A Double Screening Orthogonal-Matching-Pursuit Algorithm for Compressed Sensing Receiver with High Column Correlation Sensing Matrix

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Abstract Modulated wideband converter (MWC) is a multi-branch structure for sub-Nyquist sampling the signals which spectra are sparse. With several band-limited sampling sequences, MWC can recover the signals by compressed sensing (CS) reconstruction algorithms. However, for hardware-implemented MWC, the hardware scale and imperfection of the physical devices lead to strong column correlations of the sensing matrix which may invalidate the classic CS algorithms. Combined with the characteristics of the sensing matrix of the CS receiver, this paper proposes the double screening orthogonal matching pursuit algorithm (DSOMP) to solve this problem. DSOMP updates the support based on the distance from the residual to the column vector subspace of the sensing matrix and adds a secondary screening mechanism to remove strong interference terms. With the strong column correlation sensing matrix of the CS receiver, DSOMP exhibits an excellent support set recovery rate.

key words: compressed sensing, greedy pursuit algorithm, modulated wideband converter, sub-Nyquist sample, hardware implement

Classification: XYZ (choose one from Table II)

1. Introduction

To meet the challenges of lack of spectrum resources, cognitive radio (CR) has been proposed to increase the utilization of spectrum [1]. Wideband spectrum sensing, as an important research topic of CR, has been widely concerned by researchers [2]. Traditional wideband spectrum sensing with ultra-high Nyquist sampling rate leads to great hardware complexities and unacceptable computing resources. Several compressed sampling structures based on CS have been proposed by researchers to sense the wideband spectrum at a sub-Nyquist rate, such as multi-coset sampling [3], analog to information converter [4,5], MWC [6–8] and so on. The MWC proposed by Mishali has been widely approved because it is friendly to multi-band signals and commercial devices.

Signal reconstruction of MWC relies on solving an under-determined equation which is a multiple measurement vectors (MMV) problem in CS. Since CS was proposed by Donoho in 2006 [9], researchers have proposed several categories of optimization algorithms, such as greedy pursuits, convex relaxation, Bayesian algorithm, and so on [10–13]. Greedy pursuits build an approximation by making locally optimal choices at each step, and it includes matching pursuit (MP) [14], orthogonal MP (OMP) [15,16], regularized OMP (ROMP) [17], compressive sampling MP (CoSaMP) [18,19], and so on. Some researchers have extended these classic greedy algorithms to solve the MMV problem [20,21].

However, for a hardware-implemented MWC, its sensing matrix is constrained by physical factors, including the non-ideality of hardware circuits and the achievable hardware scale [22,23]. It will cause the column correlations of its sensing matrix are so strong that it is difficult to meet restricted isometry property (RIP) [24]. With the presence of noise, the background of the CS reconstruction algorithms becomes so harsh that the classic greedy pursuits are difficult to work with.

This paper proposes the DSOMP signal reconstruction algorithm. Combined with the characteristic that the sensing matrix of MWC has a small size, the algorithm will consider more on the reconstruction accuracy than calculation speed. The DSOMP adds a double screening mechanism called "loose-in and strict-out" to ensure that the bases are not missed and that the strong interference terms are filtered out with high probability. Also, to improve the accuracy of the screening, the algorithm uses the distance from the residual to the column vector subspace of the sensing matrix as standard for screening the index number in each iteration.

2. Modulated wideband converter

MWC is a multi-branch structure which can sub-Nyquist sample multi-band sparse signal. The multi-band sparse signal model requires $x(t)$ has no more than $N$ sub-bands in $[-f_{Nyq}/2, f_{Nyq}/2]$, and the bandwidth of each sub-band does not exceed $B$ Hz. Symbol $f_{Nyq}$ represents the Nyquist frequency of $x(t)$. Since the spectrum of a real signal is conjugate symmetric, $N$ is an even number. Fig. 1 shows a
multi-band sparse signal, where \( X(f) \) represents the spectrum of \( x(t) \).

\[
p_i(t) = \sum_{l=-\infty}^{\infty} c_{il} e^{j2\pi lf p t}\]

(1)

where \( c_{il} \) is the Fourier coefficients at the frequency of \( lf p \).

