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A Simplified Compressive Sampling Approach based on Weights for Efficient Spectrum usage in Wideband DSA Networks

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***Abstract*—The comprehensive compressive sampling method is indeed a path breaking approach in the field of wideband DSA networks. The block samples of cognitive radio spectrum used for intelligent spectrum allocation based on respective block weights. Reconstruction of the available spectrum is the designating factor of compressive sampling and which acts as the backbone of the cognitive radio architecture. The wideband spectrum sensing is the trending research area in the field of communication. A significant amount of research work has been done in the past decade which enables the wideband spectrum recovery by utilizing the comprehensive compressive sampling at sub-Nyquist rates. In practical, the wideband spectrum is not heterogeneous as each band has its occupancy pattern and, the applications with criteria's often allocate the same bock spectrum and, this development makes the wideband spectrum as heterogeneous. As discussed, in our proposed method, the core idea is taking the wideband spectrum as the heterogeneous which helps to exploit the block like structures and, these structures helps to design the effective compressive spectrum sensing methods that are well accommodated for heterogeneous wideband spectrum. The recovery spectrum by the weighted based recovery algorithm is more stable and robust when compared to the conventional algorithms. The recovery spectrum by the weighted based recovery algorithm is more stable and robust when compared to the conventional algorithms. The proposed method is profound to show variations in the occupancy both in terms of time and frequency dimensions. Finally, the biggest and the significant achievement of this paper is recovering the unused frequencies smaller number of sensing measurements when compared to the traditional state of art methods.**

***Index Terms*— Wideband spectrum, Sensing matrix, Recovery algorithm, Block like structures, Analysis of the Mean Square Error PU Traffic Characterization.**

I. Introduction

Radio frequency (RF) spectrum is an undoubtedly valuable resource used for communication. It is closely monitored and regulated by various high profile regulation agencies and standards for being the most valuable resource of the 21st century. The modern wireless communications rely on this source to support high prolific wireless services around the globe [1]. The RF spectrum is now facing the scarcity issue due to the excessive use and, the noted international telecommunication agencies like Federal Communications

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Commission (FCC) and International telecom union (ITU) are busy in developing the new policies which allow the secondary users to use the unused primary user's bandwidth. The cognitive radio is the tending technology came up with unique bandwidth recovery and reuse theory which makes it popular technology in short span of time [2]. The cognitive radio architecture has the adaptability to detect the RF in an intelligent fashion and, the same is used to meet the user's demands. It allows the secondary users (SU) to use the spectrum allocated to the primary user (PU) without affecting the primary user in any way.

Unlike these previous works and as motivated by the block-like wideband spectrum sparsity structure, our proposed framework considers time-varying and heterogeneous wideband spectrum occupancy [3]. We exploit this fine-grained sparsity structure to propose, which to the best of our knowledge, the first spectrum sensing information recovery scheme for heterogeneous wideband spectrum sensing with noisy measurements. We want to emphasize that the use of spectrum recovery methods as the approach for locating spectrum vacancies has benefits over the use of detection methods ([4]). They, for instance, allow us to determine not only whether there is a signal or not in the wideband, but also which band(s) this signal is occupying. Also, they help to identify the type of signals/devices operating in such bands, a capability of great importance to dynamic spectrum sharing [5]. This work focuses on spectrum recovery methods.

The remainder of the paper is structured as follows.

In Section II, Background, Literature survey in Section III. The proposed methodology is then presented in Section IV. Finally, the results and analysis in section 5 and our conclusions are given in Section V.

II. BACKGROUND

A. Wideband Spectrum Sensing

The narrowband techniques don't have the ability to sense the bandwidth frequencies which exceeds the channel bandwidth [8]. In contrast to it, the wideband spectrum poses the ability to sense the exceeding frequencies with stimulating efficiency and, later on, it is used for spectrum allocation. The modern generation applications such as ultra-high frequency (UHF) TV will operate by exploiting the spectral opportunities and, it is done flawlessly by wideband spectrum and its allocation design. The narrowband spectrum operates based on a single binary decision for the total spectrum, thus making it unable to detect the individual spectral bands as wideband [18].

The classification of the wideband spectrum classified into two types is done based on the-Nyquist rate as below,

Nyquist wideband sensing

It will process the digital signal which lies on or above the Nyquist rate

Sub-Nyquist wideband sensing

It will use the signal which lies the below the Nyquist rate.

