SAR Images Compression via Independent Component Analysis and Compressive Sampling

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***Abstract*—In this paper the performance of two compression methods for SAR images, based on an overcomplete Independent Component Analysis and on a Compressive Sampling approach are analyzed. The two approaches are analyzed and compared on different set of real SAR COSMO-SkyMed data.**

Keywords-Synthetic Aperture Radar; Compression; Independent Component Analysis; Compressive Sampling

I. INTRODUCTION

In the last few years, high quality images of the Earth produced by SAR systems, carried on a variety of airborne and space borne platforms, have become increasingly available. With the increasing resolution of SAR images, it is of great interest to find efficient ways to store the high volume of SAR image data at real time or to compress SAR images with higher compression performances for limited bandwidth of communication channel.

The most widely used compression techniques for raw SAR data are based on Block Adaptive Quantization (BAQ), due to its simplicity for coding and decoding [1].

Transform coding algorithms have been also applied on SAR intensity images [2] and on SAR raw data [3]. They are based on the decomposition of the signal to be encoded in an orthonormal basis. Then, each decomposition coefficient is approximated by a quantized variable. The role of the signal decomposition is to decorrelate the signal and to make the subsequent quantization process easier. The coding performance depends on the choice of the basis. The best basis compacts the image energy into the fewest coefficients. The small number of significant coefficients in the transformed domain results in a sparse representation, that can be coded with fewer bits, due to its low entropy. The significant coefficients are coded using an entropy constrained quantizer, while their position is encoded through a significance map, denoted also as "sparsity pattern". Then, the overall bit rate is given by the rate required for encoding the significant coefficients plus the rate required for encoding the significance map.

With the aim of reducing the number of significant representation coefficients, and obtaining a sparse representation, overcomplete dictionaries, or frames, have been proposed [4]. The representation of the observed data in terms of overcomplete basis in not unique, then a constraint have to be enforced to recover uniqueness. To achieve a sparse representation the introduced constraint can be the minimization of the significant coefficients by using an $\ell 1$ norm based penalty. It can be shown that in this case the problem to be solved is a linear programming problem, that can be viewed as a Maximum a Posteriori (MAP) estimation problem with a Laplacian prior distribution assumption [5].

A possible choice of the basis is the overcomplete Independent Component Analysis (ICA) basis [5] allowing to model the data as a mixture of non Gaussian and "almost" statistically independent sources, so that the representation coefficients, due to their scarce correlation, can be efficiently coded using a scalar quantizer. In [6] a compression method based on an overcomplete ICA representation, coupled with the use of an entropy constrained scalar quantizer [3], optimized for the Laplacian statistics of the ICA coefficients and using a proper bit allocation strategy, has been introduced.

In this paper we compare the approach presented in [6] with a similar approach using compressive sampling (CS) [7, 8]. CS is a model-based framework for data acquisition and signal recovery based on the premise that a signal having a sparse representation in one basis, can be reconstructed from a small number of measurements collected in a second basis, that is incoherent with the first. In this case we use an overcomplete ICA basis for the sparse representation of the signal and a random measurement matrix.

The two approaches are analyzed and compared on real COSMO-SkyMed images.

II. ICA BASED OMPRESSION METHOD

A. *Overcomplete ICA*

Independent Component Analysis (ICA) [5] has been proposed as a statistical generative model that allows to represent the observed data as a linear transformation of variables that are non Gaussian and mutually independent.

The model is the following:

$$\mathbf{x} = \mathbf{\Psi}\boldsymbol{\alpha} \quad (1)$$

where $\mathbf{x} = [x_1, x_2, \ldots x_N]^T$ is the random vector representing the observed data, $\boldsymbol{\alpha} = [\alpha_1, \alpha_2, \ldots \alpha_P]^T$ is the random vector of the independent components, $\mathbf{\Psi}$ is an unknown constant matrix, called the mixing matrix or basis matrix.

The overcomplete ICA paradigm [5] assumes $P>N$. This means we have a larger number of independent components and we can more easily adapt to signal statistics. Since the matrix $\mathbf{\Psi}$ is not invertible, even if it is known, the estimation of the independent components is an undetermined problem that does not admit a unique solution. Then a constraint on the statistical distribution of the ICA coefficients is introduced to solve the problem.

