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BLIND MULTIBAND SPECTRUM SIGNALS RECONSTRUCTION ALGORITHMS COMPARISON

Hao Shen¹, Thomas Arildsen¹, Deepaknath Tandur², and Torben Larsen¹

¹Aalborg University  
Dept. of Electronic Systems  
DK-9220 Aalborg, Denmark  
E-mail: {hsh; tha; tl} @es.aau.dk  
²Agilent Technologies, Belgium  
E-mail: deepaknath.tandur@agilent.com

ABSTRACT

This paper investigates sparse sampling techniques applied to downsampling and interference detection for multiband radio frequency (RF) signals. To reconstruct a signal from sparse samples is a compressive sensing problem. This paper compares three different reconstruction algorithms: 1) ℓ1 minimization; 2) greedy pursuit; and 3) Multiple Signal Classification (MUSIC). We compare the performance of these algorithms and investigate the robustness to noise effects. Characteristics and limitations of each algorithm are discussed.

1. INTRODUCTION

According to traditional Shannon-Nyquist sampling theory, to allow perfect reconstruction, a signal must be sampled at more than twice the highest frequency contained in the signal, also known as the Nyquist rate [1].

In traditional spectrum analyzers, a narrow band signal is usually converted to baseband and then sampled according to the Nyquist rate. However, when the signal is affected by interference or frequency shifting effects, down-converting the signal to baseband may introduce aliasing unless an anti-aliasing filter is applied. On the other hand, to sample such RF signals at Nyquist rate (e.g. 100GHz) is usually very difficult or impossible in practice. Therefore, reducing the sampling rate is highly needed.

In order to reduce the sampling rate, the signal structure should be studied first. Suppose a bandpass signal occupies a spectrum from \( f_{b1} \) to \( f_{b1} \). Meanwhile, several interference signals are randomly allocated in the intervals \( [f_{a1}, f_{b1}] \), where \( f_{a1} < \cdots < f_{aN} \). Then, the Nyquist rate for such signals is \( f_{nyq} = 2f_{bN} \). According to the theory of compressive sensing [2], a signal can be reconstructed from far fewer samples, i.e. below the Nyquist rate, if the signal is sparse in a certain domain. Since it is known that there are only \( N \) frequency bands in the entire spectrum, the width of each band is \( B_i = f_{bi} - f_{a1} > 0 \), \( B_N = f_{bN} - f_{aN} > 0 \), the signal spectrum can be regarded as sparse if \( \sum B_i < f_{nyq} \). Therefore, compressive sensing can theoretically be applied to reconstruct a multiband RF signal using a sampling rate significantly below the Nyquist rate.

In practice, the number of subbands \( N \) and the location of the subbands are unknown for interference signals. It becomes a blind multiband signal reconstruction (BMSR) problem, which was first discussed by Feng in 1996 [3]. In 2009, Mishali and Eldar applied compressed sensing theory to the BMSR problem [4]. They formulated the problem as a multiple measurement vector (MMV) problem. Chen and Huo later applied convex optimization and greedy pursuit to solve the MMV problem [5].

In this paper, we mainly investigate three reconstruction algorithms to solve the BMSR problem. The first is a general MUSIC algorithm, which is very suitable for the BMSR problem [6]. The other two are widely used reconstruction algorithms in traditional compressive sensing theory. One is Multiple Basis Pursuit De-Noising (M-BPDN) [7], which belongs to the family of ℓ1-minimization in convex optimization, and the other belongs to the category of greedy pursuit algorithms. Instead of using multi-orthogonal matching pursuit (M-OMP) [5], we apply a stagewise factor as Multiple Stagewise Orthogonal Matching Pursuit (M-StOMP) [8]. Then, we investigate the performance of these algorithms from the view of detecting spectrum allocation and evaluate the mean square error (MSE) in the frequency domain between the reconstructed signal and the signal sampled at Nyquist rate. We also investigate the robustness of these algorithms under various levels of additive white Gaussian noise (AWGN). Finally, the disadvantages and limitations of each algorithm are listed.

