SAR IMAGES COMPRESSION VIA INDEPENDENT COMPONENT ANALYSIS AND COMPRESSIVE SAMPLING

Alessandra Budillon
Gilda Schirinzi
Dipartimento di Ingegneria
Università degli Studi di Napoli “Parthenope”
Napoli, Italy

The aim of the work

- Can SAR image compression performance be improved assuming an appropriate sparse representation?

- Can Compressive Sampling (CS) provide an efficient tool for compression of a sparse signal?

- How does CS behave with respect to a Transform Coding method such as Overcomplete Independent Component Analysis (ICA) which can sparsify a signal?

Compressive sampling and lossy compression

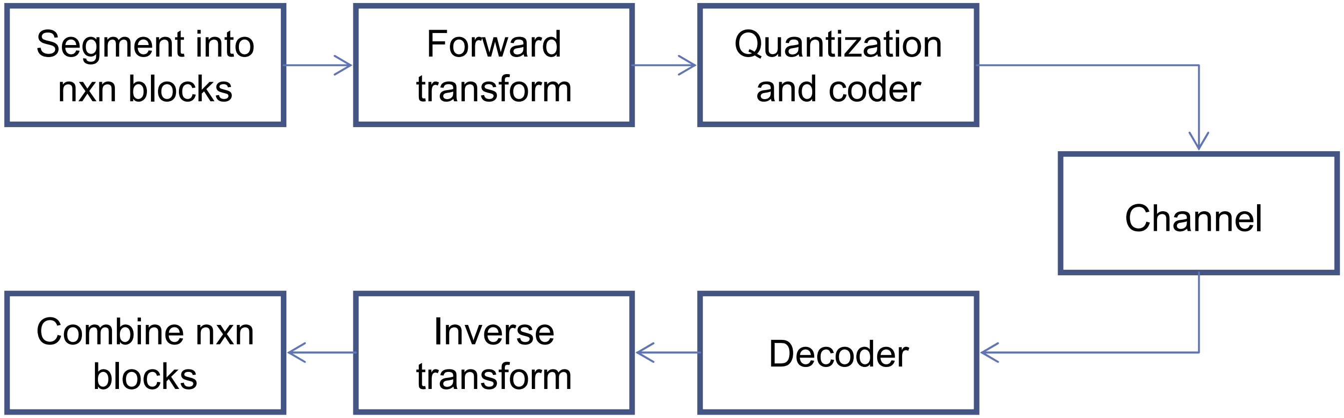
- «Through both theoretical and experimental results, we show that encoding a sparse signal through simple scalar quantization of random measurements incurs a significant penalty relative to direct or adaptive encoding of the sparse signal. Information theory provides alternative quantization strategies, but they come at the cost of much greater estimation complexity.»
- “Compressive sampling and lossy compression ”- Goyal, Fletcher, et al. - 2008

SAR image

- High volume of SAR image data: interest to find efficient ways to store
- Characteristics of SAR image data:
  - Speckle phenomena: coherent radiation and processing with constructive or destructive interference
  - Low correlation between adjacent pixels: speckle consequence
  - Very high dynamic: most natural terrain, being rough relative to the wavelengths employed, exhibit very low values while manmade objects, especially of conducting materials with large flat surfaces and right angles, can have specific cross sections with very high values
- Encoding/decoding algorithms designed for optical data may not be optimized or even appropriate for SAR data

Transform coding methods

- Convert data into a form where compression is easier
- Transform pixels which are correlated into a representation where they are decorrelated
- Few values are usually significative (sparse representation, their locations can be stored in a binary significance map)
- Transformed coefficients are coded using a quantizer optimized according to their statistical distributions
- The significance map needs also to be coded



Overcomplete ICA

- ICA: represent the observed data as a linear transformation of variables that are non Gaussian and mutually independent

$$\mathbf{x} = \Psi\alpha$$

- $\mathbf{x}$ observed data
- α independent components
- Ψ basis matrix, NxP, $P>N$

- The matrix is not invertible
- The estimation of the independent components is an undetermined problem
- We assume a constraint on the statistical distribution of the ICA coefficients:
  - Laplacian distribution $\Rightarrow$ K-sparse

