SIPL SIGNAL & IMAGE PROCESSING LAB

Model-Based Adaptive Non-Local Means Image Denoising

M.Sc. Research by

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Outline

- Introduction to Image Denoising
- Standard Non-Local Means (NLM)
- Proposed NLM Modifications
- Correlation Analysis Between Dissimilarities
- Integration of NLM Modifications into Block Matching 3D (BM3D)
- Poisson Image Denoising
- Summary
- Future Work

Introduction to Image Denoising

- Image denoising is used to estimate the original image given its noisy version.
- Common noise model:

$$Y = X + N, \ \ N \sim \mathcal{N}\left(0, \sigma_n^2\right)$$

$Y =$ noisy image

$X =$ original image (unknown)

$N =$ additive white noise

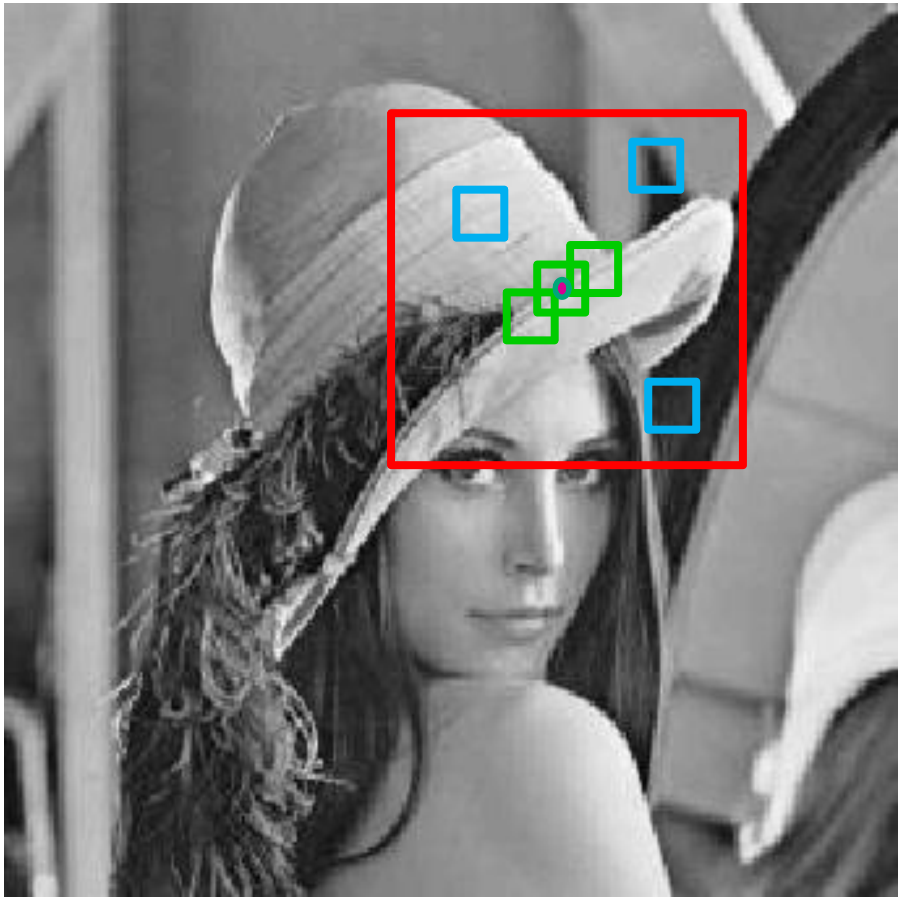
It is assumed that X and N are independent

- Patch-based denoising methods have drawn much attention.

Standard Non-Local Means (NLM)

- Introduced by Buades et. al (2005).
- Exploits image redundancy.
- Pixel restoration: Weighted average of all gray values within the defined search region.

$$\hat{X}_i = \sum_{j \in S_i} w_{i,j} Y_i$$



Standard Non-Local Means (NLM)

Weights Definition

- The weights are based on similarity between pixel neighborhoods

$$w_{i,k} = \frac{1}{W_i} \exp\left(-\frac{d_i(k)}{h^2} \right),\ k \in S_i,\ i \text{ is the Pixel of Interest (POI)}$$

$$d_i(k) = \frac{1}{p^2} \left\| Y(A_i) - Y(A_k) \right\|_2^2$$

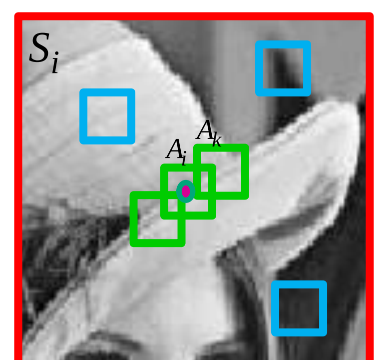
$d_i(k) =$ dissimilarity measure between neighboorhoods of pixels i and k

$A_i,\ A_k =$ similarity patches of size $p \times p$ centered at pixels i, k respectively

$S_i =$ rectangular search region of size $M \times M$

$h =$ weight smoothing parameter

$W_i =$ normalization factor $\left(\sum_{k \in S_i} w_{i,k} \right)$



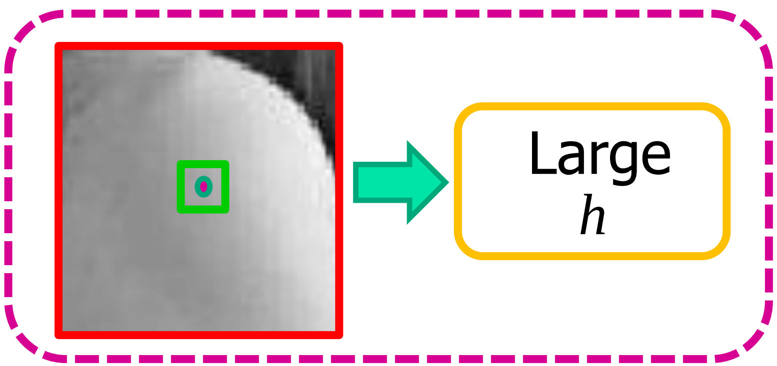
Standard Non-Local Means (NLM)

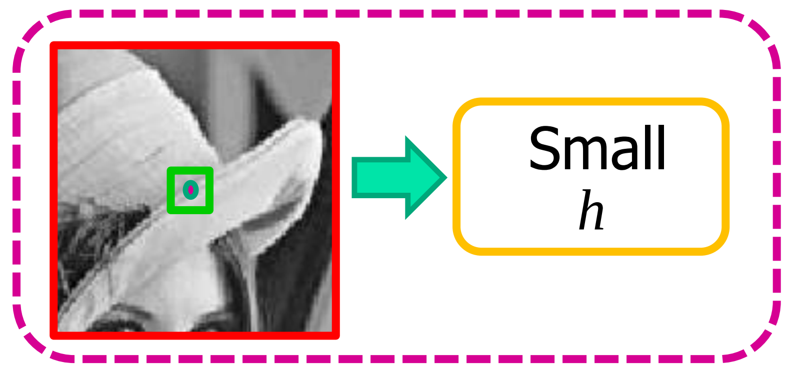
The Parameter *h*

- The NLM algorithm is sensitive to the selection of the parameter *h*

$$w_{i,j} = \frac{1}{W_i} e^{-\frac{d_i(j)}{h^2}}, \quad j \in S_i$$

- It is usually set to be proportional to σ_n .
- In addition, simulations suggest that *h* should match local structure:



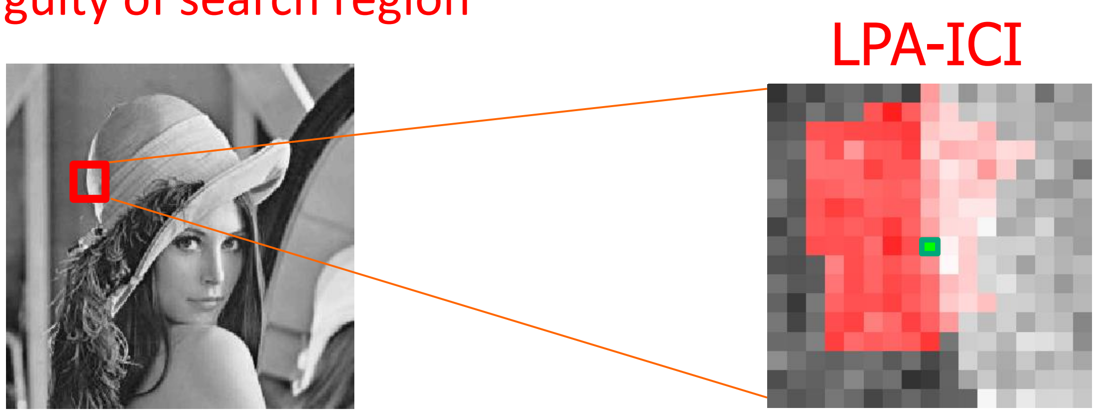


- There are NLM modifications that suggest to use an adaptive *h*, matched to local structure (e.g., Duval et al. 2010, Dinesh et al. 2009)

→ **High computational complexity**

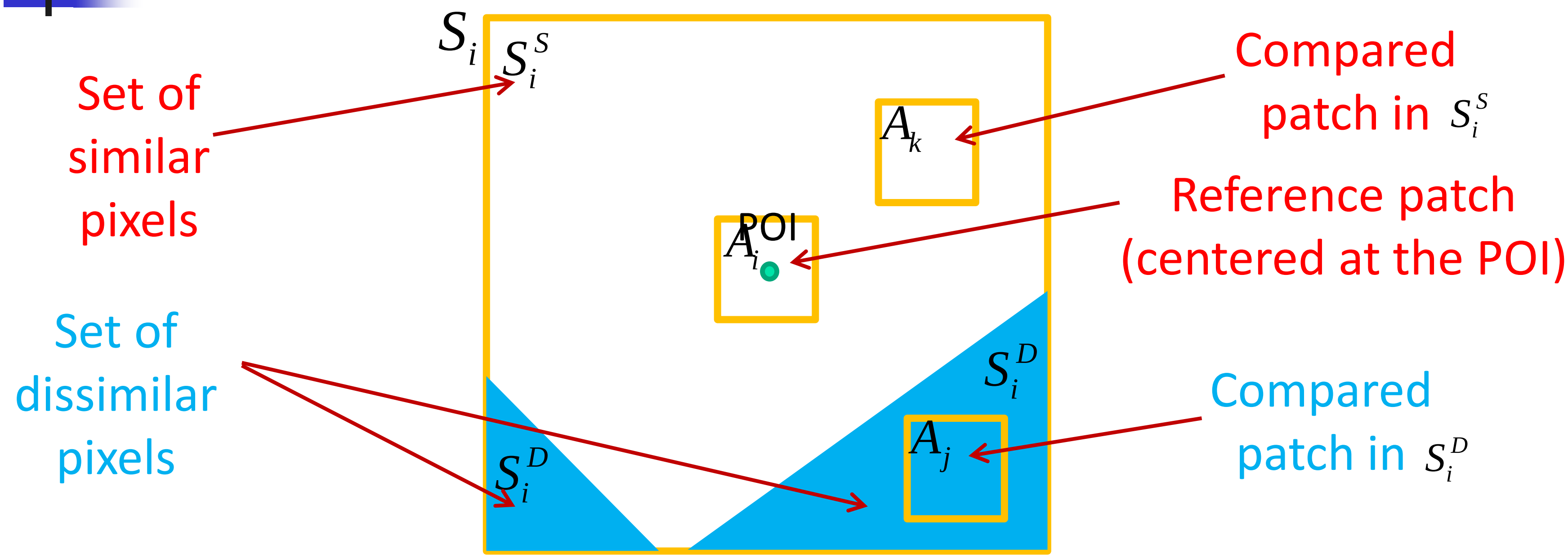
Adaptive Search Region As An Alternative to Local *h*