2. PROBLEM AND BACKGROUND

2.1 Single Measurement Vector Model

In compressive sensing [2], one single measurement vector model is given by,

\[
\mathbf{y} = \mathbf{A}\mathbf{x},
\]

where \( \mathbf{y} \in \mathbb{R}^{p \times 1}, \mathbf{A} \in \mathbb{R}^{p \times L}, \mathbf{x} \in \mathbb{C}^{L \times 1}, \) and \( p < L \). Suppose \( \mathbf{z} \in \mathbb{C}^{L \times 1} \) is a linear transformation of the signal \( \mathbf{x} \) in the basis \( \mathbf{Y} \), \( \mathbf{z} = \Psi\mathbf{x} \), and \( \mathbf{x} = \Psi^{-1}\mathbf{z} \). If \( \|\mathbf{x}\|_0 = q \), and \( q < L \), \( \mathbf{x} \) is a sparse representation of \( \mathbf{z} \) and \( \Psi \in \mathbb{C}^{L \times p} \) is the dictionary matrix of \( \mathbf{z} \). Here \( \|\cdot\|_0 \) is a zero norm calculation, which is defined as, \( \|\mathbf{x}\|_0 = T, T = \{i| x_i \neq 0\} \). Transforming the signal \( \mathbf{z} \) by the measurement matrix \( \Phi \in \mathbb{R}^{p \times L} \), the compressed vector \( \mathbf{y} \) is obtained: \( \mathbf{y} = \Phi\mathbf{z} \). Then, the matrix \( \mathbf{A} \) in (1) is \( \mathbf{A} = \Phi \Psi \).

2.2 Multiple Measurement Vector Model

The MMV problem is an extension of the single measurement vector problem as follows [5]:

\[
\mathbf{Y} = \mathbf{A}\mathbf{X},
\]
where $Y \in \mathbb{C}^{p \times B}$, $A \in \mathbb{C}^{p \times L}$, $X \in \mathbb{C}^{L \times B}$.

Here $A$ is a similar combination matrix as in (1), with $p < L$. $X$ is a row-sparse matrix, i.e., has few non-zero rows, and $Y$ is an observed matrix. The vectors $\tilde{x}_i$ and $\tilde{y}_i$, $i = 1, \ldots, B$, are the columns of $X$ and $Y$. When $B = 1$, (2) reduces to the single measurement vector problem. Therefore, the MMV problem can be regarded as solving $B$ parallel single measurement vector problems. (2) can be rewritten as,

$$\tilde{y}_i = A\tilde{x}_i, \quad i = 1, \ldots, B. \quad (3)$$

Meanwhile, considering the effect of AWGN $\epsilon$, (2) is extended by

$$Y = AX + \epsilon, \quad (4)$$

where $\epsilon \sim \mathcal{N}(0, \frac{1}{n} \delta^2 \mathbf{I})$, and $\mathbb{E}[\epsilon_i \epsilon_j] = \delta_\epsilon^2$.

### 2.3 Multiband Signal Model

Here, we use a multiband signal model [9]. Suppose $x(f)$ is the spectrum of $\zeta(t)$. Let $\mathcal{F}$ denote the spectrum support set in the whole spectrum $[0, f_{nyq}]$. We define a signal as multiband if $\mathcal{F} = \bigcup_{i=1}^N \{f_{i}, f_{i+1}\}$, and $x(f) = 0$, if $f \notin \mathcal{F}$. Since the maximum frequency $f_{n, N}$ in $\mathcal{F}$ is unknown, the signal is bandlimited to $f_{nyq}$. As mentioned before, the spectrum of a signal is sparse if $\sum_{i=1}^N B_i \ll f_{nyq}$. How to sample this kind of signal in a sparse way is discussed below.

Instead of using one sampler on $\zeta(t)$ uniformly at the Nyquist rate, i.e., $\zeta[n] = \zeta(nT)$, $T = 1/f_{nyq}$, Feng and Bresler proposed a parallel structure with $p$ samplers [3]. Each one samples at rate of $1/(pT)$ with a different time shifting. Consequently, the $x(f)$ in frequency is divided into $L$ consecutive subbands, i.e. $x_i(f_i)$, $f_i \in [\frac{i}{pT}, \frac{i+1}{pT}]$, $i = 1, \ldots, L$.