Overcomplete ICA

- Estimation problem
  1. Basis
  2. Coefficients

1. FastICA algorithm that searches for "quasi orthogonal" basis on a training set data
2. The optimal estimation of the coefficients leads to the minimization of their ℓ_1-norm with the constraint $\mathbf{x}=\mathbf{\Psi\alpha}$

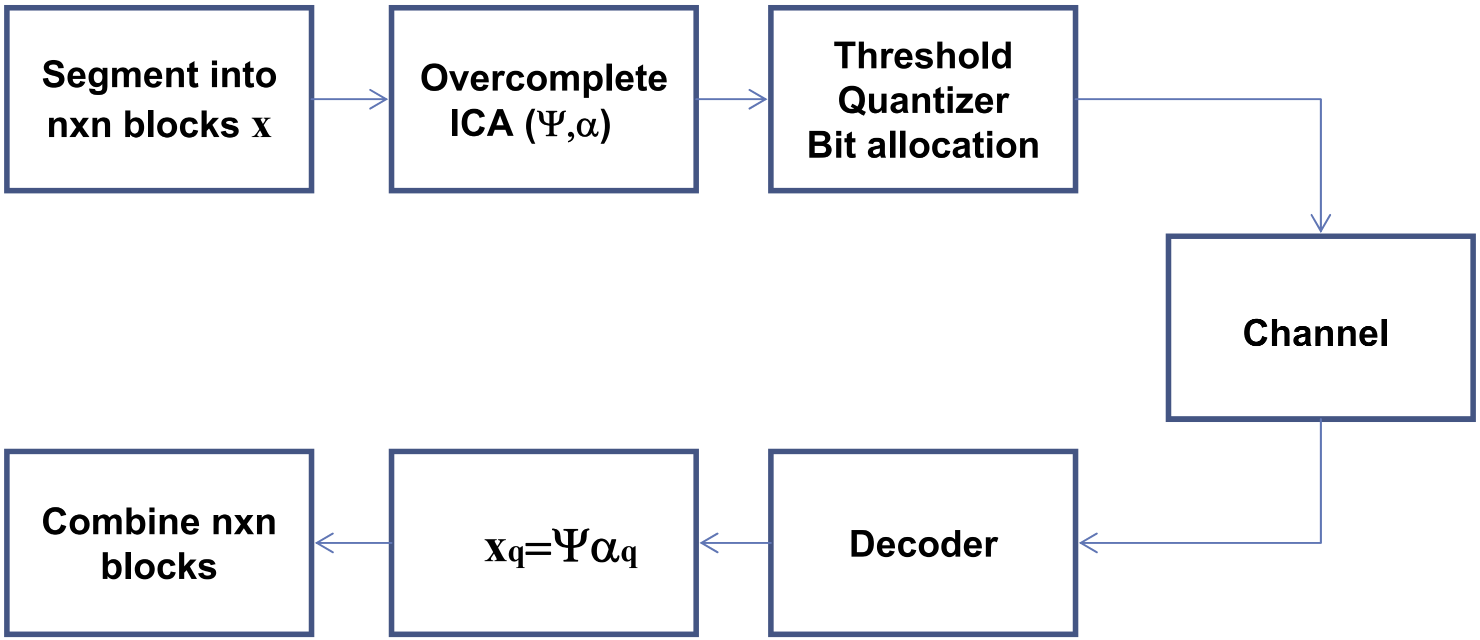
$$\hat{\boldsymbol{\alpha}} = \underset{\mathbf{x}=\mathbf{\Psi\alpha}}{\operatorname{argmin}} \sum_{i} |\alpha_i|$$

Quantization and bit allocation

- Scalar quantizer optimal for
  - Low bit rate
  - Laplacian distribution
- Entropy constrained scalar quantizer

  minimize the quadratic distortion for a given value of the entropy of the quantized coefficient
- Bit allocation:
  - Average bit rate per sample budget R is assigned
  - Equal average distorsion D per block is imposed
  - More bits are assigned to the blocks with a larger variance respect to those assigned to the blocks with a lower variance
- Entropy coding for the significance map

