SPARSE SIGNAL RECOVERY WITH SIDE INFORMATION

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ABSTRACT

The paper proposes an algorithm for signal recovery with side information. It is assumed that the decoder has *a priori* knowledge about the sparse source signal in the form of side information, that can be used to estimate positions of significant elements in the source. The proposed iterative algorithm extends the orthogonal matching pursuit (OMP) algorithm used in compressive sampling, and is robust to partially noisy side information. Thus it is suitable for scenarios whereby a correlated source is available at the decoder. We apply the algorithm to spectrum sensing and image acquisition, and show great advantages of the proposed solution, compared to OMP (no side information) in terms of improved performance and reduced execution time.

1. INTRODUCTION

Compressive sampling is a technique for data acquisition and estimation that aims to sample signals sparsely in transform domains. The process of compressive sampling replaces conventional sampling and reconstruction with a more general linear measurement scheme and an optimization procedure to acquire a subset of signals within a source at a rate that is below Nyquist. However, this will work only if the source is sparse in the transform domain of choice.

A number of theoretical contributions have appeared on compressive sampling (see [1, 2, 3, 4]) over the past few years. One of the main challenges is the design of efficient and fast signal recovery algorithms, that are able to reconstruct an N-dimensional signal using $M < N$ measurements by exploiting sparsity of the signal. Since optimal recovery is an NP-hard problem, several sub-optimal solutions have been reported (see [4, 5, 6] and references therein). One of them is the orthogonal matching pursuit (OMP) algorithm [7], which is very popular due to its relatively lower complexity compared to other proposed reconstruction methods (see [1, 2]). However, the execution time of OMP is still too high for many practical applications where sparsity of the signal and its dimensions are high. One such example is image/video acquisition [8], where frame sizes are usually too large for the OMP recovery. To rectify this problem, in our previous work [9], we suggested splitting each frame into small non-overlapping blocks and performing sampling and the OMP recovery on only sparse blocks. However, the method of [9] reconstructs each block in the frame without exploiting useful information about previously reconstructed blocks.

Inspired by compressive image/video sampling [8, 9], in this paper, we propose a novel algorithm for signal recovery with side information. The algorithm extends OMP to the case when *a priori* information about the source is present at the decoder in the form of estimated positions of significant elements of the signal. If the side information is correct, the algorithm finds the solution with fewer iterations than OMP. In addition, the reconstruction quality is generally better, which indicates that fewer measurements are needed. If the side information is noisy, i.e., some of the assumed positions at the decoder are not correct, the proposed algorithm has a mechanism to correct them and converge to the correct solution.

We test the algorithm in two practical application scenarios. The first application is spectrum sensing by cognitive radios, which sense the spectrum environment to exploit spectrum holes [10] and send their measurements to a central point. Since the spectrum is expected to be sparse, compressive sampling can be exploited to reduce the number of measurements. We assume that the measurements are corrupted by independent Additive White Gaussian Noise (AWGN). Since acquired samples by different radios in a localized area are correlated, a central point recovers the reading of a cognitive radio, using the results from other neighboring radios as side information.

The second application that we consider is image/video acquisition, where a previously recovered video frame serves as side information for recovery of successive frames.

In [11], an algorithm for signal recovery from noisy observations is proposed. In [12], joint sparsity between measurements of different sensors was discussed and several models proposed. In [13], a greedy pursuit method, simultaneous OMP, was proposed for simultaneous recovery of several correlated sparse signals. In parallel work [14, 15] a similar problem as in this paper is studied but not in the context of OMP.

In this paper, we assume that knowledge about the signal is present already at the decoder, either as a previously recovered correlated signal, or information sent *a priori*. For example, when recovering a frame, previous frames are already available. Thus, we do not address joint sparsity directly; however, our result does indicate that with side information, the number of measurements needed is reduced. The setup considered in this paper can be seen as the asymmetric version of the scenarios of [12, 13]. We also develop an effective technique to cope with "corrupted" side information, i.e., the case when some of the estimated significant positions at the decoder are wrong. We apply the algorithm to cognitive radio spectrum sensing and compressive image sampling showing improved performance with faster recovery compared to OMP and the method of [9].

