Image Denoising: Review and Recent Breakthrough

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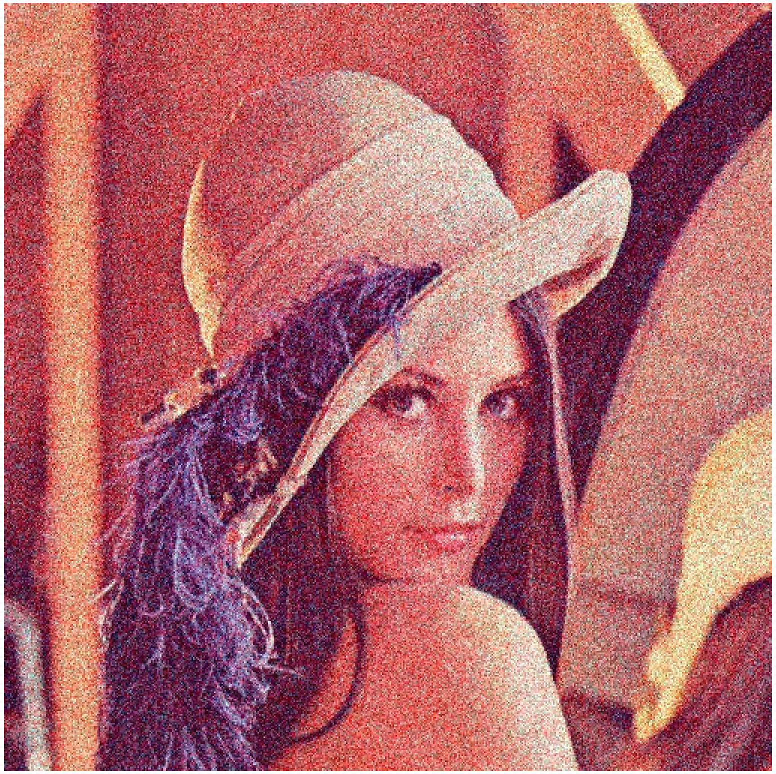
Outline

- Image denoising overview
- Adaptive Nonlocal Means Algorithm
- Experimental Results
- Conclusions and Future Works

Image Denoising



Noisy image

ANL Denoised image

Viola.usc.edu

Image Denoising Overview

Brief History of Image Denoising

1950s

- Television engineering
- Rely on autocovariance function for optimal signal representation and transmission

1960s

- First Digital Image

Have you ever see the first digital image?

First Digital Image

The first film photo registered by a computer and recreated in pixels—30,976 to be exact. (1957) (176 x 176)

“image of three-month-old baby”

Brief History of Image Denoising

1970s

- USC
- Frequency domain techniques, direct inversion, or recursive Kalman filtering, etc

Lena Image

•Lena = Lena Söderberg
•Swedish model who posed nude for the November 1972 issue
•Signal and Image Processing Institute (SIPI)
•Reason:
    •Tired of usual test images
    •Good output dynamic range
    •Human face
•"Somebody happened have a recent issue of *Playboy*"

Brief History of Image Denoising

1980s

•J-S. LEE, "*Digital image enhancement and noise filtering by use of local statistics*," IEEE Transactions on Pattern Analysis and Machine Intelligence. Vol. PAMI-2, pp. 165-168. Mar. 1980 (Cited by 759)

1990s

- Wavelet transforms
- Wiener filter
- Total variation minimization

Brief History of Image Denoising

2003

- Gaussian scalar mixture (GSM) algorithm

2005

- Nonlocal mean (NLM) algorithm

Image Denoising Overview

- Summary
  - Classical problem in image/video processing
  - X = S+N
    - X = noisy signal
    - S = original signal
    - N = Noise
  - Nonlocal means (NL-means) algorithm
    - A. Buades, B. Coll., and J. Morel, "*A non local algorithm for image denoising*," in Proc. Int. Conf. Computer Vision and Pattern Recognition (CVPR), vol. 2, 2005, pp. 60–65.
    - Sep 2009 ➔ cited by 153

Basic Concept: Image Denoising

- $X_1 = S+N_1$
- $X_2 = S+N_2$
- .
- .
- $X_n = S+N_n$

- $(X_1+X_2+\ldots+X_n)/N = (S+S+\ldots+S)/N + (N_1+N_2+\ldots+N_n)/N$

  $= S+(N_1+N_2+\ldots+N_n)/N$

N is AWGN $\Rightarrow$ $(N_1+N_2+\ldots+N_n)/N \sim 0$


1 Sample
10 Samples
100 Samples

Concept Evolution – Repeated Pattern

Repeated Pattern
"High correlation"

