# An Efficient Greedy Algorithm for Wideband Spectrum Sensing for Cognitive Radio Networks

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***Abstract*—In Cognitive Radio Networks (CRNs), secondary users (unlicensed users) can use spectrum when their transmissions cause no interference to primary users (licensed users). The spectrum sensing is a necessity to achieve this spectrum sharing scheme. However, it is challenging to achieve wideband spectrum sensing due to the computational complexity. In this paper, we propose a novel greedy algorithm to solve the wideband spectrum compressive sensing problem. The main idea of our algorithm is to reconstruct spectrum for wideband signals without any prior knowledge of spectrum. The proposed greedy algorithm will reconstruct wideband spectrum along with sub-bands of frequency in which spectrum is divided. The proposed greedy algorithm can sense the range of each sub-band of frequency efficiently without any apriori information. Extensive simulation results show that our proposed algorithm outperforms existing greedy algorithms such as Orthogonal Matching Pursuit (OMP) in terms of accuracy and computational speed, Block OMP in terms of computational speed.**

## I. Introduction

Cognitive Radio Networks (CRNs) are predominantly proposed to solve issues regarding spectrum efficiency. The Cognitive Radio may reduce the quality of service due to interfering with primary users. It can also detect weak primary users and sense the availability of spectrum for secondary users with knowledge of presence and absence of primary users. This can be done by utilizing the spectrum in opportunistic fashion through which Cognitive Radio enable secondary users to search available spectrum for transmission without causing any disturbance in transmission of primary users. Due to high demand for data transmission and increasing number of users, different and more efficient spectrum management approaches are needed to be developed to solve the challenges in spectrum sensing and spectrum sharing. Spectrum sensing techniques are used to detect the spectrum holes for data transmission of secondary users without interfering primary users data transmission [1]. The frequency bands allocated to primary users for data transmission are called spectrum holes. The spectrum sensing techniques can improve transmission of both primary and secondary users by allocating spectrum dynamically. Therefore, Spectrum sensing is the most important technique in Cognitive Radio networks. Cognitive Radio has the ability to access sparse portion of spectrum and monitor the spectrum to make sure that Cognitive Radio cause no unexpected interference which depends on spectrum sensing. In this paper, Compressive spectrum sensing is used to access the sparsity in the given spectrum.There are numerous techniques and methods used for spectrum sensing e.g., Energy detector based sensing, Coherent based sensing, Cyclo-stationary based sensing, Matched filter detector based sensing and other hybrid techniques (that use two or more techniques at a time/ their hybrid version) [2].

There are various techniques proposed to sense and detect spectrum for narrowband spectrum and wideband spectrum. In this paper, only wideband spectrum sensing techniques have been discussed. Nowadays most of the transmission is based on wideband spectrum in terms of communication such as 5G. For narrowband spectrum sensing, many efficient and reliable techniques have already been proposed but in case of wideband spectrum sensing, there is a vast chance of improvement in sensing spectrum more efficiently and accurately in significant time without losing useful data.Numerous techniques and methods have been proposed in past decade to detect wideband spectrum. In this paper, Various Compressive sensing techniques are discussed to detect Wideband spectrum for Cognitive Radio Networks. To understand compressive sensing better, one can say that it is used to recover or reconstruct the sparse signal present in the spectrum. The core idea of compressive sensing is to sample analog signals at sub Nyquist sampling rate by exploiting the sparsity in the signals using a linear sampling process. To reconstruct/recover signal for spectrum using compressive sensing, there is a variety of methods proposed from last decade such as; Basic Pursuit (BP), Orthogonal Matching Pursuit (OMP) [3], Block Orthogonal Matching Pursuit (Block_OMP) [4], Least Absolute Shrinkage Operator (LASSO), Group Least Absolute Shrinkage Operator (G_LASSO) [5].

In this paper, we have recovered wideband spectrum through existing compressive sensing algorithms such as OMP, Block_OMP, compared these existing algorithms (OMP, Block_OMP) and proposed a novel greedy algorithm whose performance is better than OMP in both noiseless environment and noisy environment. Block_OMP still preforms the best because it has prior knowledge of sub bands of frequency in which spectrum is divided. To some extent, the proposed greedy algorithm is also better than Block_OMP in those cases where there is no prior knowledge of sub bands of frequency. We have experimented all of these algorithms by taking wideband spectrum and wideband signals into assumptions i.e, OFDM (Orthogonal Frequency Division Multiplexing) signals. The performance of all algorithms have been observed in ideal conditions as well as in noisy interference.

## II. Background and Existing Algorithms

For Wideband spectrum sensing, spectrum sensing has been facing plentiful challenges. The researchers from past few decades have been concentrating, primarily, on narrowband spectrum sensing for exploiting spectrum holes over narrowband frequency range. The wideband spectrum sensing can help to enact more clusters of information or more throughput by taking advantage of available wideband frequency range in spectrum as much as possible. For compressive spectrum sensing, Richard G. Baraniuk [6] first proposed that the signal acquisition based on compressive sensing is more efficient than traditional sampling for sparse/compress signals. In this paper, we have compared two existing sparse approaches: Orthogonal Matching Pursuit (OMP) [7], [8] and Block_Orthogonal Matching Pursuit (Block_OMP) [3]. In comparison, we have analyzed the results of both algorithms for reconstruction of signals. Furthermore, we have discussed their limitations and recovery conditions for wideband spectrum sensing and sparsity in ideal and noisy circumstances. We have proposed a novel greedy algorithm in comparison of previously described algorithms and compared the reconstructed signal from proposed greedy algorithm with existing algorithms.