It can be shown [5] that assuming a Laplacian distribution, the optimal estimation of the coefficients $\hat{\alpha}_i$ leads to the minimization of their ℓ_1 -norm with the constraint $\mathbf{x} = \mathbf{\Psi}\boldsymbol{\alpha}$:

$$\hat{\boldsymbol{\alpha}} = \underset{\mathbf{x}=\mathbf{\Psi}\boldsymbol{\alpha}}{\operatorname{argmin}} \sum_{i} |\alpha_i| \quad (2)$$

The choice of the Laplacian distribution is convenient with respect to the compression application since permits to have a sparse representation with a small number of non zero coefficients $\hat{\alpha}_i$.

For the estimation of the basis matrix we adopted a modification of FastICA proposed in [5], that searches for “quasi-orthogonal” basis.

B. *Quantization and bit allocation*

It is already known [11] that under the high-resolution quantization hypothesis, i. e. if the number of quantization levels is sufficiently large a uniform quantizer is optimal for a large class of probability distributions. However, at low bit rates, a uniform quantizer is not optimal.

Using the overcomplete ICA approach, the representation coefficients are Laplacian distributed. Moreover, the decomposition basis is chosen so that many coefficients are close to zero and few of them have a large amplitude. In this case the threshold quantizer tends to an optimal entropy constrained quantizer [12]. Then, the significant coefficients are coded using an entropy constrained threshold quantizer optimized for the Laplacian distribution [7].

The position of the significant coefficients needs also to be encoded using a significance map, which is a binary map containing a bit ‘1’ in correspondence of the position of the significant coefficients and the bit ‘0’ in the other positions. This map is also entropy encoded. For sparse representations the entropy of this map can be noticeably smaller than one.

Then, the total number of bits necessary to encode a data frame is given by the number of bits necessary to encode the significance map, plus the number of bits necessary to encode the significant coefficients.

A procedure that can be used for optimally distributing the assigned number of bits among the different blocks is described in [3]. It imposes an equal average distortion per each block in which is subdivided the image and assigns more bits to the blocks with a larger variance respect to those assigned to the blocks with a lower variance.

III. CS-ICA BASED COMPRESSION METHOD

A. *Compressive Sampling*

CS theory [7, 8] provides a framework for recovering the coefficients of a sparse representation of starting from a reduced number of observations.

The signal $\mathbf{x} = [x_1, x_2, \ldots x_N]^T$ is sparsely representable if there exists a sparsity basis $\{\boldsymbol{\psi}_i\}$ that provides a representation (1) of $\mathbf{x}$; with a $\boldsymbol{\alpha}$ a *K*-sparse vector.

An estimate of the representation coefficients $\hat{\alpha}_i$ are determined by minimizing their ℓ_1 -norm of $\boldsymbol{\alpha}$ with the constraint $\mathbf{x} = \mathbf{\Psi}\boldsymbol{\alpha}$, i.e. using (2).

Since the signal $\mathbf{x}$ has a very compact representation in terms of the significant coefficients $\hat{\alpha}_i$; the method followed for data compression in the previous approach is simply be to compute $\hat{\alpha}_i$ from $\mathbf{x}$ (via (2)) and then encode the locations (significance map) and values of the *K* significant coefficients Alternatively, in order to avoid the encoding of the significance map, another more interesting implication of CS can be exploited for data compression. It can be shown that under certain conditions sparse signals can actually be acquired using far fewer samples than the signal size apparently demands.

We suppose that, rather than computing the *N* coefficients $\boldsymbol{\alpha}$ directly using (2), we collect and encode $M<N$ measurements $\mathbf{y} \in \mathcal{R}^M$:

$$\mathbf{y} = \mathbf{\Phi}\mathbf{x} \quad (3)$$

using the measurement $M \times N$ matrix $\mathbf{\Phi}$ that is fixed in advance and not dependent on $\mathbf{\Psi}$.

The process of recovering the signal $\mathbf{x}$ from the measurements $\mathbf{y}$ is ill-posed in general, when $M<N$ there exist an infinite number of candidate signals $\mathbf{x}$ that satisfy (3). The key to CS recovery is to select among these candidates by imposing the model of sparsity.

If $\mathbf{x}$ is *K*-sparse in the dictionary $\mathbf{\Psi}$, and assuming suitable incoherence between $\mathbf{\Psi}$ and $\mathbf{\Phi}$ (and hence that $M = O(K \log N)$), then the convex optimization problem (2) becomes:

$$\hat{\boldsymbol{\alpha}} = \underset{\mathbf{y}=\mathbf{\Phi}\,\mathbf{\Psi}\boldsymbol{\alpha}}{\operatorname{argmin}} \sum_{i} |\alpha_i| \quad (4)$$

which will return the correct coefficients $\hat{\alpha}_i$ and hence the correct signal $\mathbf{x} = \mathbf{\Psi}\boldsymbol{\alpha}$ [7, 8, 9, 10].