The paper is organized as follows. The next section briefly reviews compressive sampling and the OMP reconstruction algorithm. Section 3 describes the algorithm for signal recovery with side information. Section 4 shows our experimental results, and the last section concludes the paper and outlines future work.

2. BACKGROUND

In this section we briefly describe compressive sampling and signal recovery via the OMP algorithm [7]. We also set the notation used throughout the paper.

2.1. Compressive Sampling

Compressive sampling or compressed sensing [1, 2] is a novel framework that enables sampling below the Nyquist rate, without (or with a small) sacrifice in reconstruction quality. It is based on exploiting sparsity of the signal in some domain. In this section we briefly review compressive sampling following closely notation of [3]. Matrices will be denoted by bold capital letters, vectors by bold low-case letters, and sets by capital letters.

Let $\mathbf{x}$ be a set of N samples of a real-valued, discrete-time random process X. Let

$$\mathbf{x} = \mathbf{\Psi}\mathbf{s} = \sum_{i=1}^{N} s_i \psi_i, \tag{1}$$

where $\mathbf{s} = [s_1, \ldots, s_N]$ is an N-vector of weighted coefficients $s_i = \langle \mathbf{x}, \psi_i \rangle$, and $\mathbf{\Psi} = [\psi_1|\psi_2|\cdots|\psi_N]$ is an $N \times N$ orthonormal basis matrix with ψ_i being the i-th basis column vector.

Vector $\mathbf{x}$ is considered K-sparse in the domain $\mathbf{\Psi}$, for $K \ll N$, if only K out of N elements of $\mathbf{s}$ are non-zero. Many natural signals can be approximated as sparse since they have many non-significant (close to zero) coefficients after transform. Sparsity of a signal is used for compression with conventional transform coding, where the whole signal is first acquired (all N samples), then the N transform coefficients $\mathbf{s}$ are obtained via $\mathbf{s} = \mathbf{\Psi}^{-1}\mathbf{x}$, and finally $N-K$ non-significant coefficients of $\mathbf{s}$ are discarded and the remaining are encoded. The resulting acquisition redundancy is due to large amounts of data being discarded because they carry negligible or no energy.

The main idea of compressive sampling is to remove this "sampling redundancy" by requiring only M samples of the signal, where $K < M \ll N$. Let $\mathbf{y}$ be an M-length measurement vector given by: $\mathbf{y} = \mathbf{\Phi}\mathbf{x}$, where $\mathbf{\Phi}$ is an $M \times N$ measurement matrix. The above expression can be written in terms of $\mathbf{s}$ as

$$\mathbf{y} = \mathbf{\Phi}\mathbf{\Psi}\mathbf{s} = \mathbf{\Phi}'\mathbf{s}. \tag{2}$$

Matrix $\mathbf{\Psi}$ determines the domain in which the signal is sparse. For example, if $\mathbf{s}_i$'s are discrete cosine coefficients, then we collect samples in the DCT domain assuming that the image will be sparse in this domain. On the other hand, if $\mathbf{s}_i$'s are sinusoids at different frequencies, we collect Fourier coefficients.

Note that (2) is a dimensionality reduction thus leading to a loss in information in general. That is, there are infinitely many $\mathbf{x}'$ that when multiplied by $\mathbf{\Phi}$ give $\mathbf{y}$. However, it has been shown in [1, 2] that signal $\mathbf{x}$ can be recovered losslessly from $M \approx K$ or slightly more measurements if the measurement matrix $\mathbf{\Phi}$ is properly designed, so that $\mathbf{\Phi}\mathbf{\Psi}$ satisfies the so-called restricted isometry property (RIP) [2]. This will always be true if $\mathbf{\Phi}$ and $\mathbf{\Psi}$ are incoherent, that is, the vectors of $\mathbf{\Phi}$ cannot sparsely represent basis vectors and vice versa.