B. Adaptive Wideband Spectrum Sensing

The sub-Nyquist wideband sensing systems have the N number of measurements which will vary once the sparsity level of the wideband signal varies [15]. Therefore, in cognitive radio networks, the number of measurements selected is chosen with utter care. However, the wideband spectrum signal sensing is a challenging task in practice and this uncertainty forces the system to select the appropriate number of measurements.

III. EXISTING WORKS

The spectrum scarcity leads to many unexplained issues and a lot of research has been carried out in the last one decade and N number of research works has proposed by high profile authors. The CR and its ability to reuse the unused spectrum is the key factor and the research work will give a glimpse of the previous works with respect to the key terms as follows [11].

Previous works based on key terms
Spectrum Sensing The cognitive radio networks have diversified spectrum and, its spectrum sensing is initially defined the **Haykin et al., 2009; Tomar et al., 2017 [10]**. They made this detection while detecting the hole and interference in the signal transmission and this

breakthrough helps the further experiments to be done with great accuracy. With this definite fashion of spectrum sensing the CR's can able to serve the interference-free bandwidth to it users. The cost of this approach is low and it is an encouraging factor for the future and won't be any modifications done in the primary systems. **Sun et al., 2013; Lundén et al., 2015** brings this cost-effective method in a theoretical way and it is considered as the stepping stone in CR networks [9].
Channel uncertainty When a signal is transmitted from the Tx to the Rx, then it has to pass through the various obstacles and which makes the channel weak and it results in the channel fading. Due to the channel fading the signal loses its strength and the weak signal will receive at the receiver end and it was proposed by (**Haykin et al., 2009**).
Noise uncertainty The minimum signal to noise ratio (SNR) at the primary signal boosts the system performance and its robustness in an unprecedented way. (**Rawat et al., 2010**) [14] has proposed the signal uncertainty years ago and they made it clear that the noise uncertainty will be low if the received signal will receive in a good manner and vice Versa.
Awareness, adaptability, reliability **(Fette, 2004**) [17] proposed the cognitive radio advantages in detail. They highlight the awareness factor at first, the CR is well aware of the environment in which it is going to operate. The second factor is adaptability; irrespective of the situation the CR has the tendency to adapt itself in a efficient way to give the best outcome as result.

IV. PROPOSED METHODOLOGY

The design of the comprehensive compressive sensing approach has two challenging components to address as the sensing matrix and recovery algorithm. The sensing matrix is popular in reducing the measurements which in turn reduce the time and, the recovery algorithm maintains the stability and robustness in the system. The previous works have similar algorithms like recover algorithm, but the proposed recovery algorithm outperforms them in following factors,

a) Minimizing the recovery error rate for attaining more stability and robustness
b) The number of measurements is reduced drastically using the sensing matrix which eventually increase the system performance.

The following subsections present the proposed method and its performance. The parameters such as mean square errors and its measurements give the experimental numbers which prove the superiority of the proposed methodology over the existing works [7].

A. The Proposed Framework

The spectrum allocation and the spectrum recovery are two different concepts which are interlinked to each other. The spectrum allocation can be done based on the licensing process, but once the spectrum is allocated to the clients and the users, it becomes a challenging task to identify the unused spectrum [19]. The spectrum recovery process is a quite expensive task and, it needs high-level detection algorithms to detect the null spectrum availability in the wideband spectrum. The location identification of the unused spectrum remains a challenging task even after identifying the unused spectrum availability in the wideband spectrum. Finally, the identification of the type of signals occupied the spectrum is mandatory to justify whether the unused spectrum is useful for DSA applications or not. The spectrum users are classified as primary users and the secondary users. The primary users are licensed users who buy the spectrum while the secondary users use the received signal frequency domain by using the recovery signal algorithm. The ideal recovery of the spectrum is only possible by minimizing the norm of the signal using the efficient normalization algorithms. The sparsest solution for the l normalization is notated as follows

$$\mathcal{P}_1 : \begin{array}{c} \text{mimimizex} \|x\|_{l_1} \\ \text{subject to } \|Ax - y\|_{l_2 \leq \epsilon} \end{array} \quad (1)$$

The above notation has the Epsilon which is a user-defined parameter and, the above formulation is technically known as Least Absolute Shrinkage and Selection Operator (LASSO). The proposed algorithm uses the LASSO formulation to achieve excellent performance in recovering the spectrum from the wideband spectrum using the recovery sensing algorithm.

