spectrum assets [1][2]. The radio spectrum is a confined aid managed by means of guidelines and the diagnosed authorities, such as the national agency for the legalization of communications (ANRT) in Morocco and the federal communications fee (FCC) in the US. The contemporary radio spectrum allocation policy consists of assigning the channels to precise customers with licenses for unique wireless technologies and services. Those licensed customers have get admission to to that spectrum parts to transmit their data, whilst others are forbidden even when the spectrum is unoccupied [3].

Recent research suggested that the spectrum utilization tiers from 15% to 85% in the US under the constant spectrum allocation (FSA) coverage [4]. FCC measurements additionally exhibit that some channels are closely used whilst others are carefully used Allocated spectrum parts are now not used all the time through their owners, known as foremost users (PUs), which creates spectrum holes. A spectrum hole, additionally known as white space, is a frequency band assigned to a PU however it is no longer being used at a specific time and at a specific location. Therefore, the radio spectrum is inefficiently exploited [8,9]. Thus, the shortage and inefficiency of the spectrum administration require an pressing intervention to decorate the radio spectrum access and reap excessive community performance. A higher way to overcome the spectrum scarcity issue is to dynamically control it by using sharing unoccupied channels with unlicensed users, called secondary customers (SUs), except interfering with the PUs signals. The opportunistic spectrum access (OSA), additionally known as dynamic spectrum get entry to (DSA), has been proposed to tackle the spectrum allocation problems. In distinction to the FSA, DSA permits the spectrum to be shared between licensed and non-licensed users, in which the spectrum is divided into numerous bandwidths assigned to one or greater committed customers [10,11].

II. RELATED WORK

Compressive sensing involves three main processes: sparse representation, encoding, and decoding. In the first process, a signal, x , is projected in a sparse basis. In the second process, x is multiplied by a sampling matrix, M_c , of $M \times N$ elements to extract M samples from N of the signal where $M \ll N$. In the last process, x is recovered from few M measurements. A variety of sampling matrices have been proposed in the literature, inclusive of random matrix [16], Circulant matrix [17], Toeplitz matrix [18], and deterministic matrix [19]. Because of their simplicity, extra hobby has

been paid to random matrices. These matrices are randomly generated with unbiased and identically dispensed factors such as Gaussian and Bernoulli distributions [16,17]. Random matrices fulfill the hinder isometry property for small RIC [15,16]. However, these matrices require an extraordinary deal of processing time and excessive reminiscence capability to shop the matrix coefficients [18]. Because of the randomness, the outcomes are uncertain, which makes the sign reconstruction inefficient. Unlike random matrices, Circulant matrices are efficient, speedy in phrases of sign acquisition, require fewer measurements to perform, and much less time to procedure [17].

A Circulant matrix is a structured matrix related and decided the usage of a predefined vector by means of cyclic permutation [18]. It satisfies the hinder isometry property for a small wide variety of measurements [12]. Unlike random matrices, Circulant matrices are no longer universal. They have been used solely with the L1 Enorm minimization approach [15-18]. Unlike random matrices, Circulant matrices are efficient, speedy in phrases of sign acquisition, require fewer measurements to perform, and require much less time to process.

A variety of algorithms that make the most the sparsity characteristic have been proposed in the literature for sign recuperation [13,20]. A sparse sign can be estimated from a few measurements via fixing the underdetermined machine the usage of exclusive recuperation algorithms. The iterative leisure methods resolve the underdetermined gadget the use of linear programming. They are greater correct in contrast to Greedy algorithms, however they are complex, uncertain, require excessive measurements, and, consequently excessive processing time [15,21,22]. Greedy algorithms consist of deciding on a neighborhood best at every step in order to locate the international optimum, which corresponds to the estimated sign coefficient. They are fast; however, they are inefficient, uncertain, and require extra measurements for the healing method [14]. Bayesian compressive sensing algorithms consist of the use of a Bayesian mannequin to estimate the unknown parameters in order to deal with uncertainty in measurements. They are fast, accurate, require few measurements for a excessive healing rate, and can deal with uncertainty [20]. They mix the strengths of the different two categories. Indeed, these methods have been used solely with random matrices. Therefore, we advise to combines the strengths of each Circulant matrices and Bayesian fashions to tackle the in the past cited troubles throughout the encoding and decoding techniques for speedy and environment friendly compressive sensing [13].

III. PROPOSED METHODOLOGY

Bayesian Compressive Sensing

Fig 1 represents the proposed approach. For sparsity representation process, we assume the signal to be sparse because of the underutilization of the spectrum. For the sensing matrix process, we adopt Circulant matrix. For the recovery process, we adopt the Bayesian recovery.

