A Largest Matching Area Approach to Image Denoising

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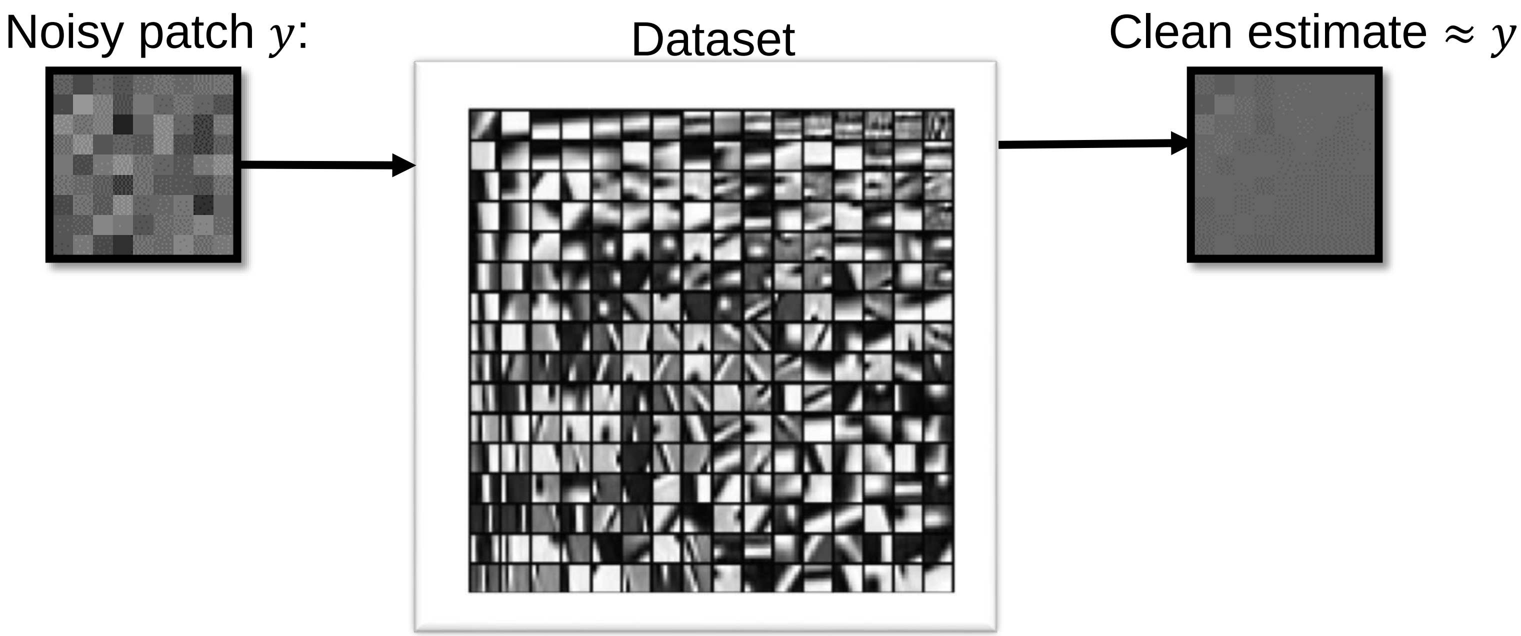
Outline

- The Problem
  - Patch-based image denoising
- Our Largest Matching Area (LMA) Approach
  - Also using LMA to extend existing approaches
- Experiments
- Summary

The Problem – Patch-Based Image Denoising

- State-of-the-art approaches denoise images in patches



- The choice of patch-size is ill-posed
  - Large patches are more robust to noise
    - However, good matches are hard to find – the *rare patch* effect
  - Small patches risk over-fitting to the noise
    - But can retain fine details, by avoiding the *rare patch* effect

The Problem – Patch-Based Image Denoising

- Prior work on the patch-size problem
  - Use larger patches to handle higher noise
  - Use a locally adaptive region of the patch for reconstruction
    - Retain edges and fine details
  - Multi-scale
    - Combine reconstructions at several patch-sizes

- We propose a Largest Matching Area (LMA) approach
  - Find the largest noisy patch with a good clean estimate, subject to the constraints of the available data

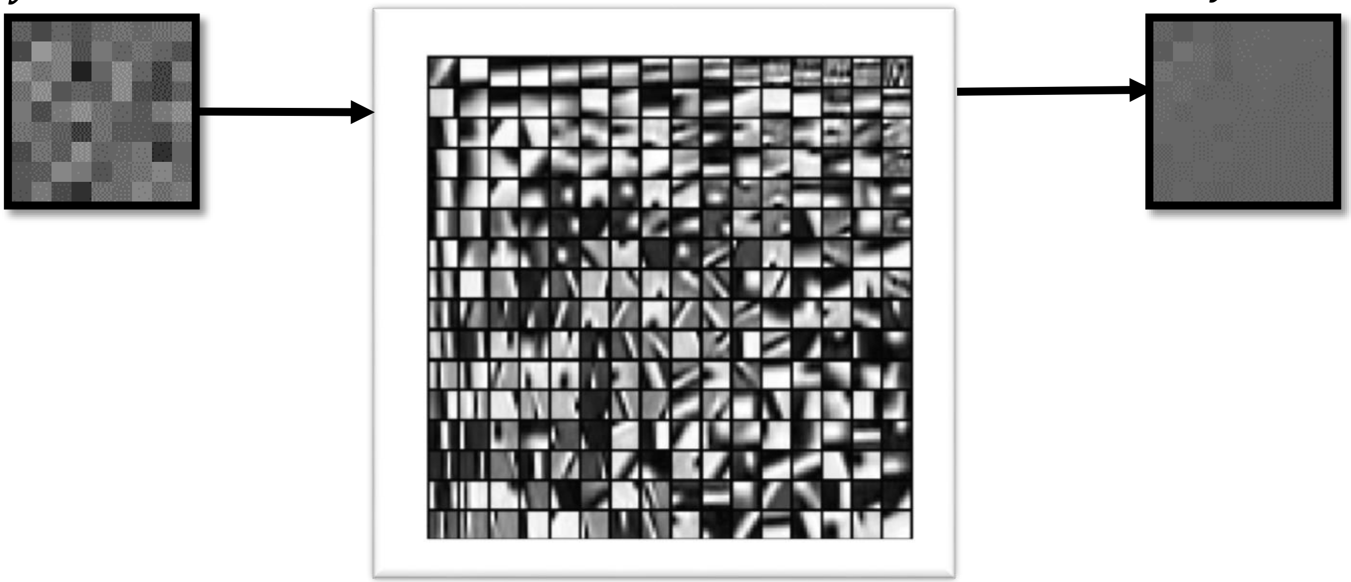
The Problem – Patch-Based Image Denoising

