MULTIFRAME RAW-DATA DENOISING BASED ON BLOCK-MATCHING AND 3-D FILTERING FOR LOW-LIGHT IMAGING AND STABILIZATION

LNLA 2008 *- The 2008 International Workshop on*
Local and Non-Local Approximation in Image Processing,
23, 24 August, Lausanne, Switzerland

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Introduction

- Taking satisfactory pictures at low-light conditions is challenging.

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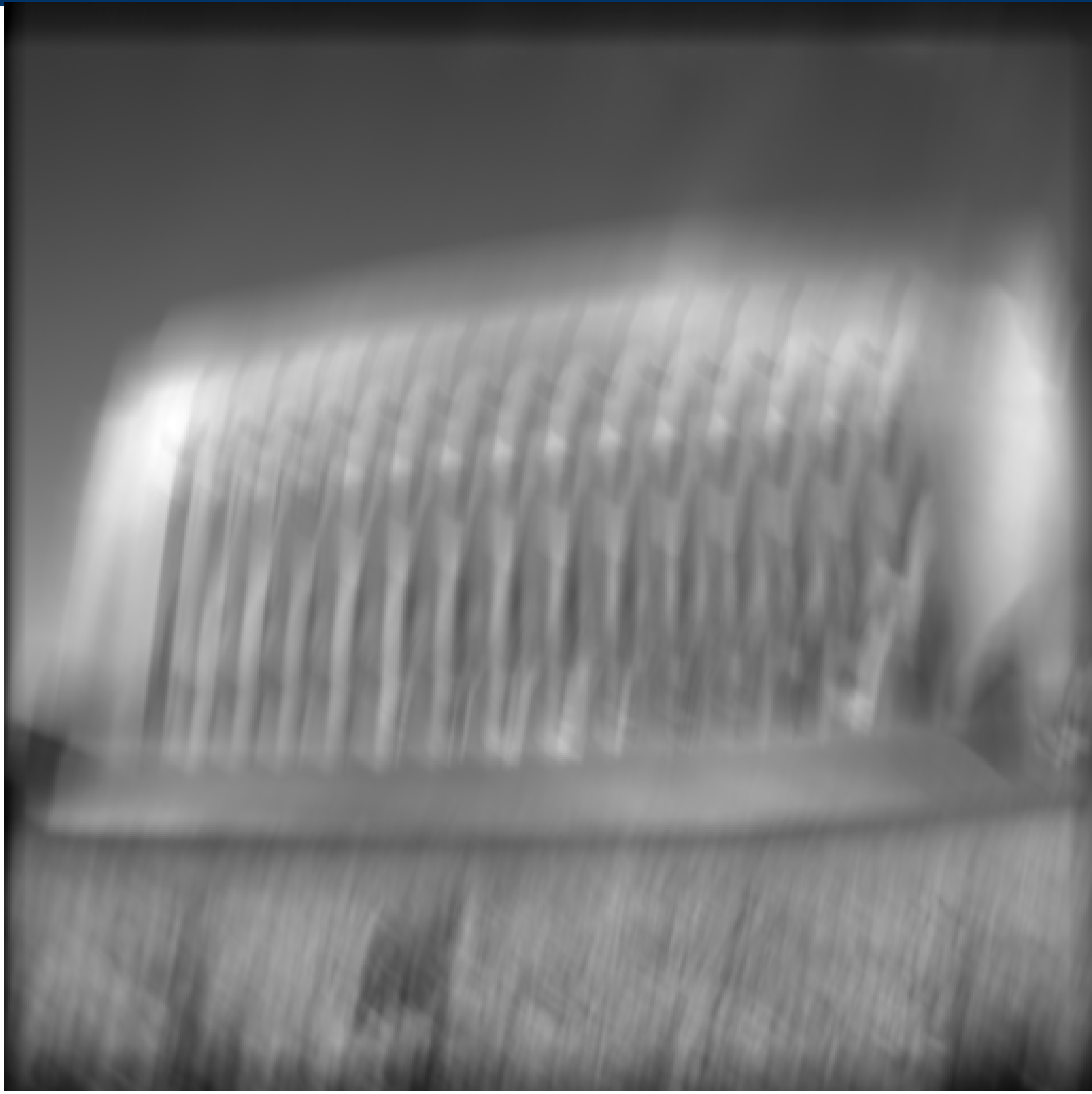
- Pictures acquired with a *short* exposure-time have low SNR and are **very noisy** because of a high gain (ISO number).
- Typically the exposure time is increased in order to improve the SNR of the acquired image.
- But this also increases the risk of blur, because of movements occurring in the extended exposure.

Introduction



Solutions

- A variety of solutions:
  - Lenses Stabilization
  - Different Acquisition Strategies