Overcomplete ICA coder



CS-ICA Based Compression Method

- Assume a K-sparse signal $\mathbf{x}$ with respect to a basis Ψ

$$\mathbf{x}=\Psi\alpha$$

- The "sampling" of $\mathbf{x}$ is represented as a linear transformation by a matrix $\mathbf{\Phi}$ (MxN random noise like) yielding a sample vector of M measurements ($M<N$ and $M = \mathrm{O}(K\, log(N/K))$)

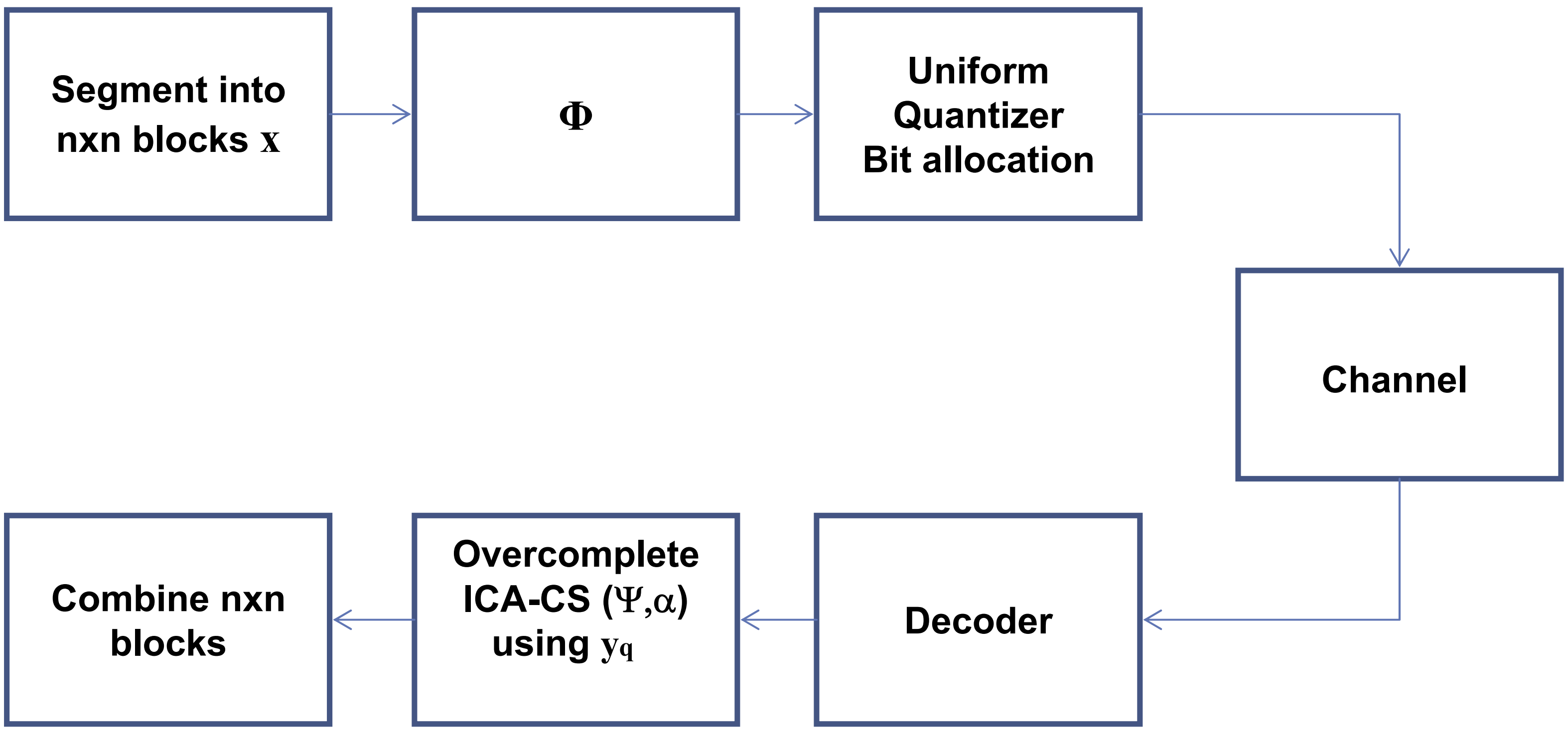
$$\mathbf{y} = \mathbf{\Phi}\ \mathbf{x}$$

