

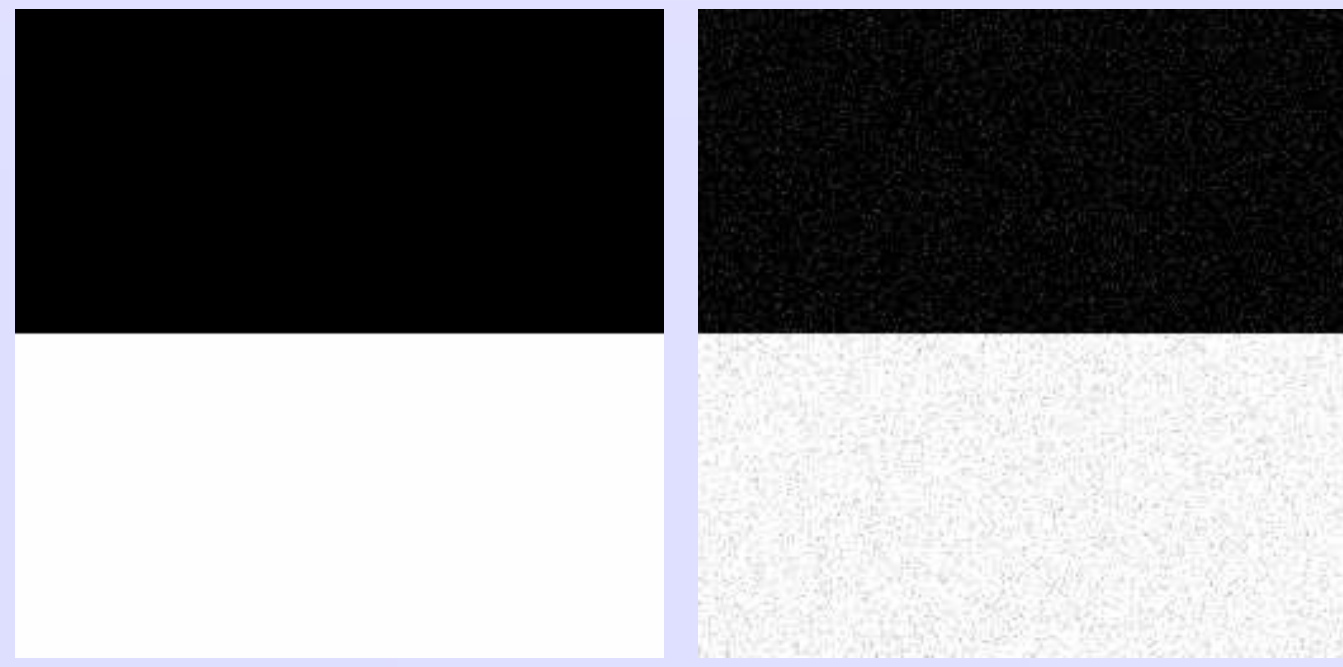
From Patches to Pixels in Non-Local Methods: Weighted-Average Reprojection (Wav)

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Noisy image (AWGN)



$$I(\mathbf{x}) = I^*(\mathbf{x}) + \varepsilon(\mathbf{x})$$

$\mathbf{x} \in \Omega$: pixel in the image Ω , ε : centered Gaussian noise with known variance σ^2

Problem: denoise I

Non-Local Means (NLM)

Patches: square indexed by upper left corner, width W

$$P_{\mathbf{x}}^I = (I(\mathbf{x} + \tau), \tau \in \{0, \dots, W-1\}^2)$$

NLM Denoiser:

$$\hat{I}(\mathbf{x}) = \frac{\sum_{\mathbf{x}'} \theta^I(\mathbf{x}, \mathbf{x}') I(\mathbf{x}')}{\sum_{\mathbf{x}''} \theta^I(\mathbf{x}, \mathbf{x}'')}$$

where $\theta^I(\mathbf{x}, \mathbf{x}') = K(\|P_{\mathbf{x}}^I - P_{\mathbf{x}'}^I\|/h)$