### A. Orthogonal Matching Pursuit (OMP)

The orthonormal basis gets inclination over linear method, notably when input signals are compatible with the basis. Some other problems faced by this type of data which can deal with redundant systems are called dictionaries. The dictionaries are used for analyzing and representing complicated functions. The problems procreate from the redundant systems known as sparse approximation can be overcome by Orthogonal Matching Pursuit (OMP). For input signal, OMP can persuade sparse estimation containing error slightly worse than optimal error (which is obtained by same number of terms). OMP can get the common constraints from all optimal representation of non_sparse signal. Matching Pursuit (MP) also known as greedy algorithm, selects dictionary vector one by one according to the applications of compression, denoising and pattern recognition. MP selects iteratively one vector at a time for computing signal estimation from redundant dictionary. It contains a single adequate condition under which both OMP and Basic Pursuit (BP) can recover exactly same sparse signal. Matching Pursuit estimations are improved by orthogonalizing the direction of projection with techniques processed by numerous researchers in different time span. The outcome of OMP is very promising and beneficiary for convergence of finite number of iterations [7]. High dimensional sparse signal recovery is based on linear measurements that is possibly corrupted by noise and modeling error. We consider the following linear model for reconstruction of signal:

$$y = Ax + w \tag{1}$$

where $y \in \mathbb{R}^m$ is measurement vector, the sensing/measurement matrix is $A \in \mathbb{R}^{m*n}$, the signal is $x \in \mathbb{R}^n$ and $w \in \mathbb{R}^m$ is the measurement error. Let $A = (A_1, A_2, .........., A_m)$ such that $A_i$ is the $i^{th}$ column of matrix $A$. In this case, our assumption is that matrix $A$ is normalized, i.e., $||A_i||_2 = 1$ for all values of $i$. Our ambition is to reconstruct $x \in \mathbb{R}^n$from given values of $y$ and $A$. For a vector $x = (x_1, x_2, .........., x_m) \in \mathbb{R}^n$ , the support for $x$ is $|supp(x)| \leq k$. The sparsity of signal could measure by various methods such as Restricted Isometry Property (RIP), mutual coherence and exact recovery conditions. In this paper, we will reconstruct signal by keeping the mutual coherence limitations.

The OMP algorithm is forward selection algorithm advancing step by step and it is easy to implement. The stopping rule of OMP algorithm depends on set noise threshold. OMP analyzes the limitation of mutual coherence. Mutual coherence of matrix $A$ is defined as the maximum absolute value of cross correlations between column of matrix $A$, given in linear model equation. The mutual coherence property is :

$$\mu = \max_{i \neq j} |(A_i, A_j)| \tag{2}$$

### B. Block_ Orthogonal Matching Pursuit (Block_OMP)

Block OMP used block sparsity to improve the results and also to check the melioration as compared to OMP. Block_OMP is block version of OMP to recover auspiciously block sparse signal. The Block_OMP will also improve the recovery of signal through OMP in presence and absence of noise. In Block_OMP, it is our assumptions that the problems occur for recovery of block sparse signal whose non zero elements are fixed. Block sparse signal can be recovered or reconstructed through Basic Pursuit, LASSO and OMP. These algorithms could analyze through Restricted Isometry Property (RIP), Mutual Coherence and Exact Recovery Condition. Aside from this, recovery will be robust from noise and other errors e.g., modeling errors. Consider the problem of recovering a block sparse signal $x \in \mathbb{R}^n$ from noisy measurements, as linear equation:

$$y = Ax + w \tag{3}$$

where $A \in \mathbb{R}^{m*n}$ $(m \ll n)$ is the measurement matrix and $w$ is an arbitrary vector of errors. Let the number of rows in $A$ is multiple integer of $n$ where $m = Rd$ and $R$ is integer. Such conditions are assigned on dictionary $A$ that will recover the block sparse vector $x$ from the measurements of $y$ by computationally efficient algorithm [3]. To describe block sparsity, concatenate model $x$ of equal length blocks.

$$x = [\quad x_1^T \quad x_2^T \quad . \quad . \quad x_L^T]^T \tag{4}$$

In this paper, Block_ OMP will analyze through mutual coherence property. For Block_OMP, if $[x_L]$ has non zero Euclidean norm for $k$ indices $L$, the vector $x$ is known as block $k-sparse$. When $L = 1$, the block sparsity reduces to conventional sparsity. As in , the conventional coherence matrix of dictionary $A$ is:

$$\mu \triangleq \underset{i,j \neq i}{max} |a_i^T a_j| \tag{5}$$

where $a_i$represents $i^{th}$ column of given dictionary $A$. The conventional coherence matrix is not sufficient for block sparsity. To fully utilize block sparsity property, the block coherence $\mu_B$ and sub coherence $v$ are defined respectively as:

$$\mu_B \triangleq \underset{i,j \neq i}{max} \frac{1}{d} \rho |A_i^T A_j| \tag{6}$$

and

$$v \triangleq \underset{L}{max} \underset{i,j \neq i}{max} |A_i^T A_j|, a_i, a_j \in A_L \tag{7}$$

where $\rho(A)$ denotes the spectral norm of $A$ which is Eigen values of square root of maximum value of $A^T A$. The block coherence defines the coherence between blocks of $A$, while the coherence within the block is sub coherence. When $L = 1$ and $v = 0$ , the columns of dictionary $A_l$ are orthonormal. When the columns of $A$ have unit norm, then the coherence $\mu \in [0, 1]$ and $v \in [0, 1]$. Hence same limits are valid for block coherence.