- Incoherence between Ψ and $\mathbf{\Phi}$
- A decoder must recover the signal $\mathbf{x}$ from $\mathbf{y}\mathbf{q}$, a coded version of $\mathbf{y}$, knowing Ψ and $\mathbf{\Phi}$, and estimating α:

$$\hat{\boldsymbol{\alpha}}:\ \min \sum_{\mathrm{i}} |\alpha_i| \ \text{ subject to} \left\| \mathbf{y}_q - \mathbf{\Phi\Psi\alpha} \right\|_2 \le \varepsilon$$

- No need to transmit significance map

CS-ICA Based Compression Method



Experimental results on COSMO-SkyMed data

- Single look COSMO-SkyMed intensity image of Naples surroundings, Italy
- Average bit rate per sample R=1 bps

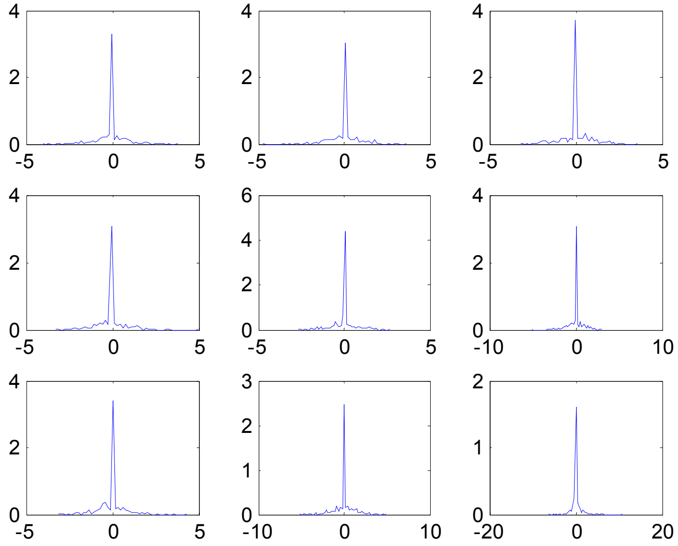
Experimental results on COSMO-SkyMed data