B. The Recovery Algorithm (Stability)

The core idea of the proposed method is to implement the intelligent search solution for identifying the unused spectrum in the wideband and, this approach encourages the search of non-zero elements with higher average sparsity levels. The core idea mainly focuses on the variability of sparsity levels for different spectrum levels with notable blocks the incorporation and the exploitation of these levels are accomplished by the intelligent search approach. The incorporation process of the block sparsity levels in the formulation is done by using the carefully selected weights and, its notation is as follows

$$\mathcal{P}_{1}^{\omega}{}_{1}: \text{mimimizex} \sum_{l=1}^{g} \omega_l \|x\|_{l_1} \quad (2)$$
$$\text{subject to } \|Ax - y\|_{l_2 \leq \epsilon}$$

The below parameters and factors are used in the above notation,

ω- This parameter represents of block weight.

x- It represents the samples, initiating from x_1^T and end at x_l^T

The crucial thing in the implementation of the proposed methodology is to the selection of the weights based on the system design. If the average sparsity level of a block is high then, it shows that the respective block is occupied to its fullest extent. The proposed methodology explains the weights concept by considering the two different blocks namely k1 and k2 with respective weights. The weights of the blocks are inversely proportional to the average sparsity levels as follows

$$\omega_i = \frac{1/\overline{k_i}}{\sum_{j=1}^{g} 1/\overline{k_j}} \quad \forall i \in \{1, \dots, g\} \quad (3)$$

Note1 (The acumen (insights) of the proposed methodology)

The two-block approach for spectrum k1 & k2 with their respective weights are taken into consideration. The recovery algorithm acts in a different way to minimize the normalization weights and to eliminate the denser parts.

Note2 (Weights design)

The weights are designed based on various parameters to improve the spectrum recovery accuracy from the specified blocks. The weights design can be attained by calculating the average occupancy of each block during the certain specified amount of duration. In overall, the whole wideband spectrum is considered as one block to complete the process in less time for increasing the efficiency and the performance.

C. Analysis of the Mean Square Error (MSE)

Although the simulation results attained by the proposed method is same as LASSO method in all segments excluding the error rates. The proposed method tends to incur lesser errors than its preceding algorithms [18] including the LASSO.

Theorem 1

The following mathematical equations show the optimal solution with a probability exceeding. The optimal solution is as follows

$$\|x^{\#} - x_0\|l_2 \leq \|x^{\dagger} - x_0\|l_2$$

and, the probability which is exceeding is notated as follows

$$1 - \sum_{i=1}^{g-1} \sum_{j=i+1}^{g} \sum_{k=1}^{\min(n_i, n_j)} \sum_{l=0}^{k-1} \binom{n_i}{l} q_i^l (1 - q_i)^{n_i - l} \binom{n_j}{k} q_j^k (1 - q_j)^{n_j - k} \quad (4)$$

Definition for stability and robustness

The recovery algorithm specified to recover the unused allocated spectrum with accuracy and, the recovered spectrum should be stable and as well as robust as shown in following notation,

$$||\Delta y - x||_{l_2} \le C_0 \in + C_1 \frac{\sigma_{k(x,||.||} l_p)}{\sqrt{k}} \quad (5)$$

The stability is related to small perturbations of the received signal and, the robustness depends upon noise relativity. The less noise will reflect the most robustness and vice versa.

Time-Variability and its effect

The core idea of the proposed method is to outperform the existing methods [8] performance on an average, not on a stepwise basis. The proposed method uses blocks with higher average sparsity levels with much lesser weights than existing ones. This is the profound reason behind the fact of attaining average performance but better than the existing.