## III. Methodology

In this paper, the total frequency $F\ Hz$ in the range of $[\quad f_o \quad , \quad f_n \quad ]$ is available for transmission on wideband spectrum. Cognitive radio networks receive a signal $r(t)$ which contains spectrum band adjacent to each other of length $n$ and their frequency band will be $f_o < \quad f_1 < \quad . \quad . \quad . < \quad f_n$ [9]. At first, assume that time window for sensing spectrum is $t \in [0, mT_o]$ where $T_o$ is Nyquist rate sampling. Due to Nyquist rate sampling, the signal $r(t)$ could reconstruct having samples $m$ without aliasing. The receiver is digital so the continuous-time domain signal $r(t)$ is converted into discrete-time domain which will be represented as $x(t)$ and is belongs to $x \in \mathbb{C}^{\mathbb{L}}$of length $L$. So the linear system model/sampling process in discrete time domain represents as:

$$x(t) = A^T * r(t) \tag{8}$$

where $r(t)$ is $m * 1$ dimension vector and $.^T$ represents transposition. The columns of $\{A_n\}_{n=1}^L$ of$A$ can also view as a set of signal or matched filter and the measurements $\{x_t[n]\}_{n=1}^L$ are the projections of $r(t)$ onto the process in reality. For instance, $A = I_m$ represents uniform sampling at Nyquist rate and $I_m$ represents identity matrix of size same as rows of matrix $A$. We can take $A = F_m$ as a random matrix of dimension $m*n$ or aggregates frequency domain sampling and $F_m$ is DFT matrix (Discrete Fourier Transform). In this paper, matrix $\mathbb{A} \in \mathbb{R}^{m*n}$ is DFT and the basis $\psi$, where $\psi = F^{-1}$ is also a DFT matrix which reconstruct the sparse signal/ sparse coefficient vector $x$. For $m-sparse$ signals, since $m > n$ , there are infinitely many $x'$ that will satisfy $\Theta x' = y$ . This is due to the linear model, if that is $\Theta x = y$, then $\Theta(x + s) = y$ for any vector $s$ in null space $\mathbb{N}(\Theta)$ of $\Theta$. Therefore, the algorithms for reconstructing signals are proposed to find the sparse signal coefficient vector in $n-m$ dimensional translated in null space [6]. Let $N-point$ DFT $a[n]$ and $0 \leq n \leq N-1$ is defined as:

$$A[i] \triangleq \frac{1}{\sqrt{N}} \overset{[}{n}= 0]N-1 \sum a[n] e^{-j\frac{2\pi n i}{N}}, 0 \leq i \leq N-1 \tag{9}$$

The DFT is discrete-time equivalent to continuous-time Fourier transform, where $A[i] = DFT\{a[n]\}$, $A[i]$ shows the frequency content of samples in time domain of $a[n]$ associated with original signal $a(t)$. Both C-T FT and DFT are based on the parameters as complex exponential are eigen function of any linear model. The $a[n]$ can cover from its DFT form through IDFT, which is:

$$a[n] \triangleq \frac{1}{\sqrt{N}} \overset{[}{i}= 0]N-1 \sum A[i] e^{-j\frac{2\pi n i}{N}}, 0 \leq i \leq N-1 \tag{10}$$

$a[n] = IDFT\{A[i]\}$.The DFT and IDFT can be performed using FFT and IFFT in hardware [10]. When $n < m$ , sub-Nyquist sampling rate or reduced sampling rate appears. The basic idea of compressive sensing for wideband spectrum in cognitive radio is to arrange and approximation the spectrum of signal$r(t)$ , whose samples are give as $x(t)$ where $n < m$. For that purpose, spectrum is organized in number of sub-bands and their locations can be determined through given frequency range.

### A. Steps for Compressive sensing

For compressive sensing, the following steps bestow how to minimize the complexity.

1) Compress the sampling rate to obtain measurements of $x(t)$ from $r(t)$ signal primitively.
2) Reconstruct the signal from time domain to frequency domain: $r(f) = A * r(t)$ from $x(t)$ measurements.

3) Estimate the number of frequency bands(or one can say signal present at bands on spectrum) and their location in spectrum.
4) Recover the amplitude of signals present in spectrum through compressive sensing, then check the accuracy of algorithms by recovery of signal spectrum at Nyquist rate and sub-Nyquist sampling rate (where$n < m$ ).