Then, the $x(f)$ is reformulated as $X(f) = \{x_i(f_i), f_i \in [\frac{i}{pT}, \frac{i+1}{pT}], i = 1, \ldots, L\}$, which corresponds to $x_i(f_i)$. Suppose the bandwidth of each subband in $x(f)$ does not exceed a maximum bandwidth $B_{\max}$, the maximum $f$ should be larger than $B_{\max}$, i.e. $\max(B_i) \leq B_{\max} \leq 1/(pT)$. Here we discretize the $\hat{f}$ to $B$ samples with $B \geq B_{\max}$, we get $X \in \mathbb{C}^{L \times B}$, and $L \leq 1/(BT)$. Then, the model of multiband signal is given by

$$Y = AX, \quad (5)$$

where $A \in \mathbb{C}^{p \times L}$ is referred as a universal sampling matrix [3]. The structure can be a multiciset sampler [3] or a random demodulator [10]. Here $p$ is the number of samplers, and $L$ is the sampling period. The overall sampling rate is $f_s = \frac{p}{B} f_{nyq}$, with $p < L$. It is clear that (5) is exactly the same type of problem (MMV) as (2).

In this paper, the investigated reconstruction algorithms are based on the discretized frequency model (2). As long as $X$ is reconstructed, $\zeta$ can be easily calculated [4]. The effects of frequency discretization and quantization are out of the scope of this paper, as well as the design of the $A$ matrix.

### 2.4 Optimization Problem

Since $p < L$, (2) is an underdetermined equation, satisfied by infinitely many solutions. Therefore a unique solution of (3) should be the sparsest $\hat{X}$.

To reconstruct the original signal from the observed signal, several algorithms have been proposed in the literature. The sparsest solution to (2) can be found by solving the below optimization problem,

$$\min \|\mathcal{R}(X)\|_0 \quad \text{subject to} \quad Y = AX, \quad (6)$$

where $\mathcal{R}(\cdot)$ calculates the $\ell_2$ norm of the $i$th row in $X$, $i = 1, \ldots, L$, and $\|\mathcal{R}(\cdot)\|_0$ returns the number of rows containing non-zeros elements.

Here recall the multiband signal model. Before reformulating the frequency, the sparsity $q = \|x\|_0$ in (1) counts the number of non-zero frequencies in the whole spectrum. However, in (5), $N = \|\mathcal{R}(X)\|_0$, $N = 1, \ldots, L$, is the number of subbands allocated in the support $\mathcal{F}$.

### 3. RECONSTRUCTION ALGORITHMS

We define $S$ as the support of $X$. $S \triangleq \{i \mid \|x_i\|_0 \neq 0\}$, where $x_i$ is the $i$th row of $X$. In the MMV problem, we have $X^S \triangleq [x_1^H, \ldots, x_N^H]^H$, where $x_i = x_i(i), i = 1, \ldots, N$. $x_j$ is the $j$th row of $X$, and $(\cdot)^H$ is the Hermitian transpose. Correspondingly, $A = [a_1, \ldots, a_L]$, where $a_i$ is the $i$th column in $A$. Then, $A_S \triangleq [a_1^H, \ldots, a_L^H]^H$, where $a_i = x_i(i)$.

Obviously, if the support $S$ is known, (2) reduces to

$$Y = A_S^S \tilde{X}, \quad (7)$$

where $A_S \in \mathbb{C}^{p \times N}$, and $X^S \in \mathbb{C}^{L \times B}$. If $p > N$, (7) becomes an overdetermined equation. Then, $\tilde{X}$ can be reconstructed as the least-squares estimate

$$\tilde{X} = A_S^S Y, \quad (8)$$

where $(\cdot)^\dagger$ is the pseudoinverse operation.

However, $S$ is usually unknown in (2). To solve (6) is an NP-hard combinatorial optimization problem [5], since $\binom{L}{N}$ combinations must be evaluated to find the correct support $S$. This computation increases exponentially with the size $L$, and $N$. For multiband signal models, when $S$ is unknown, (5) becomes a blind spectrum signal model. Therefore, many suboptimal algorithms are proposed to reconstruct $S$ and $X$.

The other problem is how to be sure that $\tilde{X}$ is the sparsest solution of (6) even if support $S$ is reconstructed. Will there exist another solution $\hat{X}$ such that $\|\tilde{X}\|_0 < \|\hat{X}\|_0$? Therefore, some properties of the matrix $A$ should be discussed to meet the uniqueness condition of (5).