- Existing patch-based denoising approaches fall into two camps
  - External denoising approaches use a priori knowledge such as training data
    - Eg. Sparse Representation (SR)

Noisy patch y:

Sparse Representation Dictionary D:

Clean estimate $\alpha D \approx y$:



The Problem – Patch-Based Image Denoising

- Existing patch-based denoising approaches fall into two camps
  - External denoising approaches use a priori knowledge such as training data
    - Eg. Sparse Representation (SR)
  - Internal denoising approaches use the noisy image itself
    - Eg. Block-Matching 3D (BM3D)

Noisy image:

Final reconstruction:

The Problem – Patch-Based Image Denoising

- Existing patch-based denoising approaches fall into two camps
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    - Eg. Sparse Representation (SR)
  - Internal denoising approaches use the noisy image itself
    - Eg. Block-Matching 3D (BM3D)

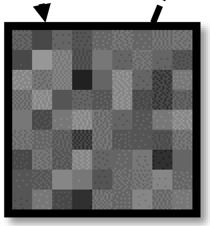
- Structured regions are better denoised by external approaches
- Smooth regions are better denoised by internal approaches

- Our Largest Matching Area (LMA) approach finds a patch-size where the structure of the clean signal is easily recognisable
  - The LMA approach has a preference for external denoising