### *B. Reconstruction of Spectrum*

We have inspected the spectrum recovery or reconstruction through compressive sensing using existing greedy algorithms along with proposed greedy algorithm. The proposed greedy algorithm is much faster and accurate than OMP but not as accurate as Block_OMP. With $N$ measurements of $x(t) = A^T * r(t)$ , estimate frequency response of $r(t)$ as $r(f) = A * r$ where $A$ is DFT matrix. We have reconstructed a signal $r(f) \in \mathbb{C}^m$from time domain sparse signal $x(t) \in \mathbb{C}^n$ through a non-linear reconstruction function at sub-Nyquist sampling rate for a linear sampler $A \in \mathbb{R}^{m*n}$ i.e., based on linear transformation equality $x(t) = (A^T F_M^{-1}) r(f)$ . This is NP-hard problem with sparsity. An intuitive approach for recovery of signal is through BP (Basic Pursuit) technique also known as greedy technique which convert sparseness into convex optimization problem which can be solved by linear programming [9].

$$r_f = \underset{r_f}{argmax} ||r(f)||_1 \qquad s.t.\ x(t) = (A^T F_M^{-1}) r(f) \tag{11}$$

Besides this approach, there are numerous recovery techniques such as : OMP, Block_OMP (also called greedy algorithms) and some dynamic approaches (LASSO,G_LASSO ). In this paper, only greedy approaches are used to recover the spectrum. Assume that the problem of recovering sparse signal $x \in \mathbb{R}^n$ from noisy measurements as linear equation (1):

$$y = Ax + w \tag{12}$$

where $A \in \mathbb{R}^{m*n}$ $(m < n)$ is the measurement matrix and $w$ is arbitrary vector of errors in case of noise (in our assumptions, it is AWGN case). Let $A = [\ A_1,\ \ A_2,\ \ ..\ \ ..\ \ ..\ \ ..,\ \ A_m\ ]$ where $A_t$ is the $t^{th}$ column of matrix. In this paper, we assumed that the matrix $A$ is normalized that is $||A_t||_2 = 1$ for all values of $i$ . The intention of proposed greedy technique is to reconstruct $x \in \mathbb{R}^n$ from the given and measured values of $y$ and $A$. The core benefit of this greedy approach is that there is no prior knowledge of sub bands of frequency but the wideband signal can be recovered through proposed algorithm for the reconstruction of spectrum. We added a noise threshold through matched filter threshold for noisy environment [11].

$$\gamma = \sqrt{\sigma^2 E Q^{-1}(P_{FA})} \tag{13}$$

where $E$ is energy of matrix $A$, $\sigma^2$ is variance and $P_{FA}$ is probability of false alarm which is usually $0.01 \leq P_{FA} \leq 1$.

The preeminent ambition of proposing greedy algorithm is to detect the sparse signal in case of unknown length of frequency bands. In OMP case, only one atom/index at a time has been recovered and subtracted from residual. It takes too much time and too many iteration while executing the loop. On contrary, Block OMP performs approximate 100% and is much faster than OMP because the size of frequency bands is known in which spectrum is divided. The proposed greedy algorithm have no prior knowledge of the length of sub bands of frequency and it recovered the whole sub band of frequency at a time by detecting a single peak value which cause execution much faster and also number of iterations are much less than OMP, near to the iterations of Block_OMP. The essential objective of proposed greedy algorithm is to achieve the results better than OMP and near to Block_OMP. This can be ascertained in next section. The proposed greedy algorithm is better than Block_OMP in such a way that the length of sub bands of frequency is unknown while for Block_OMP, it is prerequisite to have aforementioned knowledge of size of sub bands of frequency. The only drawback of the proposed greedy approach as compared to Block_OMP is, this approach can not recover the tail of signal in noisy environment while Block_OMP can recover spectrum along with the tail.

**Algorithm 1** Steps followed by Proposed Greedy Algorithm

1) Initialize the residual $r_o = y$ and the variable that stores the blocks of different length (or signals in sub bands of frequency) $s_j = \emptyset$ for iteration $j$.
2) Find the maximum value of variable $x$ for $t^{th}$ step along with the index.
$$j_t = \underset{t}{argmax} ||A_t^T r_{j-1}||_2 \tag{14}$$
3) Find all the peaks greater than the noise threshold and store them in a variable. Find their location in spectrum.
4) Initially, choose the block having maximum value of $x$ . Update the $s_j = s_{j-1} \cup \{t_j\}$ and $S^{(j)} = [S^{(j-1)} A_{t_j}]$ .
5) Solve the optimization problem to obtain new estimated signal $x(t) = argmin_x ||y - S^{(j)} x||_2$.
6) Calculate the new residual from above equation as $r(t) = y - S^{(j)} x(t) = y - P_{S^{(j)}} y$, where $P_{S^{(j)}} = S^{(j)} (S^{(j)})^{\dagger}$ is the orthogonal projection onto the column space and $.^{\dagger}$ stands for pseudo_inverse.
7) If $||r_j||_2 \geq w$ , return to Step 2; Otherwise Stop.

The number of iterations for execution of loop in each algorithm e.g., existing greedy algorithms and proposed greedy algorithm shows that the proposed greedy takes least time for execution. It is much faster in implementation as compared existing greedy algorithms. OMP algorithm is slow because it takes only one atom at a time to recover the sparse signal. Block_OMP is slower than proposed greedy algorithm because of the prior knowledge of length of sub bands/block size and it will take time to check all the blocks either there is any signal present in respective sub band. On the other hand, the proposed greedy algorithm only checked peaks greater than noise threshold and would execute the whole block of peak. This is main reason for faster execution time. Other reason is Block_OMP is recovering tail along with signal meanwhile

OMP and proposed greedy algorithm do not recover tail of signal.