#### 3.1 Uniqueness and Minimum Sampling Rate

By following the theorem and definition of Kruskal-rank of the matrix $A$ in [4], we have:

**Definition 1** Kruskal-rank: Given a matrix $A$, define $\eta = \text{KruskR}(A)$ as the maximal number such that every $\eta$ columns of matrix $A$ are linearly independent.

**Theorem 1** Uniqueness: The matrix $X$ is the unique sparsest solution of (6), if $\|\mathcal{R}(X)\|_0 \leq \text{KruskR}(A)/2$.

Calculating the Kruskal-rank of a matrix $A$ is a combinatorial problem. In this paper, we apply a universal sampling matrix $A$ which guarantees that $X$ is uniquely reconstructable [3]. For a specific number of samplers $p$, one distinct sampling matrix $A$ is found via solving a minimax optimization problem. For details, please refer to [3].
Regarding to the minimum sampling rate, since $A \in \mathbb{C}^{p \times L}$ with $p < L$, it is easy to get $p \geq \eta \geq 2\|R(X)\|_0 = 2N$.

**Theorem 2** Minimum rate: The theoretical minimum sampling rate of the overall parallel structure is $f_s = 2\|R(X)\|_0 \frac{f_{\text{nyq}}}{L}$.

In the following parts, we discuss how to reconstruct the support $S$, and solve (4) by three suboptimal algorithms.

### 3.2 MUSIC with Spectral Analysis

MUSIC is a technique of spectral estimation, which was first invented by Schmidt [6] in 1986 to solve the problem of direction-of-arrival (DOA). In this paper, we use the traditional MUSIC algorithm [4] to solve (2). The detailed steps are listed in Algorithm 1.

**Algorithm 1 MUSIC Algorithm**

**Input:** $A$, $Y$, and $N$

1. Estimate the autocorrelation, $Q = E[YY^H]$
2. Eigendecomposition, $Q = U\Lambda U^H$
3. Find the $2N$ signal subspace, $U_s = \text{sub}_\text{sig}(U)$
4. Calculate the MUSIC spectrum, $P_{\text{mu}} = \{a_i^H(I - U_sU_s^H)a_i\}^{-1}, i = 1, \ldots, L$
5. Set $S$ as the indices of peak values of $P_{\text{mu}}$
6. return $S$ and $\hat{X} = A_S^HY$

In step 2, $Q$ is decomposed as, $Q = U\Lambda U^H$, or $Q = \sum_{i=1}^p \lambda_i u_iu_i^H$. One of the crucial steps in MUSIC is to separate the signal subspace and noise subspace from $U$. For the noiseless case, the order of eigenvalues is,

$$\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_{2N} \geq \lambda_{2N+1} = \cdots = \lambda_p = 0,$$

(9)

Then, in step 3, the first $2N$ eigenvalues, $\lambda_i, i = 1, \ldots, 2N$, are referred as signal subspace eigenvalues, and $u_i, i = 1, \ldots, 2N$, are referred as signal subspace eigenvectors.

However, with increasing noise level $\epsilon$, the difference between signal eigenvalues and noise eigenvalues is more and more difficult to distinguish, which affects the performance of MUSIC dramatically.

### 3.3 Basis Pursuit Minimization

Basis pursuit [11] is a convex relaxation of $\ell_0$ minimization in (6),

$$\min \|R(X)\|_1 \quad \text{subject to} \quad Y = AX.$$  

(10)

Considering the effect of noise (4), basis pursuit de-noising (BPDN) is an approximation of basis pursuit,

$$\min \|R(X)\|_1 \quad \text{subject to} \quad \|y_i - AX_i\|_2^2 \leq \delta^2, i = 1, \cdots, B.$$  

(11)

In this paper, we use the function $\text{spgl1}_{\text{mmv}}$ from the SPGL1 toolbox to solve the BPDN in MMV problem [7].

### 3.4 Greedy Pursuit

Orthogonal matching pursuit (OMP) is an improvement of matching pursuit (MP) [12]. In relation to the MMV problem, several greedy algorithms have been proposed [5]. One of the improved M-OMP is listed in Algorithm 2 [5].