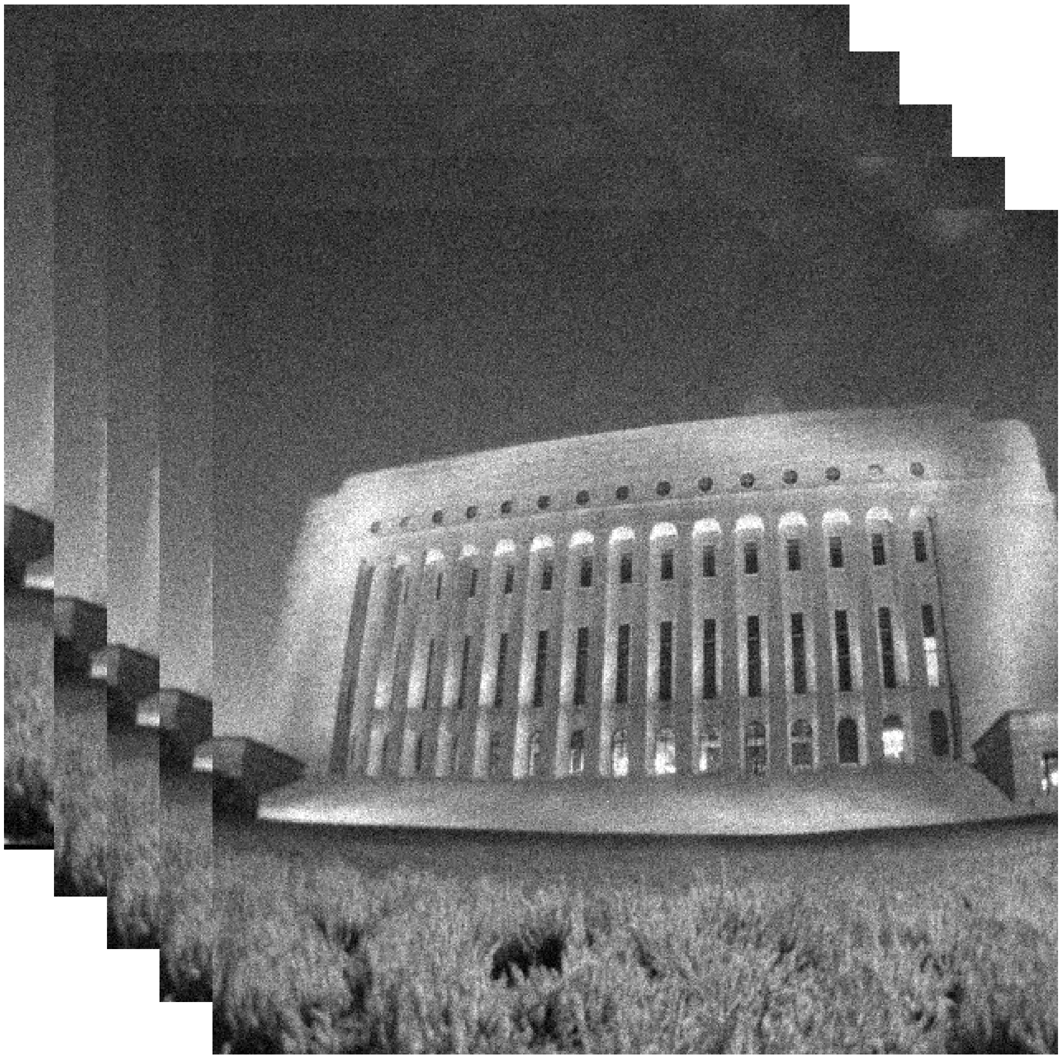
- In particular **[Tico06]** and **[Yuan07]** proposed two methods that use differently exposed images
  - one with a **long** exposure time (blurred but with negligible noise)
  - one with a **short** exposure time (noisy but with negligible blur)

- The noisy image is used to estimate the blur PSF allowing to restore the blurred image (deblurring)

[Tico06] Tico, M., "Estimation of motion blur point spread function from differently exposed image frames," Proc. 14th Eur. Signal Process. Conf., EUSIPCO 2006, Florence, Italy, September 2006
[Yuan07] Yuan, L., J. Sun, L. Quan, and H.-Y. Shum, "Image deblurring with blurred/noisy image pairs," ACM Trans. Graph., vol. 26, no. 3, July 2007

Alternative Solution

- Acquire a sequence of short exposure images (frames) and jointly denoise them, using a video denoising algorithm



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- Issues that has to be considered
  - **Movements** (camera viewpoint or scene objects) between frames
  - **Noise**
  - **Clipping**

  raw-data processing

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- The proposed solution combines
  - An algorithm for estimating noise in clipped raw data
  - Homomorphic transformations
  - Video Denoising Algorithm (V-BM3D) for AWGN

The Observation Model

- The observation is a sequence of *N* raw-data frames $\{\tilde{z}_i\}_{i=1}^{N}$ modeled as the **noisy** and **clipped** images

$$\tilde{z}_i(x) = \max\{0, \min\{z_i(x), 1\}\}, \qquad x \in X \subset \mathbb{Z}^2,$$

where

$$z_i(x) = y_i(x) + \sigma(y_i(x))\,\xi_i(x),$$

$y_i : X \to Y \subseteq \mathbb{R}$ is an *original* frame

$\sigma(y_i(x))\,\xi_i(x)$ is an zero-mean random error

$\xi_i(\cdot) \sim \mathcal{N}(0,1)$

$\sigma : \mathbb{R} \to \mathbb{R}^+$

Raw Data

- For raw data

$$\sigma^2(y_i(x)) = a y_i(x) + b,$$

a and *b* depend on the sensor hardware characteristics and on the acquisition settings only.

- The noisy clipped observation can be expressed as

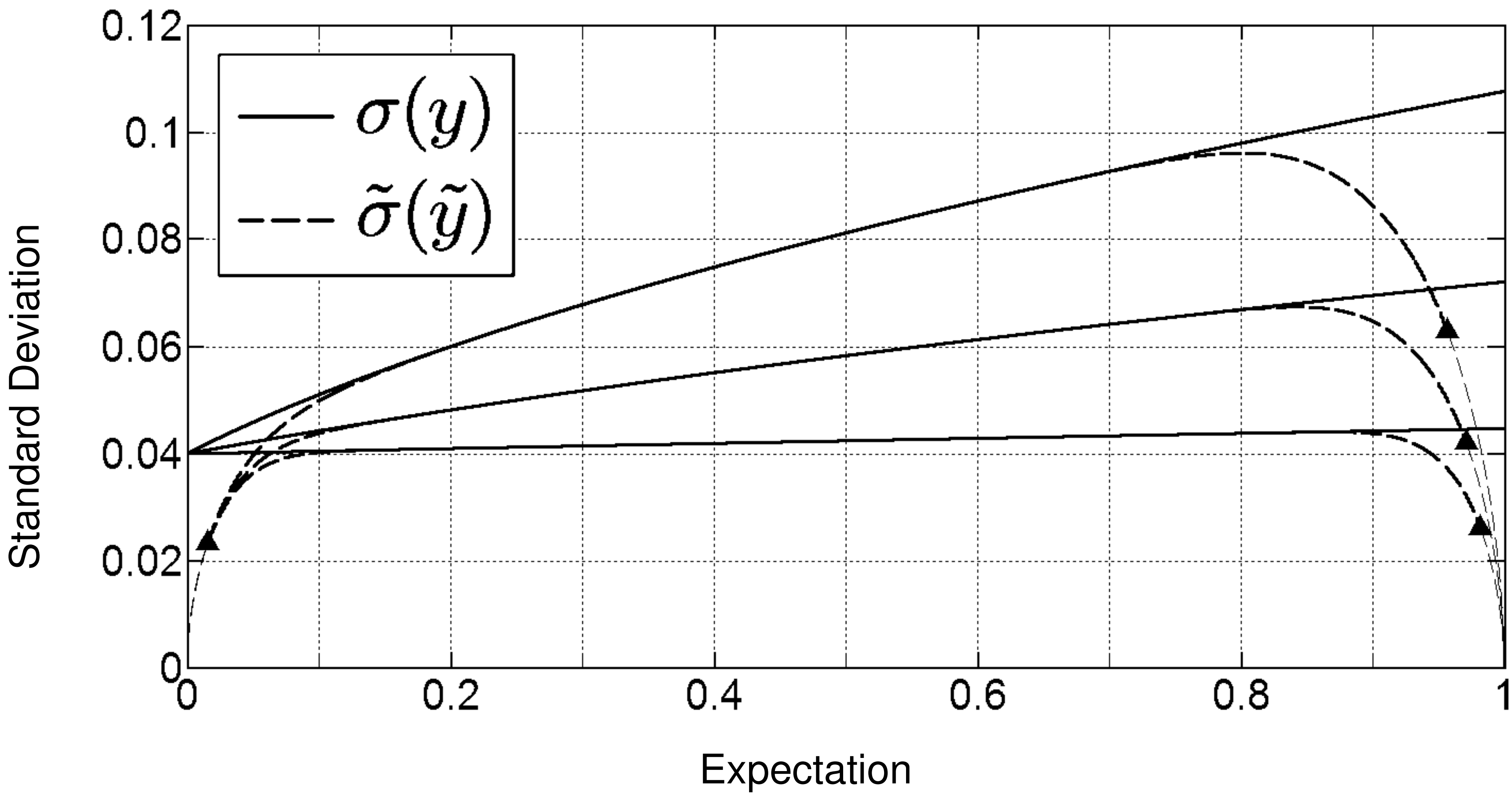
$$\tilde{z}_i(x) = \tilde{y}_i(x) + \tilde{\sigma}(\tilde{y}_i(x))\,\tilde{\xi}_i(x)\,, \qquad x \in X \subset \mathbb{Z}$$