Concept Evolution – Self Similarity

Self-similarity
"High correlation"

Nonlocal Means Algorithm

- For given noisy image $f = \{ f(i) \mid i \in \Omega \}$, the NL-means denoised value $\hat{f}(i)$ at pixel i is obtained by a weighted average of all pixels in its neighborhood

$$\hat{f}(i) = \frac{1}{C(i)} \sum_{j \in \Omega_S} w(i,j) f(j)$$

$C(i) = \sum_{j \in \Omega_S} w(i,j)$ is a normalization constant

$w(i,j)$ is determined by the similarity of the Gaussian neighborhood between pixels i and j

$$w(i,j) = \exp\left(-\frac{\left\| N_i - N_j \right\|_{2,a}^2}{h^2}\right)$$

Adaptive Nonlocal Means Algorithm

- Proposed Algorithm
- Experimental Results
- Medical Image Denoising

Adaptive NL-means Algorithm

- Summarized idea
  - Adjust denoising parameter based on local content
  - Enhance the similarity matching process in order to fully exploit self-similarity existing within an image

- Proposed scheme
  1. Block classification
  2. Adaptive block matching

I. Block Classification

- Summarized idea
  - Determine block type of each local point so that different approach can be selectively applied to each block type
- Challenge
  - Noisy data ➔ difficult to classify
- Solution
  - Gradient vector
  - Singular Value Decomposition (SVD)
  - K-means clustering technique (K-means)

Simple Edge Detection (Canny)

Block Classification Scheme

- For given noisy image, $f = \{ f(i) \mid i \in \Omega \}$

- Gradient vector: $G = \left[\nabla f(1)^T \ \nabla f(2)^T \cdots \nabla f(N)^T \right]^T ; \nabla f(i) = \left[\frac{\partial f(i)}{\partial x} \quad \frac{\partial f(i)}{\partial y} \right]^T$

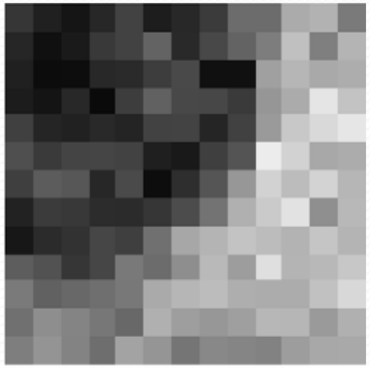
- SVD: $G = USV^T$
  - U is an N x N orthogonal matrix
  - S is a diagonal 2 x 2 matrix contains singular values
  - V is an 2 x 2 orthogonal matrix which describes the dominant orientation of the gradient field

Block Classification Scheme

- SVD
  - Singular value ~ Eigenvalue ➔ energy in dominant direction
  - Classification feature
    - Smooth region: no dominant direction and small eigenvalues
    - Oriented edge/texture region: dominant direction and the corresponding eigenvalue is significantly larger than others
    - Noise has minimal effect ➔ noise does not have any preferred direction

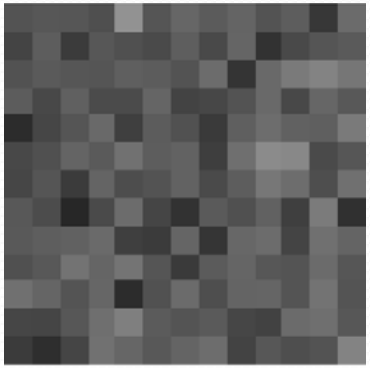
Example Of Energy In Dominant Direction

Texture/Edge region



E = 7.66

Smooth region



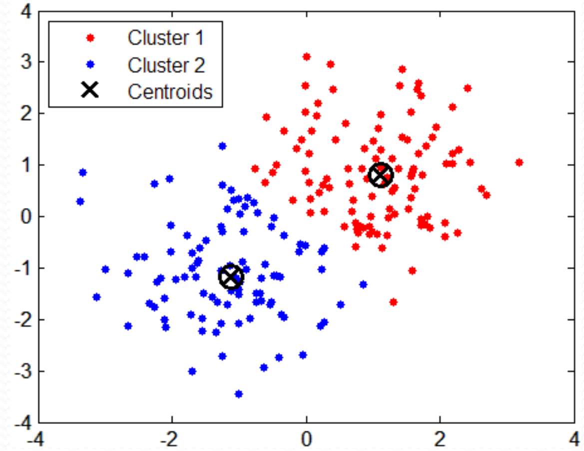
E = 2.73

Block Classification Scheme

- K-means
  - Adaptively classify the acquired data
  - K-means algorithm partitions $\{s(i) \mid i \in \Omega\}$ into K classes $C = \{c_1, c_2 \ldots, c_K\}$ while minimizing the within-cluster sum of squares