**Algorithm 2 Multi-orthogonal matching pursuit (M-OMP)**

**Input:** residual $R^{(0)} = Y$, subset $S^0 = \emptyset$, iteration $n = 1$

1. while stop criterion is not met do
2. $g_r^{(n)} = R^{(n-1)^T}a_i$
3. $S^0 = S^{(n-1)} \cup \{i: \|g_r^{(n)}\|_r \geq \lambda \max_j \|g_r^{(n)}\|_r\}$
4. $X_r^{(n)} = A_{S^0}^HY$
5. $R^{(n)} = Y - AX_r^{(n)}$
6. check stop criteria
7. $n := n + 1$
8. end while
9. return $X$ and $S$

In Algorithm 2, $S^{(n)}$ denotes a set containing the indices of the elements selected up to $n$th iteration. $R^{(n)}$ is the residual in the $n$th iteration. $g_r^{(n)}$ is the projection of the residual on the $r$th column of $A$. The main change of the M-OMP in [5] is the step 3, where $\|\cdot\|_r$ calculates the $r$-norm of $g_r^{(n)}$. In this paper, we set $r = 2$.

Usually, when $A$ is not an orthogonal basis, the orthogonality of M-OMP is not preserved. In step 3, it is unnecessary to find a new column vector of $a_i$, which must be orthogonal to the previous ones. By introducing the concept of a stage-wise weak factor $\lambda$ [8], we change step 3 in Algorithm 2, resulting in Algorithm 3. Instead of selecting the index with max $\|g_r^{(n)}\|_r$, we select indices which are no less than $\lambda \cdot \|g_r^{(n)}\|_r$, where $\lambda = 0, \ldots, 1$. When $\lambda = 1$, Algorithm 3 is exactly the same as Algorithm 2.

**Algorithm 3 Multiple Stagewise Orthogonal Matching Pursuit (M-StOMP)**

**Input:** residual $R^{(0)} = Y$, subset $S^0 = \emptyset$, $\lambda$, iteration $n = 1$

1. while stop criterion is not met do
2. $g_r^{(n)} = R^{(n-1)^T}a_i$
3. $S^0 = S^{(n-1)} \cup \{i: \|g_r^{(n)}\|_r \geq \lambda \max_j \|g_r^{(n)}\|_r\}$
4. $X_r^{(n)} = A_{S^0}^HY$
5. $R^{(n)} = Y - AX_r^{(n)}$
6. check stop criteria
7. $n := n + 1$
8. end while
9. return $X$ and $S$

### 4. NUMERICAL EXPERIMENTS

In this section, we discuss the performance of each algorithm. First, we describe the simulation set-up. Second, two aspects of performance are discussed.

#### 4.1 Simulation Set-up

Fig. 1 shows the spectrum of a multi-band signal. We set the entire bandwidth as 5kHz. The Nyquist frequency is $f_{\text{nyq}} = 1/10kHz$. There are $N = 3$ subbands in total. We set the maximum bandwidth of each subband $B_i \leq 200Hz$. Since the number of allocated subbands is 3, 6 samplers are used, and each sampling at the rate $1/(LT)$, where $L \leq 1/(BT) = 50$, so $1/(LT) = 200Hz$. The overall sampling rate is $p/LT = \ldots$
In this paper, we analyzed three multiple measurement vector (MMV) reconstruction algorithms, namely as MUSIC, M-StOMP, and M-BPDN, for blind reconstruction of multiband signals from samples below the Nyquist rate. M-StOMP is a parallel greedy pursuit algorithm, and M-BPDN is a parallel basis pursuit de-noising algorithm. After evaluating numerous simulations, we see that MUSIC can achieve the theoretical lowest sampling rate when $\text{SNR}_{\text{in}} \geq 30\text{dB}$. We also identify that it is a bottleneck for MUSIC to separate the signal and noise eigenvalues when $\text{SNR}_{\text{in}} \leq 0\text{dB}$. For M-StOMP, and M-BPDN, we find M-StOMP to outperform M-BPDN in all tested cases. However, when $\text{SNR}_{\text{in}} < 0\text{dB}$,
the M-BPDN is the only algorithm which can reconstruct a signal successfully at the Nyquist rate. Future work can be focused on the sampling matrix A design or reconstruction algorithm improvement. It’s not trivial to design a universal sampling matrix (5). Meanwhile, eigenvalue separation is crucial for MUSIC when SNR_in is low, and \( N \) is unknown.

REFERENCES