where

$$\tilde{y}_i(x) = E\{\tilde{z}_i(x)\} \in [0,1]\,,$$
$$\tilde{\sigma}(\tilde{y}_i(x)) = \mathrm{std}\{\tilde{z}_i(x)\} \geq 0.$$

Expectation vs. Standard Deviation curves

- Each curve is determined by *a* and *b* only.

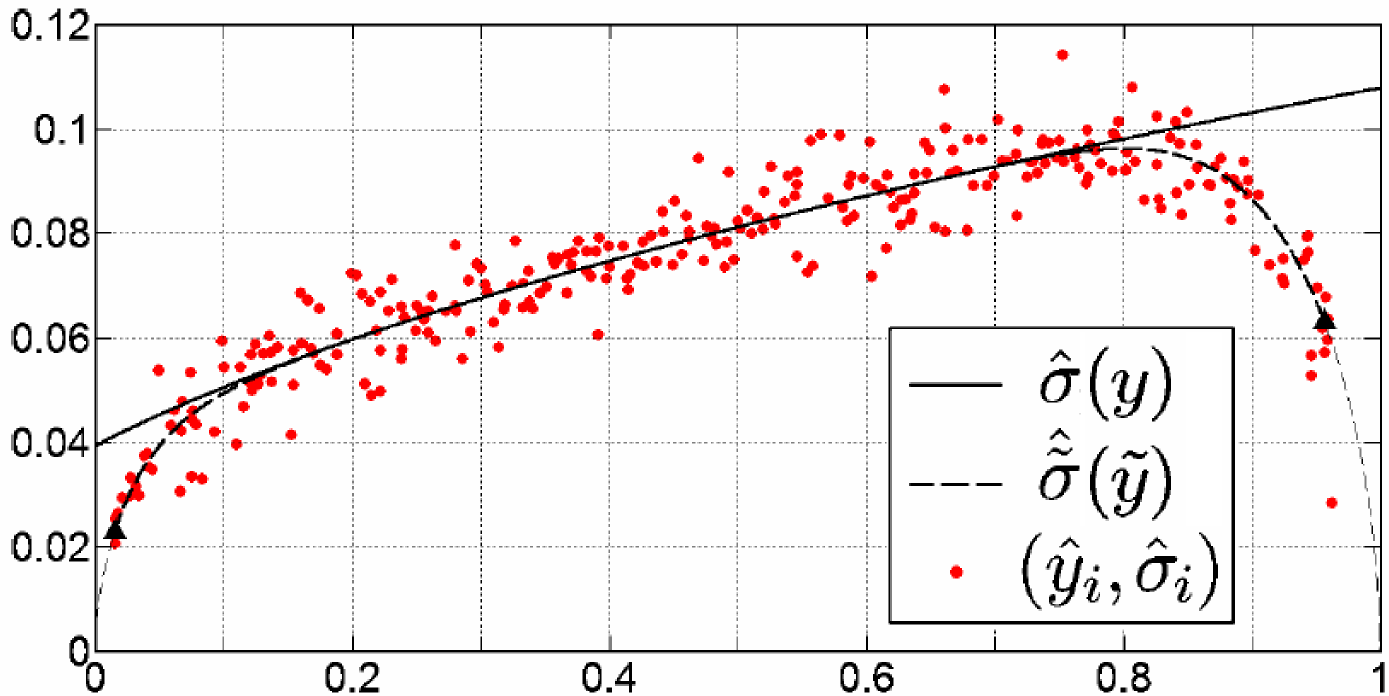


Algorithm Outline

- Noise Parameters Estimation
- Noise Variance Stabilization
- Video Denoising
- Debiasing and Inversion of Noise Variance Stabilizing Transformation
- Declipping

Noise Estimation

- The parameters *a* and *b* of the noise can estimated from a single noisy and clipped image using the algorithm presented in **[Foi08a]**
- This algorithm can be used on a single frame of the original sequence as *a* and *b* are constant.