Overcomplete ICA, SNR= 9.2 dB

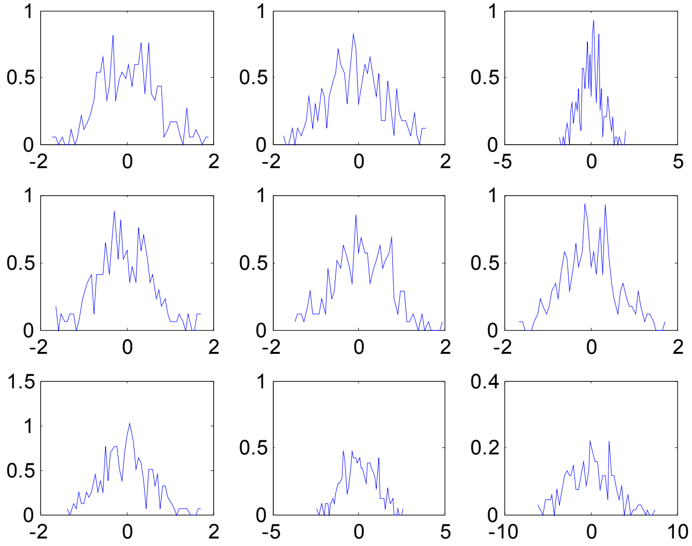
ICA-CS, SNR= 8.19 dB

Experimental results on COSMO-SkyMed data

Empirical statistical distribution of ICA coefficients

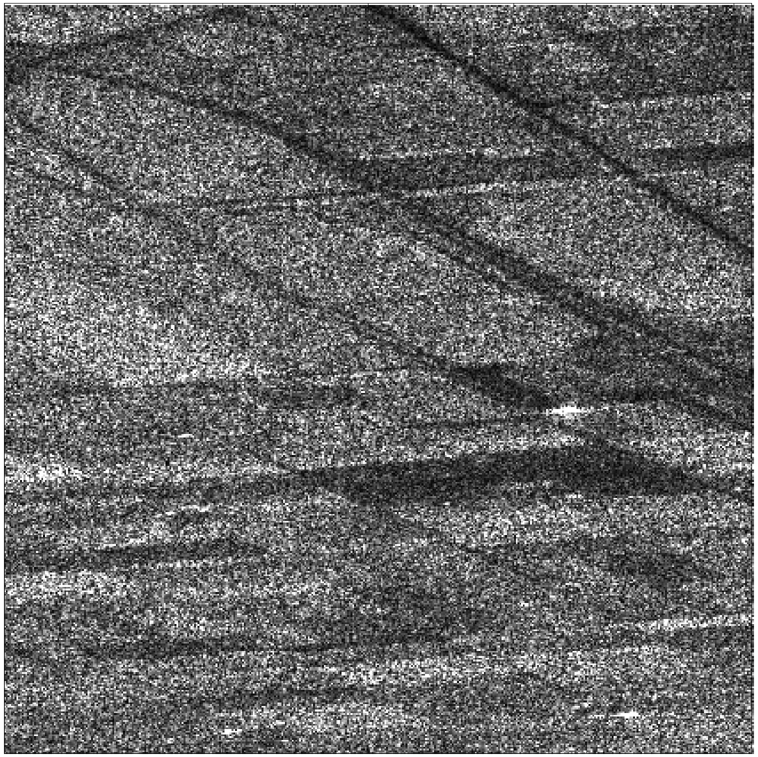


Empirical statistical distribution of CS measurements vectors



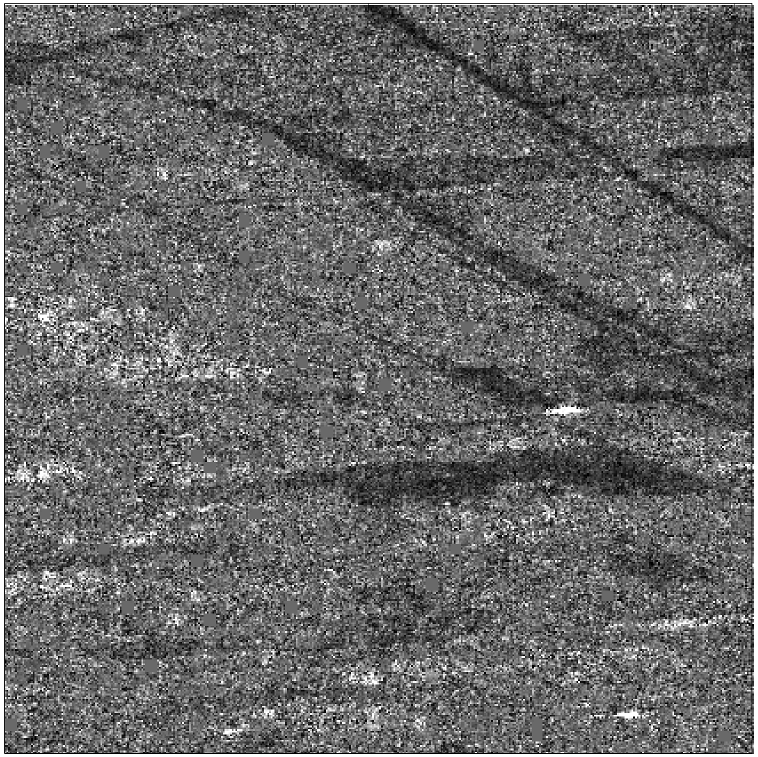
Experimental results on ERS1 data

- Single look ERS-1 intensity image of Fleevoland, The Netherlands
- Average bit rate per sample R=1 bps