$\mathbf{x}', \mathbf{x}'' \in \Omega_R(\mathbf{x})$ (searching window)

K : kernel function, $h > 0$ bandwidth

$\|\cdot\|$: Euclidean norm

Patch point of view:

$$\hat{P}_{\mathbf{x}}^I = \sum_{\mathbf{x}' \in \Omega_R(\mathbf{x})} \frac{\theta^I(\mathbf{x}, \mathbf{x}') \cdot P_{\mathbf{x}'}^I}{\sum_{\mathbf{x}'' \in \Omega_R(\mathbf{x})} \theta^I(\mathbf{x}, \mathbf{x}'')}$$

Central-Reprojection: ($W = 2W_1 + 1$)

$$\hat{I}_{\text{Cent}}(\mathbf{x}) = \hat{P}_{\mathbf{x}-\delta_W}^I(\delta_W), \delta_W = (W_1, W_1)$$

Uniform-Reprojection:

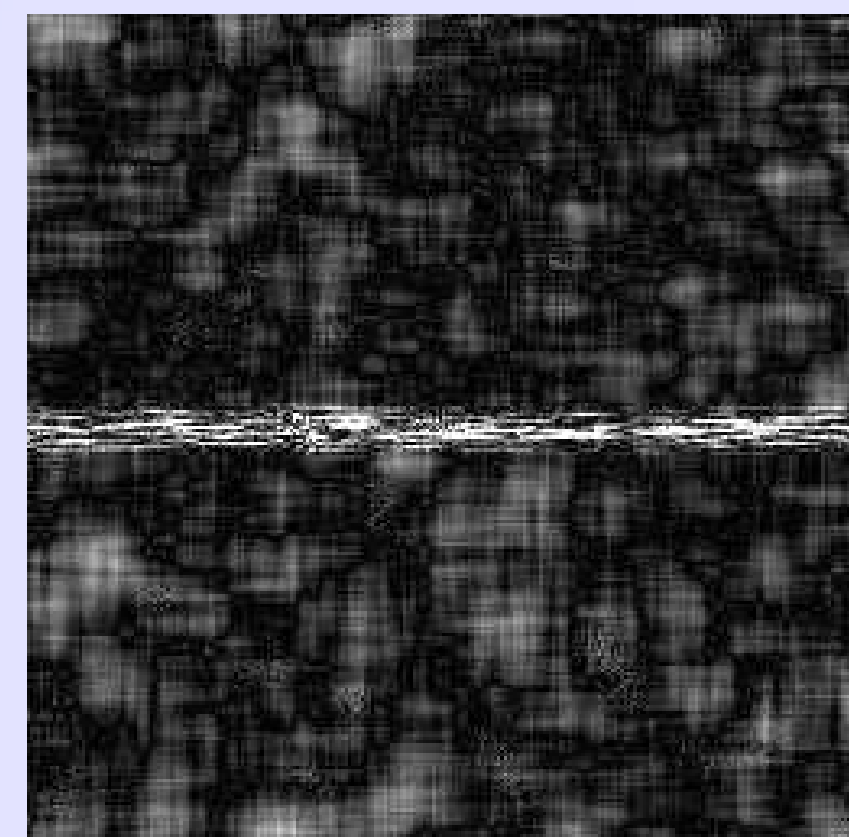
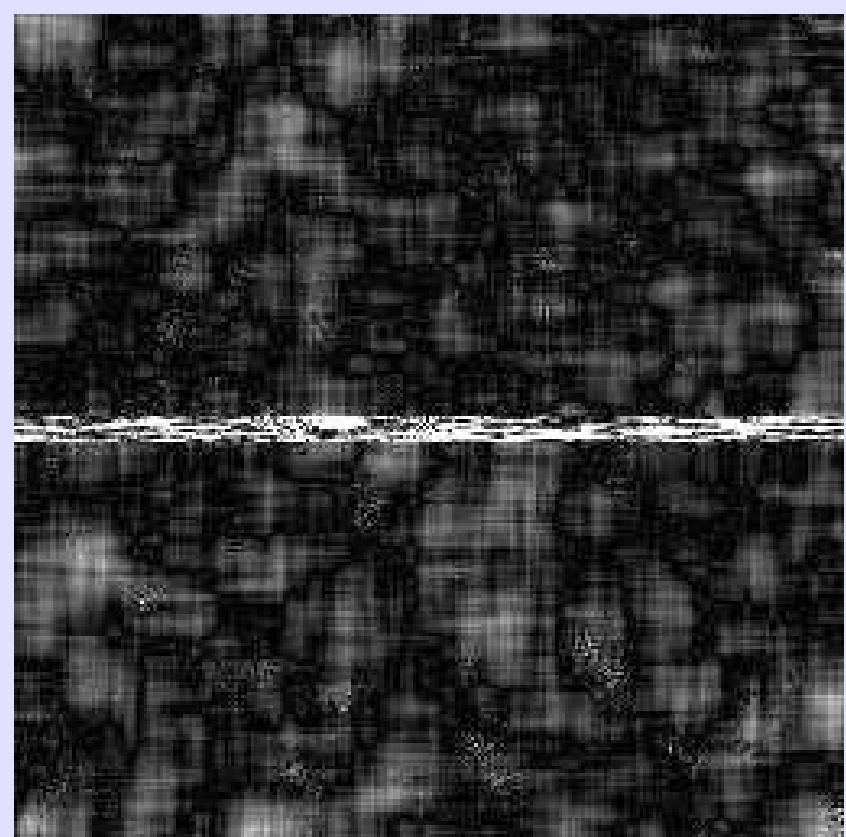
$$\hat{I}_{\text{Uae}}(\mathbf{x}) = \frac{1}{W^2} \sum_{\delta \in \{0, \dots, W-1\}^2} \hat{P}_{\mathbf{x}-\delta}^I(\delta)$$