TABLE I
NUMBER OF ITERATIONS FROM EXECUTION OF EACH ALGORITHM

| SNR(dB) | OMP | Block_OMP | Proposed Algo |
|---|---|---|---|
| 20 | 35 | 3 | 3 |
| 15 | 32 | 3 | 3 |
| 10 | 33 | 4 | 3 |
| 5 | 40 | 4 | 3 |
| 3 | 45 | 4 | 3 |

## IV. RESULTS

TABLE II
MUTUAL COHERENCE OF PROJECTION MATRIX AT DIFFERENT SAMPLING RATE

| Sampling Rate | Mutual Coherence of Projection Matrix |
|---|---|
| 100% | 0 |
| 75% | 0.0595 |
| 65% | 0.0759 |
| 50% | 0.0905 |

TABLE III
PERFORMANCE EVALUATION PARAMETERS

| Bandwidth of Spectrum | 3GHz |
|---|---|
| Sparsity of Spectrum | 60% |
| Modulation Scheme for OFDM | QAM-MOD |
| Signal-to-noise Ratio(SNR) | 3-15dB |
| Number of transmitted bits in OFDM signal 1 | 64 bits |
| Number of transmitted bits in OFDM signal 2 | 128bits |

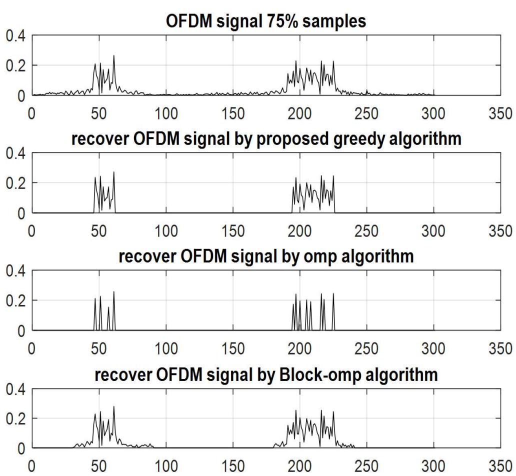


Fig. 1. OFDM signal generated in Spectrum under noisy Conditions at sub-Nyquist rate using 75% samples and having $\mu = 0$,$\sigma^2 = 1$ and $SNR = 10dB$, Recovered signal spectrum through Proposed Algorithm, OMP and Block_OMP respectively

To contemplate the performance of these algorithms more manifestly, We have used Orthogonal Frequency Division Multiplexing (OFDM). We have scrutinized the existing greedy algorithms with proposed one by transmitting OFDM signals through spectrum without causing any interference among each other and recovered the signals through existing greedy algorithms and proposed greedy algorithm. We have checked the accuracy of proposed greedy algorithm by simulating existing and proposed greedy algorithms in noisy and noiseless environment. It is rough reckoning that Block_OMP would work the best in all circumstances as in Block_OMP, the size of sub bands are already known and can easily recover the signals spread in the spectrum more precisely and conveniently. On the other hand, OMP is less complex and

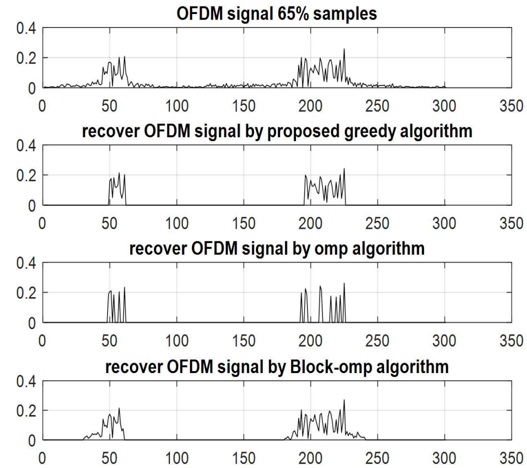


Fig. 2. OFDM signal generated in Spectrum under noisy Conditions at sub-Nyquist rate using 65% samples and having $\mu = 0$,$\sigma^2 = 1$ and $SNR = 10dB$, Recovered signal spectrum through Proposed Algorithm, OMP and Block_OMP respectively

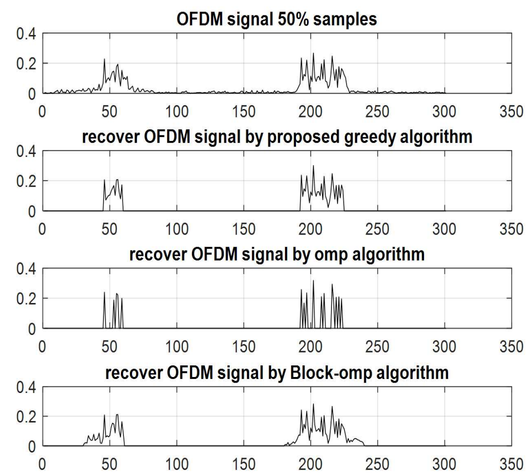


Fig. 3. OFDM signal generated in Spectrum under noisy Conditions at sub-Nyquist rate using 50% samples and having $\mu = 0$,$\sigma^2 = 1$ and $SNR = 10dB$, Recovered signal spectrum through Proposed Algorithm, OMP and Block_OMP respectively

