

Statistical Modeling of the Patches DC Component for Low-Frequency Noise Reduction

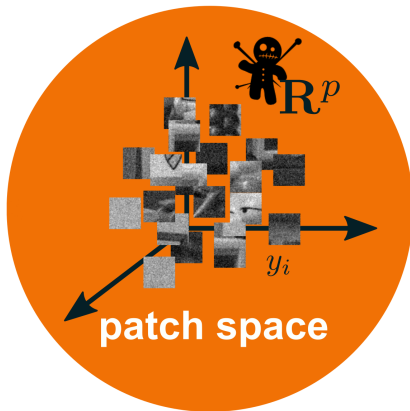
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27th European Signal Processing Conference

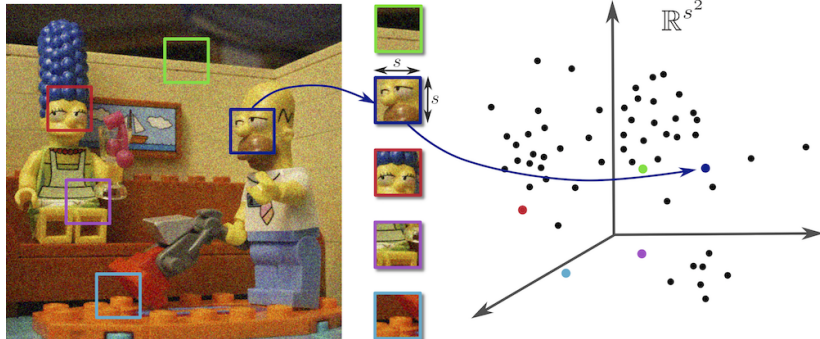
A Coruña, September 2–6, 2019

Context

patch-based image denoising



1. Patch extraction



observed patches $\{y_1, \dots, y_n\}$

2. Put a prior model on the clean patches

$$Y_i = X_i + N_i$$

2. Put a prior model on the clean patches

white gaussian noise

$$\mathcal{N}(0, \sigma^2 \mathbf{I}_p)$$

$$Y_i = X_i + N_i$$



2. Put a prior model on the clean patches

white gaussian noise

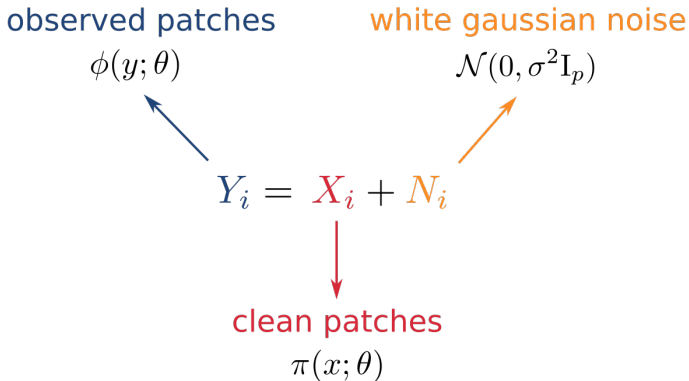
$$\mathcal{N}(0, \sigma^2 \mathbf{I}_p)$$
$$Y_i = X_i + N_i$$

clean patches

$$\pi(x; \theta)$$

The diagram illustrates the relationship between the observed data Y_i , the clean patches X_i , and the white gaussian noise N_i . The equation $Y_i = X_i + N_i$ is shown in the center. A red arrow points from X_i down to the text "clean patches" and the prior model $\pi(x; \theta)$. An orange arrow points from N_i up and to the right to the text "white gaussian noise" and the noise distribution $\mathcal{N}(0, \sigma^2 \mathbf{I}_p)$.

2. Put a prior model on the clean patches



3. inference of the parameters θ

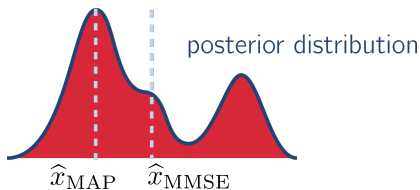
$$\mathcal{L}(y, \theta) = - \sum_i \log (\phi(y_i; \theta))$$