- <u>Method</u>: use an anisotropic **adaptive** region, which includes only pixels with similar neighborhoods to that of the POI.
- <u>Prior art</u>:
  - Gradient-based classification (Mahmoudi et al. 2005) – sensitive to noise
  - Similarity patch correlation (Dinesh et al. 2009) – a threshold is required
  - **L**ocal **P**olynomial **A**pproximation combined with the **I**ntersection of **C**onfidence **I**ntervals (LPA-ICI) (Sun et al. 2009) – complex and enforces contiguity of search region



Creates wide edge → causes over-smoothing

Proposed Modification I: Adaptive Model-Based Search Region



Assumptions:

$$\forall k \in S_i^S : \; X(A_i) = X(A_k) \rightarrow Y(A_i) - Y(A_k) = N(A_i) - N(A_k)$$

$$\forall j \in S_i^D : \; X(A_i) = C_j + X(A_j) \rightarrow Y(A_i) - Y(A_j) = C_j + N(A_i) - N(A_j)$$

Distribution of Dissimilarity Measure

- For a compared patch included in S_i^S:

$$\forall k \in S_i^S \setminus \{i\}: \ \frac{d_i(k)}{2\sigma_n^2} = \frac{1}{p^2}\frac{\left\|Y(A_i)-Y(A_k)\right\|_2^2}{2\sigma_n^2} = \frac{1}{p^2}\sum_{\substack{m\in A_i\\ l\in A_k}}\left(\frac{N_m - N_l}{\sqrt{2}\sigma_n}\right)^2 \sim \chi^2_{p^2}$$

Chi-Square

$$\frac{N_m - N_l}{\sqrt{2}\sigma_n} \sim \mathcal{N}(0,1)$$

$$\Rightarrow \quad \mathrm{E}\left[\frac{d_i(k)}{2\sigma_n^2}\right] = 1, \quad Var\left[\frac{d_i(k)}{2\sigma_n^2}\right] = \frac{2}{p^2}$$

- For a compared patch included in S_i^D:

$$\forall j \in S_i^D: \ \frac{d_i(j)}{2\sigma_n^2} = \frac{1}{p^2}\frac{\left\|Y(A_i)-Y(A_j)\right\|_2^2}{2\sigma_n^2} = \frac{1}{p^2}\sum_{\substack{m\in A_i\\ l\in A_j}}\left(\frac{C_j + N_m - N_l}{\sqrt{2}\sigma_n}\right)^2 \sim \chi^2_{p^2}(\lambda_j)$$

Non-Central Chi-Square

$$\lambda_j = f(C_j)$$

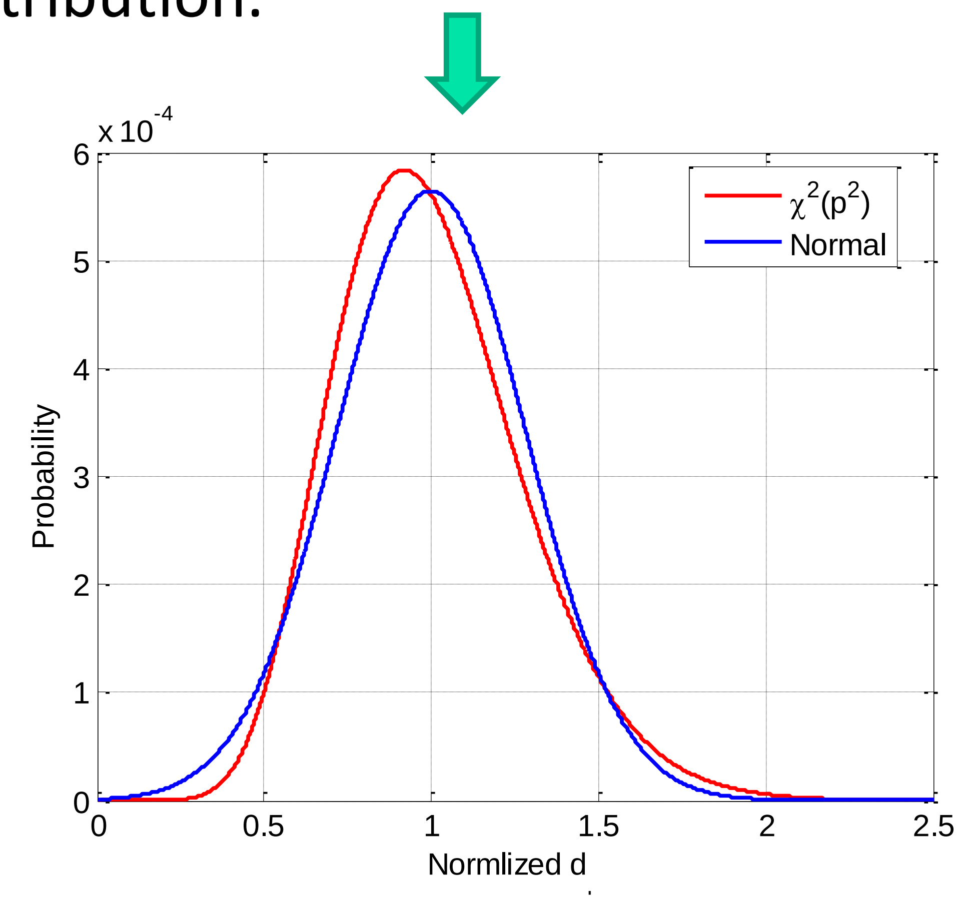
$$\frac{C_j + N_m - N_l}{\sqrt{2}\sigma_n} \sim \mathcal{N}\left(\frac{C_j}{\sqrt{2}\sigma_n}, 1\right)$$

$$\Rightarrow \quad \mathrm{E}\left[\frac{d_i(j)}{2\sigma_n^2}\right] = 1 + \frac{\lambda_j}{p^2}, \quad Var\left[\frac{d_i(j)}{2\sigma_n^2}\right] = \frac{2}{p^2} + \frac{4\lambda_j}{p^4}$$

Distribution Approximation

- For $p^2 \gg 1$, the Chi-Square distribution converges to a Normal distribution.

For $p^2 = 25$

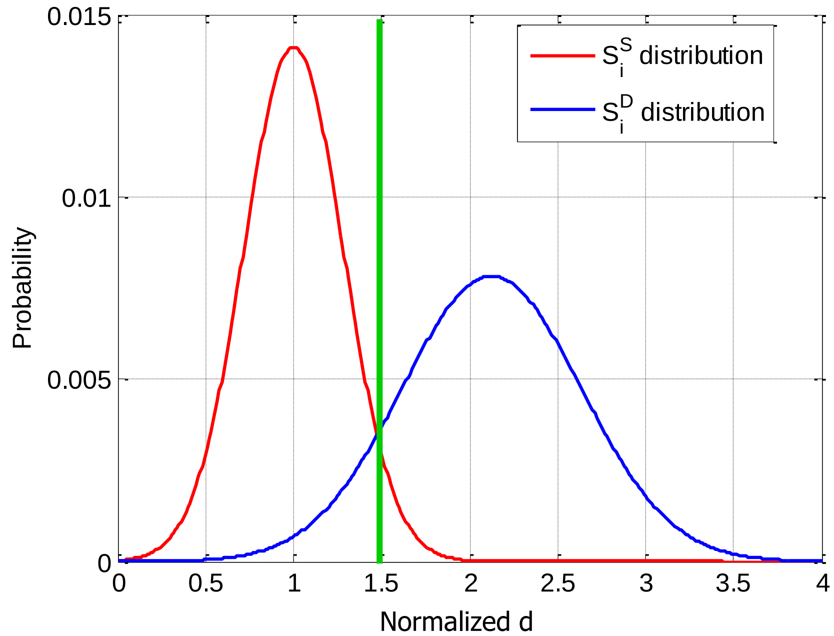


Difference Between Distributions

$$\forall k \in S_i^S \setminus \{i\}: \quad \frac{d_i(k)}{2\sigma_n^2} \sim \mathcal{N}\left(1, \frac{2}{p^2}\right)$$

$$\forall j \in S_i^D: \quad \frac{d_i(j)}{2\sigma_n^2} \sim \mathcal{N}\left(1+\frac{\lambda_j}{p^2}, \frac{2}{p^2}+\frac{4\lambda_j}{p^4}\right)$$

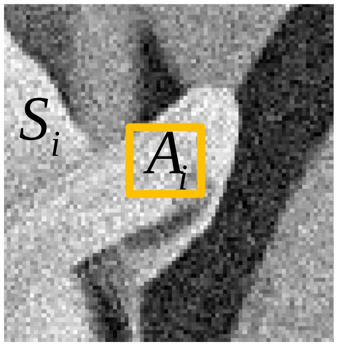
* For $p^2 = 25$

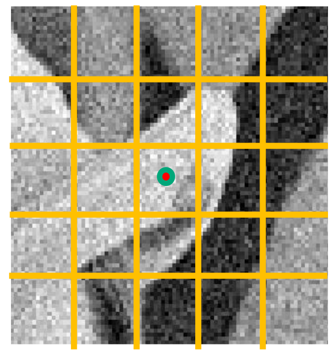


- The difference between the distributions of the two sets can serve as a classification measure.
- Since λ_j is unknown, we use a one-side hypothesis based on the dissimilarity variance:

Pixels included in S_i^S are characterized by a normalized dissimilarity variance $\leq 2/p^2$

Classification Via Accumulated Variance





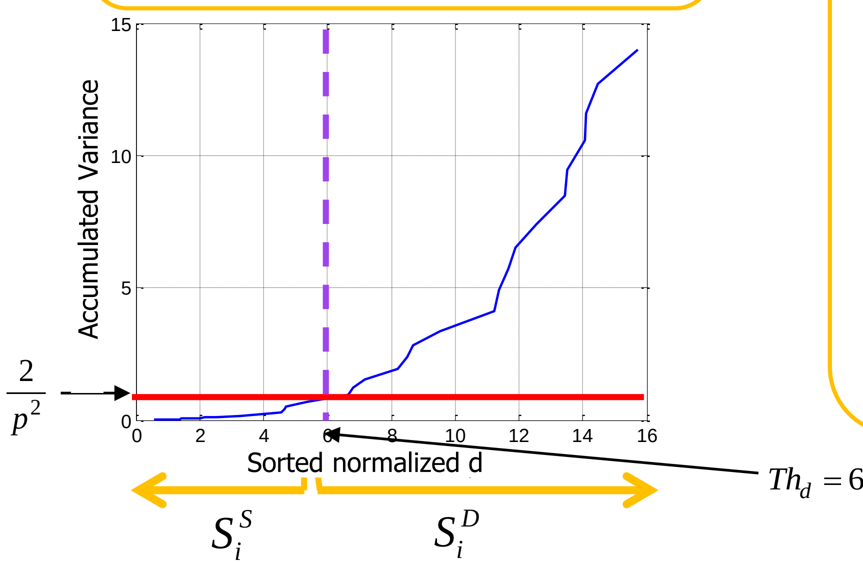
$$\forall k \in S_i : \frac{d_i(k)}{2\sigma_n^2}$$