It was further shown [1, 2, 3] that an independent identically distributed (i.i.d.) zero-mean Gaussian matrix satisfies the above property for any orthonormal $\mathbf{\Psi}$ with high probability. Some other choices of $\mathbf{\Psi}$ that satisfy RIP are random matrices with +1/-1 entries drawn from uniform Bernoulli distribution, randomly permuted vectors from standard orthonormal bases, such as Fourier and Walsh-Hadamard. Also, it has been shown that it is enough for a signal $\mathbf{x}$ to be r-compressible (the sorted coefficients decay under a power law with scaling exponent $-r$), instead of K sparse (see [4]).

Unfortunately, reconstruction of $\mathbf{x}$ (or equivalently, $\mathbf{s}$) from vector $\mathbf{y}$ of M samples is not trivial. The exact solution [1, 2, 3] is NP hard and consists of finding the minimum l_0 norm (the number of non-zero elements). However, an excellent approximation can be obtained via the l_1 norm minimization given by:

$$\hat{\mathbf{s}} = \arg\min ||s'||_1, \quad \text{such that} \quad \mathbf{\Phi}\mathbf{\Psi}\mathbf{s}' = \mathbf{y}. \tag{3}$$

It has been shown in [1, 2] that a K-sparse signal can be recovered with high probability using (3) if $M \geq cK\log(N/K)$ for some small constant c. Thus, one can recover N measurements of $\mathbf{x}$ with high probability from only $M \approx cK\log(N/K) < N$ random measurements $\mathbf{y}$ under the assumption that $\mathbf{x}$ is K-sparse in domain $\mathbf{\Psi}$.

This convex optimization problem, namely, basis pursuit [1, 2], can be solved using a linear program algorithm of $O(N^3)$ complexity. Due to complexity and low speed of linear programming algorithms, faster solutions were proposed at the expense of slightly more measurements, such as matching pursuit, tree matching pursuit [5], orthogonal matching pursuit [7], and group testing [6].

If noise is present in the collected measurements, then (3) should be replaced by minimization of

$$\hat{\mathbf{s}} = \arg\min ||s'||_1, \quad \text{subject to} \quad ||\mathbf{\Phi}\mathbf{\Psi}\mathbf{s}' - \mathbf{y}||_2 \leq \varepsilon, \tag{4}$$

where ε is estimated upper bound on the noise magnitude [3]. Several recovery algorithms have been proposed that are able to cope with measurement noise, such as [11, 17].

2.2. Orthogonal Matching Pursuit (OMP)

The OMP algorithm [7] is a greedy algorithm that can reliably recover a K-sparse signal given $O(K\ln N)$ random linear measurements. The main idea of the algorithm is to select columns of the measurement matrix $\mathbf{\Phi}$ that contribute in generating measurements $\mathbf{y}$ in a greedy way. That is, due to sparsity of the signal, only some of the columns in $\mathbf{\Phi}$ (exactly K) will be used when calculating $\mathbf{y}$. These K columns correspond to the positions of significant elements in the sparse signal. All other, $N-K$ columns will not contribute in calculating $\mathbf{y}$. OMP iteratively finds K columns of $\mathbf{\Phi}$, by choosing in each iteration the column that is most strongly correlated with the residual, the part of the sparse signal that has not yet been approximated. In the initialization step, the set of contributing columns of $\mathbf{\Phi}$ is empty and residual is set to $\mathbf{y}$.

It was shown in [7] that $M \geq cK\log(N/\delta)$ measurements are enough for recovery of the signal with probability exceeding $1-\delta$ with $\delta \in (0, 0.36)$, $c \leq 20$ ($c \approx 4$ for Gaussian measurement matrix).