Fixed Patch-Size Example-Based Denoising

Test Image y, σ=25

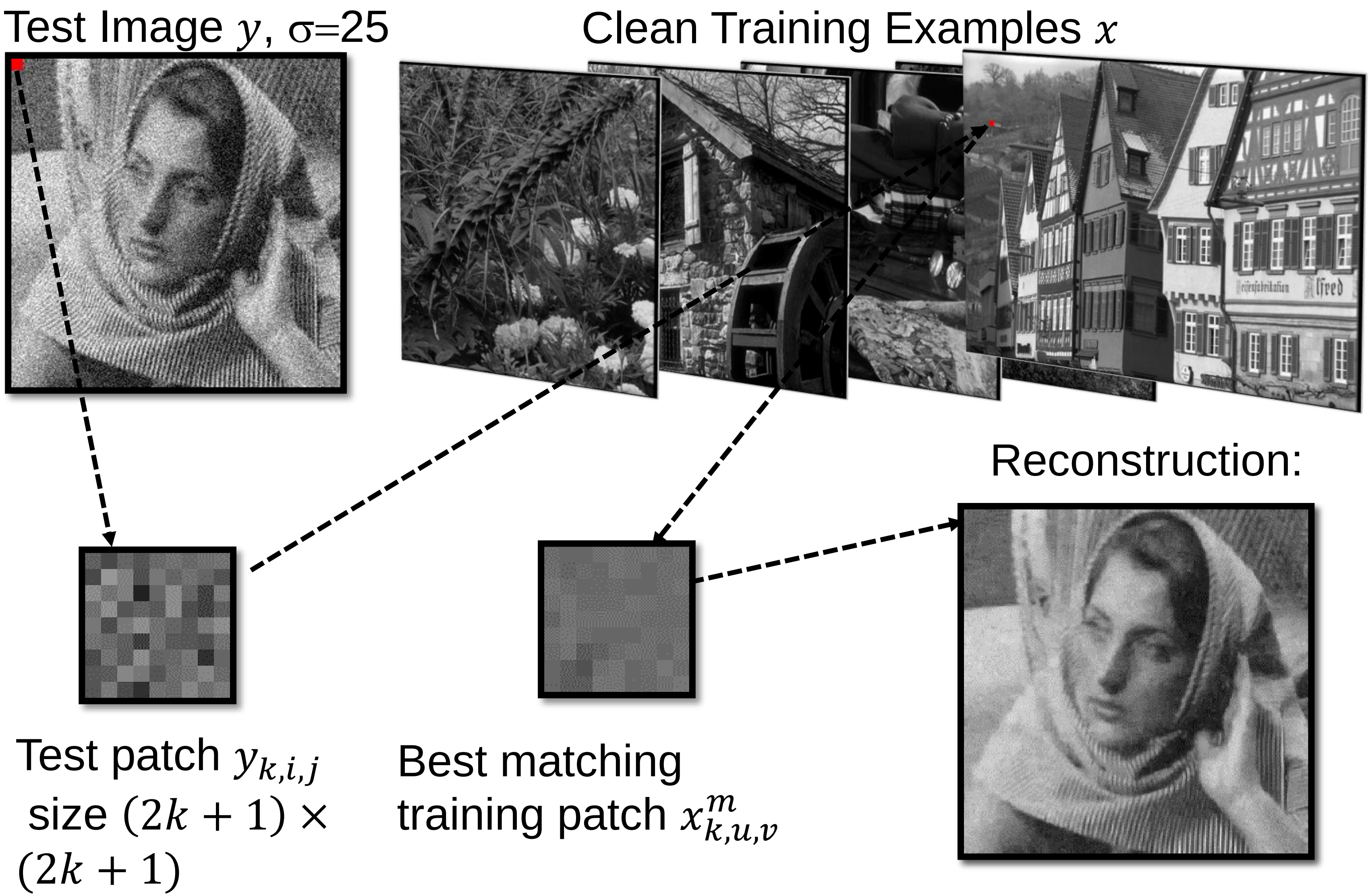
Clean Training Examples x



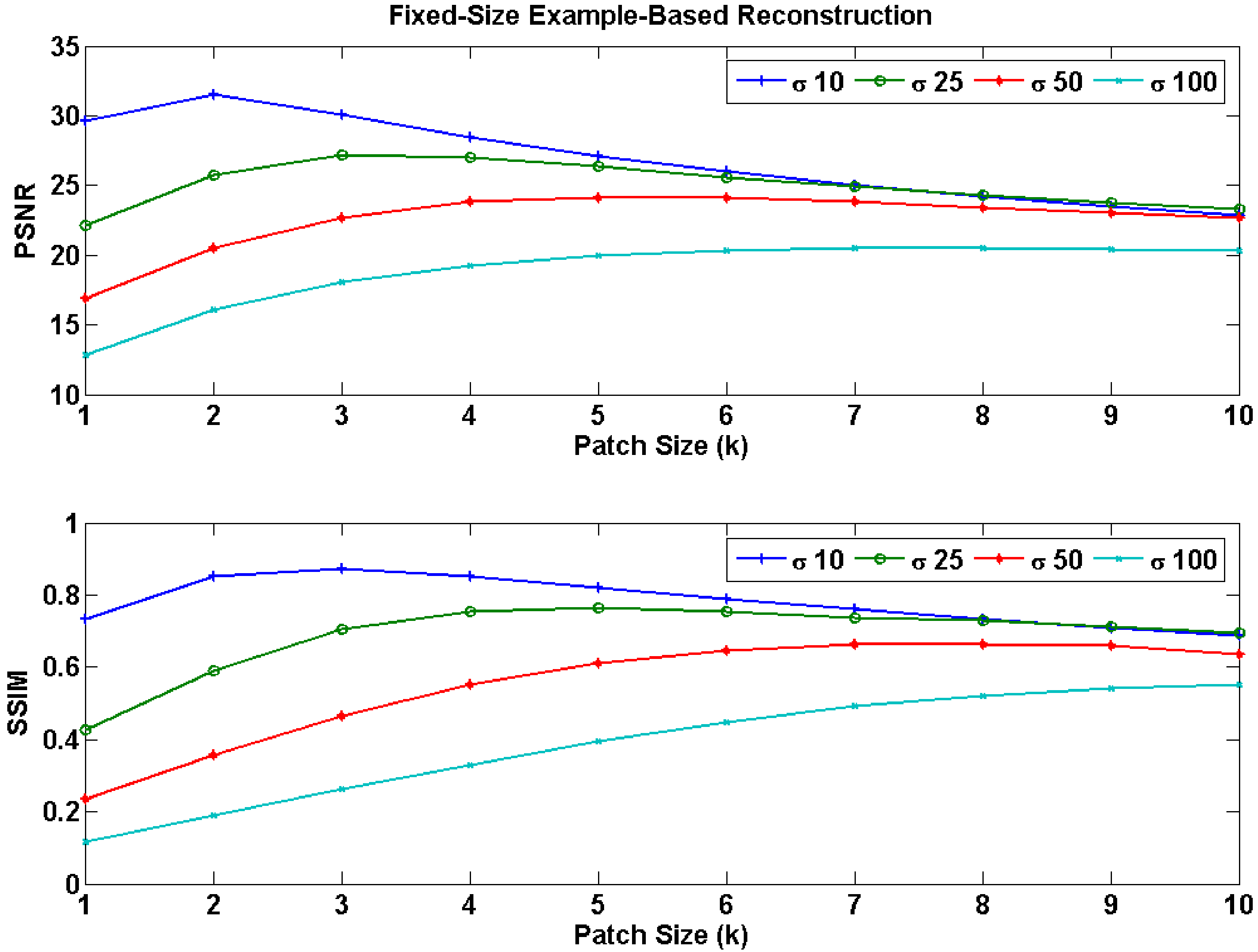
$$p\left(y_{k,i,j} \middle| x^m_{k,u,v}\right) = a\ \exp\left(-\frac{\left\| y_{k,i,j} - x^m_{k,u,v} \right\|^2}{h^2}\right)$$

Test patch $y_{k,i,j}$
size $(2k+1) \times (2k+1)$

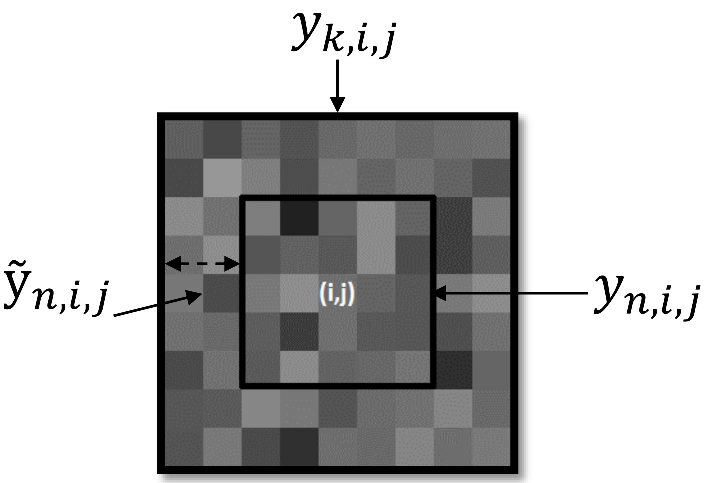
Fixed Patch-Size Example-Based Denoising