The key to reconstructing the signal is to solve Eq. 4 which is underdetermined. Because \( f \) is continuous, it is an infinite measurement vectors (IMV) problem which is very difficult to solve directly in CS. CTF block can translate an IMV problem to an MMV problem. As shown in Fig 3, CTF block constructs a new underdetermined Eq. 6 which is an MMV problem. In [25], Mishali proved that \( U \) and \( z S(f) \) have the same support \( S \).

\[
V = CU
\]

(6)

According to the support \( S \), the Eq. 4 is simplified as

\[
y(f) = C_S z_S(f)
\]

(7)

where \( C_S \) contain the columns of \( C \) indexed by \( S \), and \( z_S(f) \) contains the non-zero elements of \( z(f) \). Due to \( z(f) \) has no more than \( 2N \) non-zero elements, the Eq. 7 is overdetermined or well-posed when \( mq \geq 2N \). And it can be solved as

\[
z_S(f) = C_S^t y(f)
\]

(8)

where \( C_S^t \) is the generalized inverse matrix of \( C_S \).

3. Background Analysis of Signal Reconstruction

For MWC-based CS receivers, the input signal \( x(t) \) is blind. The CS algorithm does not have accurate prior information of the sparsity of \( z(f) \). It only knows that the number of the non-zero elements does not exceed \( 2N \).

The sensing matrix of a circuit-level MWC is not well-controlled due to the imperfections of the physical devices. As described in [22,23,26], the Fourier coefficients of the PRBSes are not the only factor determining the sensing matrix. Moreover, these Fourier coefficients are also inaccurate due to the waveforms of high-speed PRBSes are distorted during generation and transmission. The mixer in the circuit is not exactly equivalent to a multiplier in the theoretical analysis, so the mixing response also acts on the sensing matrix. The
channel response of the radio frequency (RF) link, intermediate frequency (IF) link, and local oscillator link can also change the sensing matrix. In addition, the sensing matrix is also affected by gain mismatch and delay mismatch between branches. Among the above factors, except for the selection of PRBSes, the rest cannot be easily controlled by the designers. And these non-ideal factors increase the column correlations of the sensing matrix, which is not conducive to signal reconstruction. The experiment in Section 5 will confirm this point.

In CS, the sensing matrix needs to meet restricted isometry property (RIP) to ensure that the sparse signal is stably and accurately reconstructed, and most CS algorithms are based on RIP [19]. However, RIP will result in a large number of branches of MWC, and it is completely unacceptable in physical implementation [24]. RIP costs too much for the worst case considerations, but the distribution of signals rarely encounters the worst case. Literature [24] relax the RIP to Expected RIP which leads to a suitable hardware complexity. As a compromise, some PRBSes with small cross-correlation, such as maximal codes or Gold codes, are selected to improve the randomness of the sensing matrix [24,27]. However, there is still a high correlation between the columns of the sensing matrix. These features are enough to disable some classic CS algorithms.

The sensing matrix of a circuit-level MWC usually has a small size. For example, the size of the sensing matrix of the CS receiver in Section 5 is 20 × 155. This advantage allows the CS algorithm to relax on the computational complexity considerations, and put more considerations on the support reconstruction accuracy.

The characteristics of the situation faced by the CS signal reconstruction algorithm is summarized as

1. The accurate sparsity is unknown.
2. The column correlations of the sensing matrix are strong.
3. The sensing matrix may not satisfy the RIP condition.
4. The size of the sensing matrix is not large.

4. Signal reconstruction algorithm

Combined with the characteristics of the sensing matrix of MWC-based receiver, this paper proposes a DSOMP signal reconstruction algorithm.

First of all, we clarify the meanings of several corners and functions. $A(m \times n)$ indicates the size of $A$ is $m \times n$. $A_i$ indicates the $i$-th column of $A$ and $\hat{A}$ indicates the estimate of $A$. Symbol $A^T$ indicates the transposition of $A$. In the reconstruction algorithms, $A^{[n]}$ is the value of $A$ in the $n$-th iterative. Symbol $A_{[i]}, i \in B$, represents a set consists of the element $A_{[i]}, i \in B$, and the subscript $(i)$ indicates the index number. For example, the set $A_{[1]}, A_{[3]}, A_{[7]}$ can be expressed as $A_{[1]}$. The function $\min\limits_{i \in B}(A_{[i]}, g)$ returns the index number $i \in \{1,3,7\}$ set corresponding to the smallest $g$ elements of the set $A_{[i]}$.