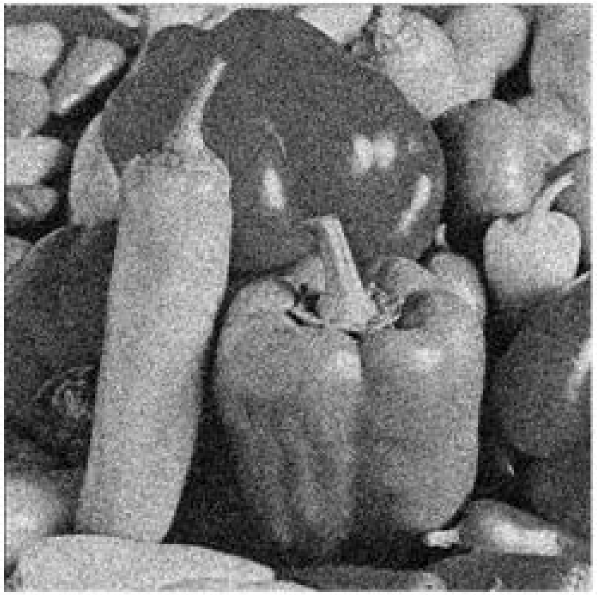
$$\arg\min_{C} \sum_{k=1}^{K} \sum_{s(i)\in c_k} \left| s(i) - \mu_k \right|^2$$

where μ_k is the mean of c_k

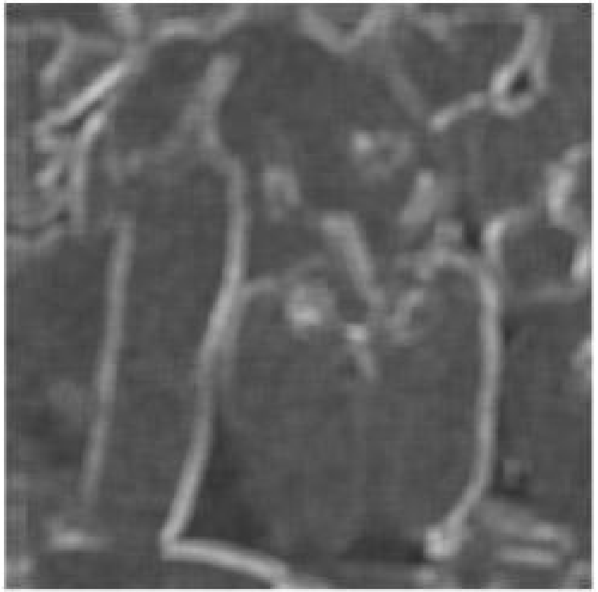


Sample: Block Classification

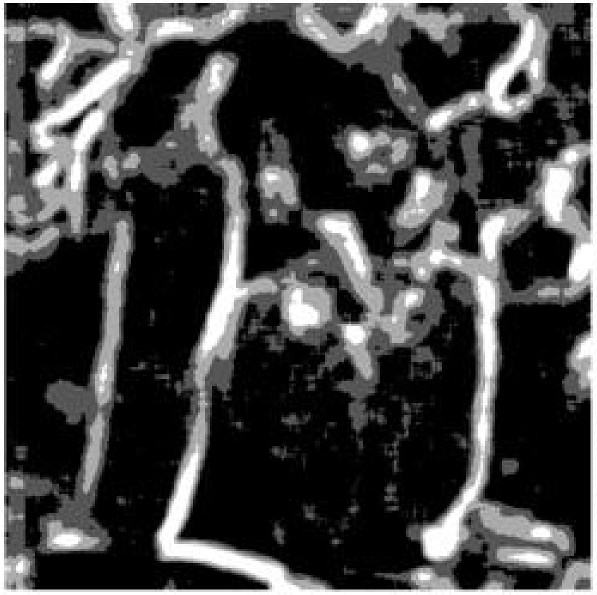
- Singular value decomposition / K-means clustering



Noisy image (σ=40)
PSNR = 16.48 dB



Energy in the dominant directions (SVD)