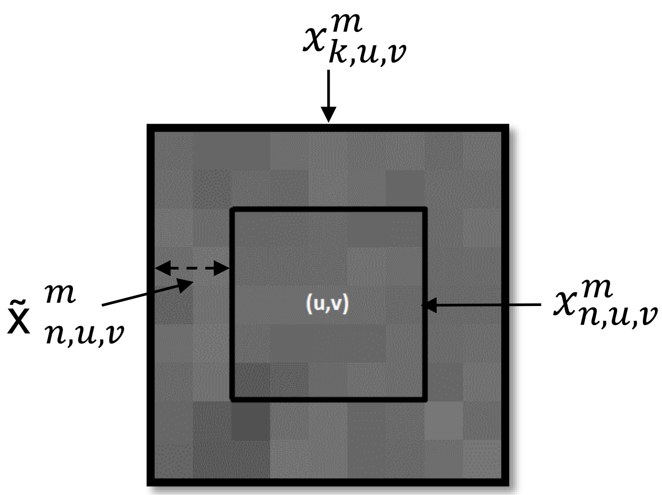


Average Example-Based Reconstructed Accuracy Across Fixed Patch-Sizes



The LMA Approach – A MAP Algorithm



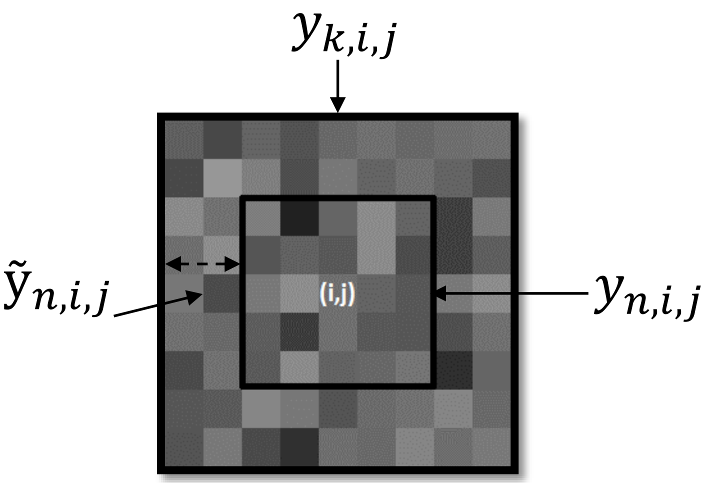


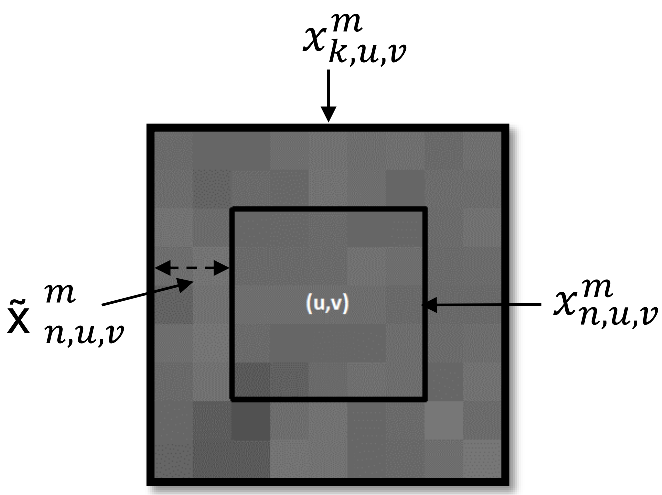
- For each test image location
  - Iteratively increase the patch-size
    - Find the most likely matching patch
    - Break when posterior probability is maximised

$$\mathbf{x}^m_{k,u,v} = \arg\max_{\eta} \max_{m',u',v'} P(\mathbf{x}^{m'}_{\eta,u',v'} | \mathbf{y}_{\eta,i,j})$$

