Rethinking Natural Image Priors

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Outline

- “Position part” — relation between BV and CV.
Relationship

- Biological and Human Vision.
- Machine Vision
Relationship

- Biological and Human Vision.
- Visual World
- Machine Vision
Robust Computer Vision ⇒ Properties of Visual World

Input

SSD based (early 80s)

Energy Minimization (mid 90s)
Checker-shadow illusion:
The squares marked A and B
are the same shade of gray.

Edward H. Adelson
Relationship

- Biological and Human Vision.
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- Machine Vision
Natural Image Priors

Given a $N \times N$ matrix $x$, return $Pr(x)$ “Probability that $x$ is a natural image”.

Zhu and Mumford, Portilla and Simoncelli, Roth and Black, Weiss and Freeman, Osindero, Welling and Hinton, Ranzato and Lecun, Olshausen, Lewicki, Ng, Aharon and Elad, Mairal, Sapiro, · · ·

Biological Vison $\Leftrightarrow$ Computer Vision
Prior based methods vs. Prior Free methods

- Prior based. Training set $\Rightarrow$ natural image prior.

- Prior free. No training set. No explicit notion of natural image prior.

- Best performance in image denoising?
Prior based methods vs. Prior Free methods

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- Best performance in image denoising?
- Prior free methods.
The BM3D Prior free method

Buades et al. 05, Dabov et al. 06, Elad et a. 07, Mairal et al. 10, Liu and Simoncelli 08
Comparison

100 different test images.

- BM3D vs. Fields of Expert (Roth and Black)
  - BM3D is better 100/100 times.
  - BM3D vs. generic KSVD (Elad and Aharon)
  - BM3D is better 89/100 times.
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Noisy
FOE
BM3D
What’s going on?

- “generic natural image” — too general?
- Training using maximum likelihood the wrong thing?
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- “generic natural image” — too general?
- Training using maximum likelihood the wrong thing?
- Current prior models poor (even in the likelihood sense).
What’s going on

- High Likelihood $\Rightarrow$ Good Denoising Performance.
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- High Likelihood $\Rightarrow$ Good Denoising Performance.
- But a simple, unconstrained Gaussian Mixture Model (200 mixture components for 8x8 image patches) $\cdots$
- Gives log likelihood 164.52. Much better than all existing models.
- Outperforms all existing prior based models in denoising.
GMM
GMM vs. BM3D

100 different test images.

- BM3D vs. GMM.
GMM vs. BM3D

100 different test images.

- BM3D vs. GMM.
- GMM is better 81/100 times.
GMM vs. BM3D

100 different test images.

- BM3D vs. GMM.
- GMM is better 81/100 times.
- GMM can be used for any application.

![Image](image.png)

(a) Blurred  
(b) Krishnan et al.  
(c) EPLL GMM

References
Blurred
Sparse Derivative
Secret of GMM

- Sparse coding, ICA, FOE all assume some sort of independence between filter outputs.
- GMM suggests extremely structured sparse coding. Only filters within same block can be active together. (Yu et al. 2010)
Summary

• Robust Computer/Human/Biological Vision ⇒ Properties of the visual world.

• Natural Image Priors. Biological Vision ⇔ Computer Vision.

• Simple GMM model for image patches. No independence assumptions ⇒ much better model.