3. inference of the parameters θ

$$\mathcal{L}(y, \theta) = - \sum_i \log(\phi(y_i; \theta))$$

4. clean patches estimation

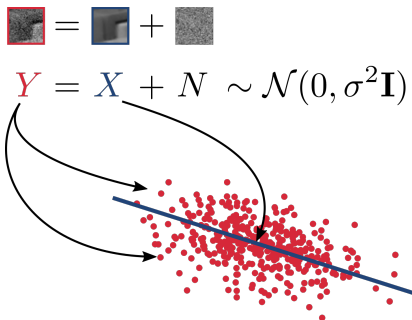
$$\hat{x}_{\text{MMSE}_i} = \mathbf{E}[X_i | Y_i = y_i]$$



in the literature

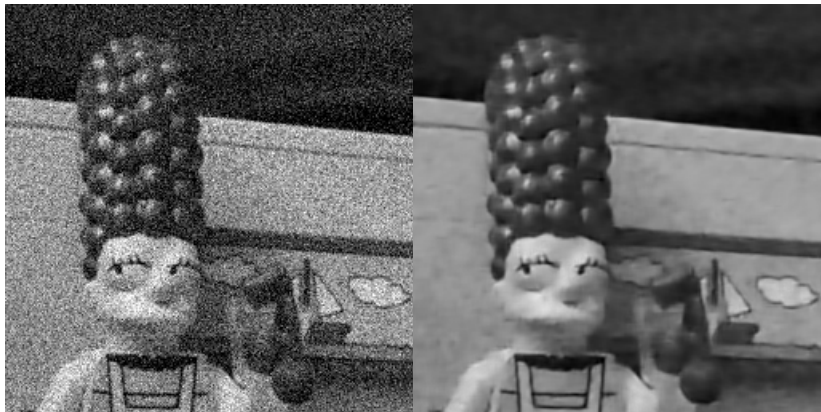
- ★ Patch-based PCA [Deledalle, Salmon, Dalalyan, 2011]
- ★ EPLL [Zora, Weiss, 2011]
- ★ NL-Bayes [Lebrun, Buades, Morel 2012]
- ★ SURE Guided Gaussian Mixture Image Denoising [Wang, Morel, 2013]
- ★ Single-frame image denoising using gaussian mixtures [Teodoro, Almeida, Figueiredo, 2015]
- ★ HDMI [H., Bouveyron, Delon, 2018]
- ★ ...

This work: HDMI enhancement



1. **Modeling** of the patches distribution with a GMM with dimension reduction
2. **Inference** of the parameters with EM algorithm
3. **Estimation** of the clean patches with conditional expectation

Good for textures but low-frequency residual noise



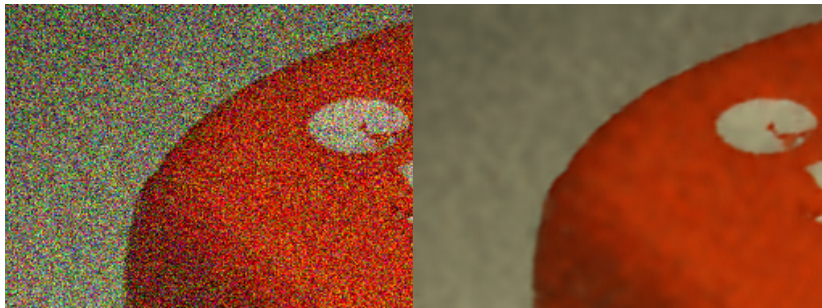
noise 20% & patches 7×7

Good for textures but low-frequency residual noise



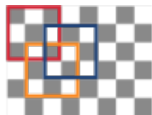
noise 20% & patches 7×7

Good for textures but low-frequency residual noise

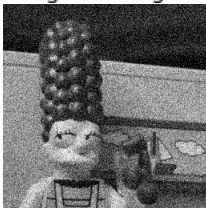


noise 20% & patches 7×7

Observation: this comes from the patches DC component



original image



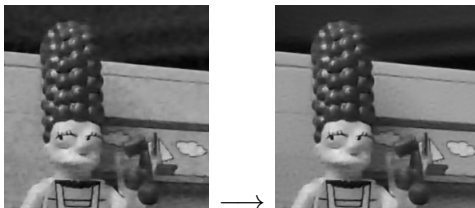
DC component image



Idea: denoise the DC component image separately



the denoising can therefore be enhanced



Noise modeling on the DC image

- ▶ the DC component $\overline{Y}_i = \frac{1}{p} \sum_{j=1}^p Y_i(j)$ correspond to the pixel i of the DC image
- ▶ noise model on the DC component

$$\overline{Y}_i = \overline{X}_i + \overline{N}_i \in \mathbf{R},$$

with \overline{N}_i not independent Gaussian random variables

Noise modeling on the DC image

extraction of patches from the DC image

$$Z_i = W_i + M_i,$$

where $Z_i = \pi_i(\overline{Y})$, $W_i = \pi_i(\overline{X})$ and $M_i = \pi_i(\overline{N})$.

Proposition

$M_i \sim \mathcal{N}(0_p, \Sigma_{M_i})$ with

$$\Sigma_{M_i} = \frac{\sigma^2}{p^2} B \otimes B,$$

where

$$B = \begin{pmatrix} s & (s-1) & \cdots & 1 \\ (s-1) & s & \ddots & \vdots \\ \vdots & \ddots & \ddots & (s-1) \\ 1 & \cdots & (s-1) & s \end{pmatrix},$$

Noise whitening

Proposition

Σ_{M_i} is symmetric positive-definite and there exists L invertible such that $B \otimes B = LL^T$.

