How to improve your denoising result without changing your denoising algorithm

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Universitat Pompeu Fabra, Spain

Joint work with Gabriela Ghimpeteanu and Thomas Batard from UPF, and Stacey Levine from Duquesne University


TITLE
El niño
SEQUENCE
1
1
TAKE
1
SOUND
X
DIRECTORA
TONI VIDAL
CAMERA
Mr. ADRIÀ GUARDI
INDOOR
OUTDOOR

$$I = a + n$$

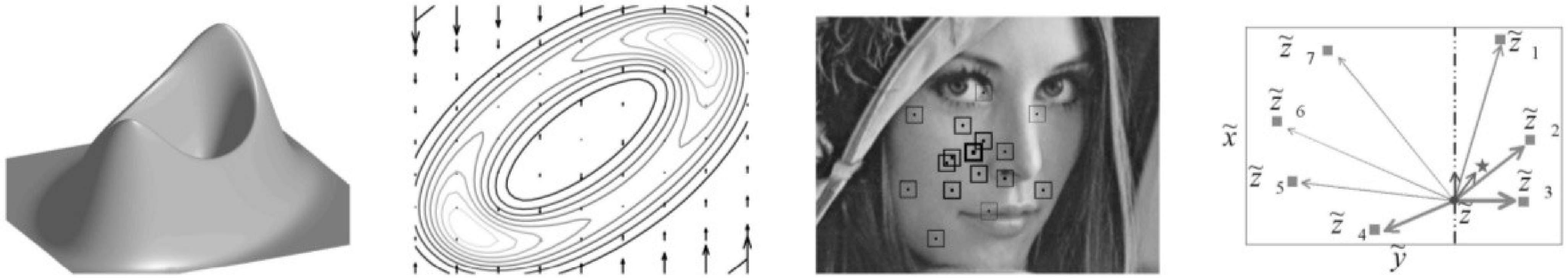
Classic techniques based on: natural images are band-limited, noise isn't

Two types of approach:
-Attenuation of transform coefficients
-Averaging of neighboring values

FIG. 2.2. *Denoising experience on a natural image. From left to right and from top to bottom: noisy image (standard deviation 20), gaussian convolution, anisotropic filter, total variation minimization, Tadmor et al. iterated total variation, Osher et al. iterated total variation and the Yaroslavsky neighborhood filter.*

Buades et al. (2005)

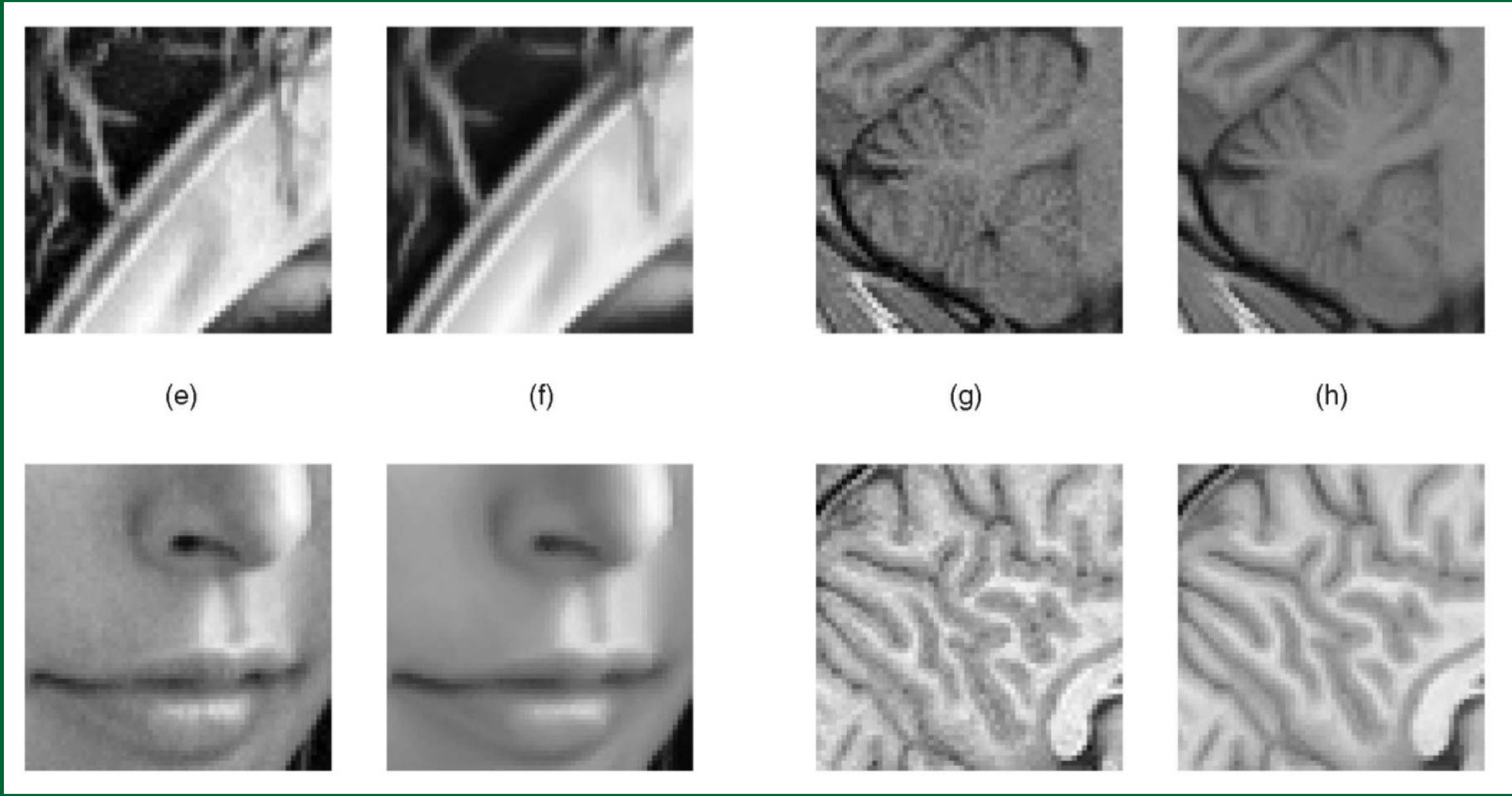
Game-change in 2005: Non-local approaches