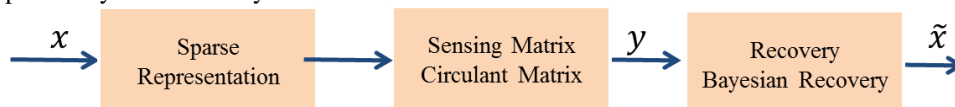


Fig 1: Block diagram of compressive sensing model [13].

A vector, c , is given as $(c_0, c_1, \dots, c_{N-1})$. The Circulant matrix, C , is generated from c , where $i, j = 0 \dots N$. It can be expressed as:

$$C = \begin{bmatrix} c_0 & c_1 & \dots & \dots & c_{N-1} \\ c_{N-1} & c_0 & c_1 & \dots & c_{N-2} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ c_1 & c_2 & \dots & c_{N-1} & c_0 \end{bmatrix}$$

where c is a vector given $c_0, c_1, \dots, c_{N-1}$. The values of c are chosen randomly according to a suitable probability distribution to reduce the amount of randomness of the sensing matrix compared to random matrices [18]. During the encoding process, each column of the matrix C is obtained by right cyclic shifting the previous column. Then, a $M \times N$ partial Circulant matrix, M_c , is defined as the sub-matrix of C and considered for the signal sampling, where $M \ll N$. The signal, S , is then multiplied by M_c for signal compression. This multiplication is fast because of the reduced number of random coefficients in the Circulant matrix [17][18].

Under the Bayesian recovery, the k -sparse signal is acquired through a product with the Circulant matrix. A noise, w , is added to the signal measurements, which includes the noise measurements and the sparse representation error. Fig 2 illustrates the simulation methodology of our proposed model.

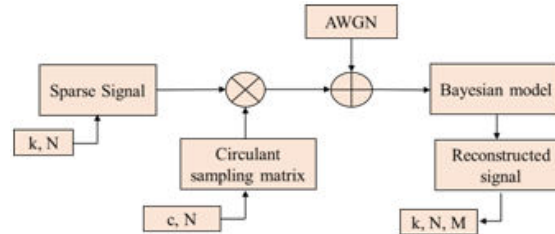


Fig 2: The model of the Bayesian compressive sensing with Circulant matrix [13].

The noisy measurements can be formulated as:

$$y = M_c x + w \quad (1)$$

According to the theorem of central limit for $N \gg M$, W can be approximated as a zero mean Gaussian noise with unknown variance δ_w , which can be expressed as $N(0, \delta_w)$. The signal to be approximated can be considered as a Gaussian variable with $x = (x_1, x_2, \dots, x_N)$. Therefore, the Bayesian model implies that the noisy measurements, y , is an i.i.d Gaussian and depends on the unknown S and δ_w , which is given by

$$y | x \sim N(x, \delta_w) \quad (2)$$

The proposed Bayesian model in which the unknown signal, noise, and vector to generate the Circulant sampling matrix are parents of the noisy measurements. Noise variance δ_w , signal mean μ_s , and signal variance δ_s are the unknown parameters to estimate.

IV. SIMULATION AND RESULTS

In order to evaluate the efficiency of our model, its results have been compared to the results of the basis pursuit technique [19] using several metrics. These metrics are: mean square error, reconstruction error, correlation coefficients, processing time, recovery time, and sampling time. The reconstruction error, R_e , is a metric that calculates the norm of the difference between the expected signal, $\tilde{x}$, and the original signal, x , divided by the norm of the original signal. It is expressed as:

$$R_e = \frac{\|\tilde{x} - x\|}{\|x\|} \quad (3)$$

Mean square error ($\tilde{MSE}$) is a metric that measures the average magnitude of the squared difference between the reconstructed signal and the original signal. It corresponds to one of the loss functions used for error estimation. It is given by

$$MSE = \frac{1}{N} \sum_N (x - \tilde{x})^2 \quad (4)$$

It has the same measurement unit as the data being estimated. It is utilized for predictive modeling in order to analyze the variation in the error in the reconstruction algorithm for multiple times. Correlation measures the similarity between the original signal, x , and the reconstructed signal, $\tilde{x}$, to measure how similar they are. The measure of correlation is known as correlation coefficient, C_c , which is a scalar quantity. It can take values between -1 and 1. It is expressed as:

$$C_c = \frac{N \sum (x\tilde{x}) - (\sum x)(\sum \tilde{x})}{\sqrt{N(\sum x^2) - (\sum x)^2} \sqrt{N(\sum \tilde{x}^2) - (\sum \tilde{x})^2}} \quad (5)$$

When C_c is positive and less than 1, it implies that the two signals are positively correlated and the strength of the correlation is expressed as a percentage value. When C_c is null, it implies there is no relationship between the two signals. When C_c is negative and greater than -1, it implies that the two signals are negatively correlated and the strength of the correlation is expressed as a percentage value.