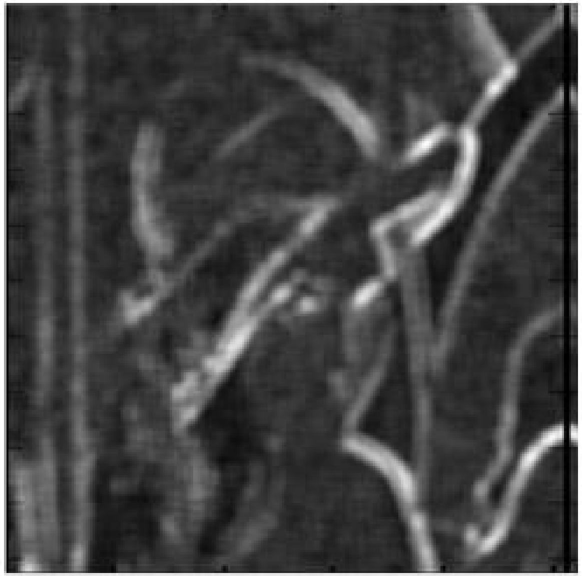


Classification Results (K-means)

Sample: Block Classification

- Singular value decomposition / K-means clustering

Noisy image (σ=40)
PSNR = 16.35 dB



Energy in the dominant
directions (SVD)

Classification Results (K-means)

II. Adaptive Block Matching

- Summarized idea
  - Adjust denoising parameter based on block type and enhance the similarity matching process

- Solution
  - Adaptive block matching
    - Edge / Texture area ➔ Block transformation (Fractal-like matching)
    - Smooth area ➔ Adaptively adjusted window size

Block Transformation

- Summarized idea
  - Increase the number of matching candidate so that the better matching similarity can be determined
- Challenge
  - Matching candidate ⬆ ➔ Complexity ⬆
- Solutions
  - Smart block transformation ➔ dominant orientation alignment
  - Selectively apply ➔ Edge / Texture area

Block Transformation Scheme

Normal Scheme

- T1: Identity
- T2: Orthogonal reflection about mid-vertical axis of block
- T3: Orthogonal reflection about mid-horizontal axis of block
- T4: Orthogonal reflection about first diagonal (i = j) of block
- T5: Orthogonal reflection about second diagonal (i + j = B - 1) of block
- T6: Rotation around center of block, through +90
- T7: Rotation around center of block, through +180
- T8: Rotation around center of block, through -90
- T9: Luminance shift by constant [-20 - 20]
- T10: Contrast scaling [0.85 – 1.15]

Proposed scheme

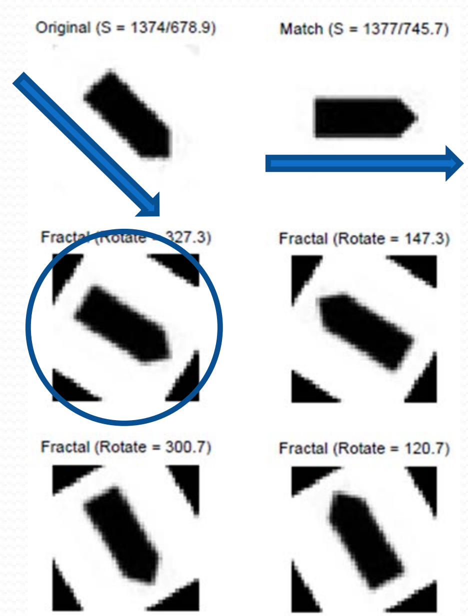
- SVD: $G = USV^T$
- V is an 2 x 2 orthogonal matrix which describes the dominant orientation of the gradient field
- Let $v_1 = [\upsilon_1 \ \upsilon_2]^T$ be the first column of V
- Dominant orientation