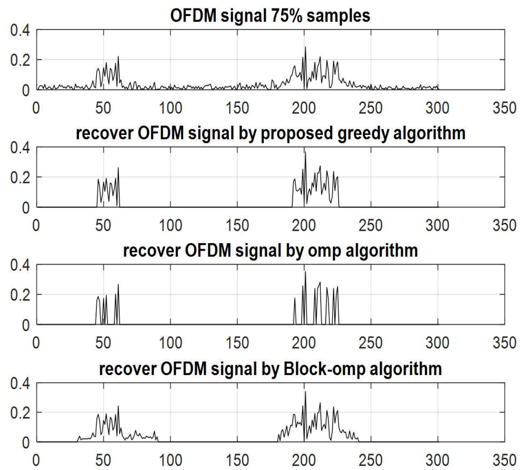


Fig. 4. OFDM signal generated in Spectrum under noisy Conditions at sub-Nyquist rate using 75% samples and having $\mu = 0, \sigma^2 = 1$ and $SNR = 5dB$, Recovered signal spectrum through Proposed Algorithm, OMP and Block_OMP respectively

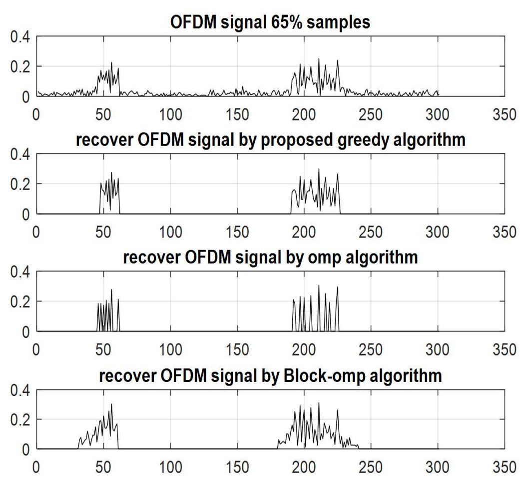


Fig. 5. OFDM signal generated in Spectrum under noisy Conditions at sub-Nyquist rate using 65% samples and having $\mu = 0, \sigma^2 = 1$ and $SNR = 5dB$, Recovered signal spectrum through Proposed Algorithm, OMP and Block_OMP respectively

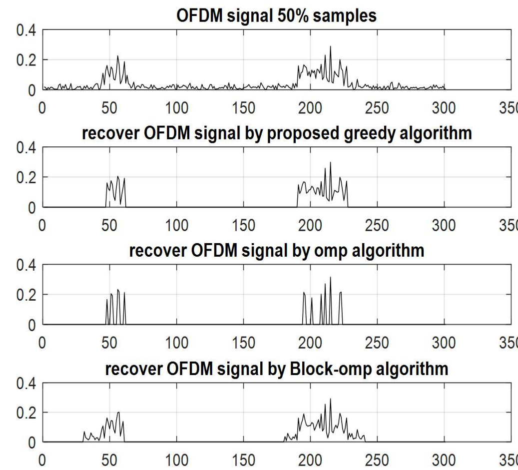


Fig. 6. OFDM signal generated in Spectrum under noisy Conditions at sub-Nyquist rate using 50% samples and having $\mu = 0, \sigma^2 = 1$ and $SNR = 5dB$, Recovered signal spectrum through Proposed Algorithm, OMP and Block_OMP respectively

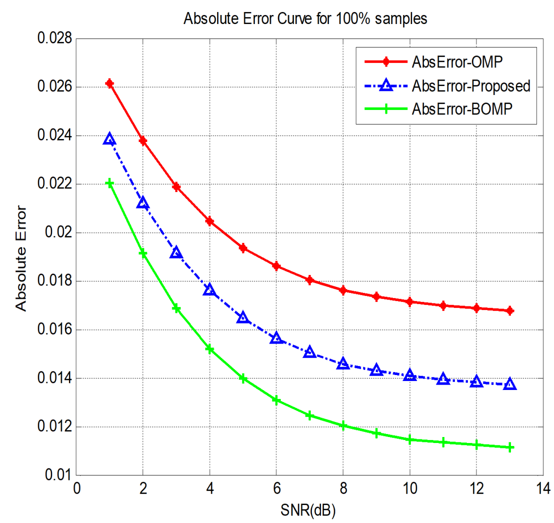


Fig. 7. Absolute Error Curve of OMP, Proposed Algorithm and Block_OMP for 100% samples and 5000 iterations for each SNR

easy to implement but it is not an intelligent algorithm to sense the presence of signal in the spectrum and have no idea of sub frequency bands whether it is recovering consecutive signals or not. On contrary to this, the proposed greedy algorithm is intelligent enough to sense the sub frequency bands which are divided randomly and numerous length of signals are present in the spectrum for data transmission depending on the user demand. The proposed greedy algorithm can sense and recover the sub bands of frequency by sensing a single peak of signal in the sub band. It is easy to implement and fast computationally. It preforms better than OMP in noisy circumstances in compressive sensing case. Other performance evaluation parameters are described in table. These parameters are keep into mind to observe the recovery performance of the greedy algorithms while simulations.