Sort $\left\{\frac{d_i(k)}{2\sigma_n^2}\right\}_{k\in S_i}$ in an ascending order

Compute **Accumulated Variance** by starting with the first 2 elements and adding one element at a time

Stop accumulation once

$$Var\left\{\frac{d_i(k)}{2\sigma_n^2}\right\}_{k\in S_i} > \frac{2}{p^2}$$



Variance Estimation Error

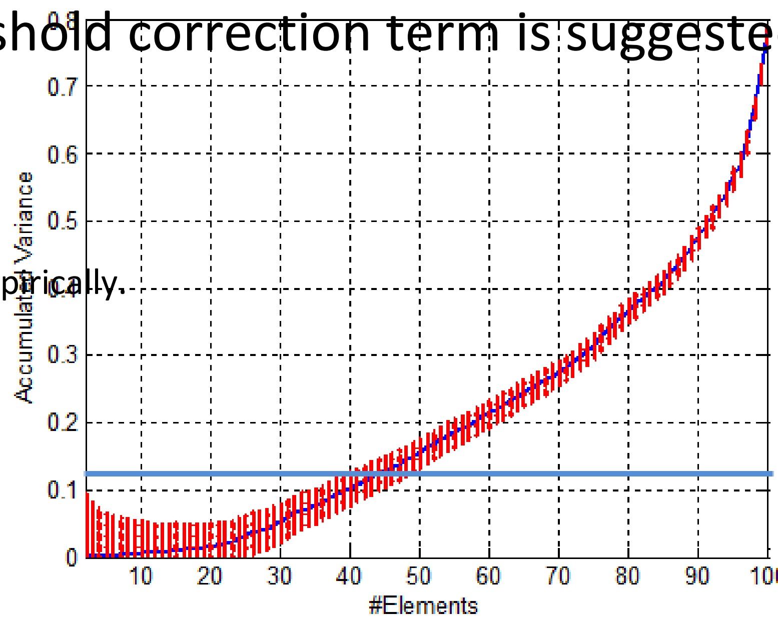
- Estimated variance is based on number of accumulated elements (L)
- Small L values result in a bigger variance estimation error:

$$\hat{V} = Var\left\{\frac{d_i(k)}{2\sigma_n^2}\right\}_{k\in S_i} \rightarrow Std\left[\hat{V}\right] = \frac{2}{p^2}\sqrt{\frac{2}{L-1}},\ L\in\left[2, M^2\right]$$

- Variance threshold correction term is suggested:

$$TH^G = \mathrm{E}\Big[\quad \ldots \quad \in \left[2, M^2\right]$$

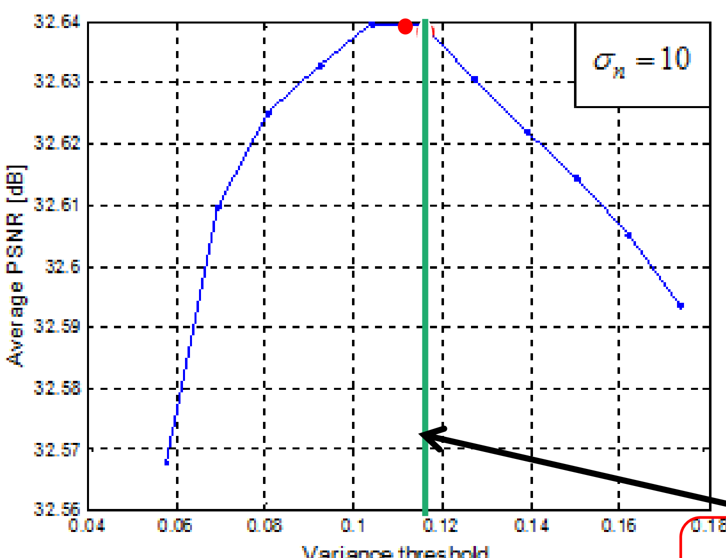
  - f is selected empirically.

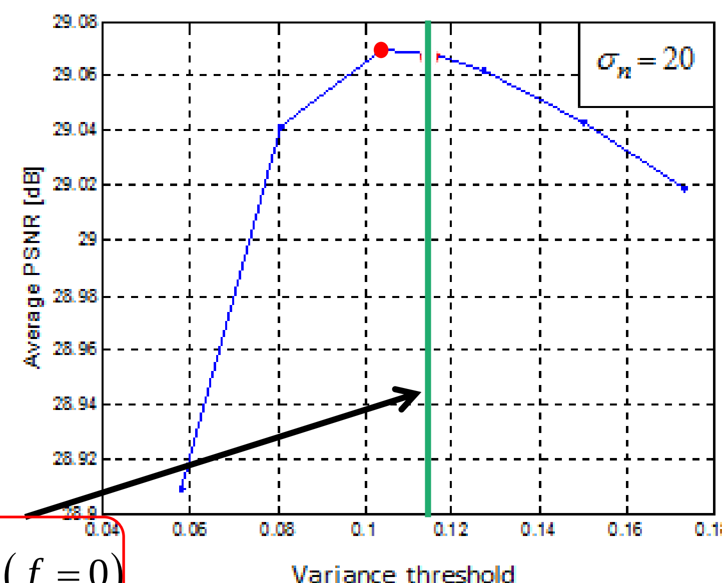


Adaptive Model-Based Search Region

Variance Threshold Validation

- The denoising performance, given the model-based scheme, was explored using different variance threshold values for various noise levels, and averaged over 10 natural images.

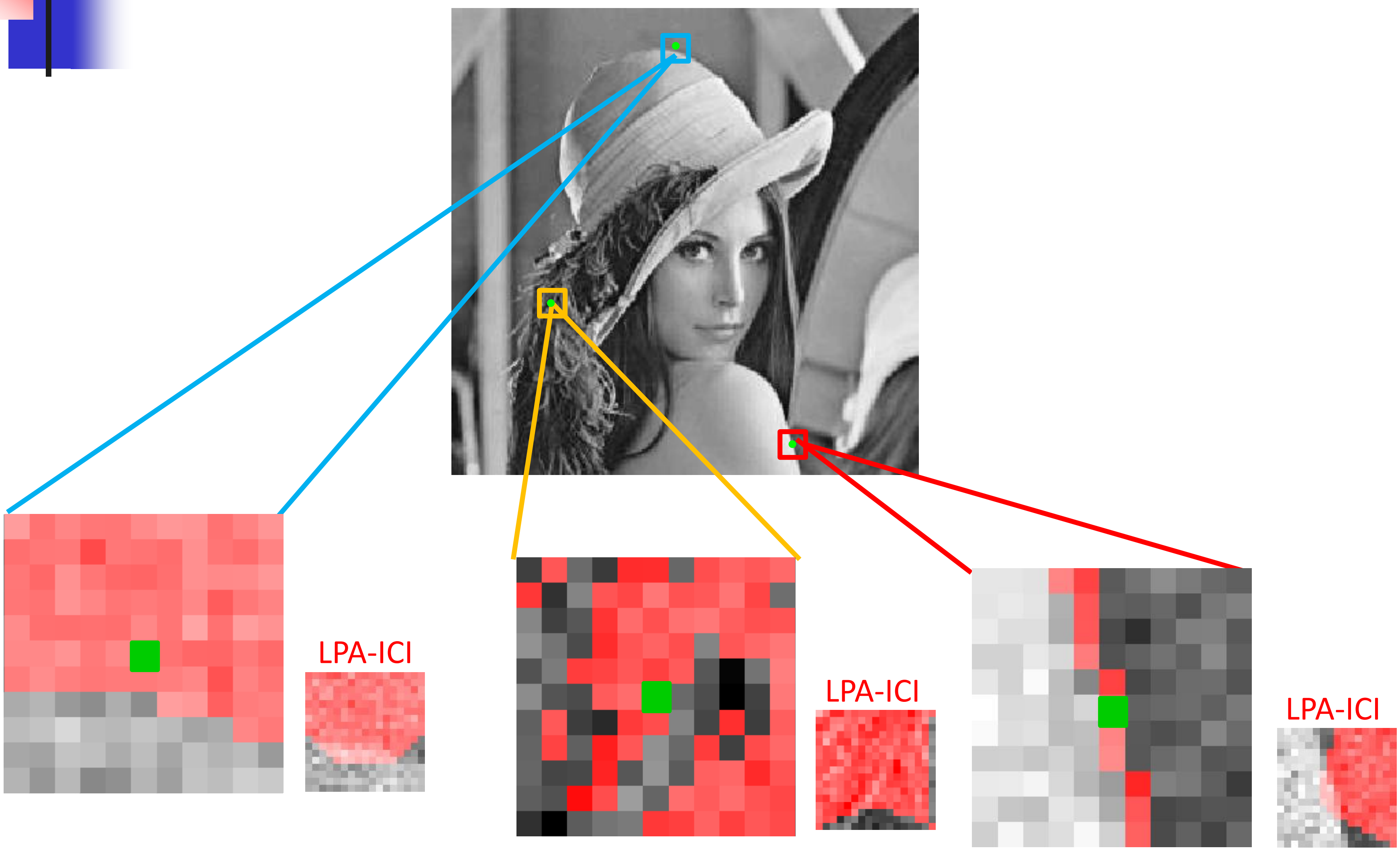




$$TH^{G} = \frac{2}{p^{2}}, \ (f = 0)$$

- The blue curve corresponds to different variance thresholds
- The red dot corresponds to the global maximum

Examples of Adaptive Search Region of Different Local Structures

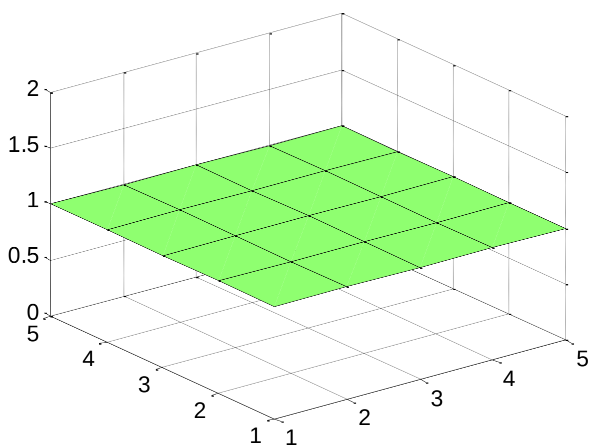


NLM with Patch–Kernel

- 2 types of patch (dissimilarity)-kernels are used frequently in NLM denoising:

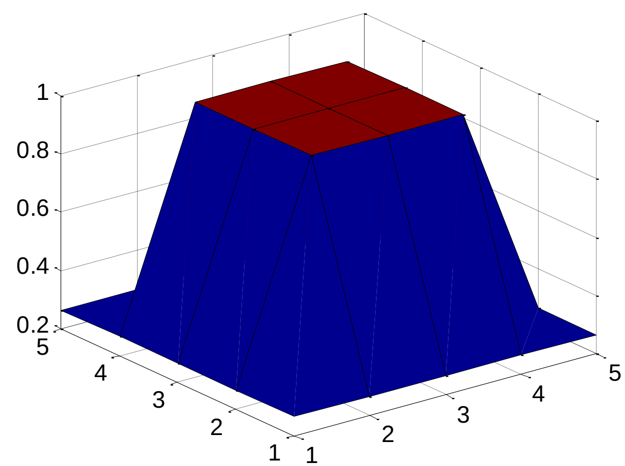
$$d_i(k) = \left\| Y(A_i) - Y(A_k) \right\|_{2,a}^2 = \sum_{\substack{m \in A_i, l \in A_k \\ s \in [1, p^2]}} \alpha_s \left(Y_m - Y_l \right)^2$$