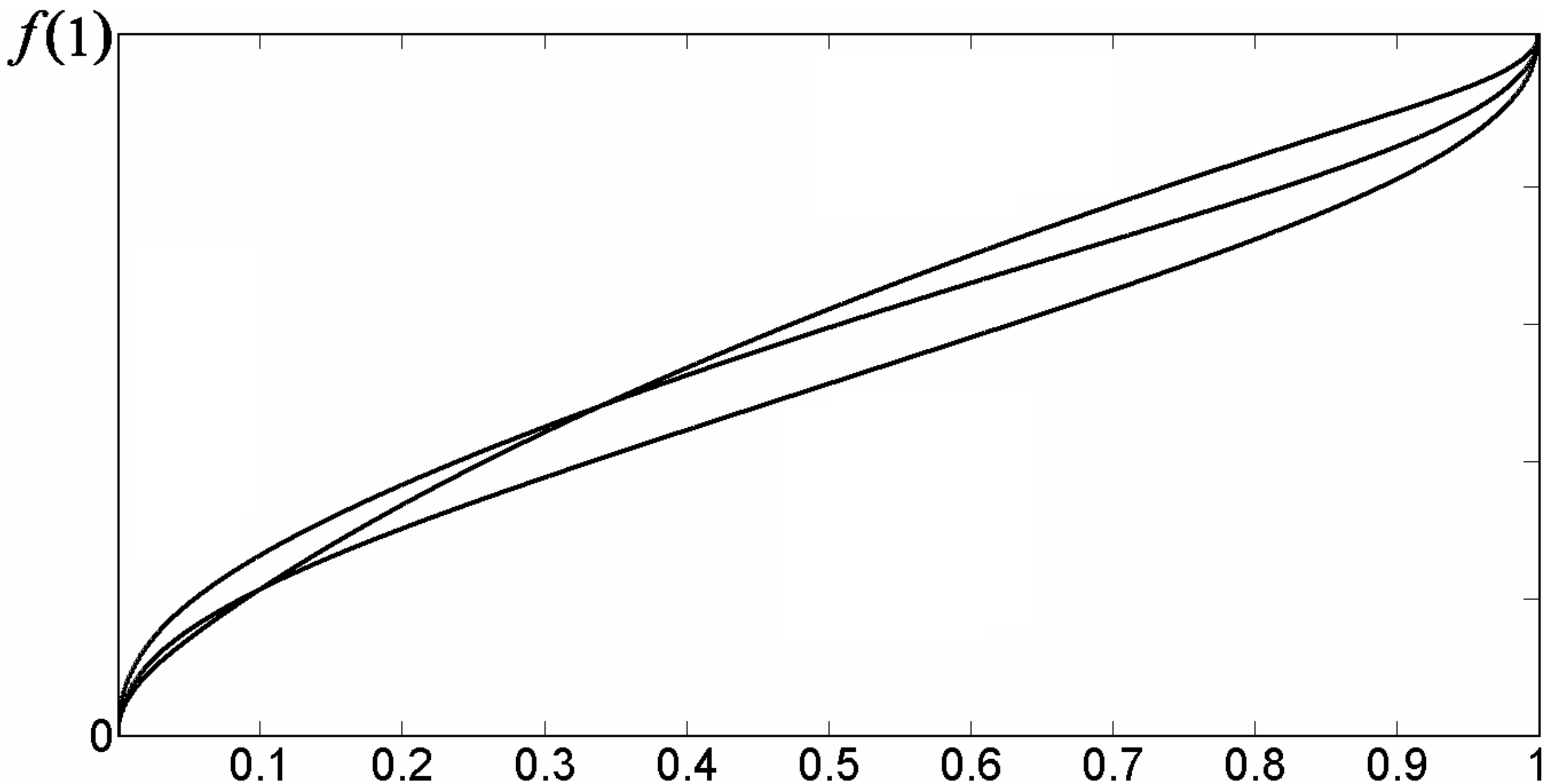


[Foi08a] Foi,A.,M.Trimeche,V.Katkovnik, and K.Egiazarian, "Practical Poissonian-Gaussian noise modeling and Þtting for single image raw-data", to appear in *IEEE Trans. Image Process*.

Noise Variance Stabilization

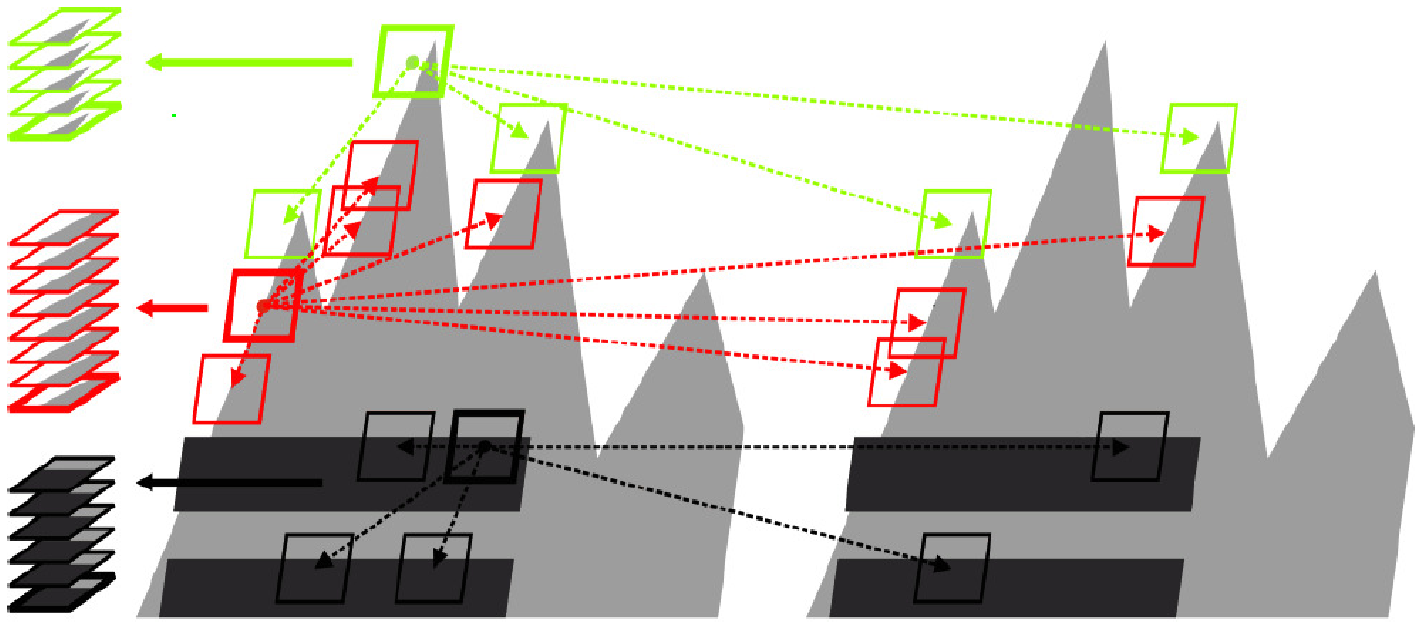
- Each frame is pixel-wise transformed in the following way

$$f(t) = \int_{t_0}^{t} \frac{c}{\tilde{\sigma}(s)} ds, \qquad t, t_0 \in [0,1]$$



Video Denoising

- Video Block Matching 3D (V-BM3D) **[Dabov07],** is a **spatiotemporal nonlocal** method that filters the image in a block-wise manner as