$$\theta = \arctan(\frac{\upsilon_1}{\upsilon_2})$$

Dominant Orientation Alignment

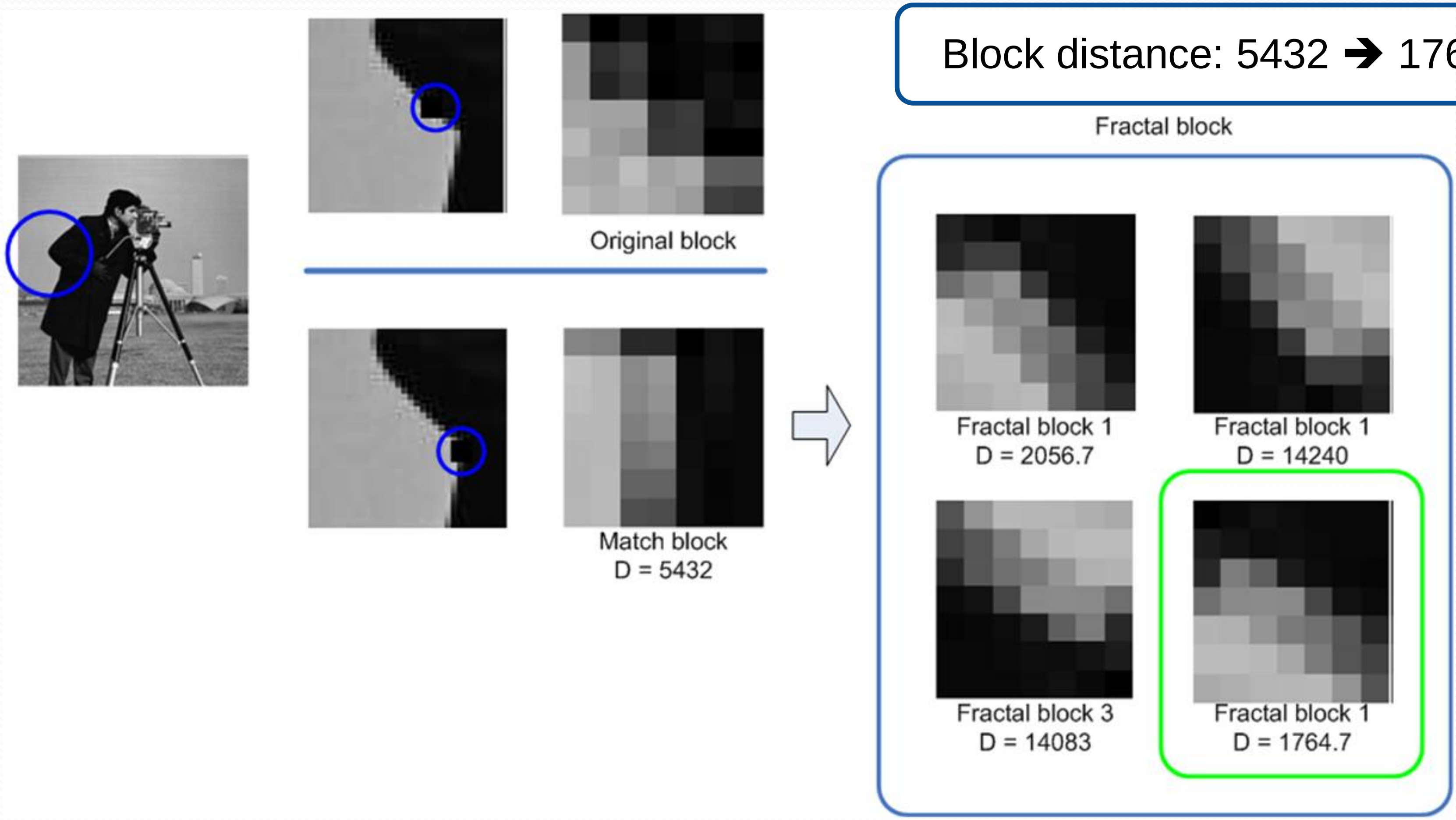
- Summarized idea
  - Rely on a set of rotated blocks that have their dominant orientation aligned well with that of the target block

- Solution
  - 4 fractal blocks ➔ Capture all possible gradient direction
  - Block rotation ➔ bilinear



Example: Dominant Orientation Alignment

Block distance: 5432 → 1764.7



Adaptive Matching Window

- Summarized idea
  - Adaptively adjust the size of matching window so that it can capture the local structure for better matching
  - Ex: Smooth + small matching window ➔ confuse noise as local structure/texture
- Solution
  - Adaptively choose the matching window size based on the block type
    - Strong edge/texture region ➔ small window (7x7)
    - Smooth region ➔ large window (25x25)
    - other regions ➔ medium window (13x13)

Adaptive Nonlocal Means Algorithm

- Proposed Algorithm
- Experimental Results
- Medical Image Denoising

Denoising Benchmark

- Denoising algorithm
  - Mean filter (MF)
  - Gaussian filter (GF)
  - Partial differential equation (PDE)
  - Total variation minimization (TV)
  - Nonlocal-means (NL)

- Proposed technique
  - Adaptive nonlocal-means (ANL)