In our approach we assume the overcomplete ICA matrix as the dictionary in which $\mathbf{x}$ is K-sparse and, in order to ensure incoherence between the two matrices, a Gaussian random matrix $\mathbf{\Phi}$ has been assumed.

B. Quantization and bit allocation

In the CS-ICA approach since we encode the vector $\mathbf{y}$ that is not sparse and whose statistic is not known it is more convenient to adopt a uniform quantizer coupled with the same bit allocation procedure considered for the ICA approach. However in this case we do not need to encode the significance map and the total number of bits are the bits necessary to encode each vector $\mathbf{y}$, of size $M\times1$, with $M<N$, corresponding to each block of the image $\mathbf{x}$, of size $N\times1$.

IV. Experimental Results and conclusions

We tested the performance and compared the two proposed methods on real COSMO SkyMed intensity images.

The image has been subdivided in blocks of 8x8 pixels both in azimuth and range directions. Note that the SAR image pixels are floating point valued with a dynamic range of about 50 dB. Moreover, SAR images are affected by the presence of speckle noise, typical of images generated by coherent systems, that has to be preserved to keep the information contained in the image.

The overcomplete ICA basis have been computed using the algorithms presented in [6], and starting from a set of 8x8 training vectors.

Then, for the overcomplete ICA approach, the ICA coefficients of each block have been computed using Eq. (2) and then, they have been quantized using the threshold quantizer optimized for the coefficients Laplacian distribution, that, besides exhibiting a better performance, has the advantage of allowing any fractional bit rate value. For the bit budget distribution among the different coefficients vectors, the bit allocation procedure referred in Section II has been adopted.

For the CS approach, first the $\mathbf{y}$ vector of each block has been computed using (3) and then, it has been quantized using an uniform quantizer. For the bit budget distribution among the different blocks, the bit allocation procedure referred in Section II has been adopted. Eventually, to recover the image $\mathbf{x}$ the minimization (4) has been used.

Different quality parameters can be considered to evaluate the performance of the compression method. In particular, one of the most meaningful parameters is the signal-to-noise ratio (SNR) computed on the SAR images obtained after the processing of the compressed data, it is defined as:

$$SNR = \frac{\text{SAR data power}}{\text{quantization noise power}} = \frac{\|\mathbf{x}\|^2}{\|\mathbf{x}-\hat{\mathbf{x}}\|^2}. \qquad (5)$$

The SAR image considered is a single look COSMO SkyMed of Naples surroundings, in Italy, shown in Fig. 1.

The (equalized) intensity of a frame is shown in Fig. 2. The average distortions for the two approaches obtained for different avarage bit rate are presented in Table I. The image frames recovered with an average rate R=1.5, for the two approaches are shown respectively in Figs. 3 and 4.

We note that these preliminary results show a slightly better performance using the overcomplete ICA approach. But it needs to be pointed out that the CS approach can be certainly improved optimizing the choice of the selected measurement and representation matrices, using a quantizer optimized for the statistical distribution of the observation vectors $\mathbf{y}$ and choosing the optimal number M of the observations. All these points need deeper investigations.

TABLE I. Rate-SNR values for the SAR COSMO-SkyMed image

Average bit rate	**SNR (dB)**	
	Overcomplete ICA	***CS***
1	8	7.9
1.5	10.3	9.6

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Fig 1: SAR COSMO-SkyMed intensity image of Naples surroundings, Italy.

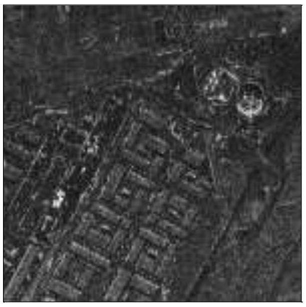

Fig 2: SAR COSMO-SkyMed frame.

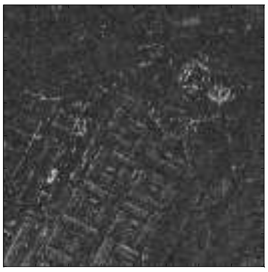

Fig 3: SAR COSMO-SkyMed frame reconstructed using the overcomplete ICA approach with R=1.5

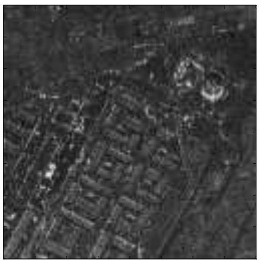

Fig 4: SAR COSMO-SkyMed frame reconstructed using the CS approach with R=1.5

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