D. Required Measurements and PU Traffic Characterization

Required Measurements

The sensing matrix of the proposed methodology will reduce the number of ample measurements and, the satisfying the Restricted Isometry Property (RIP). The equations of the Restricted Isometry Property (RIP) and the measurements (lesser than the existing methods are as follows,

$$1 - \delta_k ||x||_{l_2}^2 \le ||Ax||_{l_2}^2 \le (1 + \delta_k) ||x||_{l_2}^2 \quad (6)$$

The sensing matrix will reduce the number of measurements significantly as follows,

$$m \ge \frac{1}{2\log \frac{\sum_{i=1}^{g} \sqrt{2k_i(1+\delta_{ki}) + \max_i \sqrt{k_i(1-\delta_{ki}/8)}}}{\min_i \sqrt{k_i(1-\delta_{ki}/8)}}} \bar{k} \log \frac{n}{\bar{k}} \quad (7)$$

PU Traffic Characterization

The spectrum allocation leads to the occupancy of the bands in the wideband and it has its definite probability mass function and, its mathematical notation is as follows

$$p_r(X = k) = \sum_{\Lambda \epsilon S_k} \left[\prod_{i \epsilon \Lambda} P_i \right] \left[\prod_{J \epsilon \Lambda^c} (1 - P_i) \right] \quad (8)$$

The probability mass distribution denotes the number of occupied bands in the blocks and, it is denoted by lemma in the above equation.

V. Results and Analysis

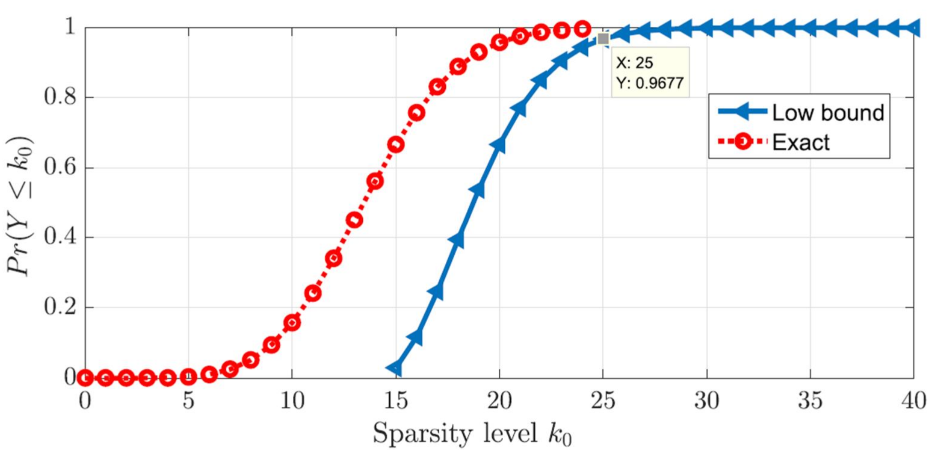

Figure 1: The lower bound of sparsity level k0

Analysis

The above figure represents the low bound and the exact sparsity levels of K0, where the red color show the exact and the blue color represent the low bound. The less number of measurements means the less the block occupied.

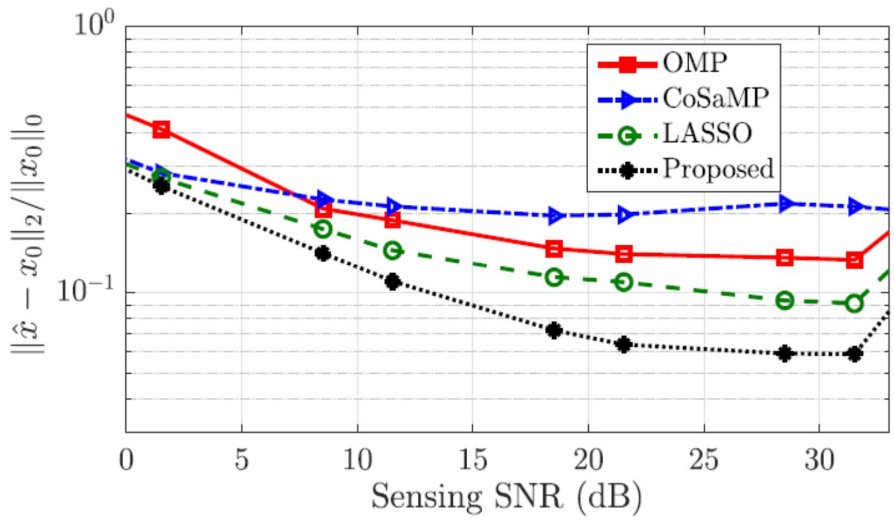

Figure 2: Comparison between the proposed and the existing works for function of the sensing

Analysis

The proposed method which is indicated by the black color has the better efficiency when we compare with its preceding methodologies which are indicating by various colors. The LASSO [13] has goo deficiency but fails to maintain the robustness which is achieved in this method.