The Frobenius norm $\mathcal{F}(\mathbf{A})$ which measures the power of $\mathbf{A}(m \times n)$ is defined as

$$\mathcal{F}(\mathbf{A}) = \| \mathbf{A} \|_F^2 = \sum_{i=1}^{m} \sum_{j=1}^{n} |A_{i,j}|^2$$

(9)

where $A_{i,j}$ is the element in $i$-th row and $j$-th column of $A$. Of course, $A$ can also be a row (column) vector.

Consider an underdetermined equation in MMV model

$$\mathbf{V} = \mathbf{C} \mathbf{U}.$$ 

(10)

where $\mathbf{V}(m \times p)$ is the observed matrix, $\mathbf{C}(m \times L)$ is the sensing matrix, and $\mathbf{U}(L \times p)$ is row-sparse matrix. $U$ contains up to $2N$ rows which has non-zero elements. We defined the residual matrix $\mathbf{R} = \mathbf{V} - \mathbf{C} \mathbf{U}$. Obviously, $\mathbf{R}$ has a size of $m \times p$ and the column vector $\mathbf{R}_i$ is called the residual vector.

4.1 Classical Greed Pursuit Algorithms

Some CS algorithms which mechanisms based on the accurate sparsity are excluded since MWC cannot provide prior information about accurate sparsity. For example, even if the ROMP and CoSaMP algorithms use $2N$ as the sparsity to force the operation, the results will contain false alarm bands with high probability. MWC considers some greed pursuit algorithms which can stop the iteration by comparing $\mathcal{F}(\mathbf{R})$ with the threshold $h_t$, such as MP and OMP [28]. Algorithm 1 represents the basic flow of MP and OMP.

**Algorithm 1: MP and OMP**

In step 3 of Algorithm 1, there are several classical methods to find $C_i$, such as the sum of projections, inner product, correlation coefficients, and so on [29]. But the sensing matrix with high column correlations may lead a wrong judgment in step 3. Two puzzles are faced by the classical algorithms, and we present a simple example in Fig. 4 to demonstrate in detail. It is easy to observe that $V_1 = C_1 + C_2$ and $V_2 = C_1 + 2C_2$. Therefore, $C_1$ and $C_2$ are called the
basis of \( \mathbf{V} \). The correct output of the reconstruction algorithms should be \( \mathbf{S} = \{1, 2\} \) and \( \mathbf{U} = [\mathbf{U}_1 \ \mathbf{U}_2] \), where \( \mathbf{U}_1 = [1, 1, 0, \cdots, 0]^T \) and \( \mathbf{U}_2 = [1, 2, 0, \cdots, 0]^T \).

\[
\begin{align*}
\mathbf{V} & = \begin{bmatrix} 3 & 4 \\ 3 & 5 \end{bmatrix} \\
\mathbf{C} & = \begin{bmatrix} c_1 & c_2 & c_3 & c_4 & c_5 & c_6 \\ 1 & 2 & 1 & 0 & -1 & \cdots \end{bmatrix}
\end{align*}
\]

Fig. 4. An underdetermined equation which is about an MMV problem

**Puzzle 1**: For MP and OMP, the initial residual \( \mathbf{R}^{[0]} = \mathbf{V} \). In the example shown in Fig. 4, the most relevant to \( \mathbf{R}^{[0]} \) is \( \mathbf{C}_3 \) in the first iteration, whether it is the sum of the projections or the sum of the correlation coefficients \( |\cdot| \). Therefore, the algorithms will add the index number 3 to the support instead of 1 or 2. In this paper, we called \( \mathbf{C}_3 \) as the strong interference term. Furthermore, after 3 is added to \( \mathbf{S} \), the algorithms tend to choose \( \mathbf{C}_2 \) to offset the component on the z-axis to minimize \( \mathbf{R}^{[1]} \). Then, the estimates \( \hat{\mathbf{S}} \) and \( \hat{\mathbf{U}} \) will deviate from the true value.