Recovery time, t_r , is the time required by the recovery process to reconstruct the signal. It allows defining the fastest reconstruction technique. Sampling time, t_s , is the time required by the sampling matrix process in order to compress

the signal using a specific matrix. It allows defining the fastest sampling matrix technique. Finally, the processing time, t_p , is the time required to perform all compressive sensing processes.

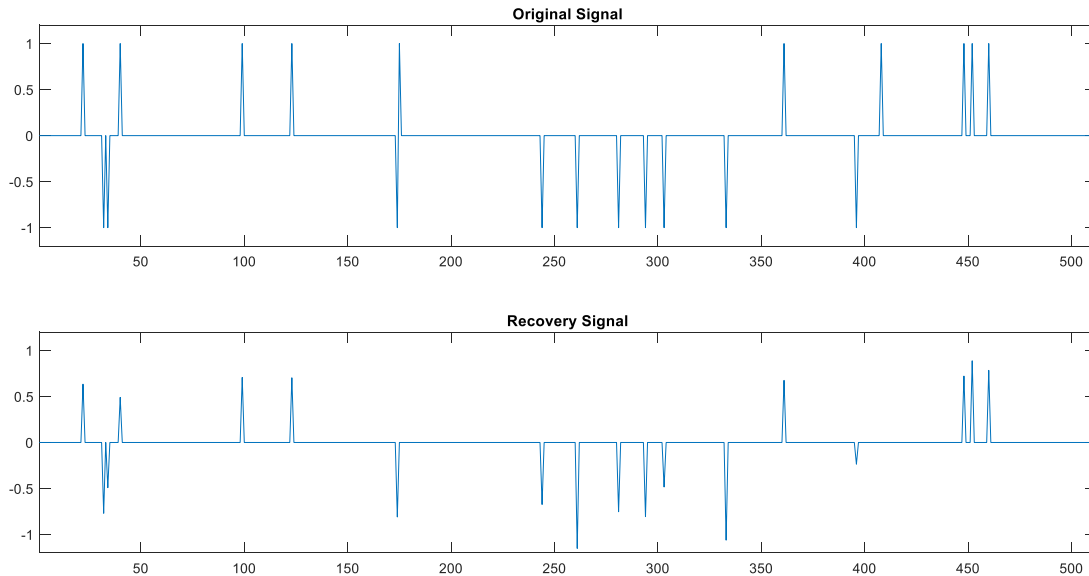


Fig 3 Original and Recover Signal

Bayesian approach has an common of 0.77% of healing error. However, groundwork pursuit has 6.7% of healing error. Thus, Bayesian is eighty instances extra particular than basis pursuit with the identical matrix. Unlike foundation pursuit, Bayesian approach allows to recover the sign with a very small blunders number, which can be defined with the aid of the truth that it is capable to deal with the uncertainty. Basis pursuit recovers the sign with excessive error level, which can be explained with the aid of the truth that it can't take care of uncertainty due to noisy measurements.

Fig 4 shows that for the correlation metric, Bayesian method gives an common of 100% of correlation whilst foundation pursuit approach offers an common of 82.87%. Thus, both techniques current high correlation with values shut to 100%, which shows that the two signals are positively correlated. However, Bayesian method affords higher correlation. For t_r , Bayesian method requires an common of 0.90 ms to get better the authentic signal, however basis pursuit requires 7.20 ms, which represents 12 instances higher, accordingly slower, than Bayesian technique. For t_p , Bayesian approach requires an common of 0.96 ms to manner whilst groundwork pursuit requires an common of 7.26 ms. Thus, Bayesian is 7 instances quicker than groundwork pursuit.

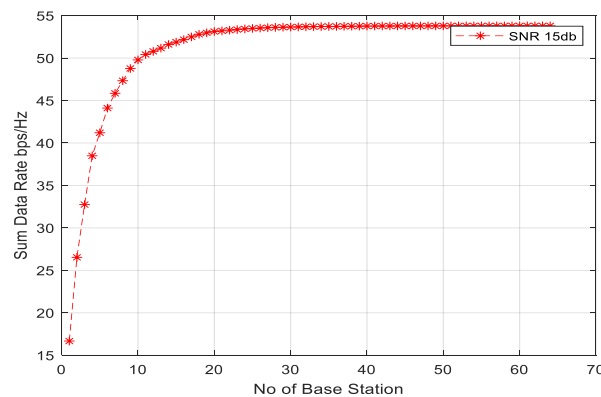


Fig 4 Sum Data Rate Vs No of Base Stations

Fig shows that for the correlation metric, Bayesian approach provides an common of 100% of correlation whilst groundwork pursuit approach affords an common of 82.87%. Thus, both techniques current excessive correlation with values shut to 100%, which shows that the two signals are positively correlated. However, Bayesian approach provides higher correlation.