Uniform patch-kernel



Smooth regions

“Box” patch-kernel

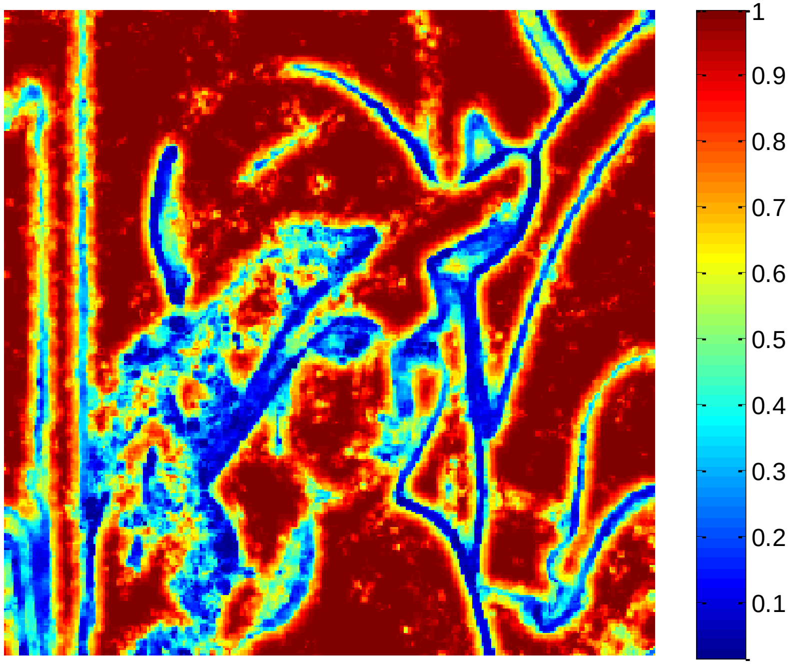


Textured regions / Edges

Proposed Modification II: Patch–Kernel Type Adaptation

- The Adaptive Model-Based Search Region output provides an S_i^S set per pixel, computed using the Uniform patch-kernel.

Normalized Cardinality map $\frac{|S_i^S|}{M^2}$



Cluster Cardinality Map Data

- Classify the data of the normalized cardinality map using K-Means with K=2.
- The classification results in 2 centroids:

Large centroid value

Weights are computed based on **Uniform** patch-kernel

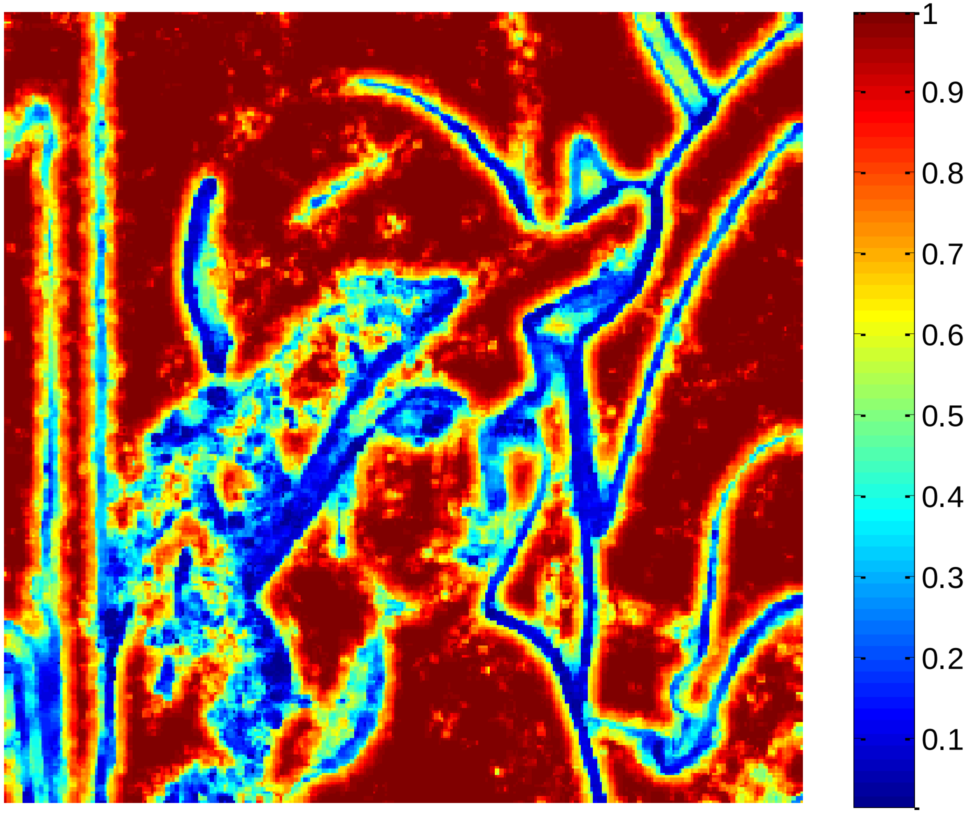
Small centroid value

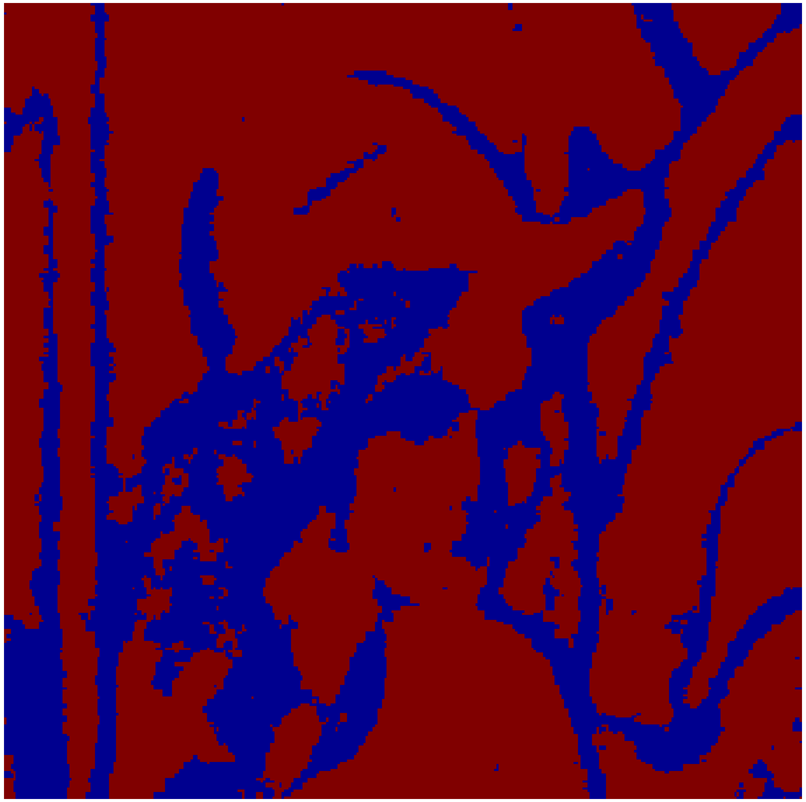
Weights are computed based on **Box** patch-kernel

Patch–Kernel Type Adaptation (Cont'd)

- Cardinality map clustered data $\frac{|S_i^S|}{M^2}$

* For $\sigma_n = 20,\ M = 11$



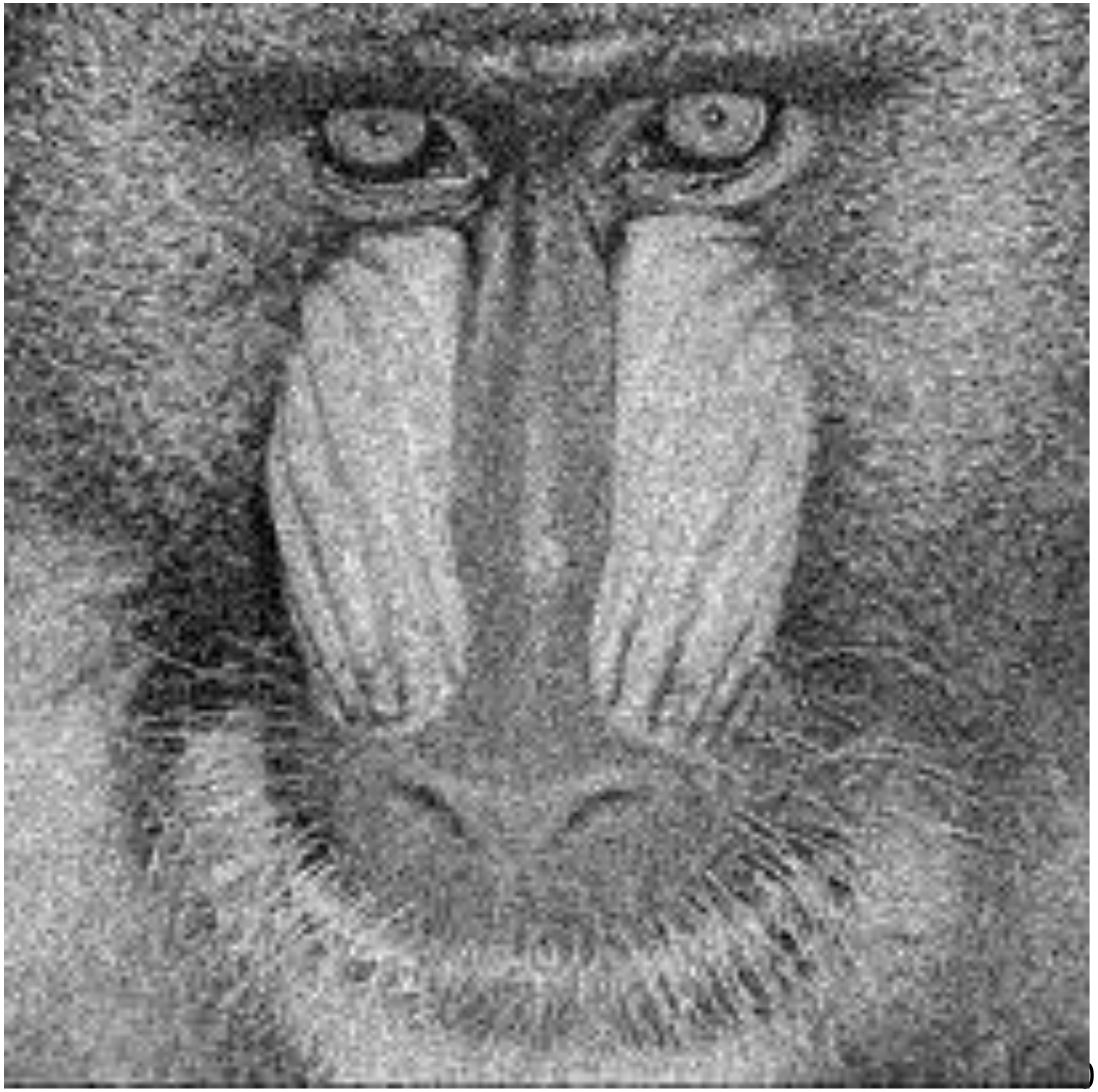


NLM Experimental Results

- Original vs. Noisy

	Noisy
PSNR [dB]	22.15
SSIM	0.67

* For $\sigma_n = 20$



NLM Experimental Results (Cont'd)