The key problem of OMP is that it is time-consuming when carried out over a large number of samples. For example, experimental results in [7] show that for 1000 trails, $K=64$, $M=250$, and $N=256$, the processor time needed for execution was roughly 50 sec, while for the same K and $M=400$ and $N=1024$, the time increased to 200 sec. This paper attempts to improve the reconstruction quality and to decrease the execution time by exploiting *a priori* knowledge about the signal in the form of decoder side information.

3. PROPOSED ALGORITHM

Suppose that $\mathbf{\Phi}$ is the $M \times N$ random measurement matrix. To simplify exposition, let $\mathbf{x}$ be the N-length K-sparse signal sparse in the time domain. (Otherwise, it is enough in the following to replace $\mathbf{x}$ by $\mathbf{s}$ and $\mathbf{\Phi}$ by $\mathbf{\Phi}'$.) The decoder has access to the M-length measurement vector $\mathbf{y} = \mathbf{\Phi}\mathbf{x}$. In addition, the decoder has *a priori* knowledge about the signal, side information, in the form of estimated positions (which might not be correct) of the significant elements in $\mathbf{x}$. The problem is to obtain the reconstructed signal, $\hat{\mathbf{x}}$, based on $\mathbf{y}$, $\mathbf{\Phi}$, and side information.

The main idea of the algorithm is to start with the estimated positions of significant elements of $\mathbf{x}$, and then in each iteration find the most strongly correlated column in $\mathbf{\Phi}$ among remaining ones. This column will either be included as an additional column or it will replace the column in the set of estimated positions that is least correlated (wrong guess). The rationale is that the result for a correlated source will be close the desired solution.

First a word about notation. For a set Θ, $|\Theta|$ is its cardinality, and $\{\}$ denotes an empty set. For a matrix $\mathbf{\Omega}$, ω_j denotes its j-th column; furthermore, $\mathbf{\Omega}_\Theta$ is a matrix of $|\Theta|$ columns of $\mathbf{\Omega}$ with indices from set Θ.

Algorithm 1 *Signal recovery with side information*

INPUT:

- *An $M \times N$ measurement matrix $\mathbf{\Phi}$*
- *An M-dimensional measurement vector $\mathbf{y}$*
- *The sparsity level of the signal K*
- *Maximum number of iterations $T \geq K$*
- *The side information set Λ_1 with at the most K elements*
- *Constants $\kappa_1, \kappa_2 \leq 1$.*

OUTPUT:

- *An N-dimensional estimate $\hat{\mathbf{x}}$ of the signal $\mathbf{x}$*
- *A set Λ_t, $t>1$, containing K elements from $\{1,\dots,N\}$*

PROCEDURE:

1. *Initialization:*
   - *Set $t=1$.*
   - *If $\Lambda_t = \{\}$ then*
     - $\Lambda_t = \{\arg\max_{j=1\dots N} |\langle \mathbf{y}, \phi_j \rangle|\}$
2. *Get weakest element from side information set:*
   - $\mathbf{\Omega}_t = \mathbf{\Phi}_{\Lambda_t}$
   - $\mathbf{x}_t = \arg\min_{\mathbf{x}} ||\mathbf{y} - \mathbf{\Omega}_t\mathbf{x}||_2$
   - *Let p be the projected value, and $\tilde{m}$ the least correlated column in $\mathbf{\Omega}_t$ to $\mathbf{y}$.*
3. *Get strongest candidate from 'outside' set:*
   - $\mathbf{r} = \mathbf{y} - \mathbf{\Phi}\mathbf{x}_t$
   - $q = \max_{j=1..N} |\langle \mathbf{r}, \phi_j \rangle|$
   - $\tilde{l} = \arg\max_{j=1..N} |\langle \mathbf{r}, \phi_j \rangle|$
4. *Test whether to remove 'wrong guess' or to exit:*
   - *If $(p < q\kappa_1)$ then*
     - $\Lambda_t = \Lambda_t / \{\tilde{m}\}$
   - *else*
     - *if $(p\kappa_2 < q)$ then*
       - $\Lambda_{t+1} = \Lambda_t$
       - *goto 6*
5. *Add strongest candidate:*
   - $\Lambda_{t+1} = \Lambda_t \bigcup \{\tilde{l}\}$
   - *If $|\Lambda_{t+1}| \geq K$ then*
     - $\mathbf{\Omega}_t = \mathbf{\Phi}_{\Lambda_{t+1}}$
     - $\mathbf{x}_t = \arg\min_{\mathbf{x}} ||\mathbf{y} - \mathbf{\Omega}_t\mathbf{x}||_2$
     - *goto 6*
   - *If $t < T$ then*
     - *increment t*
     - *goto 2*
6. *Stop: The estimate $\hat{\mathbf{x}}$ has nonzero indices at the components listed in Λ_{t+1}. The value of $\hat{\mathbf{x}}$ in component λ_j equals the j-th component of $\mathbf{x}_t$.*