## A. *Mutual Coherence*

In this paper, the recovery limitations for existing algorithms and proposed algorithm are mutual coherence of projection matrix. By observing the performances of these algorithms at Nyquist sampling rate and Sub-Nyquist sampling rate, we concluded that all these algorithms have worked as expected. By scrutinizing the given table for mutual coherence, we observed that the mutual coherence at Nyquist sampling rate

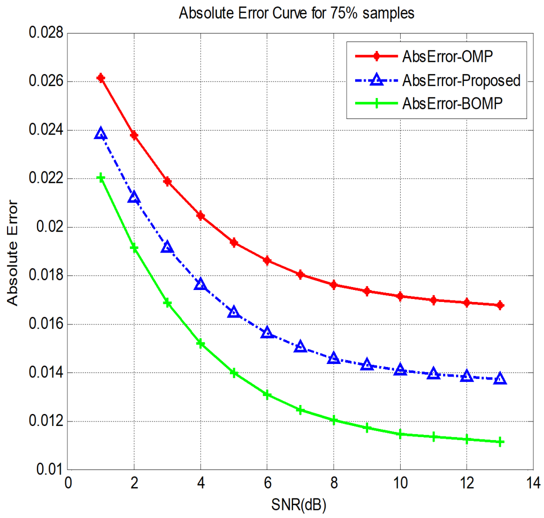


Fig. 8. Absolute Error Curve of OMP, Proposed Algorithm and Block_OMP for 75% samples and 5000 iterations for each SNR

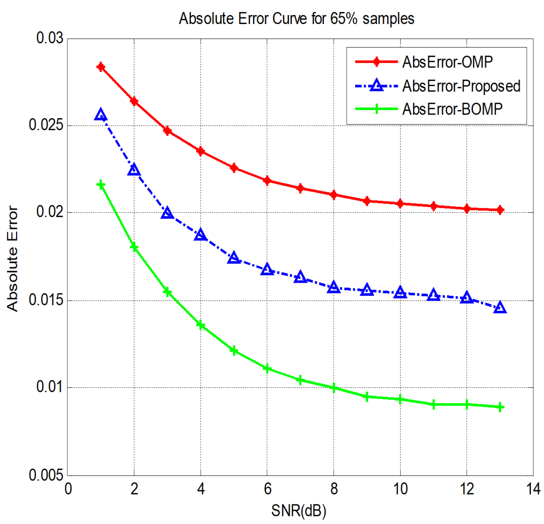


Fig. 9. Absolute Error Curve of OMP, Proposed Algorithm and Block_OMP for 65% samples and 5000 iterations for each SNR

is zero and at is changing slightly at sub-Nyquist sampling rate.

### *B. Absolute Error Curve*

For investigating the performance of all the discussed greedy algorithms, we have compared their absolute error curves at different sampling rates. To calculate absolute error cure, we use the given formula:

$$Abserr = \frac{\sum_{i=1}^{K} recoveredsig - originalsig}{len \quad of \quad original \quad sig}$$

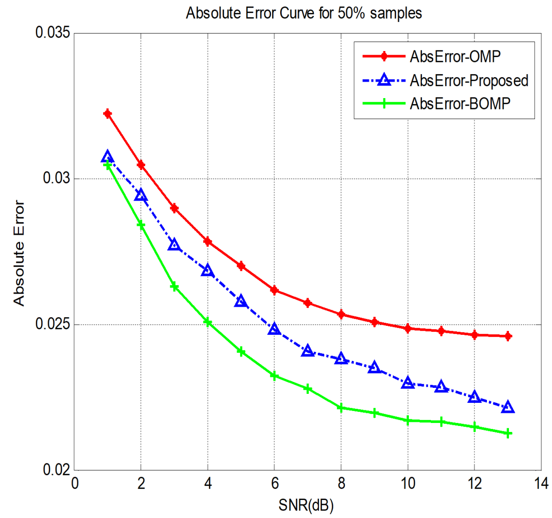


Fig. 10. Absolute Error Curve of OMP, Proposed Algorithm and Block_OMP for 50% samples and 5000 iterations for each SNR

## V. Conclusions

In this paper, we have inquired different greedy approaches to reconstruct the spectrum through compressive sensing. We have scrutinized the performance of existing greedy algorithms i.e., OMP and Block_OMP by inquiring their reconstruction preciseness and absolute error curve. In comparison to the existing greedy algorithms, we proposed a greedy algorithm and checked the preciseness of this algorithm as well. In the proposed algorithm, the length of frequency sub bands is unknown as compared to Block_OMP. The proposed algorithm has recovered the starting and ending points of each sub band along with the signal present in the spectrum without loosing its amplitude. We have inspected the reconstructed signals at Nyquist sampling rate and sub Nyquist sampling rate (using various percentage of sampling rates) in both noisy and noiseless conditions. Through this observation, We have concluded that Block_OMP performed more precisely and efficiently as compared to the other algorithms. The logic behind is; Block_OMP has prior knowledge of length of frequency sub bands. The best performance of Block_OMP, among all algorithms, also shows the succession of designed models. Other than Block_OMP, the proposed algorithm preciseness is near to Block_OMP because it is also recovering the length of sub bands along with the signal present in the spectrum in considerably much less time. The performance of proposed algorithm is much better than OMP. To check the practicality of these algorithms, the OFDM signals present in the spectrum through simulation were recovered. We have investigated the recovered OFDM signals in both noisy and noiseless conditions at Nyquist and sub Nyquist sampling rates. To recover the spectrum, we have used matched filter detection. The reason behind using matched filter detector over energy detector is that, the matched filter performs better in both low and high SNR whereas energy detector performs poorly in low SNR cases.