- Reconstruct by averaging overlapping matches, $x^m_{k,u,v}$

The LMA Approach – A MAP Algorithm



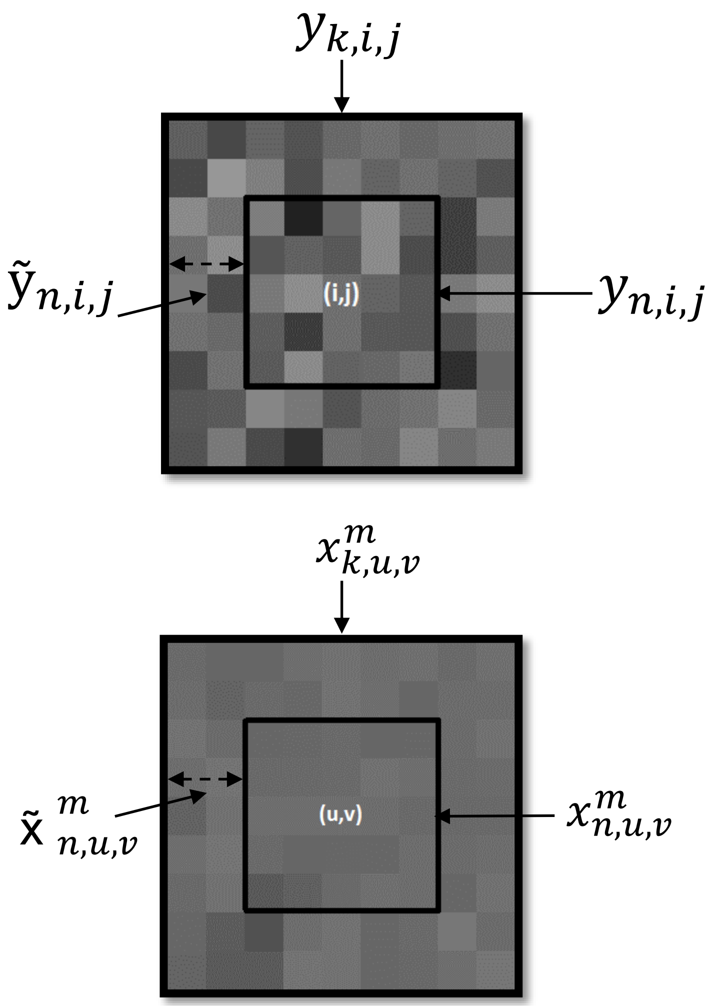


Posterior Probability:

$$P\left(x^m_{k,u,v} \middle| y_{k,i,j}\right) \approx \frac{p(y_{k,i,j} | x^m_{k,u,v})}{\Sigma_{m'} \Sigma_{u',v'} p\left(y_{k,i,j} \middle| x^{m'}_{k,u',v'}\right) + p(y_{k,i,j} | \phi_k)}$$

- $P\left(x^m_{n,u,v} \middle| y_{n,i,j}\right) \leq P\left(x^m_{k,u,v} \middle| y_{k,i,j}\right)$
- A good match at size k produces a higher posterior probability than a good match at the smaller size n
- The posterior probability can be used to identify the *largest matching* patches

The LMA Approach – A MAP Algorithm



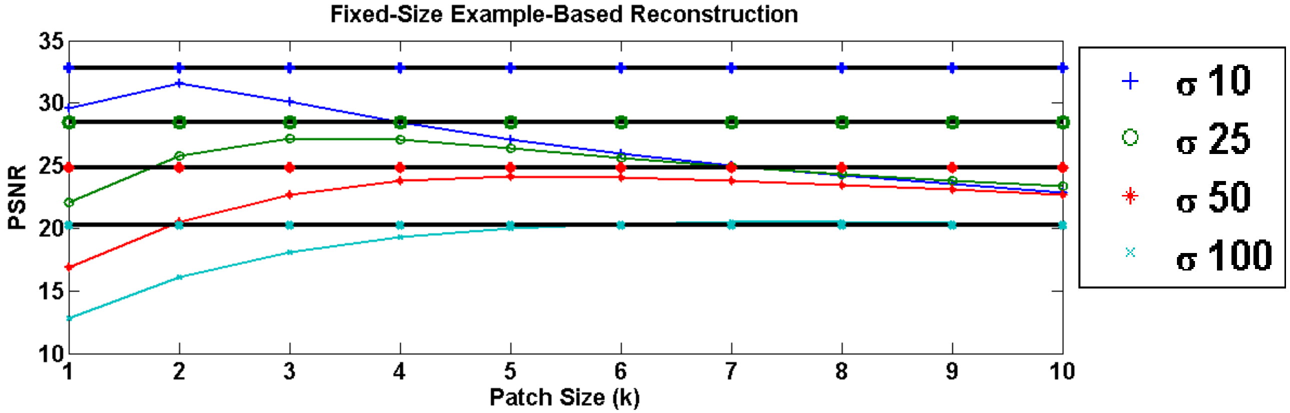
- To avoid selecting partially matching patches, we enforce monotonicity of posterior probability
  - Derivative across patch sizes ≥ 0

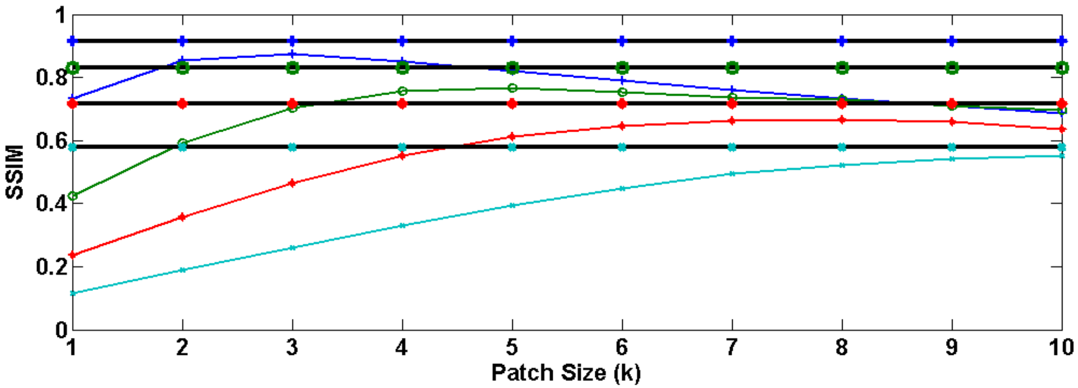
- Find the best match at each size, subject to monotonicity of posterior over previous sizes:

