New Results in Image Processing based on Sparse and Redundant Representations

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Model?
Effective removal of noise (and many other applications) relies on an proper *modeling* of the signal.
Which Model to Choose?

- There are many different ways to model signals and images with varying degrees of success.
- The following is a partial list of such models for images:
- Good models should be simple while matching the signals:

  **Simplicity** ↔ **Reliability**

- Principal-Component-Analysis
- Anisotropic diffusion
- Markov Random Field
- Wienner Filtering
- DCT and JPEG
- Wavelet & JPEG-2000
- Piece-Wise-Smooth
- C2-smoothness
- Besov-Spaces
- Total-Variation
- Beltrami-Flow
Sparseland

A new Model for Signals / Images

Wavelet Theory

Approximation Theory

Linear Algebra

Optimization Theory

Signal Transforms

Multi-Scale Analysis

Blind Source Separation

Compression

Denoising

Inpainting

Demosaicing

Super-Resolution

...
The Sparseland Model for Images

- Task: model image patches of size $10 \times 10$ pixels.
- We assume that a dictionary of such image patches is given, containing 256 atom images.
- The Model: every image patch can be described as a linear combination of few atoms.
- This model describes every image patch as a sparse combination over a redundant dictionary.
Difficulties With *Sparseland*

- Problem 1: Given an image patch, how can we find its *atom decomposition*?
- Problem 2: Given a family of signals, how do we find the dictionary to represent it well?
- Problem 3: Is this model flexible enough to describe various sources?
Difficulties With *Sparseland*

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- **Problem 3**: Is this model flexible enough to describe various sources?

**ALL ANSWERED POSITIVELY AND CONSTRUCTIVELY**
Image Denoising (Gray) [Elad & Aharon (`06)]

Source

Result 30.829dB

Noisy image
\[ \sigma = 20 \]

The obtained dictionary after 10 iterations
Image Denoising (Gray) [Elad & Aharon (’06)]

The results of this algorithm compete favorably with the state-of-the-art: E.g.,

- We get ~1dB better results compared to GSM+steerable wavelets [Portilla, Strela, Wainwright, & Simoncelli (’03)].
- Competitive works are [Hel-Or & Shaked (’06)] and [Rusanovskyy, Dabov, & Egiazarian (’07)]. Both also lean on Sparseland.

Noisy image
\[ \sigma = 20 \]

The obtained dictionary after 10 iterations
Our experiments lead to state-of-the-art denoising results, giving ~1dB better results compared to [Mcauley et. al. ('06)] which implements a learned MRF model (Field-of-Experts).
Our experiments lead to state-of-the-art inpainting results.
Our experiments lead to state-of-the-art inpainting results.

Since 1699, when French explorers landed at the great bend of the Mississippi river and celebrated the first Mardi Gras in North America, New Orleans has brewed a fascinating melange of cultures. It was French, then Spanish, then French again, then sold to the United States. Through all these years, and even into the 1900s, others arrived from everywhere: Acadians (Cajuns), Africans, indigenous...
Video Denoising [Protter & Elad ('06)]
Our experiments lead to state-of-the-art video denoising results, giving ~0.5dB better results on average, compared to [Boades, Coll & Morel ('05)] and [Rusanovskyy, Dabov, & Egiazarian ('06)].
Facial Image Compression [Brytt and Elad (`07)]

Results for 550 Bytes per each file

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Facial Image Compression [Brytt and Elad (`07)]

Results for 400 Bytes per each file

18.62  12.30  7.61
16.12  11.38  6.31
16.81  12.54  7.20
To Conclude

**Sparseland** is an emerging model with high potential. It is based on sparse and redundant representations of signals, and learned dictionaries.

Which model to choose?

Is it working well?

Effective (yet simple) model for signals/images is key in getting better algorithms for various applications.

It has been deployed to many applications, in all leading to state-of-the-art results. More work is required to extend its usability to other domains.