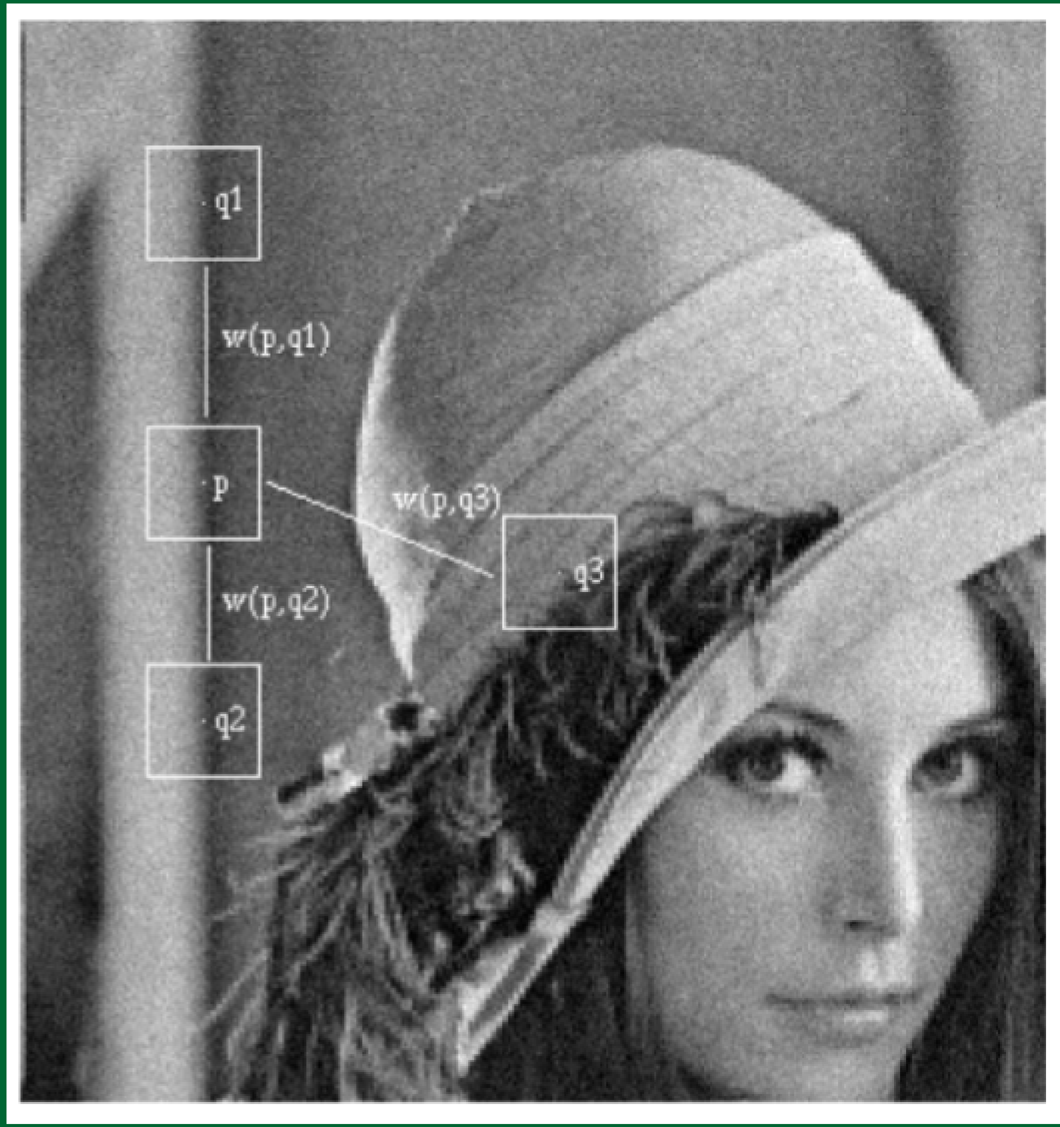
(a) (b) (c) (d)