## VI. Future Recommendations

To extend this research work further, there are many possibilities. As we have proposed greedy algorithm in comparison to existing greedy algorithms. One can focus on two main objectives for extension of this work:

- Recover signal through concept of cyclic prefix.
- Heterogeneous Spectrum

For future advancements, the OFDM signals spread over the spectrum can be recovered by using concept of cyclic prefix. We can recover whole signal by only recovering cyclic prefix of OFDM signal and check that if it is copied at the head of the data as expected. In case of heterogeneous spectrum where both narrowband and wideband signals are present, the performance of all discussed algorithms will degrade. So one can expand this work for such conditions.

## References


[1] H. Chen and C. H. Vun, "An efficient compressive spectrum sensing technique for cognitive radio system," in *2016 IEEE Region 10 Conference (TENCON)*, Nov 2016, pp. 1105–1110.

[2] L. Lu, X. Zhou, U. Onunkwo, and G. Y. Li, "Ten years of research in spectrum sensing and sharing in cognitive radio," *EURASIP Journal on Wireless Communications and Networking*, vol. 2012, no. 1, p. 28, Jan. 2012.

[3] I. Orovic, V. Papic, C. Ioana, X. Li, and S. Stankovic, "Compressive sensing in signal processing: Algorithms and transform domain formulations." *Mathematical Problems in Engineering*, pp. 1 – 16, 2016.

[4] E. Axell, G. Leus, E. Larsson, and H. Poor, "Spectrum sensing for cognitive radio : State-of-the-art and recent advances," *IEEE signal processing magazine : a publication of the IEEE Signal Processing Society*, vol. 29, no. 3, pp. 101–116, 2012.

[5] C. M. AlaÃz and J. R. Dorronsoro, "The generalized group lasso," in *2015 International Joint Conference on Neural Networks (IJCNN)*, July 2015, pp. 1–8.

[6] R. G. Baraniuk, "Compressive sensing [lecture notes]," *IEEE Signal Processing Magazine*, vol. 24, no. 4, pp. 118–121, July 2007.

[7] J. F. Determe, J. Louveaux, L. Jacques, and F. Horlin, "On the exact recovery condition of simultaneous orthogonal matching pursuit," *IEEE Signal Processing Letters*, vol. 23, no. 1, pp. 164–168, Jan 2016.

[8] R. Wu, W. Huang, and D. R. Chen, "The exact support recovery of sparse signals with noise via orthogonal matching pursuit," *IEEE Signal Processing Letters*, vol. 20, no. 4, pp. 403–406, April 2013.

[9] Z. Tian and G. B. Giannakis, "Compressed sensing for wideband cognitive radios," in *2007 IEEE International Conference on Acoustics, Speech and Signal Processing - ICASSP '07*, vol. 4, April 2007, pp. IV–1357–IV–1360.

[10] Z. Tian, Y. Tafesse, and B. M. Sadler, "Cyclic feature detection with sub-nyquist sampling for wideband spectrum sensing," *IEEE Journal of Selected Topics in Signal Processing*, vol. 6, pp. 58–69, 2012.

[11] F. Salahdine, H. el ghazi, N. Kaabouch, and W. Fassi Fihri, "Matched filter detection with dynamic threshold for cognitive radio networks," 10 2015.

[12] M. Shaban, D. Perkins, and M. Bayoumi, "An efficient compressive wideband spectrum sensing architecture for cognitive radios," pp. 130–134, 10 2013.

[13] J. Jiang, H. Sun, D. Baglee, and H. V. Poor, "Achieving autonomous compressive spectrum sensing for cognitive radios," *IEEE Transactions on Vehicular Technology*, vol. 65, no. 3, pp. 1281–1291, March 2016.

[14] T. Mehta, N. Kumar, and S. S. Saini, "Comparison of spectrum sensing techniques in cognitive radio networks 1."

[15] M. Yang and F. de Hoog, "New coherence and rip analysis for weak orthogonal matching pursuit," in *2014 IEEE Workshop on Statistical Signal Processing (SSP)*, June 2014, pp. 376–379.

[16] A. Kamali, M. A. Sahaf, A. D. Hooseini, and A. Tadaion, "Block subspace pursuit for block-sparse signal reconstruction," *Iranian Journal of Science and Technology, Transactions of Electrical Engineering*, vol. 37, no. E1, pp. 1–16, 2013.

[17] K. C. Knudson, J. Yates, A. Huk, and J. W. Pillow, "Inferring sparse representations of continuous signals with continuous orthogonal matching pursuit," in *Advances in neural information processing systems*, 2014, pp. 1215–1223.

[18] L. Lu, X. Zhou, U. Onunkwo, and G. Y. Li, "Ten years of research in spectrum sensing and sharing in cognitive radio," *EURASIP Journal on Wireless Communications and Networking*, vol. 2012, no. 1, p. 1, 2012.

[19] H. Sun, A. Nallanathan, C.-X. Wang, and Y. Chen, "Wideband spectrum sensing for cognitive radio networks: a survey," *IEEE Wireless Communications*, vol. 20, no. 2, pp. 74–81, 2013.