Algorithm 1 allows the possibility for a wrong guess, that is, the estimated position(s) of the significant elements in $\mathbf{x}$ are wrong. That is why, the number of iterations T is allowed to be higher than K. In the case when the probability of a wrong guess is zero, $T=K$.

Λ_1 is the set of known/estimated positions of the significant elements of $\mathbf{x}$ at the decoder. If $\Lambda_1 = \{\}$, the algorithm boils down to the OMP algorithm, thus in Step 1, as in OMP, Λ_1 is set to the most strongly correlated column in $\mathbf{\Phi}$ to $\mathbf{y}$.

In Step 2, $\mathbf{\Omega}_t$ is a matrix of columns of $\mathbf{\Phi}$ that correspond to significant elements of $\mathbf{x}$ based on side information. The decoder forms a projection, $\mathbf{x}_t$, of $\mathbf{y}$ onto $\mathbf{\Omega}_t$. Then, the decoder calculates the column in $\mathbf{\Omega}_t$ that is least correlated to $\mathbf{y}$. This will be a candidate for removal since it might be a wrong guess.

In Step 3, a residual is computed based on the current estimate $\mathbf{x}_t$, and as in OMP, the most strongly correlated column in $\mathbf{\Phi}$ from the remaining columns is computed and its index is set to $\tilde{l}$.

If column $\tilde{l}$ is more correlated than column $\tilde{m}$, $\tilde{m}$ is removed in the first step of Step 4. That is, $\tilde{m}$ is characterized as a wrong guess, since there are still unchecked columns outside the side information set that are more correlated. If column $\tilde{l}$ is much less correlated than column $\tilde{m}$ (regulated by constant κ_2), the decoder concludes that there cannot be further improvement of the estimate, and exits.

If this is not the case, in Step 5, the decoder adds column $\tilde{l}$ to $\mathbf{\Omega}_t$, increments t and goes to the next iteration. If there are already K columns in set Λ_t, the decoder exits, and makes reconstruction based on the selected K columns.

Introduction of the margin (regulated by κ_1) in Step 4 is in spirt of (4). That is, a column is removed from the side information set only if the newly found column is more correlated for a certain margin. On the other hand, if the newly found column is much less correlated than the least correlated column in the side information set, a conclusion is made that the estimate cannot be further improved by introducing new columns. The best values for κ_1 and κ_2 are found by simulations. Note that these deletions of coefficients are similar to CoSaMP [11].

If all initial guesses are correct, the algorithm boils down to OMP with $K - |\Lambda_1|$ iterations, hence, reduced complexity and execution time. In more realistic situations when side information is not perfect, e.g., reconstruction of correlated sources, the algorithm effectively corrects wrong guesses, as it will be shown in the next section.

If ε is the probability of a wrong guess, that is, the estimated position of the significant element is wrong, then the algorithm would roughly need εK iterations. Note that to allow for correction of wrong guesses, one iteration of the algorithm requires more computations than that of OMP. However, the algorithm has the ability of using side information to improve recovery. The algorithm is applicable to any measurement matrix as OMP.