Fig. 2. (a) An example 2D PDF, $P(\tilde{x}, \tilde{y})$, on feature space, $< \tilde{x}, \tilde{y} >$. (b) A contour plot of the PDF depicts the forces (vertical arrows) that reduce the entropy of the conditional PDFs $P(\tilde{X}|\tilde{Y} = \tilde{y})$, as in (3). (c) Some pixels in A_i (black dots) along with the neighborhoods (squares around the dots) yielding feature space samples $\tilde{z}_i$. The thickness of the squares indicate the weights, as in (4), for the intensities of pixels in A_i. The thickest square denotes the neighborhood around the pixel being processed. (d) Attractive forces (arrow width $\equiv$ force magnitude) act on a sample ($\tilde{z}$: circle) toward other samples ($\tilde{z}_j$: squares) in the set A_i, as per (4). The resultant force acts toward the weighted mean (star) and the sample $\tilde{z}$ moves based on its projection (vertical arrow).

Awate and Whitaker (2006)



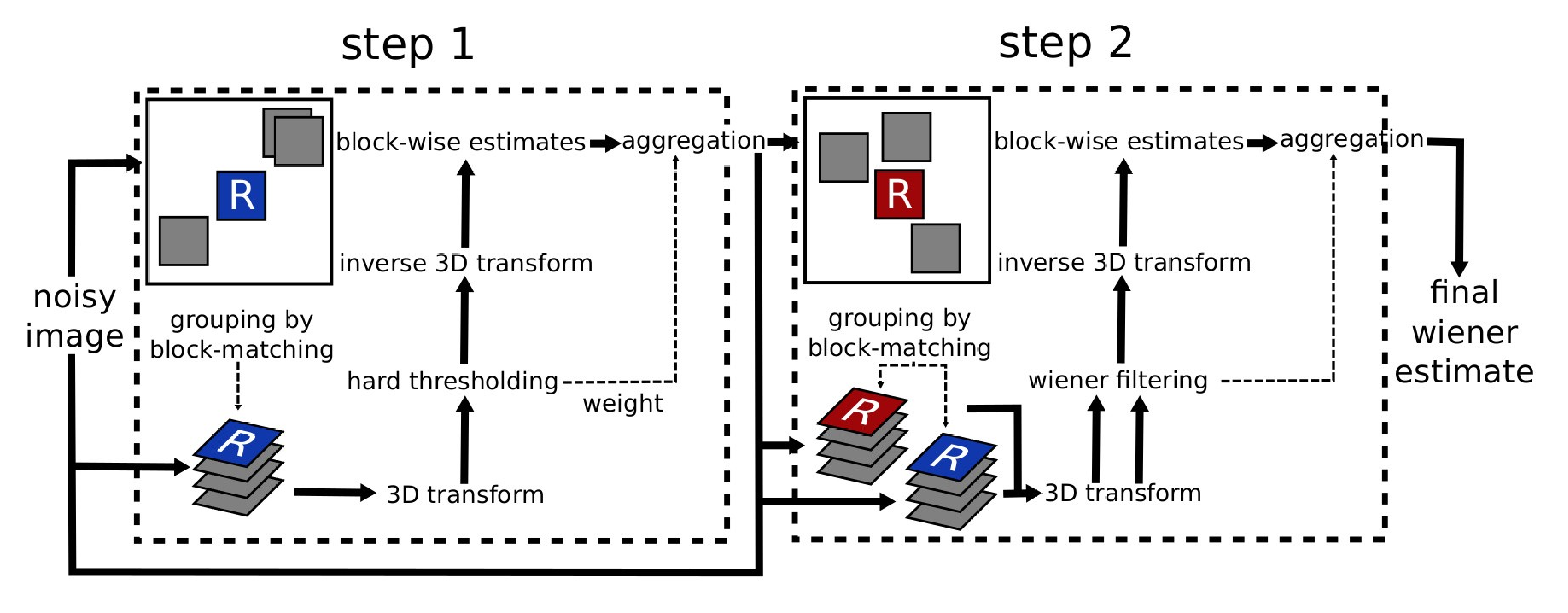
Awate and Whitaker (2006)