[Dabov07] Dabov, K., A. Foi, and K. Egiazarian, "Video denoising by sparse 3D transform-domain collaborative filtering", *Proc. 15th Eur. Signal Process. Conf., EUSIPCO 2007*, Poznan, September 2007

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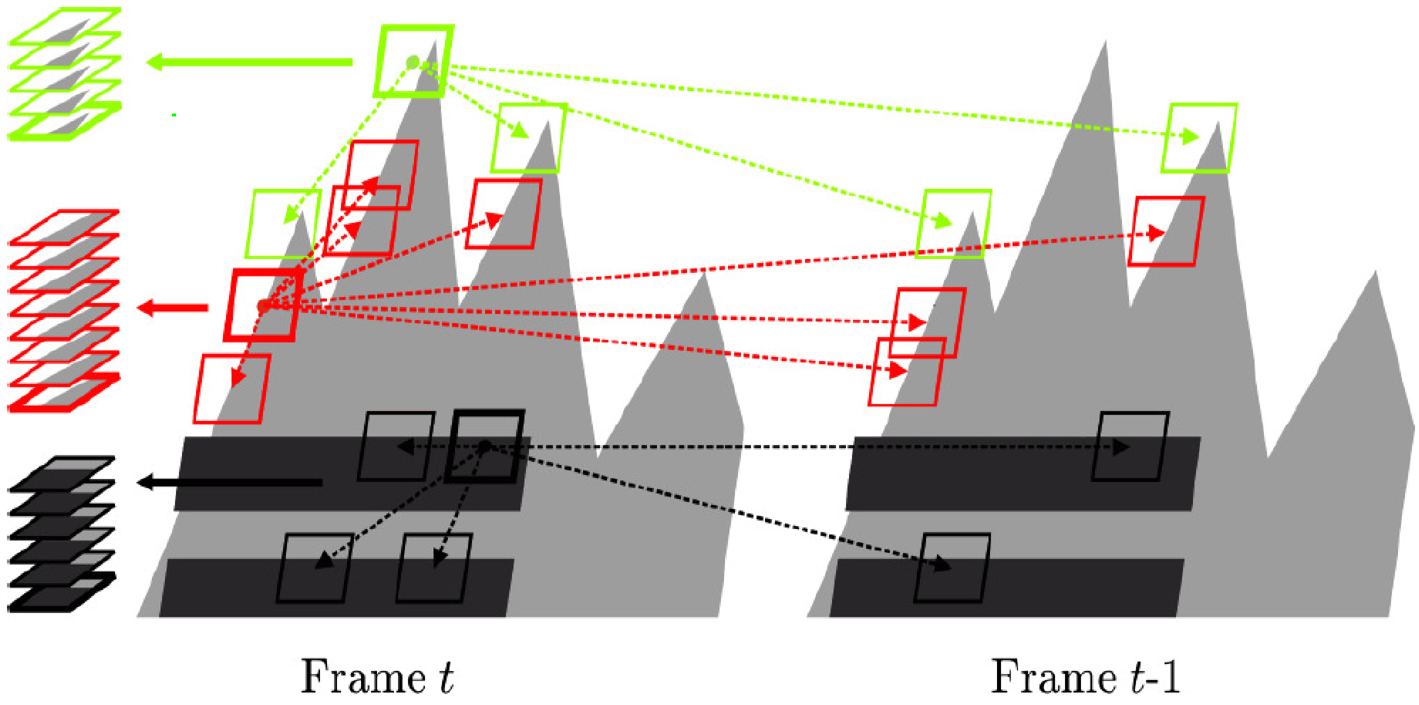

1. **Grouping**: search for similar blocks and stack them together in a 3D array

[Dabov07] Dabov, K., A. Foi, and K. Egiazarian, "Video denoising by sparse 3D transform-domain collaborative filtering", *Proc. 15th Eur. Signal Process. Conf., EUSIPCO 2007*, Poznan, September 2007

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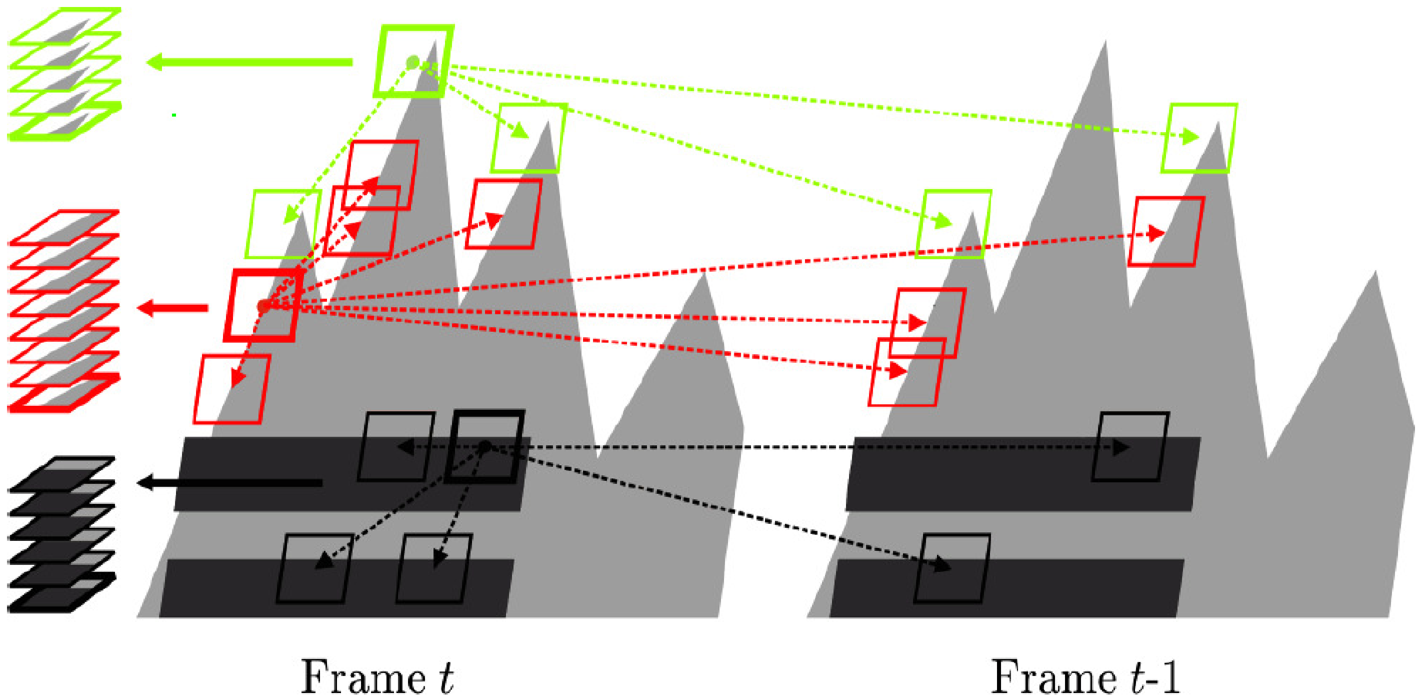