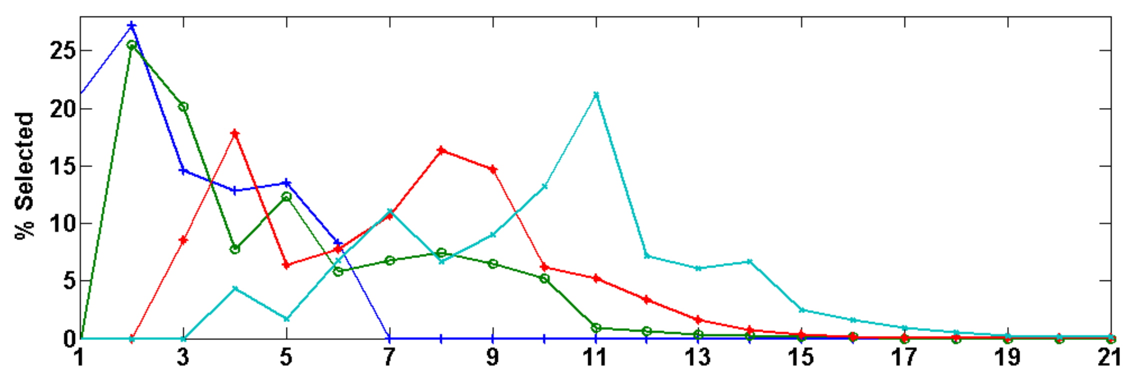
$$\mathbf{x}^m_{k,u,v} = \arg\max_{\eta} \max_{m',u',v'} P(\mathbf{x}^{m'}_{\eta,u',v'} | \mathbf{y}_{\eta,i,j})$$

$$\text{s.t. } \nabla_\eta P(\mathbf{x}^m_{\eta,u,v} | \mathbf{y}_{\eta,i,j}) \geq 0 \text{ for all } \eta \leq k$$

Average Reconstructed Accuracy of the LMA Approach vs. Fixed-Size Patches







Selected sizes at σ=25:

LMA Extensions to Existing Approaches

- Sparse Representation-LMA (SR-LMA)
  - We learn Sparse Representation (SR) dictionaries at a range of patch-sizes
  - Select the reconstruction which maximizes posterior probability
  - Combining SR training data invariance with LMA noise robustness

- BM3D-LMA
  - Search noisy image, ranking largest matching areas
  - Filter with optimal BM3D parameters
  - Improve noise robustness by identifying similar patches using a larger patch-size, where the clean signal is more recognisable

- Given the LMA approach's preference for clean external data, we expect that the LMA extension will be more beneficial in the SR framework

Experiments- Settings

- We performed tests on 4 test images at 4 noise levels.

Barbara $\sigma = 10$

Boat $\sigma = 25$

Cameraman $\sigma = 50$

Parrot $\sigma = 100$

- For external approaches we used 2 generic datasets
  - 5 natural images with varying contents

TD1:

TD2:

Experiments- Settings

- Sparse Representation (SR) - learned dictionaries of 256 8x8 patches
- Sparse Representation-LMA (SR-LMA) - learned dictionaries from 7x7 to 21x21
- All results averaged over 3 instances of noise
- We tuned the upper and lower limits of the patch-sizes to be searched
  - Lower for low noise, higher for high noise
- $h \approx \sigma$ in all experiments

Experiments – LMA Vs. Sparse Representation (External)