- Uniform NLM vs. Adaptive NLM

	Uniform	Adaptive
PSNR [dB]	24.78	25.62
SSIM	0.689	0.75

* For $\sigma_n = 20/22.5\,dB$

$p = 5$

$M = 11$

Uniform NLM

NLM Experimental Results (Cont'd)

- Uniform NLM vs. Adaptive NLM

	Uniform	Adaptive
PSNR [dB]	24.78	25.62
SSIM	0.689	0.75

* For $\sigma_n = 20/22.5\,dB$

$p = 5$

$M = 11$

Adaptive NLM

NLM Experimental Results (Cont'd)

- Box NLM vs. Adaptive NLM

	Box	Adaptive
PSNR [dB]	25.54	25.62
SSIM	0.74	0.75

* For $\sigma_n = 20/22.5\,dB$

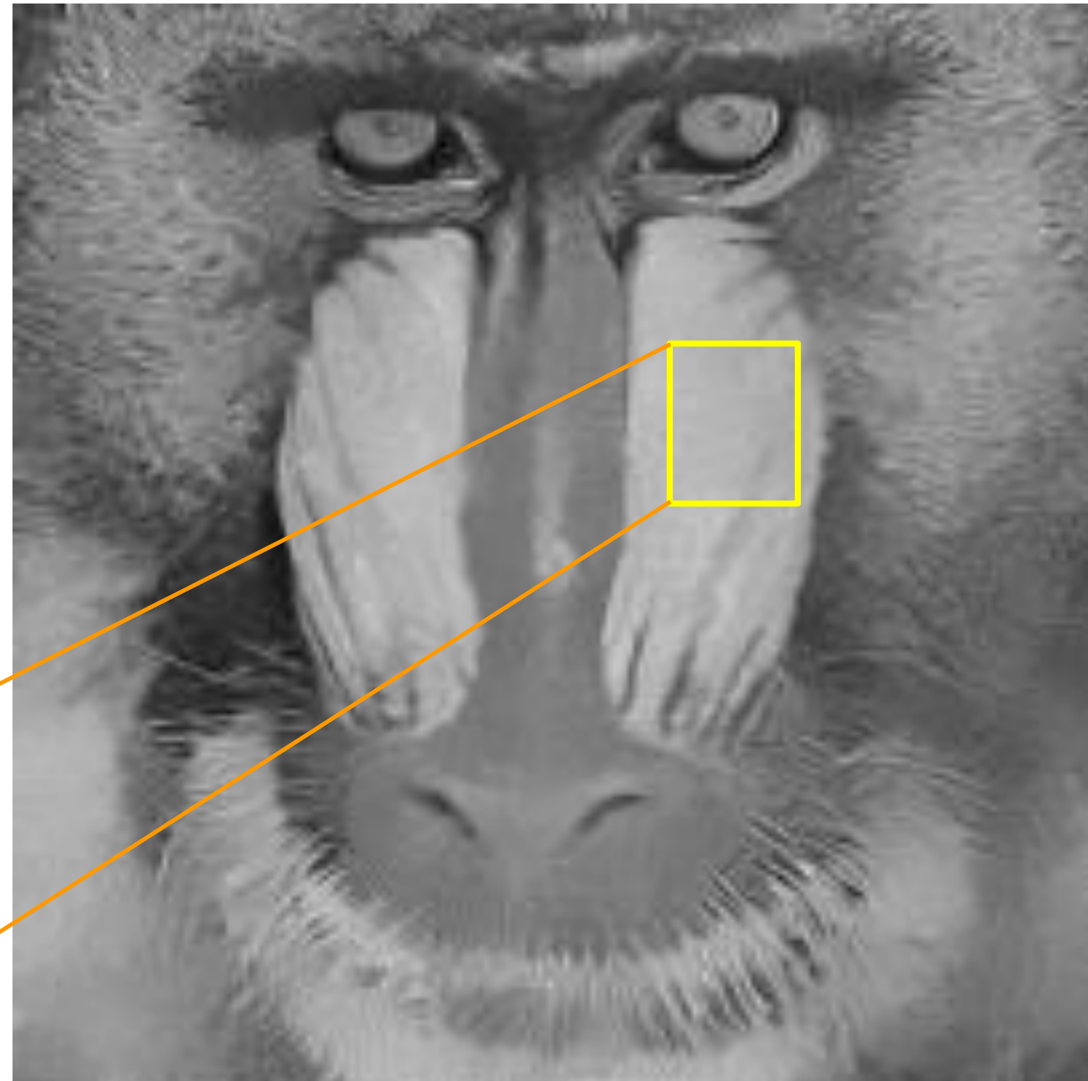
$p = 5$

$M = 11$

Box NLM

* After contrast enhancement

Box NLM



NLM Experimental Results (Cont'd)

- Box NLM vs. Adaptive NLM

	Box	Adaptive
PSNR [dB]	25.54	25.62
SSIM	0.74	0.75

* For $\sigma_n = 20/22.5\,dB$

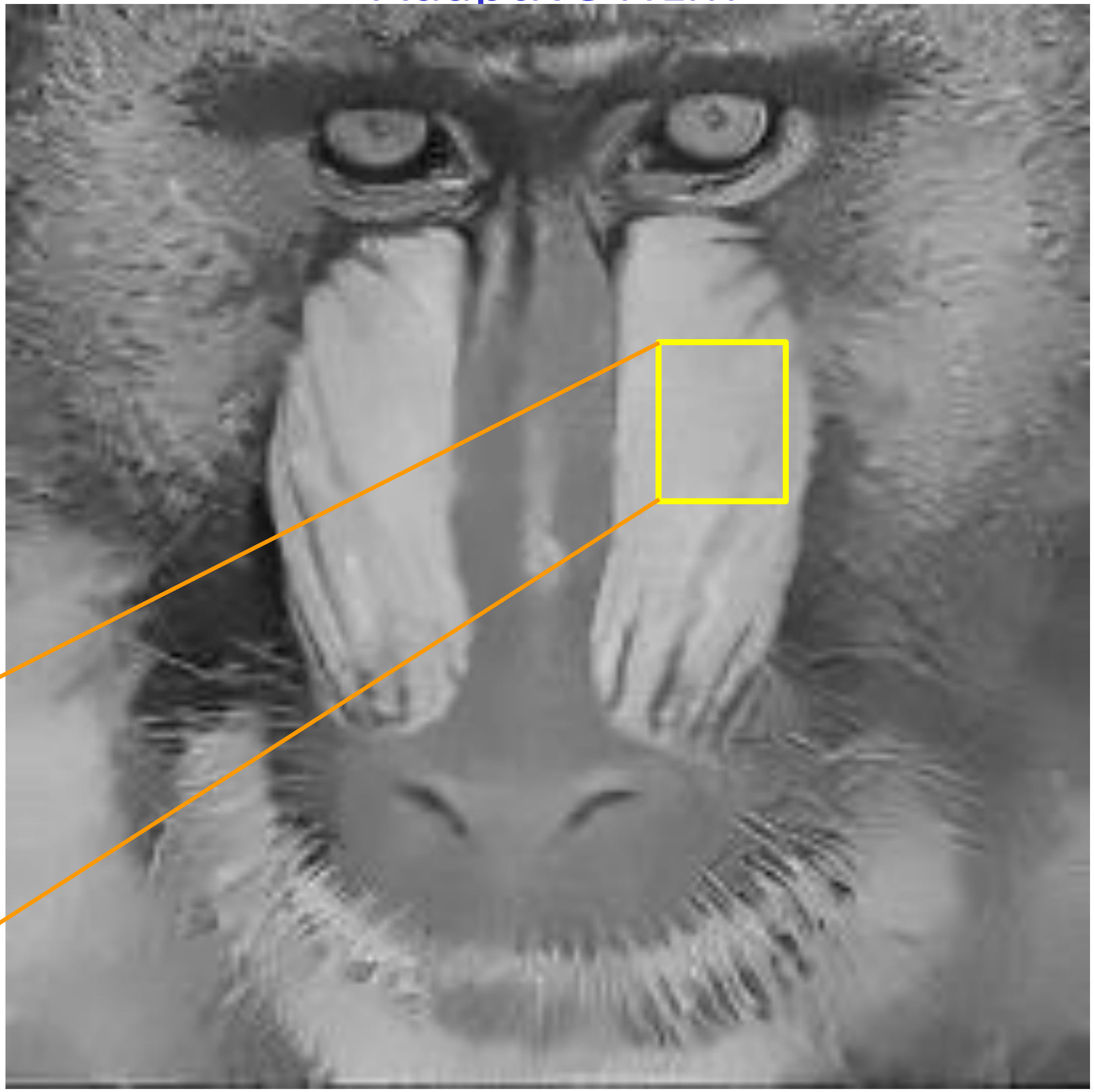
$p = 5$

$M = 11$

Adaptive NLM

* After contrast enhancement

Adaptive NLM



NLM Experimental Results (Cont'd)

Image	Noise Level/ PSNR [dB]	NLM with Uniform Kernel PSNR [dB] /SSIM	NLM with Box Kernel PSNR [dB] /SSIM	Proposed Adaptive Approach PSNR [dB] /SSIM
Lena	20/22.13	30.11/0.87	30.27/0.86	**30.48/0.88**
Baboon	20/22.15	24.78/0.69	25.54/0.74	**25.62/0.75**
Barbara	20/22.18	29.11/0.87	29.19/0.87	**29.33/0.88**
Lena	30/18.71	28.03/0.81	28.03/0.78	**28.32/0.82**
Peppers	30/18.77	28.03/0.83	28.06/0.81	**28.39/0.84**

Denoising results are improved, however computation time is increased by 14% on average

Correlation Between Dissimilarities

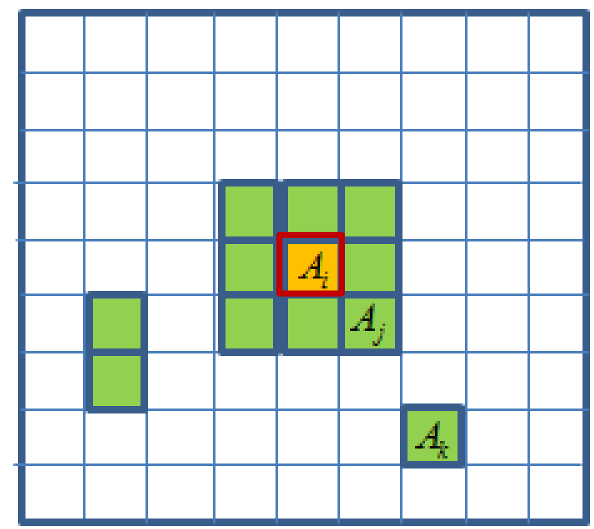
- So far, no correlation between dissimilarity elements was assumed
- 3 sources of correlation are introduced based on patches relative location, from the simplest to the most complicated:
  - Case 1: Patches do not overlap

→ Correlation due to same reference patch

$$A_k \cap A_j = \emptyset,\ A_k \cap A_i = \emptyset,\ A_j \cap A_i = \emptyset$$

$$\forall k \in S_i^S \setminus \{i\}: \ \frac{d_i(k)}{2\sigma_n^2} = \frac{1}{p^2} \sum_{\substack{m \in A_i \\ l \in A_k}} \left(\frac{N_m - N_l}{\sqrt{2}\sigma_n} \right)^2$$

$$\forall j \in S_i^S \setminus \{i\}: \ \frac{d_i(j)}{2\sigma_n^2} = \frac{1}{p^2} \sum_{\substack{m \in A_i \\ l \in A_j}} \left(\frac{N_m - N_l}{\sqrt{2}\sigma_n} \right)^2$$