2. **Collaborative Filtering**: filter the groups by 3D transform-domain shrinkage, obtaining **individual estimates for all grouped blocks**

[Dabov07] Dabov, K., A. Foi, and K. Egiazarian, "Video denoising by sparse 3D transform-domain collaborative filtering", *Proc. 15th Eur. Signal Process. Conf., EUSIPCO 2007*, Poznan, September 2007

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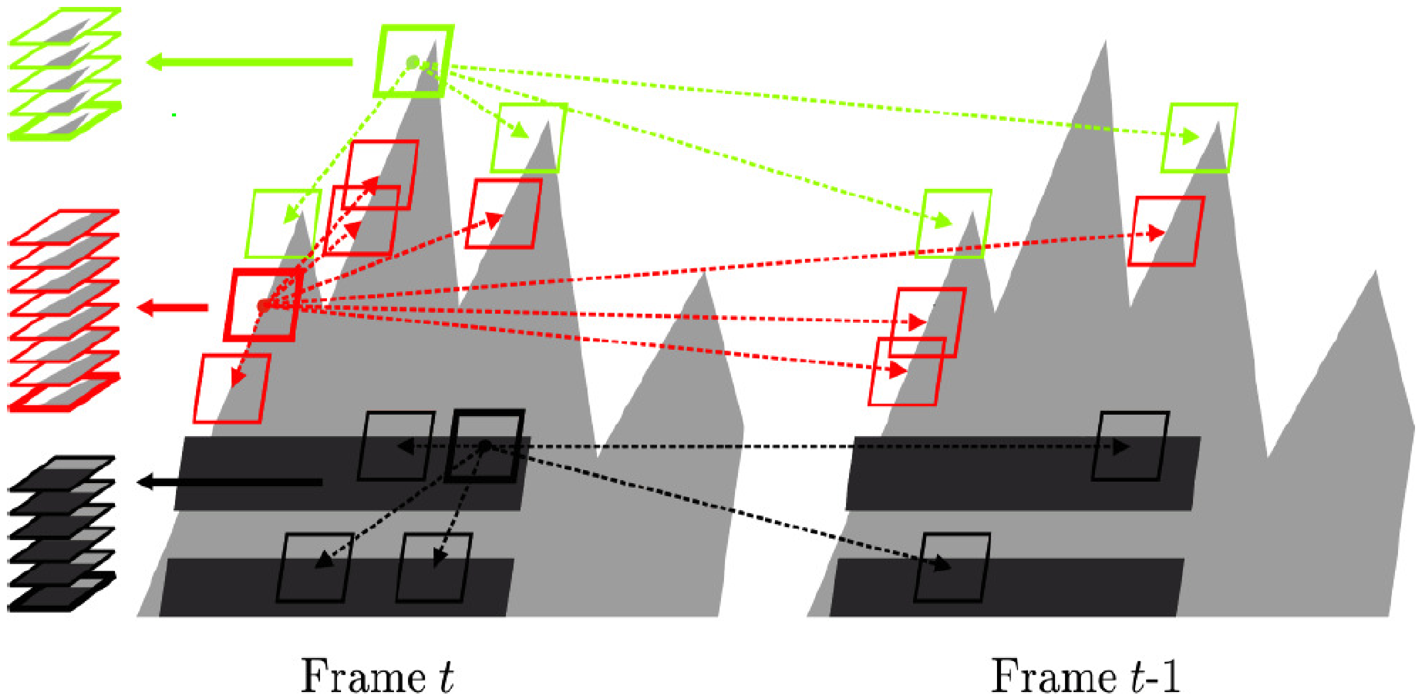


3. **Aggregation**: restored frames are obtained by weighted averages of the filtered blocks when they are overlapping

[Dabov07] Dabov, K., A. Foi, and K. Egiazarian, "Video denoising by sparse 3D transform-domain collaborative filtering", *Proc. 15th Eur. Signal Process. Conf., EUSIPCO 2007*, Poznan, September 2007

Variance Stabilizing Transform Inversion

- Since *f* is nonlinear there is estimation bias:

$$\mathbf{D}\left(f\left(\tilde{z}_i\left(x\right)\right)\right) \approx E\{f\left(\tilde{z}_i\left(x\right)\right)\} \neq f\left(E\{\tilde{z}_i\left(x\right)\}\right)$$

being **D** the V-BM3D denoising operator

- Debiasing **[Foi08b]**

$$h^{-1}\left(\mathbf{D}\left(f\left(\tilde{z}_i\left(x\right)\right)\right)\right) \approx f\left(E\{\tilde{z}_i\left(x\right)\}\right)$$

- and then inversion

$$f^{-1}\left(h^{-1}\left(\mathbf{D}\left(f\left(\tilde{z}_i\left(x\right)\right)\right)\right)\right) \approx E\{\tilde{z}_i\left(x\right)\}$$

[Foi08b] Foi, A., "Practical denoising of clipped or overexposed noisy images", Proc. 16th European Signal Process. Conf., EUSIPCO 2008, Lausanne, Switzerland, August 2008

Declipping

- We obtain an estimate of clipped data

$$E\{\tilde{z}_i\} = \tilde{y}_i \neq E\{z_i\}$$

- To obtain an estimate the **original** signal we need to invert the bias due to clipping with the transform **[Foi08b]**

$$\mathcal{C} : E\{\tilde{z}_i\} \longmapsto E\{z_i\}$$

note that $\mathcal{C} : [0,1] \longrightarrow Y$, where Y *is* the range of the original image.