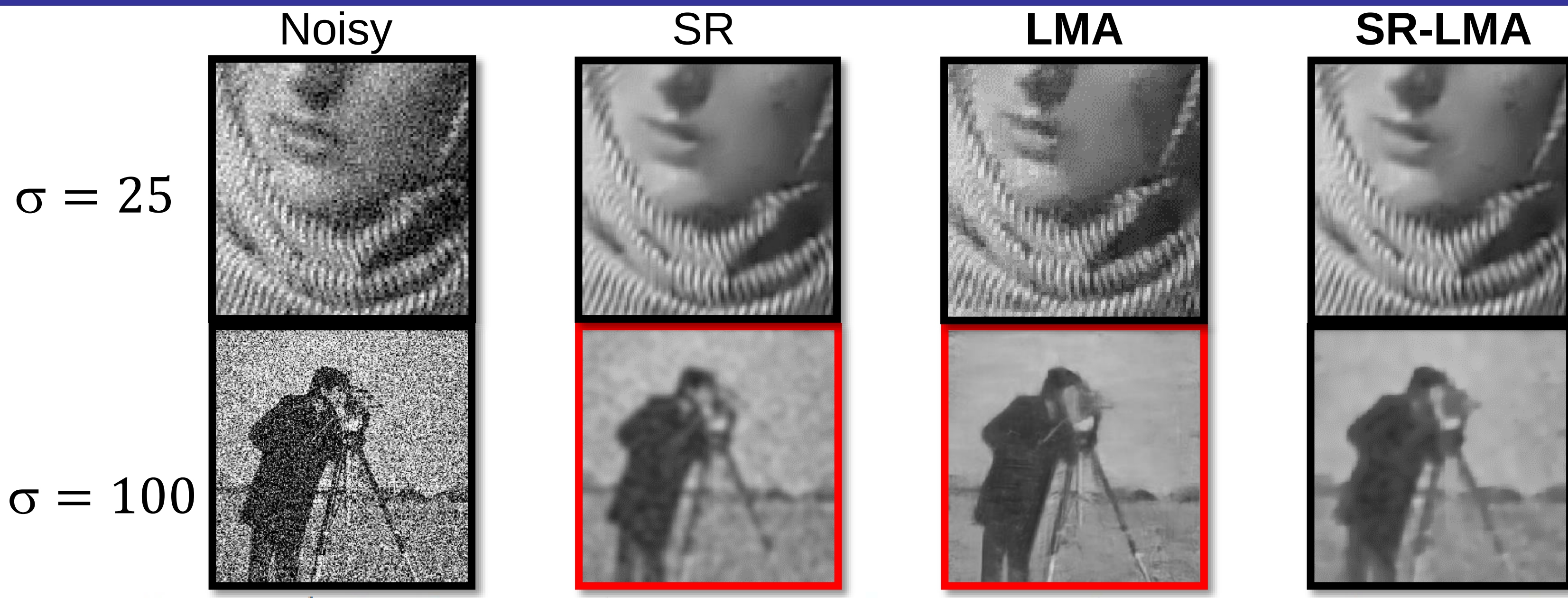
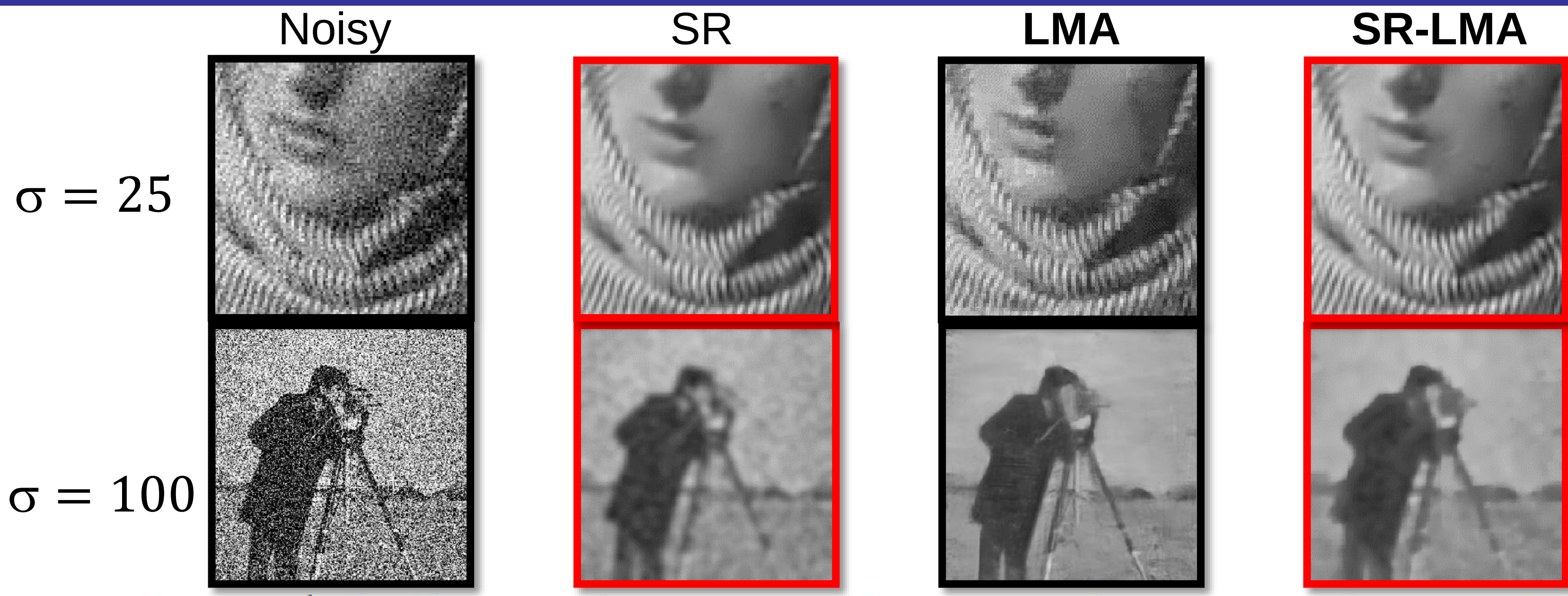


Table 1: PSNR and SSIM of 3 approaches at 4 noise levels

σ	SR		LMA		SR-LMA	
	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
10	33.81	0.9284	32.82	0.9132	33.95	0.9280
25	28.83	0.8345	28.46	0.8295	28.93	0.8382
50	24.30	0.6961	24.83	0.7174	24.76	0.7162
100	19.76	0.5472	20.24	0.5781	20.05	0.5668

Experiments – LMA Vs. Sparse Representation (External)



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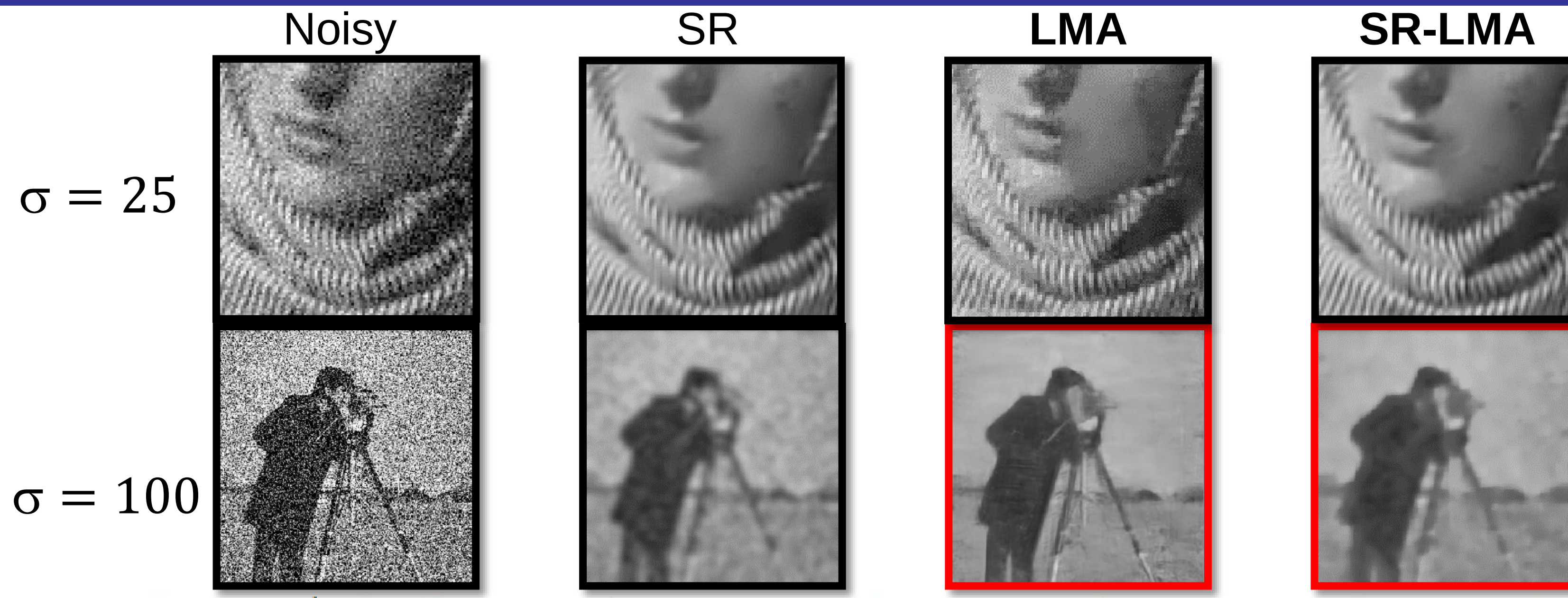