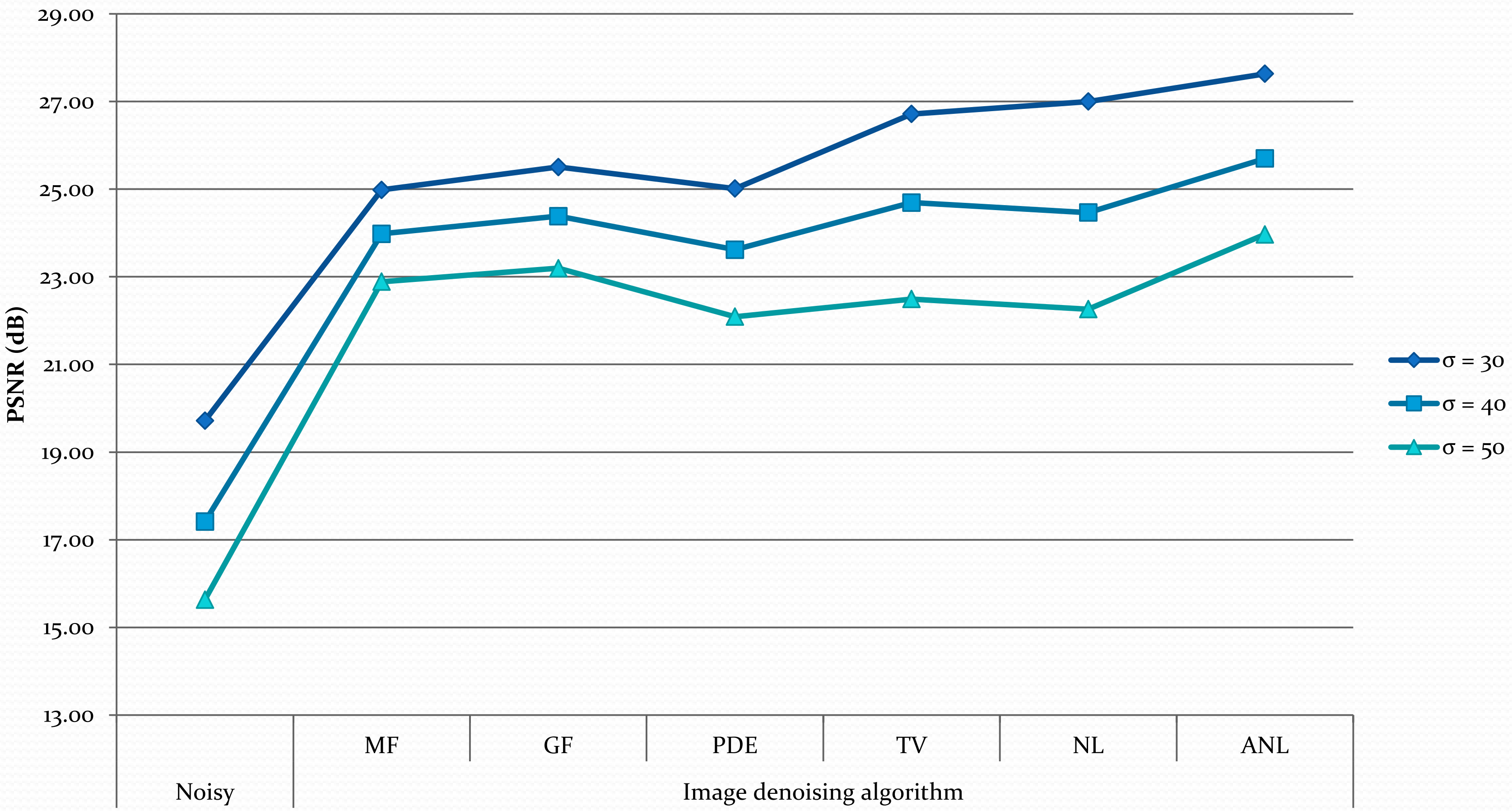
Experiment Setting

- Parameters
  - 7 representative test images
  - Additive white Gaussian noise (AWGN) with zero mean and standard deviation σ = 20, 30 and 40