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$$L^{-1}Z_i = L^{-1}W_i + L^{-1}M_i,$$

denising problem with **white Gaussian noise** of variance σ^2/p^2 .

let $f_{denoise}$ be a patch denoiser (ex. HDML), an estimate of W_i is

$$\widehat{W}_i = L f_{denoise} (L^{-1}W_i)$$

afterwards DC correction

1. estimate $\widehat{X}_i = f_{denoise}(Y_i)$ for each patch
2. estimate $\widehat{\overline{X}_i}$ by denoising the DC image
3. replace the DC component of each patch with this estimate

$$h(X_i) = \widehat{X}_i - \widehat{\overline{X}_i} \mathbf{1}_p + \widehat{\overline{X}_i} \mathbf{1}_p.$$

Results

noisy image

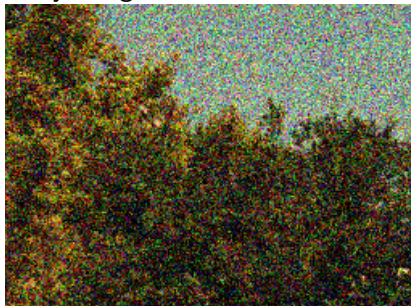


HDMI denoised



Results

noisy image

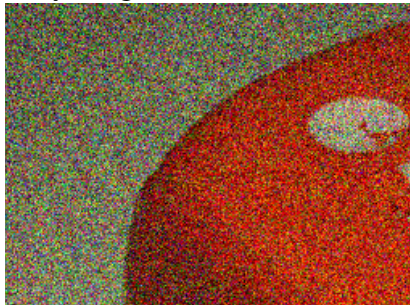


HDMI denoised DC corrected



Results

noisy image

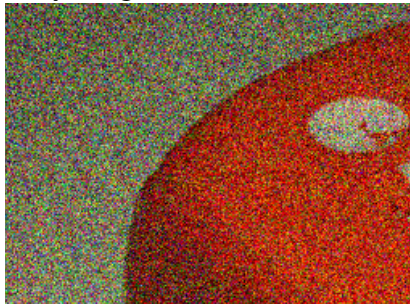


HDMI denoised



Results

noisy image



HDMI denoised DC corrected



Results

noisy image



Results

HDMI denoised



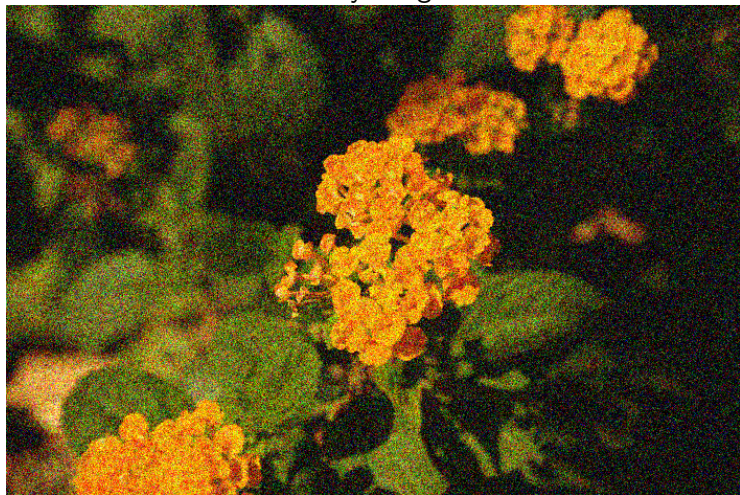
Results

HDMI denoised DC corrected



Results

noisy image



Results

HDMI denoised



Results

HDMI denoised DC corrected



Results

noisy image



Results

HDMI denoised



Results

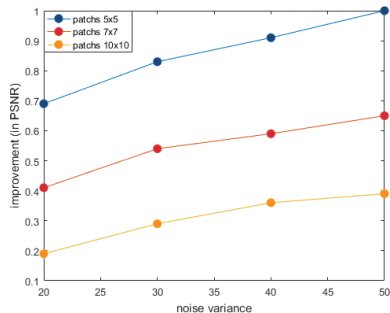
HDMI denoised DC corrected



Concluding remarks

We proposed to denoise the DC component of the patches that

- ★ can be rewritten as an **additive white Gaussian noise** problem
- ★ improves the denoising result both **visually** and **qualitatively**



- ★ can be used with **any patch denoising method** $f_{denoise}$

further work link with multi-scale frameworks and generalization

Thank you for your attention!

More information on the HDMI method and this work on:
houdard.wp.imt.fr