Halo artifacts along edges

Absolute difference $|\hat{I} - I|$:

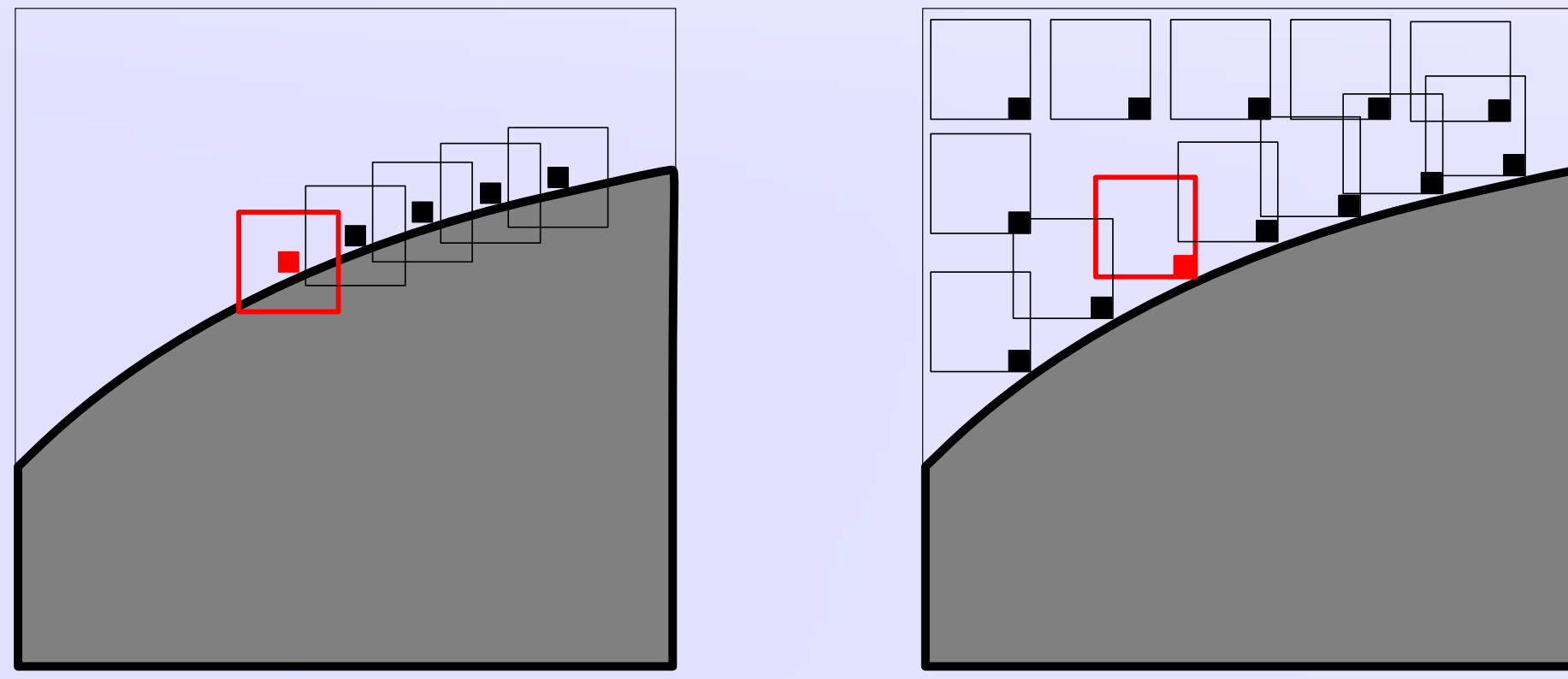
Central Reprojection
PSNR = 45.78

Uniform Reprojection
PSNR = 46.51



Number of similar patches \iff Variance

Sliding reprojections vs. halo



Why halo?

- linear number of similar patches near edges (**weak** similarity, **high** variance)
- quadratic number far from edges (**strong** similarity, **low** variance)

Solutions: weight the slided position as a function of the variance.

Variance-based reprojections

Slided estimate variance: $\text{Var}(\hat{P}_{\mathbf{x}-\delta}^I(\delta)) \approx$

$$\sigma^2 \frac{\sum_{\mathbf{x}' \in \Omega_R(\mathbf{x})} (\theta^I(\mathbf{x}, \mathbf{x}'))^2}{\left(\sum_{\mathbf{x}' \in \Omega_R(\mathbf{x})} \theta^I(\mathbf{x}, \mathbf{x}')\right)^2}$$

Min-Reprojection:

$$\hat{I}_{\text{Min}}(\mathbf{x}) = \hat{P}_{\mathbf{x}-\hat{\delta}}^I(\hat{\delta}),$$

with $\hat{\delta} = \arg \min_{\delta \in \{0, \dots, W-1\}^2} \text{Var}(\hat{P}_{\mathbf{x}-\delta}^I(\delta))$

Wav-Reprojection: same minimization but for convex combination of estimates, closed formula:

$$\hat{I}_{\text{Wav}}(\mathbf{x}) = \sum_{\delta \in \{0, \dots, W-1\}^2} \beta_{\delta} \hat{P}_{\mathbf{x}-\delta}^I(\delta),$$

with $\beta_{\delta} = \frac{[\text{Var}(\hat{P}_{\mathbf{x}-\delta}^I(\delta))]^{-1}}{\sum_{\delta \in \{0, \dots, W-1\}^2} [\text{Var}(\hat{P}_{\mathbf{x}-\delta}^I(\delta))]^{-1}}$