Correlation Between Dissimilarities

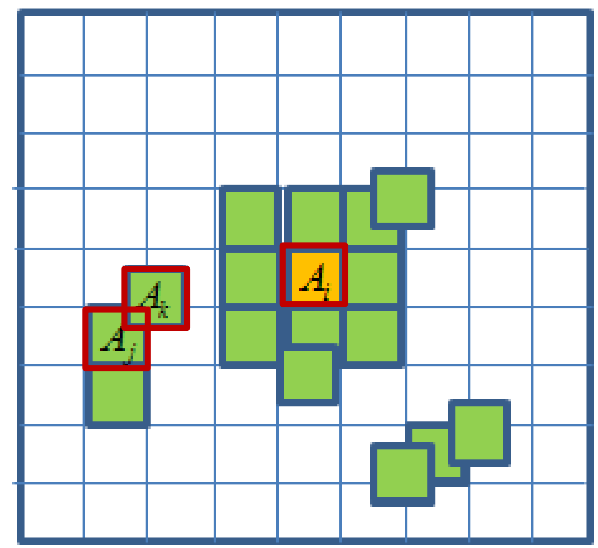
- 3 sources of correlation are introduced based on on patches relative location:
  - Case 2: Patches overlap each other

    → Correlation due to overlap of patch elements

$$A_k \cap A_j \neq \varnothing,\ A_k \cap A_i = \varnothing,\ A_j \cap A_i = \varnothing$$

$$\forall k \in S_i^S \setminus \{i\} : \frac{d_i(k)}{2\sigma_n^2} = \frac{1}{p^2} \sum_{\substack{m\in A_i \\ l\in A_k}} \left(\frac{N_m - N_l}{\sqrt{2}\sigma_n}\right)^2$$

$$\forall j \in S_i^S \setminus \{i\} : \frac{d_i(j)}{2\sigma_n^2} = \frac{1}{p^2} \sum_{\substack{m\in A_i \\ l\in A_j}} \left(\frac{N_m - N_l}{\sqrt{2}\sigma_n}\right)^2$$



Correlation Between Dissimilarities

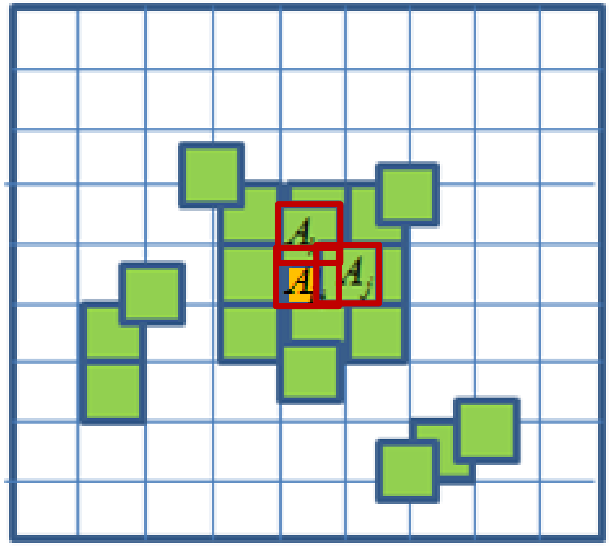
- 3 sources of correlation are introduced based on patches relative location:
  - Case 3: Patches overlap with reference

→ Correlation due to overlap with reference and with each other

$$A_k \cap A_j \neq \emptyset,\ A_k \cap A_i \neq \emptyset,\ A_j \cap A_i \neq \emptyset$$

$$\forall k \in S_i^S \setminus \{i\} : \ \frac{d_i(k)}{2\sigma_n^2} = \frac{1}{p^2} \sum_{\substack{m \in A_i \\ l \in A_k}} \left(\frac{N_m - N_l}{\sqrt{2}\sigma_n} \right)^2$$

$$\forall j \in S_i^S \setminus \{i\} : \ \frac{d_i(j)}{2\sigma_n^2} = \frac{1}{p^2} \sum_{\substack{m \in A_i \\ l \in A_j}} \left(\frac{N_m - N_l}{\sqrt{2}\sigma_n} \right)^2$$



Correlation Between Dissimilarities

- 3 sources of correlation are introduced based on patches relative location:

Simple

- Case 1: Patches do not overlap
- Case 2: Patches overlap each other
- Case 3: Patches overlap with reference

Complicated

Correlation reduces empirical variance

⟹ affects the threshold used to set S_i^s

Case 1 Analysis

- Case 1: Correlation between dissimilarities of patches that do not overlap each other, nor the reference patch
- The covariance matrix for a vector of $L \left(L \le M^2\right)$ explored dissimilarities :

$$C_d = p^{-2}\begin{bmatrix} 2 & 0.5 & .. & 0.5 \\ 0.5 & 2 & .. & 0.5 \\ | & | & | & | \\ 0.5 & .. & .. & 2 \end{bmatrix}_{L\times L}$$

- The statistical characteristics of the empirical variance:

$$\mathrm{E}\left[\hat{V}\right] = \frac{3}{2p^2}, \quad Var\left[\hat{V}\right] = \frac{9}{2p^4}\frac{1}{L-1}$$

Case 1 Analysis (Cont'd)

- Reminder: the no-correlation variance threshold:

$$TH^G = \mathrm{E}\left[\hat{V}\right] + f \cdot Std\left[\hat{V}\right] = \frac{2}{p^2}\left(1 + f\sqrt{\frac{2}{L-1}}\right), \quad L \in \left[2, M^2\right]$$

  - The factor f is selected empirically: $f=0$

- The correlation-based variance threshold:

$$TH^G = \mathrm{E}\left[\hat{V}\right] + f \cdot Std\left[\hat{V}\right] = \frac{3}{2p^2}\left(1 + f\sqrt{\frac{2}{L-1}}\right), \quad L \in \left[2, M^2\right]$$

  - The factor f is selected empirically: $f=2$

Case 2 Analysis

- Case 2: Correlation between dissimilarities of patches that overlap each other, but not the reference patch
- The covariance matrix for $L\left(L \leq M^2\right)$ explored dissimilarities:

$$C_d = p^{-2}\begin{bmatrix} 2 & 0.5 & .. & 0.5 \\ 0.5 & 2 & .. & 0.5 \\ | & | & | & | \\ 0.5 & .. & .. & 2 \end{bmatrix}_{L\times L} + 0.5p^{-4}\begin{bmatrix} 0 & \left|O_{\psi_i(1)\psi_i(2)}\right| & .. & \left|O_{\psi_i(1)\psi_i(L)}\right| \\ \left|O_{\psi_i(2)\psi_i(1)}\right| & 0 & .. & \left|O_{\psi_i(2)\psi_i(L)}\right| \\ | & | & | & | \\ \left|O_{\psi_i(L)\psi_i(1)}\right| & .. & .. & 0 \end{bmatrix}_{L\times L}$$

As in Case 1 — Overlap matrix

where ψ_i is the set of L sorted dissimilarities and $\psi_i(j)$ refers to the j^{th} element of the set . $O_{\psi_i(m)\psi_i(l)}$ is the set of indices in the region of overlap between the patches that correspond to the m^{th} and l^{th} elements of the set ψ_i .

Case 2 Analysis (Cont'd)

- The expectation of the empirical variance:

$$\mathrm{E}\left[\hat{V}\right]=\frac{3}{2p^2}-\frac{1}{2p^4L(L-1)}\sum_{l=1}^{L}\sum_{k=1,k\neq l}^{L}\left|O_{\psi_i(l)\psi_i(k)}\right|$$

As in Case 1

- Complicated terms (overlap matrices) that have to be computed for every set of accumulated dissimilarities and for every pixel in the image
- Right-hand term is smaller by 2 orders of magnitude w.r.t. case 1 term

> **No practical effect on variance threshold**
> **Impractical computation**

Case 3 Analysis

- Case 3: Correlation between dissimilarities of patches that overlap each other, and the reference patch

- In this case, the variance of the dissimilarity measure (**diagonal** terms of the covariance matrix) is changed:

$$\forall k \in S_i^S : Var\left[\frac{d_i(k)}{2\sigma_n^2}\right] = \frac{2}{p^2} + \frac{|O_{i,k}|}{p^4}$$

Variance is increased

  - where $|O_{i,k}|$ refers to the cardinality of the overlap set between pixels *i* and *k*

- The cross-variance (**off-diagonal** terms) is complicated:

$$\forall j,k \in S_i^S, j \neq k : Cov\left(d_i(j), d_i(k)\right) = \frac{1}{2p^2} + \frac{1}{2p^4}\left(|O_{i,j}| + |O_{i,k}| + |O_{j,k}|\right) + \begin{cases} \frac{|O_{i,j}|}{2p^4} & if\ |O_{i,j}| = |O_{i,k}| \\ 0 & Otherwise \end{cases}$$

As in Case 1

Supplements that stem from patches overlap

Case 3 Analysis (Cont'd)

- The expectation of the empirical variance:

$$E\left[\hat{V}\right]=\frac{3}{2p^2}+\frac{1}{p^4L}\sum_{l=1}^{L}\left|O_{i,\psi_i(l)}\right|-\frac{1}{2p^4L(L-1)}\sum_{l=1}^{L}\sum_{k=1,k\neq l}^{L}\left(\left|O_{i,\psi_i(l)}\right|+\left|O_{i,\psi_i(k)}\right|+\left|O_{\psi_i(l),\psi_i(k)}\right|\right)-\frac{1}{p^4L(L-1)}\sum_{l=1}^{L}\sum_{k=1,k\neq l}^{L}\mathbf{1}\left(\left|O_{i,\psi_i(l)}\right|=\left|O_{i,\psi_i(k)}\right|\right)\left|O_{i,\psi_i(l)}\right|$$

- Similarly to Case 2:
  - Complicated terms that have to be computed for every set of accumulated dissimilarities and for every pixel in the image
  - Right-hand terms are smaller in 2 orders of magnitude w.r.t. case 1 term