**Puzzle 2**: In the example shown in Fig. 4, even if the algorithm excludes \( \mathbf{C}_3 \) in advance, and it successfully adds 1 to \( \mathbf{S} \) in the first iteration. After calculation, \( \mathbf{R}^{[1]} = [\mathbf{R}^{[1]}_1, \mathbf{R}^{[1]}_2] \), where \( \mathbf{R}^{[1]}_1 = [-0.6, 1.2, 0]^T \) and \( \mathbf{R}^{[1]}_2 = [-1.2, 2.4, 0]^T \). In the second iteration, it’s easy to find that the column most relevant to \( \mathbf{R}^{[1]} \) is \( \mathbf{C}_5 \) rather than \( \mathbf{C}_2 \). Therefore, even if \( \mathbf{C}_1 \) is selected, \( \mathbf{C}_2 \) cannot be found smoothly in next iteration.

4.2 DSOMP Signal Reconstruction Algorithm

To solve these two puzzles, this paper proposes a DSOMP algorithm, and its pseudocode is shown in Algorithm 2. Since the PRBSes with low correlation enhance the randomness of the sensing matrix, the strong interference terms, such as \( \mathbf{C}_1 \), are rare. In the example shown in Fig. 4, although \( \mathbf{R}^{[0]} \) is the most relevant to \( \mathbf{C}_3 \), its projections on \( \mathbf{C}_1 \) and \( \mathbf{C}_2 \) are still much larger than other columns. To solve the Puzzle 1, DSOMP algorithm introduces a secondary screening mechanism called ‘loose-in and strict-out.’ ‘Loose-in’ means that the algorithm sets a loose filtering criteria to ensure that the index numbers of strong interference terms and all bases are added to the support. Specifically, in each iteration, DSOMP selects the \( t \) columns which are most relevant to the residual and adds their index numbers to the support. According to experience, \( t \) is generally set to 2 or 3. ‘Strict-out’ means that the algorithm filters out the index number of strong interference terms from the support by secondary screening. Back to the example shown in Fig. 4, when 1,2,3 are added to \( \mathbf{S}^{[n]} \) in the \( n \)-th iteration, \( \mathcal{F}(\mathbf{R}^{[n]}) \) should stop the next iteration. Then, the third row of estimate \( \mathbf{U}_{\mathbf{S}^{[n]}} \) has a very small component, and removing the third row has little effect on \( \mathcal{F}(\mathbf{R}^{[n]}) \). In each iteration of the second screening, DSOMP reevaluate the impact of the lowest energy row on \( R_{err} = \mathcal{F}(\mathbf{R}^{[m]} - \hat{\mathbf{R}}^{[m-1]}) \) and decide whether to move its number out of the support. And \( h_{err} \) is the threshold for judging this effect.

Going back to Puzzle 2, when 1 is added to the support in the example, how does the algorithm lock \( \mathbf{C}_2 \) in the next iteration? Here, we define a subspace \( \mathcal{L}(\mathbf{C}_j) \) which the column vectors \( \mathbf{C}_j, j \in \Lambda \) are located. The symbol \( \Lambda \) is an index number set. \( \mathbb{D}(\mathbf{R}, \mathcal{L}(\mathbf{C}_\Lambda)) \) denotes the distance from the matrix \( \mathbf{R} \) to \( \mathcal{L}(\mathbf{C}_\Lambda) \), and it is regarded as the sum of the distances from the columns of \( \mathbf{R} \) to \( \mathcal{L}(\mathbf{C}_\Lambda) \). Obviously, in the example of Puzzle 2, \( \mathbb{D}(\mathbf{R}^{[1]}, \mathcal{L}(\mathbf{C}_1, \mathbf{C}_2)) > \mathbb{D}(\mathbf{R}^{[1]}, \mathcal{L}(\mathbf{C}_1, \mathbf{C}_2)) = 0 \) is set up when \( j = 2 \). In this way, the algorithms can lock \( \mathbf{C}_2 \) accurately. Therefore, in \( n \)-th iteration, DSOMP calculates all distances \( \mathbb{D}(\mathbf{R}^{[n-1]}, \mathcal{L}(\mathbf{C}_{\Lambda(j)})) \) by the least squares method \( \mathbb{D}(\mathbf{R}^{[n-1]}, \mathcal{L}(\mathbf{C}_{\Lambda(j)})) = \mathcal{F}(\mathbf{R}^{[n-1]} - \mathbf{C}_{\Lambda(j)} \mathbf{C}_{\Lambda(j)}^T \mathbf{R}^{[n-1]}, \mathcal{L}(\mathbf{C}_{\Lambda(j)})) \), where \( \Lambda(j) = \mathbf{S}^{[n-1]} \cup \{ j \} \) and \( j \notin \mathbf{S}^{[n-1]} \). Then, DSOMP adds the index number set \( S_{inc} \) of the smallest \( g \) distances to \( \mathbf{S}^{[n]} \).