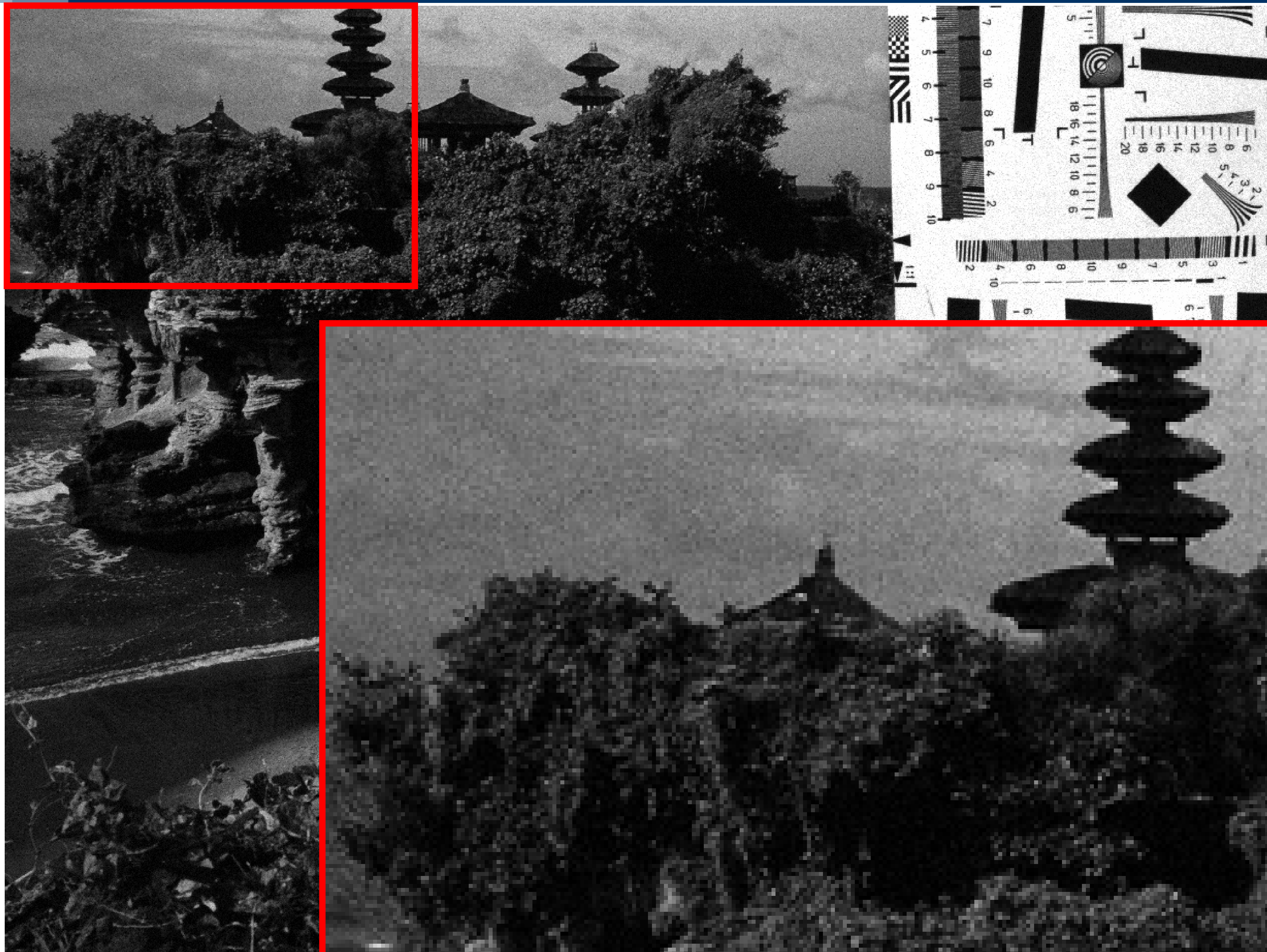
- Thus the range of the restored image is increased w.r.t. the observation range

Experiments on camera raw data

- We performed the following experiment on 3 sequences of raw data
  - “fixed” : a sequence of short exposure images acquired with the camera a tripod
  - “shaked”: a sequence of short exposure images acquired with an hand held camera
  - “mixed” : a sequence of images of depicting completely different scenes