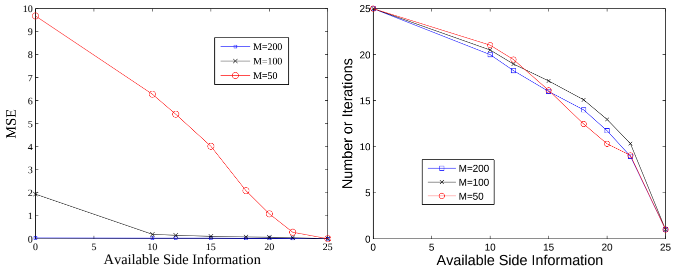
With small modifications the algorithm can be applied to Approximate Conjugate Gradient Pursuit [16] and probably some other greedy signal recovery algorithms.

4. APPLICATION EXAMPLES

In this section we apply Algorithm 1 to different application scenarios. In all our simulations, we set $\kappa_1 = 0.25$ and $\kappa_2 = 0.0001$, which empirically led to the best results.

First, we test performance of the algorithm in the case of perfect side information, $\varepsilon = 0$, that is, all estimated positions of significant elements at the decoder are correct. Signal $\mathbf{x}$ of length $N = 1000$ contains $K = 25$ non-zero elements randomly distributed. We use Gaussian measurement matrix $\mathbf{\Phi}$, and as performance indicator Mean Square Error (MSE) between the original signal and the reconstructed signal.

Fig. 1 shows MSE and the number of iterations vs the number of positions of significant elements of $\mathbf{x}$, termed available side information, known at the decoder for three different values of the number of measurements M. It can be seen from the figure, that exploiting side information can lead to a better reconstruction. Indeed, without side information $M = 100$ measurements are not enough, while with side information even with $M = 50$ and more than 20 known elements, excellent recovery can be achieved. The number of iterations drops from 25 (without side information) to less than 15 if more than 15 positions of significant elements are known. As expected, the more positions of significant elements are known, the better the quality achieved with fewer iterations.



(a) (b)

Fig. 1. Results with perfect knowledge of side information:(a) MSE, (b) the number or iterations, vs. the number of known positions of significant elements, i.e., available side information.

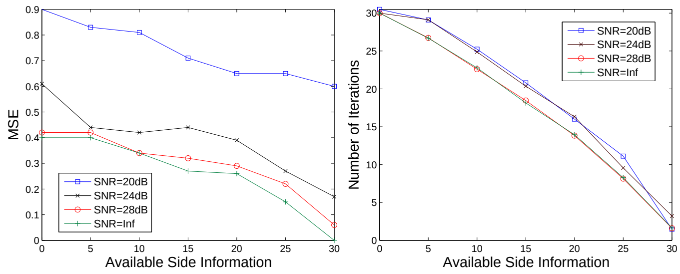
Next, we test the algorithm for the spectrum sensing with cognitive radio (CR) application. Let $x(t)$ be the signal that occupies our chosen frequency band. Then, CRi, $i = 1,2$ receives: $x_i(t) = x(t) + n_i(t)$, where $n_i(t)$ is zero-mean AWGN independent of $x(t)$ and $n_j(t)$, $j \neq i$ [10]. Let $\mathbf{x}_s$ and $\mathbf{x}_{s_i}$ be vectors of N equidistant samples of $x(t)$ and $x_i(t)$, respectively, sampled at or above the Nyquist sampling rate. CRi samples $\mathbf{x}_{s_i}$ in M points, $K < M \ll N$, as:

$$y_i = \mathbf{\Phi}\mathbf{x}_{s_i} = \mathbf{\Phi}\mathbf{\Psi}\mathbf{X}_{s_i},$$