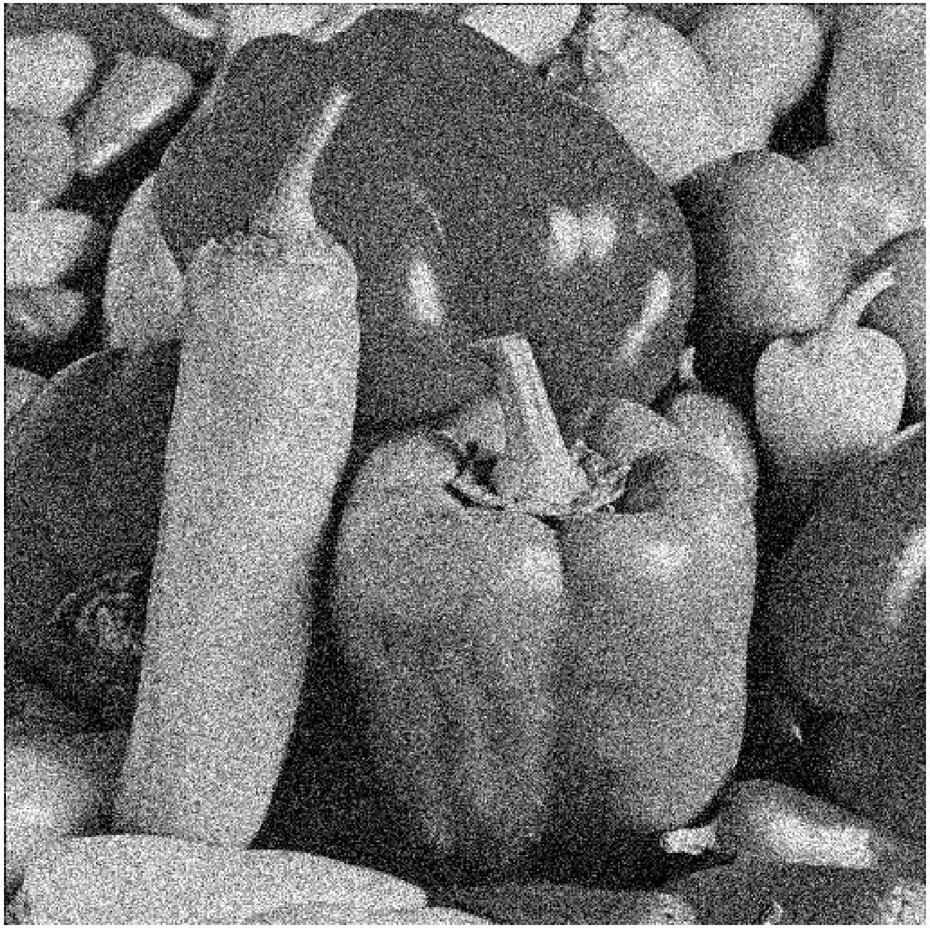
Experiment Results (NL vs. ANL)

Image	Average PSNR (dB)								
	Sigma = 20			Sigma = 30			Sigma = 40		
	NL	ANL	Δ	NL	ANL	Δ	NL	ANL	Δ
Lena	31.02	31.98	0.96	27.50	30.04	2.54	24.37	28.27	3.90
Zelda	31.85	32.83	0.98	28.18	30.72	2.55	25.06	28.76	3.70
Peppers	30.93	31.59	0.65	27.50	29.79	2.29	24.40	28.00	3.60
airplain	30.52	30.93	0.41	27.20	29.05	1.85	24.34	27.41	3.07
Barbara	29.85	30.30	0.45	26.65	28.41	1.76	23.89	26.74	2.85
Elaine	30.40	30.82	0.42	27.30	29.58	2.28	24.32	28.10	3.78
Girlface	31.75	32.29	0.54	28.12	29.98	1.86	25.06	27.92	2.86
Average	30.90	31.53	**0.63**	27.49	29.65	**2.16**	24.49	27.89	**3.39**