For t_r , Bayesian approach requires an common of 0.90 ms to get better the unique signal, however basis pursuit requires 7.20 ms, which represents 12 instances higher, for that reason slower, than Bayesian technique. For t_p , Bayesian approach requires an common of 0.96 ms to method whilst groundwork pursuit requires an common of 7.26 ms. Thus, Bayesian is 7 times quicker than foundation pursuit.

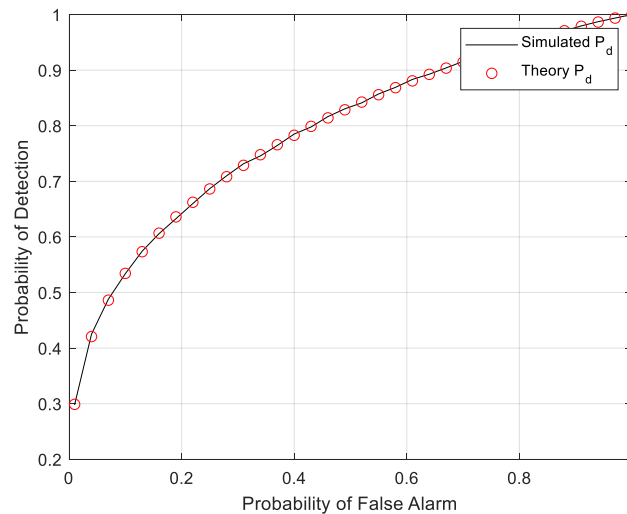


Fig 5 Probability of Detection Vs Probability of False Alarm Rate

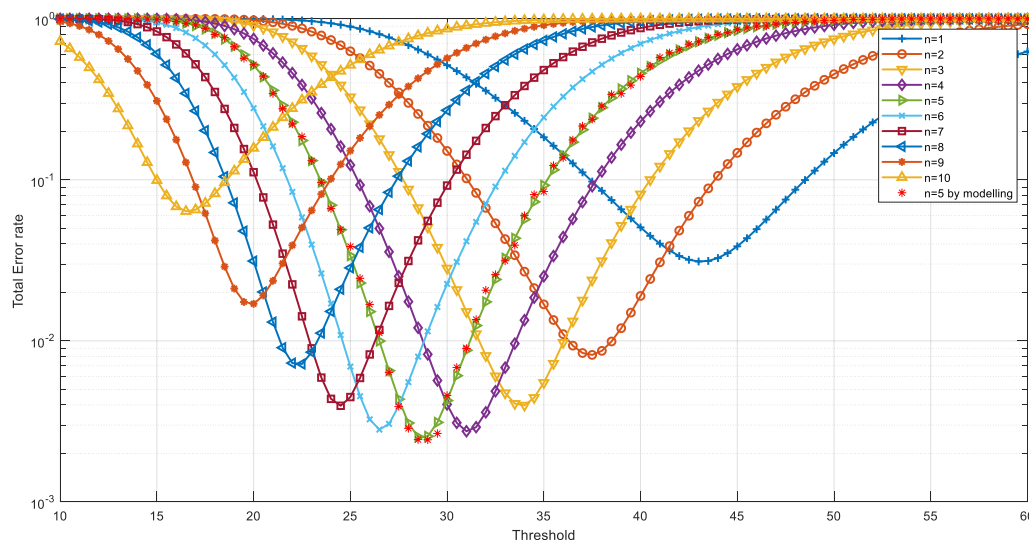


Fig 6 Error Rate Vs Threshold

Results exhibit that the Bayesian approach with Circulant matrix is more accurate, faster, and offers with the uncertainty. Thus, our proposed method consists of the strengths of each Bayesian reconstruction and Circulant sampling matrix.

V. CONCLUSION

We have proposed a compressive sensing method that combines Circulant sampling matrix with Bayesian model. This method reduces the randomness and offers with uncertainty at some point of the compressive sensing processes. It additionally speeds up the scanning of the radio spectrum in cognitive radio networks. Its outcomes are mentioned and in contrast to these it pursuit with Circulant and random matrix techniques. The overall performance contrast involves several metrics together with restoration success, speed, robustness, efficiency, memory, and certainty. The consequences exhibit that Bayesian algorithm with Circulant matrix is extra environment friendly and quicker in



compressing and improving alerts than Bayesian with random matrix as nicely as groundwork pursuit with both Circulant or random matrices.

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