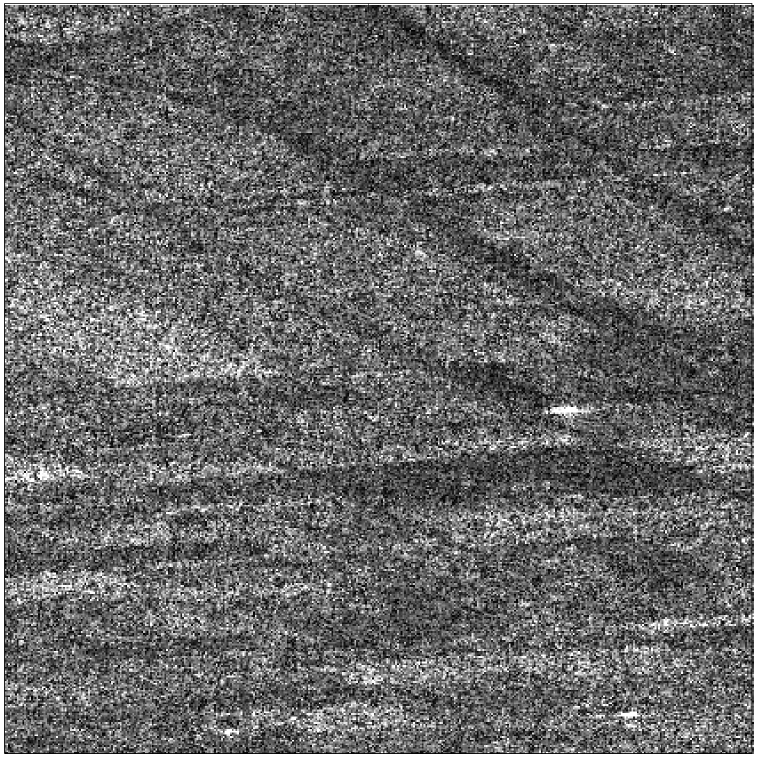


Experimental results on ERS1 data

Overcomplete ICA, SNR= 9.6 dB

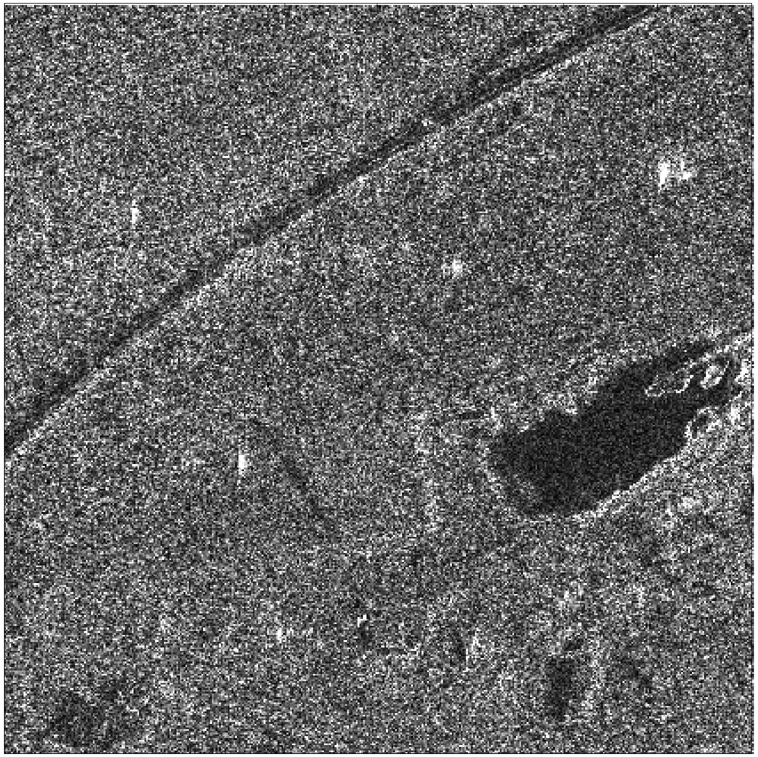


ICA-CS, SNR= 8.18 dB



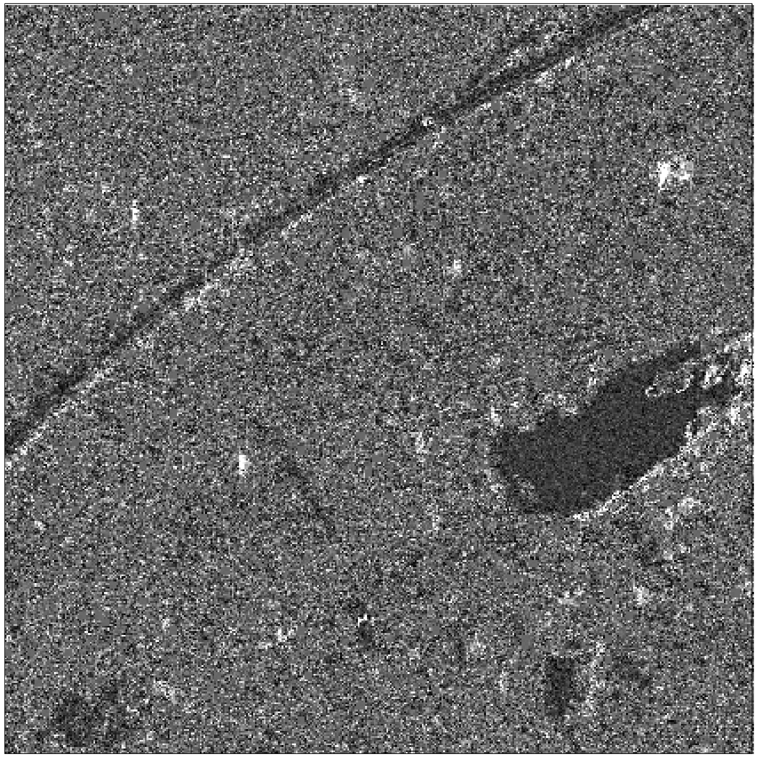
Experimental results on TerraSAR-X data

- Single look TerraSAR-X intensity image of Kalochori, Thessaloniki, Greece
- Average bit rate per sample R=1 bps

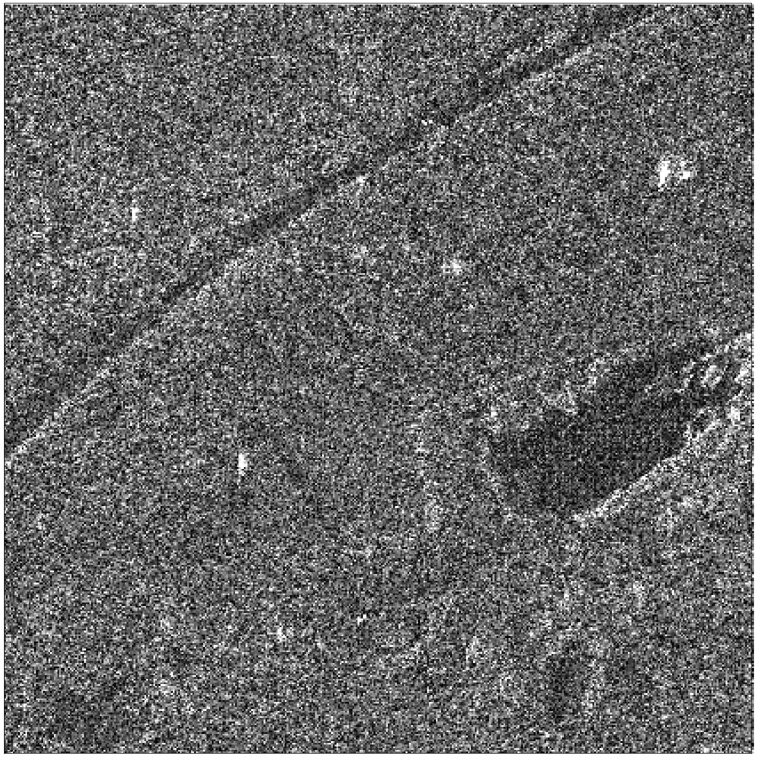


Experimental results on TerraSAR-X data

Overcomplete ICA, SNR= 9.53 dB



ICA-CS, SNR= 8.08 dB



Conclusions

- **ICA vs CS-ICA**
  - ICA:
    - K-sparse representation: coding K IC coefficients and significance map
    - Independent coefficients with a known statistical distribution
    - Scalar and optimized quantization and bit allocation
    - Complexity at the encoder
  - CS-ICA:
    - Coding M-dimensional $\mathbf{y}$ coefficients with $M<N$ but $M>K$
    - No need to code significance map
    - $\mathbf{y}$ coefficients with unknown statistical distribution
    - Scalar but not optimized quantization
    - Complexity at the decoder
  - The average distortion for ICA is better than the CS-ICA

- Open problems for CS approach:
  - Optimizing the choice of the matrices $\mathbf{\Phi}$ and $\mathbf{\Psi}$
  - Quantizer optimized for the statistical distribution of the measurement vectors $\mathbf{y}$
  - Optimal number M of the measurements