5. Simulation and Experiment

A DC-3GHz CS receiver based on MWC is designed by commercial devices, and the photo of this receiver is shown in Fig. 5. The receiver has a RF board used for gain ad-
adjustment and power division, four IF boards for mixing and sampling, an FPGA Evaluation Board named VC707 to read the sampling sequences, and a converter board which connects the other boards. The hardware design of this receiver is described in detail [30]. This CS receiver has four physical branches, and each branch is expanded to five sub-branches by the expander. Four 160-bit PRBSes with the rate of 6.4 Gbps are generated by Gigabyte Transceiver-X (GTX) of FPGA Evaluation Board. Some important design parameters related to this paper are shown in Table I. According to Table 1, the sensing matrix has a size of 20 \times 155.

As analyzed in Section 3, the imperfection of physical devices are uncontrollable factors affects the sensing matrix. We propose a method to measure the sensing matrix by some synchronized wideband signals, and the measurement method is displayed in [22] in detail. The measured sensing matrix is denoted as \( \mathbf{C}_{\text{mea}} \), and it is an accurate estimate of the sensing matrix of the hardware-implemented MWC-based receiver. And the theoretical sensing matrix \( \mathbf{C}_{\text{cal}} \) of an ideal MWC can be obtained by the Fourier coefficients of the PRBSes. Fig. 6 shows the difference in amplitude between \( \mathbf{C}_{\text{mea}} \) and \( \mathbf{C}_{\text{mea}} \) under the same PRBSes. The matrix \( \mathbf{N}_{\text{mea}} \) and \( \mathbf{N}_{\text{cal}} \) represent the normalized \( \mathbf{C}_{\text{mea}} \) and the normalized \( \mathbf{C}_{\text{cal}} \), respectively.

Fig. 7 compares the difference in amplitude between \( \mathbf{G}_{\text{mea}} \) and \( \mathbf{G}_{\text{cal}} \) which are the column correlation coefficient matrices calculated from \( \mathbf{C}_{\text{mea}} \) and \( \mathbf{C}_{\text{mea}} \), respectively. The average amplitude of \( \mathbf{G}_{\text{mea}} \) is greater than \( \mathbf{G}_{\text{cal}} \) by 0.084. Therefore, it demonstrates that the device’s imperfection deteriorates the column correlation of the sensing matrix.

Two MWC modules based on \( \mathbf{C}_{\text{mea}} \) and \( \mathbf{C}_{\text{cal}} \) are built in MATLAB respectively. Some dual-, three-, and four-carrier signals with different signal-to-noise ratios (SNR) are respectively injected the two MWC modules. The bandwidth of each subband of the signals is 5 MHz, and the carrier frequencies are randomly distributed at [0, 3 GHz]. The support is reconstructed by OMP, ROMP, CoSaMP, and DSOMP respectively, and Fig. 8 shows the support recovery rate. In the simulation, ROMP and CoSaMP obtain the prior information of accurate signal sparsity. As shown, DSOMP and OMP are more friendly to \( \mathbf{C}_{\text{mea}} \) than ROMP and CoSaMP. And DSOMP is superior to OMP both in the face of \( \mathbf{C}_{\text{mea}} \) and \( \mathbf{C}_{\text{cal}} \).

A three-carrier 5 MHz wideband signal is injected to the CS receiver, and the carrier frequencies are 1950, 1990, 2150 MHz, respectively. DSOMP recovers the support and reconstructs the three sub-bands. Fig. 9 compares the original spectrum with the reconstructed spectrum in amplitude. Further, we calculated the normalized mean square errors (NMSE) of the three reconstructed basebands and the original basebands, and -19.59 dB (1950 MHz), -19.18 dB (1990 MHz) and -22.20 dB (2150 MHz) are obtained, respectively.
6. Conclusion

This paper analyzes the characteristics of the sensing matrix of the hardware-implemented CS receiver, and proposes DSOMP signal reconstruction algorithm based on these characteristics. Both simulation and experiment prove the effectiveness of DSOMP in the face of high column correlation sensing matrix of the hardware-implemented CS receiver.

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