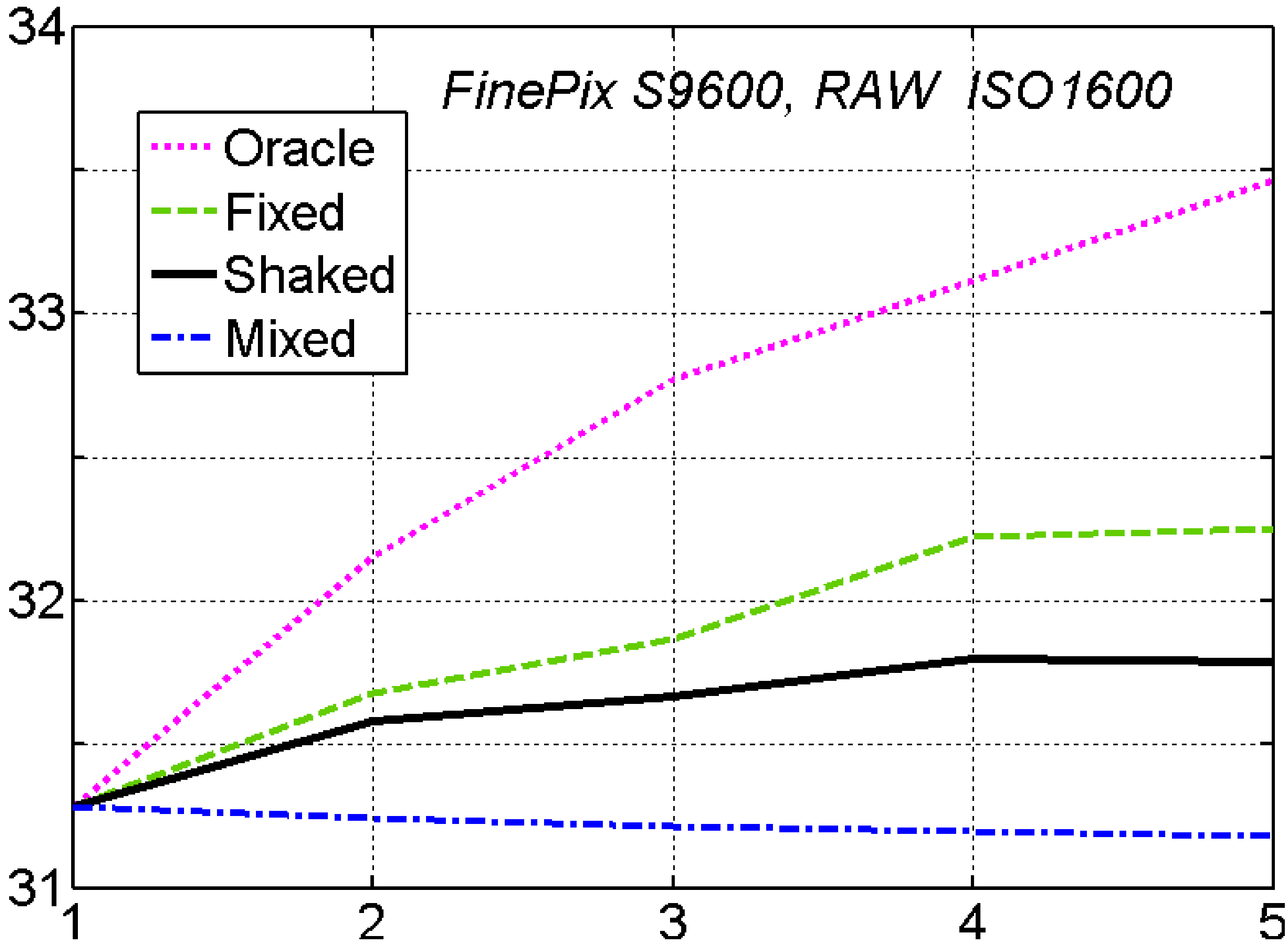
camera raw data

camera raw data



PSNR of restored images

- The behavior is consistent with synthetic experiments



restored using 5 frames[raw_shake5.tif]

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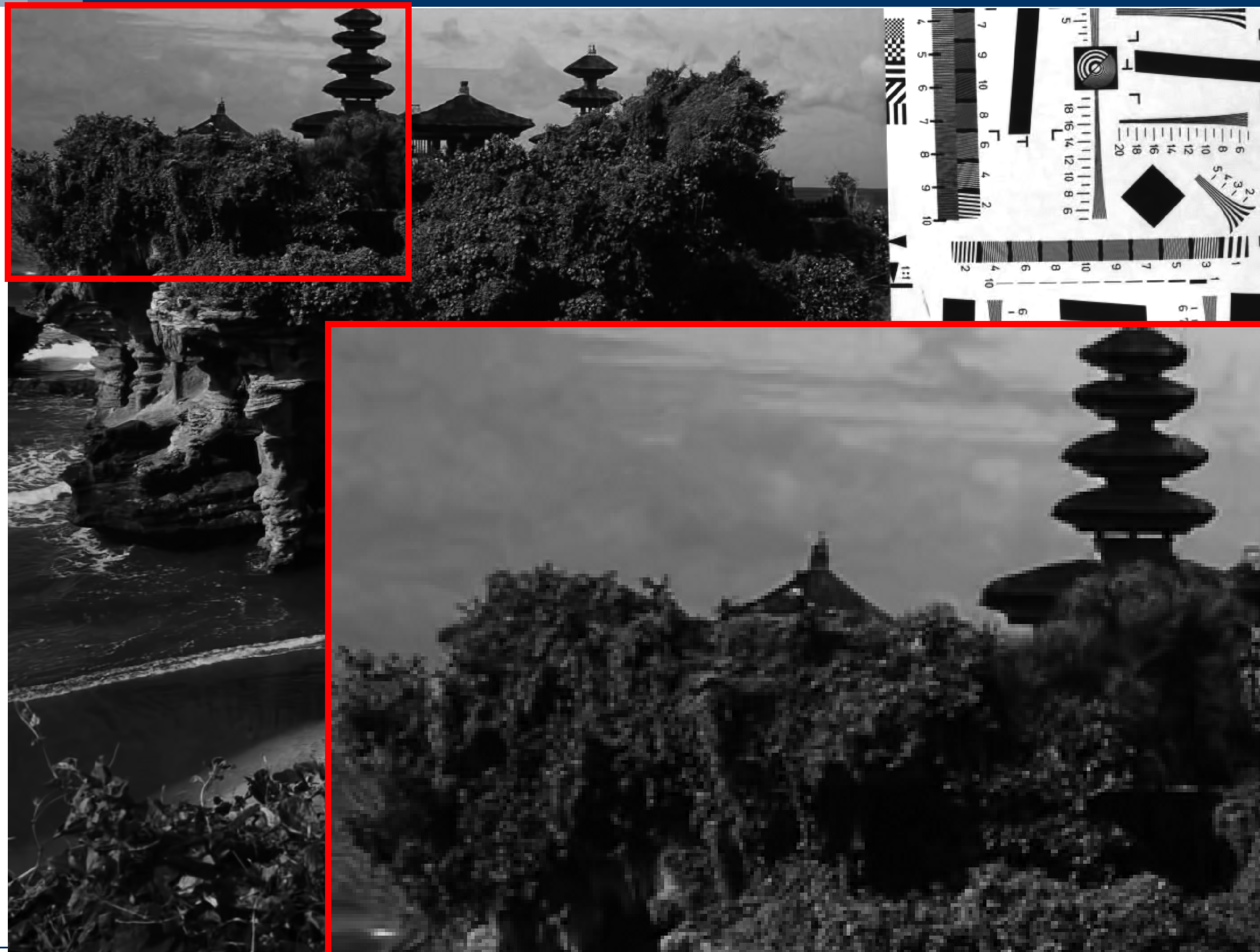

Denoising vs Deblurring

- We acquired with an hand held camera the following triplet of images of a dim scene

1. a long exposure image (ISO 100)
2. a short exposure image (ISO 1600)
3. a short exposure image (ISO 1600)

- We asked both *Tico et al.* and *Yuan et al*. to restore with their method the image pair 1,2

- While we restore with our method the pair 2,3

Denoising vs Deblurring

- Long exposure, camera shaked image

Denoising vs Deblurring

- One of the short exposure, noisy image

- A detail from image restored with *Tico et al.* algorithm
- Visible artifacts due to mismatched between assumed blur model (invariant PSF, linearity) and real.

A detail from image restored with our algorithm

- There are less artifacts.
- Modeling is accurate.
- Denoising is less ill-posed than deblurring.

- A detail from image restored with *Tico et al.* algorithm

- A detail from image restored with our algorithm

- Not all details can be recovered by denoising because SNR is too low.

Concluding Remarks

- In “shaked sequences” the denoising performances always increases with the number of frames

- The gap between the “oracle” performances and the other leaves plenty of rooms for improvements.

- The proposed algorithm works indifferently in case of camera shake and object motion.