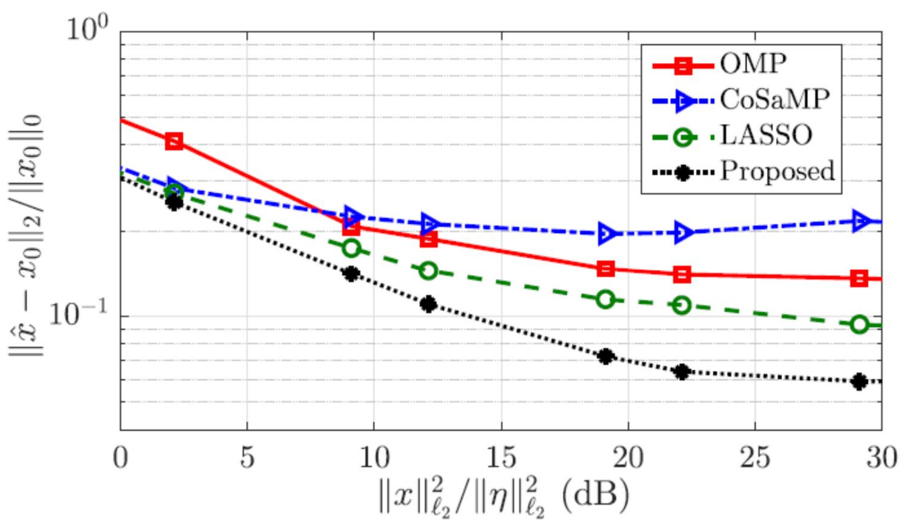

Figure 3: Comparison between the proposed and the existing works for function of received signal

Analysis

The proposed method which is indicated by the black color has the better performance when we compare with its previous methodologies which are indicating by red, green and blue colors. The LASSO [13] has goo deficiency but fails to maintain the robustness which is achieved in this method and it is for the received signal received at the other part of the communication.

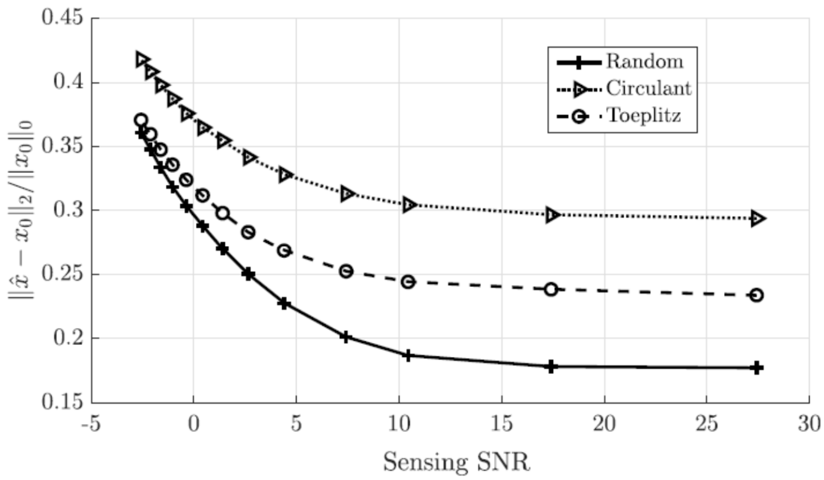

Figure 4: MSE for various sensing metrics

Analysis

The errors are less in number when compared to the existing works. The MSE [16] Parameter is used to get the desired performance and the graph indicates that various metrics has their own resultants.

VI. Conclusion

The cognitive radio architecture is known for its ability for reorganizing the allocated spectrum to secondary users by utilizing the compressive sampling sensing algorithm. This mechanism acts based on the block weights and, the intelligent allocation mechanism based on a recovery algorithm has a tendency to recover the unused spectrum with accuracy. Wideband spectrum allocation has the heterogeneous nature and it is well handled by using the compressive sensing algorithm. The comprehensive compressive sensing is key core element in the proposed method and its utilization makes the mark in the wideband spectrum and its sensing. The proposed method attains better results the LASSO method which is considered as the best method in the spectrum utilization. The main difference between the previous methods and the proposed methodology is using the less measurements which eventually increase the performance and best recovery algorithms which take less time to accomplish the process. The proposed method key achievements are lower mean square errors, enabling higher detection probability which keeps it best in the DSA networks.

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