Experiment Results – Performance Comparison



Noisy Image – σ=40

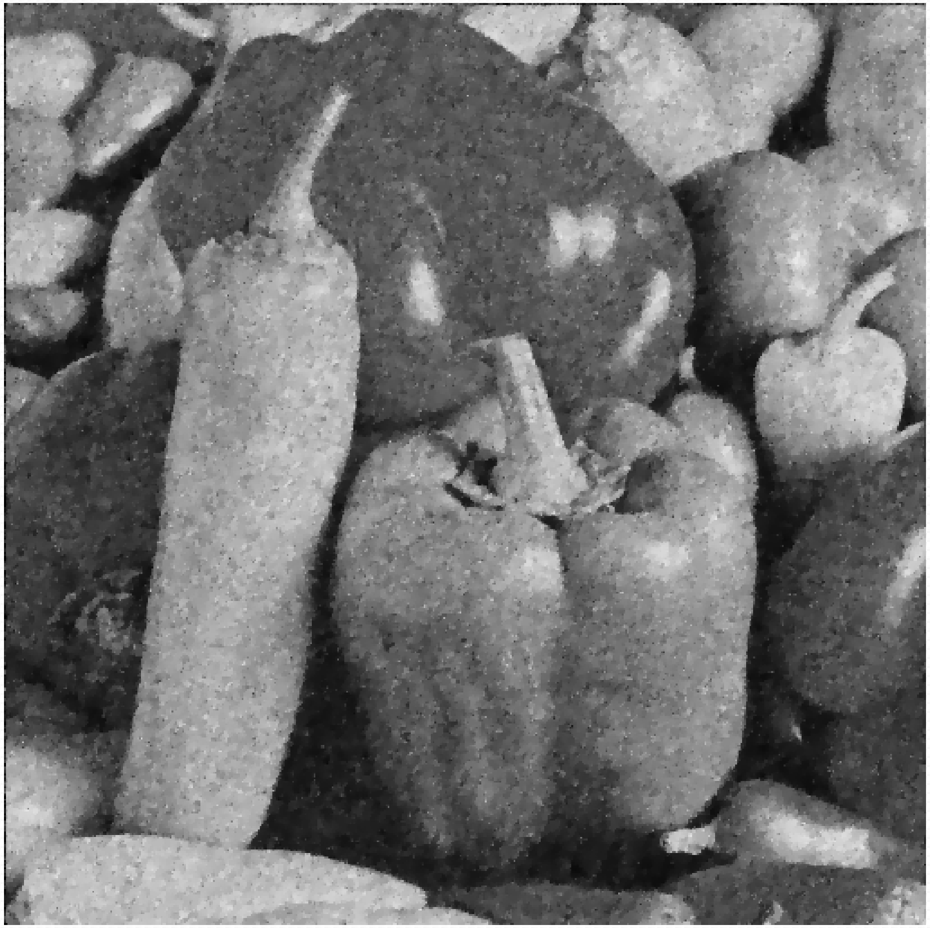


Mean Filter

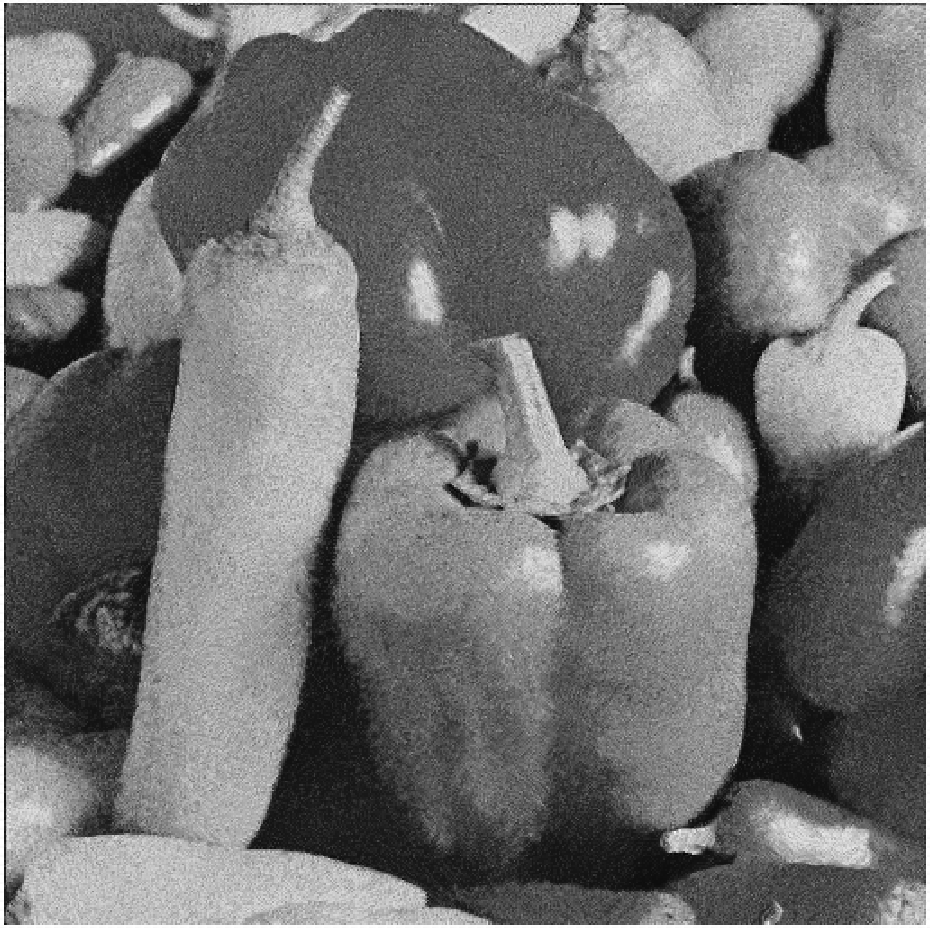
Gaussian Filter

Partial Differential Equation

Total Variation Minimization



Nonlocal Means



Adaptive Nonlocal Means

Other Example: Girlface

Noisy image (σ=40)

NL denoised image

ANL denoised image

Other Example: Zelda

Noisy image (σ=40)

NL denoised image

ANL denoised image

Conclusion And Future Work

Conclusion And Future

- Conclusions
  - Adaptive nonlocal means algorithm
    - Adjust denoising mechanism based on local content
    - Higher PSNR / Better perceptual quality
- Future works
  - NL-means ➔ exploit self-similarity
  - Scale-invariant feature transform (SIFT)

Thank you