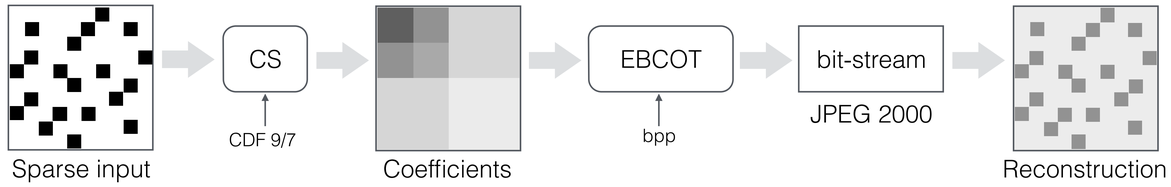
EFFICIENT SCALABLE COMPRESSION OF SPARSELY SAMPLED IMAGES

Colas Schretter, David Blinder, Tim Bruylants, Peter Schelkens and Adrian Munteanu

iMinds and ETRO Dept., Vrije Universiteit Brussel, Belgium

SUMMARY

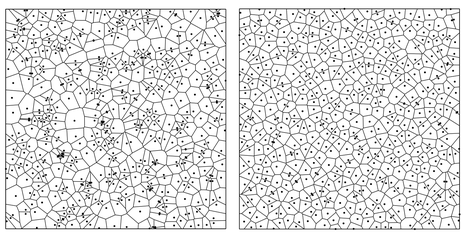
We propose a practical JPEG 2000 compression system for efficiently compressing sparsely sampled images at lossy to near-lossless rates. We rely on a compressed sensing (CS) technique to compute an interpolative sparse wavelet decomposition. The basis functions used for sparse data representation in CS correspond to the CDF 9/7 wavelets which are used in the JPEG 2000 system. The recovered coefficients are a good match for encoding with EBCOT.



From the JPEG 2000 bit-stream, a plausible interpolated image can be retrieved at the decoder side.

SYSTEM OVERVIEW

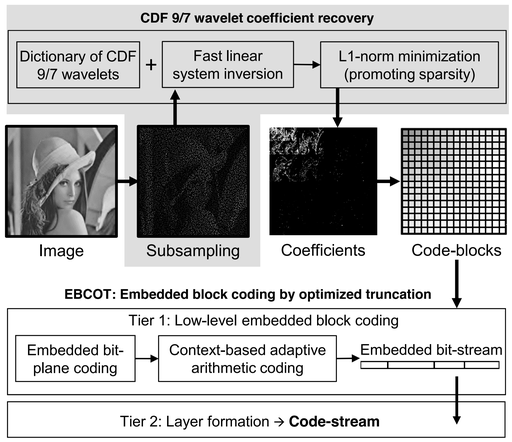
1. Sparse sampling for data acquisition
Subsampling masks may be arbitrary. We emulated the data acquisition system by using a low-discrepancy quasi-random sequence to ensure nearly even but non regular sampling.



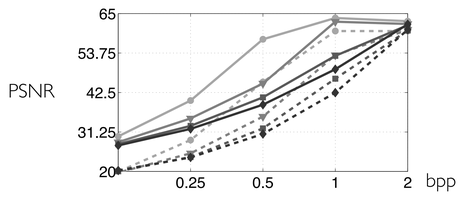
Pseudo-random *Quasi-random*

2. Recovery of wavelet coefficients
We solve a compressed sensing inverse problem for image representation. The sparse solution uses the set of CDF 9/7 wavelet basis functions used in the JPEG 2000.

3. Lossy JPEG 2000 EBCOT encoding
Fitting in the standard JPEG 2000 entropy coder with rate-distortion optimization for generating JPEG 2000 compliant bit-streams.



System overview in 3 steps

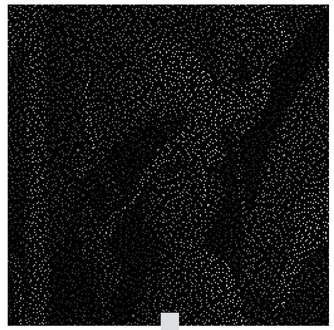


Quality in function of compression rates for 5% (light gray) to 20% (black) undersampling rates. *Dotted lines are results for direct compressions of stacked image samples. (Plots for the Lena image.)*

ILLUSTRATIVE EXAMPLE

Among all possible regularizations, we compared minimum L_2-norm and minimum L_1-norm.

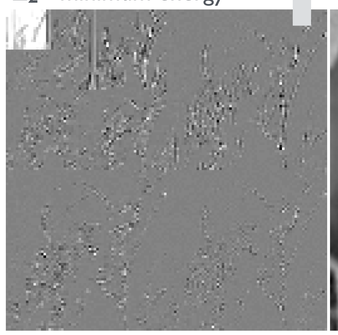
INPUT DATA
10% samples from a 256^2 image



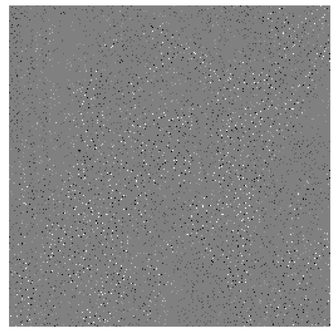
CS (CDF 9/7): Find a set of CDF 9/7 coefficients interpolating the input samples.

EBCOT (bpp): Lossy coding with EBCOT (0.5bpp).

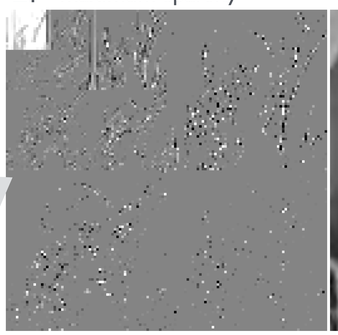
L_2 - minimum energy



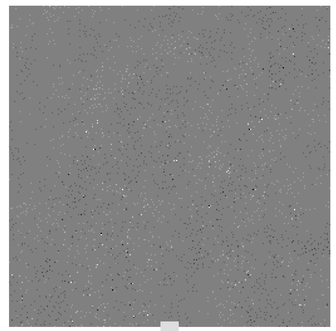
MSE: 4.10 (mean: 0.41, std-dev: 3.29, max: 196)



L_1 - maximum sparsity



MSE: 0.65 (mean: 0.06, std-dev: 0.56, max: 64)



Find coefficients x from sparse data b

$$\underbrace{\operatorname*{argmin}_x |x|_p}_{\text{Regularization prior}} \quad \text{subject to} \quad \underbrace{||b - \overbrace{\Phi W^{-1}}^{\text{Sampled inverse CDF 9/7 transform}} x||_2 = 0}_{\text{Interpolation constrain}}$$

The sparse solution yields a simpler and sharper image.

Sparse decompositions are significantly more compressible, resulting in smaller residuals.

SOLVING THE COMPRESSED SENSING PROBLEM

For large datasets, it is unpractical to explicitly store the system matrix. Instead, we implemented a fast lifting scheme for computing the transpose of the inverse CDF 9/7 wavelet transform. Then, we find a minimum norm reweighted solution of the inverse problem with a convergent iterative method such as LSMR (*http://web.stanford.edu/group/SOL/software/lsmr/*).

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