> **No practical effect on variance threshold**
> **Impractical computation**

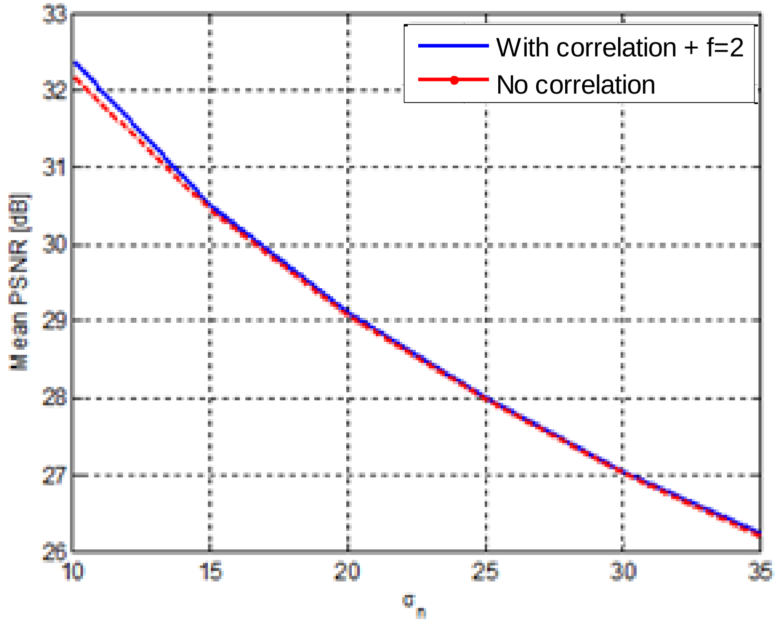
Experimental Results

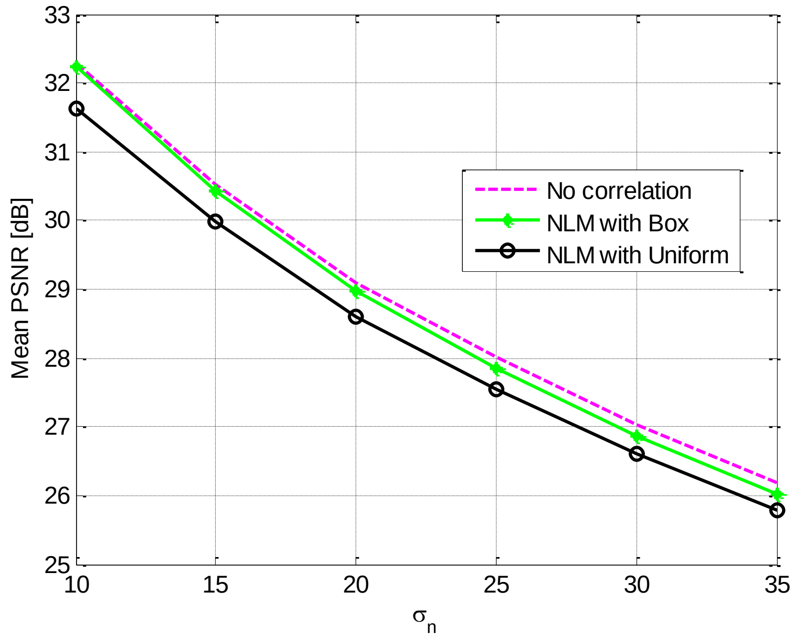
- Correlation-based scheme (Case 1) was compared to no-correlation scheme

Image	Noise Level/ PSNR [dB]	Proposed Adaptive Approach – no correlation PSNR [dB] /SSIM $TH^G = \frac{2}{p^2}\left(1 + f\sqrt{\frac{2}{L-1}}\right),\ f = 0$	Proposed Adaptive Approach – w. correlation PSNR [dB] /SSIM $TH^G = \frac{3}{2p^2}\left(1 + f\sqrt{\frac{2}{L-1}}\right),\ f = 2$
Lena	20/22.13	30.48/0.88	**30.51**/0.88
Baboon	20/22.15	25.62/0.75	**25.64**/0.75
Barbara	30/22.18	27.16/0.81	**27.18**/0.81
Pirate	15/24.63	31.08/0.85	**31.12**/0.85

Experimental Results (Cont'd)

- Comparison between the schemes with and without correlation consideration, and the standard NLM, averaged over 10 natural images

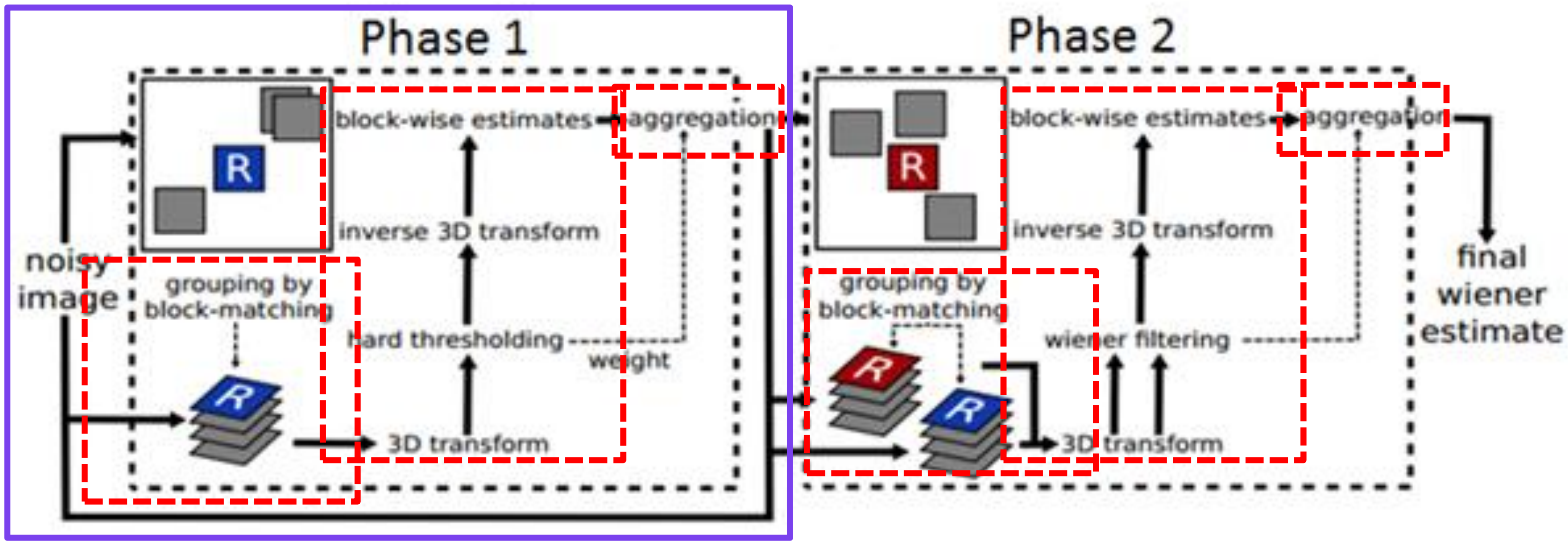




- **No significant quantitative difference between the 2 schemes**
- **No significant visual difference**

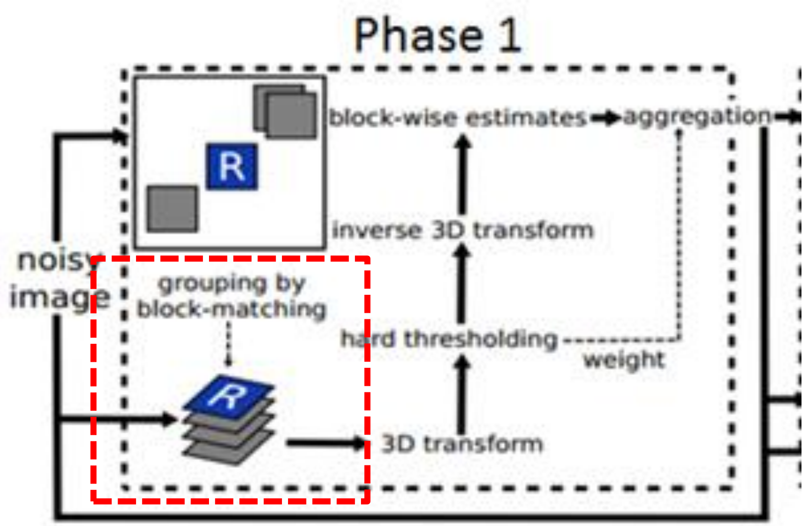
Block Matching 3D (BM3D)

- BM3D is considered as the state-of-the-art image denoising approach



Model-Based Scheme

- In Phase 1 → Noise model is assumed to be known
- In Phase 2 → Noise model is based on Phase 1 denoising
- We focus on **Phase 1 Grouping** step



Block Matching 3D (BM3D)

Model-Based Scheme

BM3D Original Phase 1 Grouping	BM3D Model-Based Phase 1 Grouping
Transform patches	-
Apply hard-thresholding operator on transformed patches	-
Compute dissimilarities in transform domain	Compute normalized dissimilarities in image domain
Sort dissimilarities in an ascending order	Sort dissimilarities in an ascending order
Apply hard-thresholding operator on computed dissimilarities	Accumulated variance computation and variance threshold application
Choose at most **B** most similar patches	Choose at most **B** most similar patches

Save Computations:

- **11% improvement in grouping running time**
- **4.5% improvement in overall running time**

Block Matching 3D (BM3D)

Model-Based Scheme – Experimental Results

- Both Phase 1 output and the final output of the standard BM3D were compared to the corresponding outputs of the Model-Based BM3D

		Phase 1 Output		Final Output	
Image	Noise Level/PSNR [dB]	BM3D Grouping PSNR [dB] /SSIM	Model-Based Grouping PSNR [dB] /SSIM	BM3D Grouping PSNR [dB] /SSIM	Model-Based Grouping PSNR [dB] /SSIM
Baboon	20/22.15	25.83/0.77	25.86/0.77	26.2/0.79	26.2/0.79
Peppers	20/22.22	30.89/0.9	30.99/0.9	31.46/0.92	31.5/0.92
Peppers	30/18.77	28.56/0.85	28.6/0.85	29.29/0.88	29.32/0.88

- The no correlation scheme results are displayed

Block Matching 3D (BM3D)

Model-Based Scheme – Experimental Results

- Phase 2 output based on BM3D grouping in Phase 1
- For $\sigma_n = 20/22.22\ dB$

Model-Based Scheme – Experimental Results

- Phase 2 output based on Model-Based grouping in Phase 1
- For $\sigma_n = 20/22.22\ dB$

Comparable results ✓

Poisson Image Denoising

- Output of a digital camera sensor
- Signal dependent
- Statistical characteristics

$$Y_i = \text{noisy pixel}, \; X_i = \text{noise-free pixel}$$

$$\mathrm{E}\left[Y_i \mid X_i\right] = \mathrm{Var}\left[Y_i \mid X_i\right] = X_i$$

- SNR decreases with decreasing signal intensity

$$SNR = \frac{Signal\ Power}{Noise\ Power} = \frac{X_i^2}{X_i} = X_i$$

Variance Stabilizing Transform (VST)

- Variance Stabilizing Transform (VST) – eliminates the dependency of the data variance on data mean
- Most image denoising algorithms are applicable for Gaussian noise
- Anscombe transform: non-linear

$$f\left(Y_i\right) = 2\sqrt{Y_i + \frac{3}{8}}$$

- Transformed data is characterized with Gaussian distribution with 0 mean and variance 1