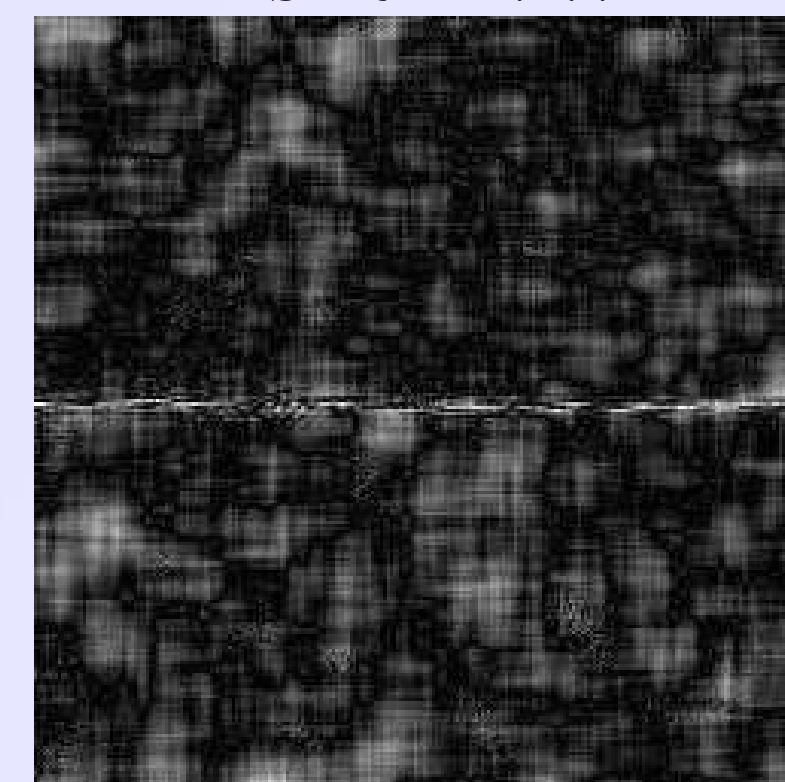
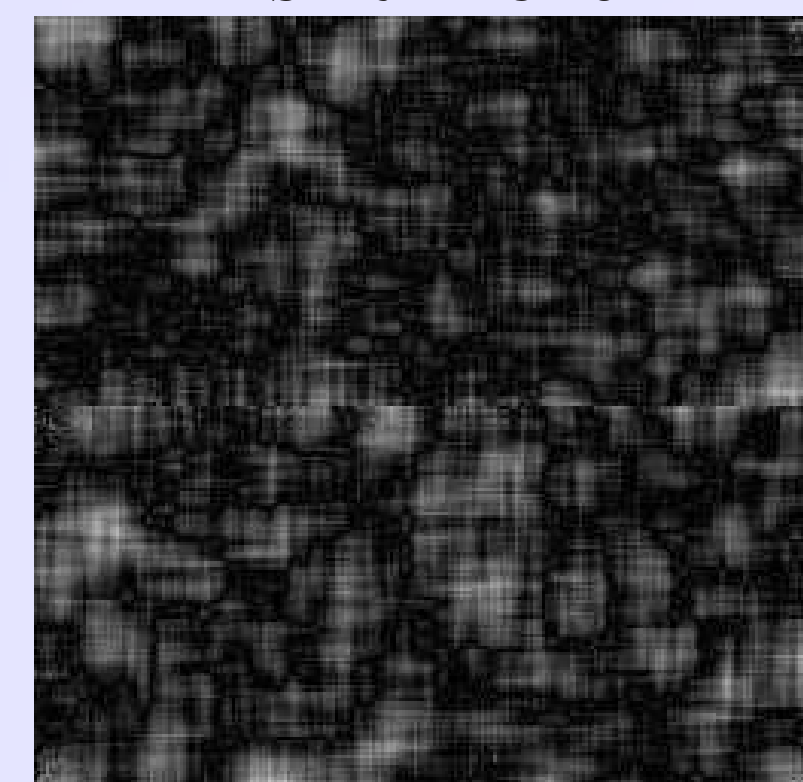
Flat kernel: $K(t) = \mathbb{1}_{[-1,1]}(t)$