where $\mathbf{\Phi}$ is an $M \times N$ measurement matrix, $\mathbf{\Psi}$ is the inverse Fourier transform, and $\mathbf{X}_{s_i}$, the Fourier representation of $\mathbf{x}_{s_i}$, has only $K \ll N$ non-zero elements when noise-free. Note that, $x_i(t)$ is down-sampled (non-uniformly) by setting measurement matrix $\mathbf{\Phi}$ to contain all zeros and only one 1 in each of M rows, where the position of 1 is random in that row. Thus, y_i contains M random (not equidistant) samples of $x_i(t)$. y_1 and y_2 can be seen as two noisy replicas of the same source, hence they are correlated. The decoder recovers first $\hat{\mathbf{x}}_{s_1}$ from y_1, and uses (some) positions of significant elements in $\hat{\mathbf{x}}_{s_1}$ to recover $\mathbf{x}_{s_2}$ with the proposed algorithm.

We set $N = 1000$, sparsity to $K = 30$, the signal power to 100 and change noise power $P_{n_1} = P_{n_2}$ to obtain different signal-to-noise ratios (SNRs) in the channels. Fig. 2 shows normalized MSE between the original spectrum and Fourier transform of the reconstructed, given by MSE $= 1/N\sum_{j=1}^{N} E[(\hat{\mathbf{X}}_{s_2}(j) - \mathbf{X}_{s_2}(j))^2]$, and the number of needed iterations vs the number of positions of significant elements that the decoder uses from $\hat{\mathbf{x}}_{s_1}$ for four different values of channel's SNRs.

It can be seen that for all SNRs in the channel the reconstruction quality improves with fewer number of iterations as more positions of significant elements are used from the other radio. If we do not use any information available from the other radio, 30 iterations are needed whereas if we use all available information, we need only few iterations in average. SNR=Inf refers to the case of no noise in the channel.

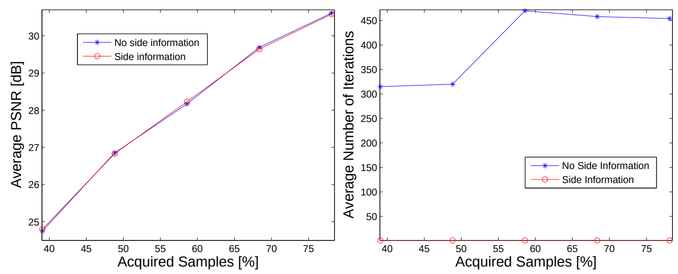


(a) (b)

Fig. 2. CR example: (a) MSE, (b) the number or iterations, vs. the number of positions of significant elements used from the other radio, i.e., available side information.

Finally, we show results for the video acquisition scenario. We simulated compressive sampling on the Y-component of the QCIF "Akiyo" sequence. We split each frame into 32×32 non-overlapping blocks and perform compressive sampling in the DCT domain on each block. We use an $M \times N$ measurement matrix with random Bernoulli +1/-1 entries, which is more realistic in this scenario [8]. The first frame was compressively sampled and recovered using OMP (without side information). It is then used as side information for recovery of the second frame.

The results as peak signal-to-noise ratio (PSNR) of the average MSE and the average number of iterations (over all blocks) vs. the percentage of acquired samples are shown in Fig. 3. Side information curves denote results obtained with independent recovery of the frame with OMP. It can be seen that for the same PSNR performance, significantly fewer iterations are needed for all sampling rates. Similar results were obtained for other frames in the "Akiyo" sequence.



(a) (b)

Fig. 3. Video acquisition: (a) PSNR, (b) the average number of iterations, vs. sampling rate.

5. CONCLUSION

We develop an algorithm for signal recovery with side information. It is an iterative algorithm based on OMP, that takes into account side information, i.e., estimated positions of significant elements of the signal, that can be acquired from the already recovered correlated source. Our experiments show great advantages of the proposed solution, compared to OMP (without side information) in terms of improved performance and reduced complexity. We apply the algorithm to cognitive radio spectrum sensing and compressive image sampling showing improved performance with faster recovery.

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