Denoising Flow

Noisy image with Poisson noise

Anscombe Transform

Transformed noisy image with AWGN, $\sigma_n = 1$

NLM/ BM3D Image Denoising

Denoised transformed image

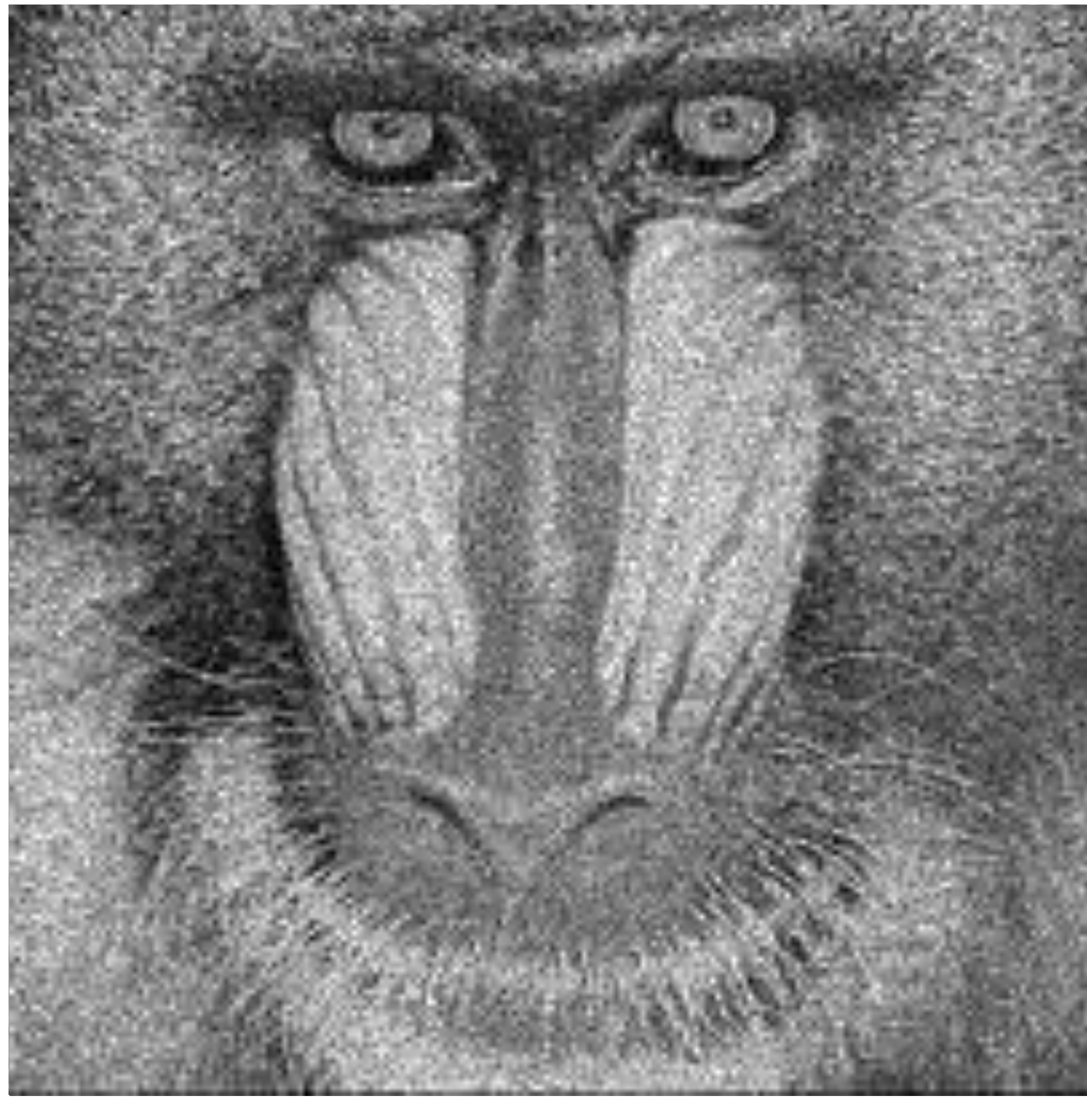
Inverse Anscombe Transform

Denoised image

NLM Experimental Results

- Original vs. Noisy

	Noisy
PSNR [dB]	22.57
SSIM	0.693



NLM Experimental Results

- Uniform NLM vs. Adaptive NLM

	Uniform	Adaptive – No correlation
PSNR [dB]	25.29	26.17
SSIM	0.72	0.78

* For: $p = 5$

$M = 11$

$\text{Initial PSNR} = 22.57\, dB$

Uniform NLM

NLM Experimental Results (Cont'd)

- Uniform NLM vs. Adaptive NLM

	Uniform	Adaptive – No correlation
PSNR [dB]	25.29	26.17
SSIM	0.72	0.78

* For: $p = 5$

$M = 11$

Initial PSNR $= 22.57\, dB$

Adaptive NLM

NLM Experimental Results (Cont'd)

- Box NLM vs. Adaptive NLM

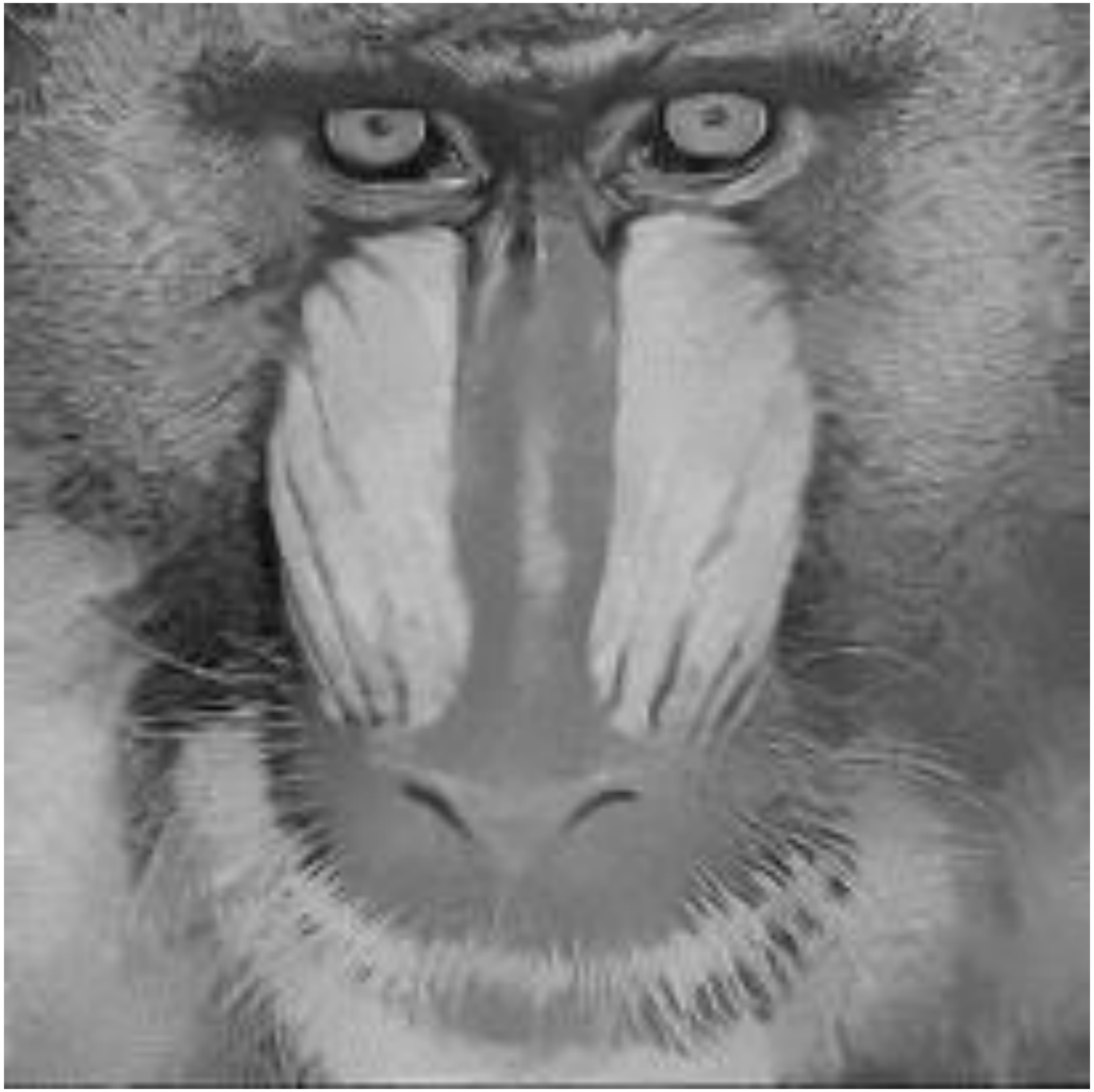
	Box	Adaptive – No correlation
PSNR [dB]	26.09	26.17
SSIM	0.77	0.78

* For: $p = 5$

$M = 11$

$\text{Initial PSNR} = 22.57\, dB$

Box NLM



NLM Experimental Results (Cont'd)

- Box NLM vs. Adaptive NLM

	Box	Adaptive – No correlation
PSNR [dB]	26.09	26.17
SSIM	0.77	0.78

* For: $p = 5$

$M = 11$

$\text{Initial PSNR} = 22.57\, dB$

Adaptive NLM

NLM Experimental Results (Cont'd)

- Adaptive NLM with and without correlation consideration

	Adaptive – W. correlation	Adaptive – No correlation
PSNR [dB]	26.19	26.17
SSIM	0.78	0.78

* For: $p = 5$

$M = 11$

$\text{Initial PSNR} = 22.57\,dB$

Adaptive NLM – With Correlation

Poisson Image Denoising

NLM Experimental Results (Cont'd)

Image	Initial PSNR [dB]	NLM with Uniform Kernel PSNR [dB] /SSIM	NLM with Box Kernel PSNR [dB] /SSIM	Proposed Adaptive Approach – No correlation PSNR [dB] /SSIM	Proposed Adaptive Approach – With correlation PSNR [dB] /SSIM
Lena	22.58	30.62/0.88	30.73/0.87	**30.9/0.89**	**30.96/0.89**
Lena	18.8	28.52/0.82	28.44/0.79	**28.82/0.83**	**28.84/0.83**
Barbara	22.27	29.17/0.87	29.25/0.87	**29.35/0.88**	**29.41/0.88**
Peppers	19.2	28.74/0.85	28.63/0.82	**28.92/0.85**	**28.95/0.85**

Better performance of adaptive scheme

BM3D Experimental Results

Image	Initial PSNR [dB]	Standard BM3D PSNR [dB] /SSIM	Model-Based BM3D – No Correlation PSNR [dB] /SSIM	Model-Based BM3D – With Correlation PSNR [dB] /SSIM
Lena	22.46	31.47/0.9	31.43/0.9	31.4/0.9
Barbara	22.23	29.8/0.89	29.83/0.89	29.81/0.89
Barbara	18.93	27.67/0.83	27.7/0.83	27.7/0.83
Baboon	19.72	24.57/0.69	24.59/0.69	24.59/0.69

Comparable performance

BM3D Experimental Results (Cont'd)

	Standard BM3D	Model-Based BM3D (No Correlation)
PSNR [dB]	31.47	31.43
SSIM	0.9	0.9

$\text{Initial PSNR}: 22.46\,dB$

Standard BM3D

BM3D Experimental Results (Cont'd)

Model-Based BM3D – No Correlation

	Standard BM3D	Model-Based BM3D (No Correlation)
PSNR [dB]	31.47	31.43
SSIM	0.9	0.9

Initial PSNR : $22.46\,dB$

Summary

- Two modifications of the NLM algorithm were introduced:
  - **Model-based** adaptive search region
    - Parameter-free, assuming correlation is not considered
    - Not restricted to be contiguous
  - **Content-based** patch-kernel type
    - Matched to local structure → smooth regions are less granular while texture and edges are preserved.
- These modifications improve denoising results both visually and quantitatively compared to standard NLM.
- Running time is increased by 14% on average, w.r.t. standard NLM.

Summary (Cont'd)

- **Correlation** between dissimilarities was explored and was found to be **insignificant to denoising results** using the proposed scheme.

- The **adaptive model-based search region** was integrated into the **Phase 1 grouping of the BM3D** image denoising scheme, such that **computational time is decreased** by 11% for the Phase 1 grouping step, while denoising results remain comparable.

- The proposed scheme was explored for **Poisson noise** using both NLM and BM3D, and found to preserve the same tendency that characterizes the AWGN denoising.

Future work

- NLM **Video** denoising using the adaptive model-based scheme
- Poisson noise – explore other VST (besides Anscombe)
- Color information – explore dissimilarities computed using the color components, not only the gray channel


THANK
YOU