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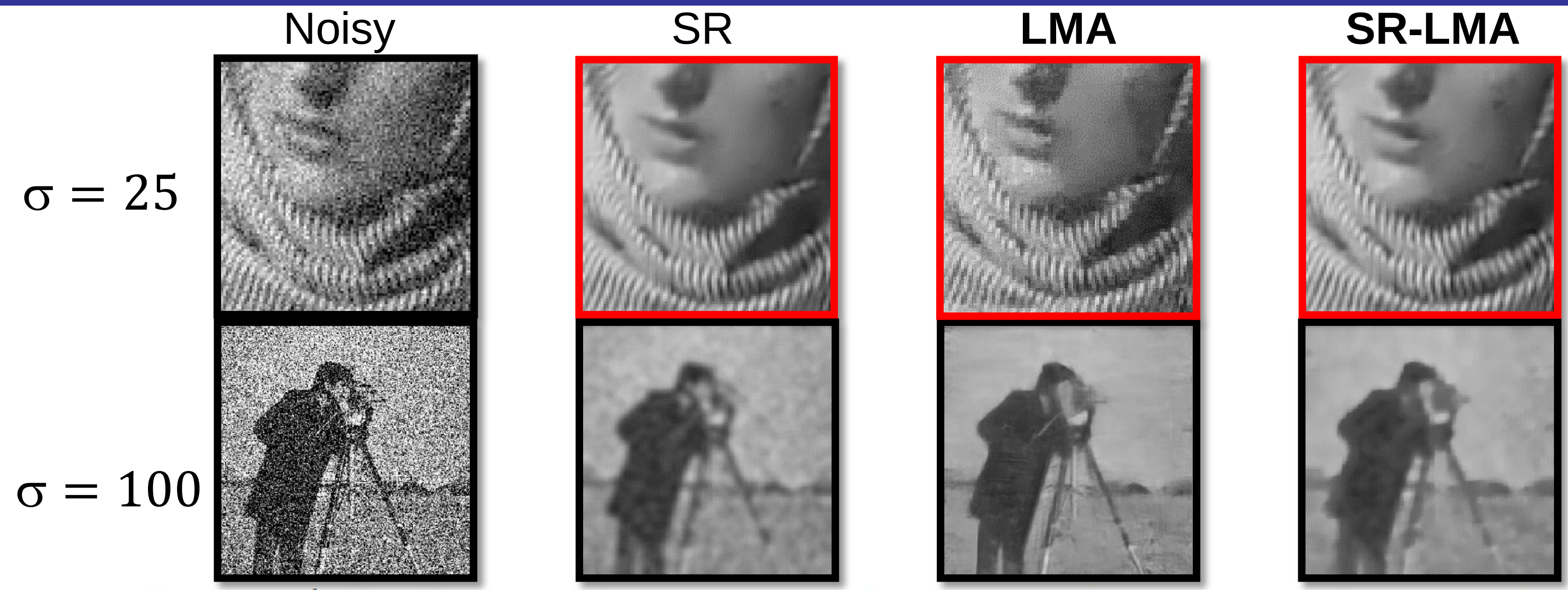

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Experiments –
LMA Vs. Sparse Representation (External)

Noisy | SR | **LMA** | **SR-LMA**

σ = 25

σ = 100

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Experiments- BM3D Vs. BM3D-LMA (Internal Results)

Table 2: PSNR and SSIM of 3 approaches at 3 noise levels

σ	Non-Local Means		BM3D		**BM3D-LMA**	
	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
10	33.37	0.9074	33.99	0.9370	34.60	0.9370
25	28.85	0.8099	29.72	0.8642	29.90	0.8612
50	24.30	0.7038	26.02	0.7575	25.68	0.7578

Experiments-
Single Noisy Inputs (Internal Results)

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	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
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σ=25

BM3D

BM3D-LMA

Summary

- A Largest Matching Area (LMA) approach to image denoising, jointly optimising the quality and size of matching patches
  - Also LMA extensions to two existing approaches
- In external denoising our approach improves reconstructed accuracy
  - Particularly at high noise levels and in uniform regions
- Our internal denoising extension produced competitive results
  - Because LMA prefers clean external data, the lack of clear improvement is unsurprising
- Targeted external data is a promising avenue for future research
  - Techniques exploiting generic external datasets are approaching performance limits
  - A small targeted dataset can reduce computational complexity