Variance=1/number of similar patches

Halo reduction by Wav-reprojection

Min-Variance Reprojection
PSNR = 48.10

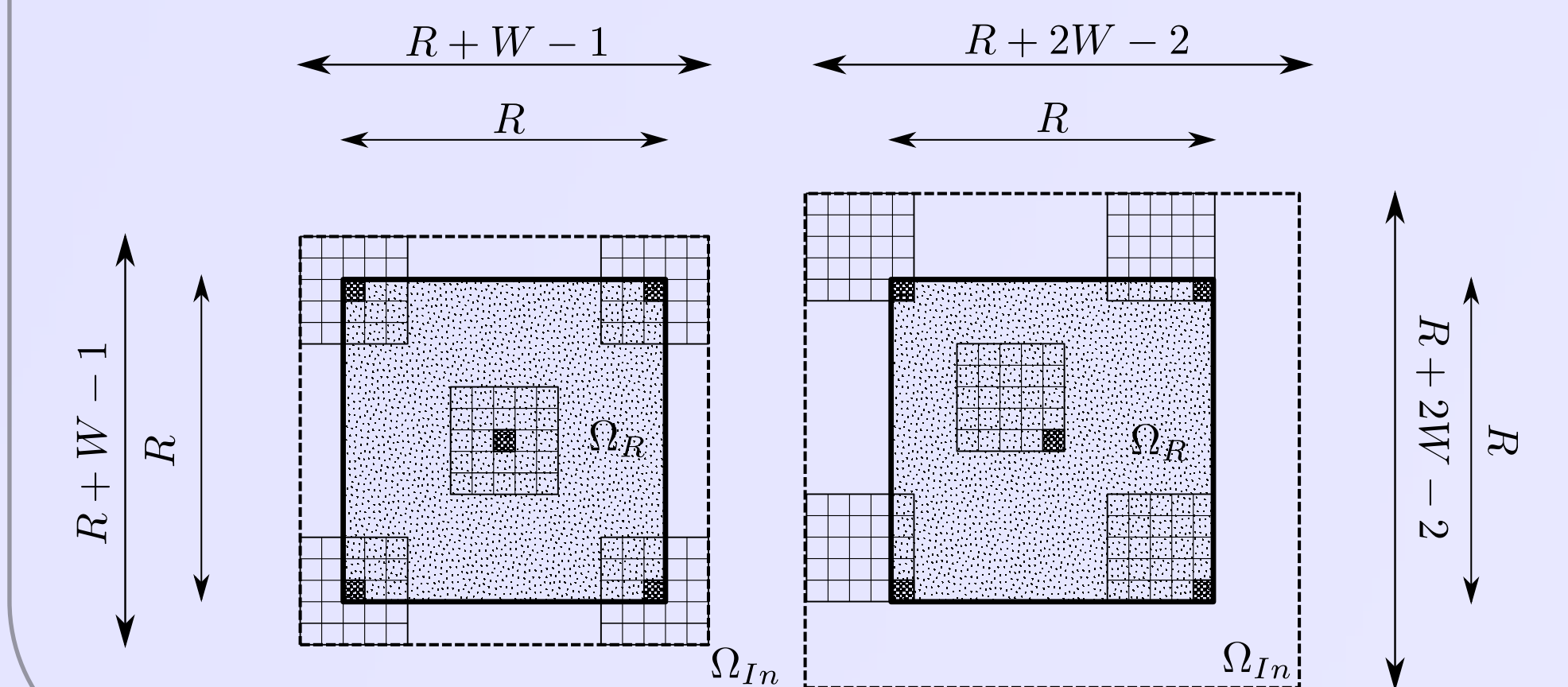
Wav-Reprojection
PSNR = 47.77



Implementation

Flat kernel: efficient implementation, only need to keep the number of “selected patches”

Searching zone: can be reduced thanks to sliding (speeds up the NLM)



Visual results



NLM variants: $R = 9, W = 9, \sigma = 20$
Gaussian kernel: $h = \sigma$
Flat kernel: $h^2 = 2\sigma^2 q_{0.99}^{W^2}$ (χ^2 quantile)

Online Matlab (mex) code:

www.math.jussieu.fr/~salmon/

References

- A. Buades and B. Coll and J-M. Morel **A review of image denoising algorithms, with a new one** (2005)
- A. Foi **Anisotropic nonparametric image processing: theory, algorithms and applications** (2005)

Conclusion

Wav-reprojection: PSNR increase between 0.1-0.5 dB, numerically efficient

Take-away message: think patch-wise and combine the slided NLM estimates, it **reduces halo artifacts**