Buades et al. (2005)

FIG. 5.4. *NL-means denoising experiment with a natural image. Left: Noisy image with standard deviation 20. Right: Restored image.*

Buades et al. (2005)

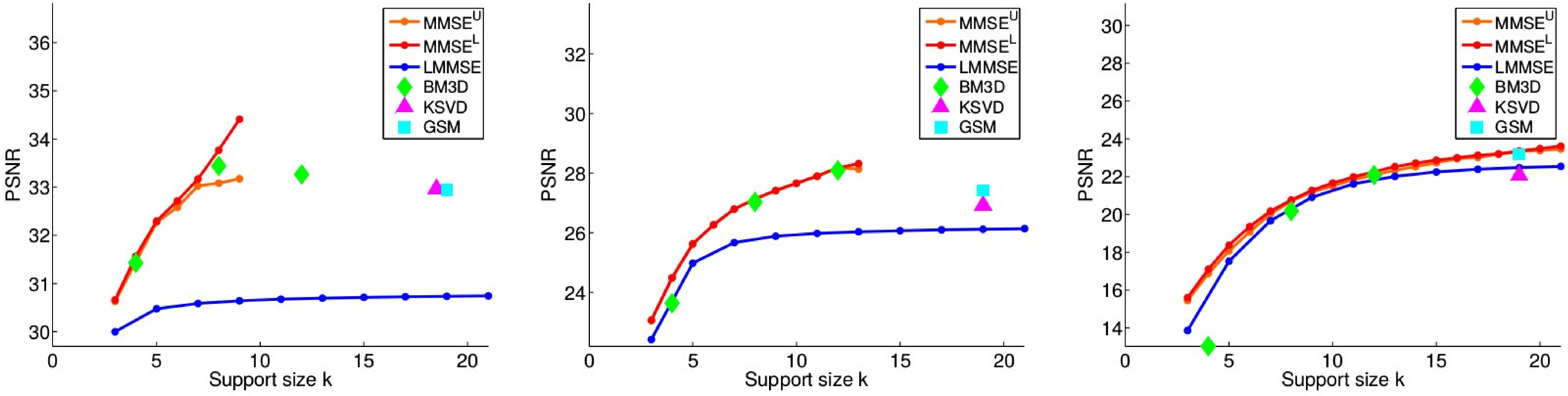


BM3D algorithm of Dabov et al. (2007)
(figure from Lebrun (2012))

IEEE TRANSACTIONS ON IMAGE PROCESSING, VOL. 19, NO. 4, APRIL 2010

Is Denoising Dead?

Priyam Chatterjee, *Student Member, IEEE*, and Peyman Milanfar, *Fellow, IEEE*



(a) $\sigma = 18$ (b) $\sigma = 55$ (c) $\sigma = 170$

Figure 2. PSNR values of several recent denoising algorithms along with our MMSE lower and upper bounds. As predicted by the theory, the performance of all algorithms are bounded by our MMSE^L estimate, although BM3D approaches the bound by fractional dB values. (Note that since $\text{PSNR} = -10 \log 10(\text{MSE})$, the MMSE lower bound turns into an upper bound on the best achievable PSNR).

Levin and Nadler (2011)

SIAM Imaging Conference 2014 and 2016: minisymposia on denoising

Acta Numerica (2012), pp. 1–102
doi:10.1017/S09624929XXXXXXXX

Secrets of image denoising cuisine*

M. Lebrun, M. Colom, A. Buades and J. M. Morel

How to improve your denoising result
without changing your denoising algorithm:

1. Apply denoising algorithm to <u>transform</u> of image, not to image itself

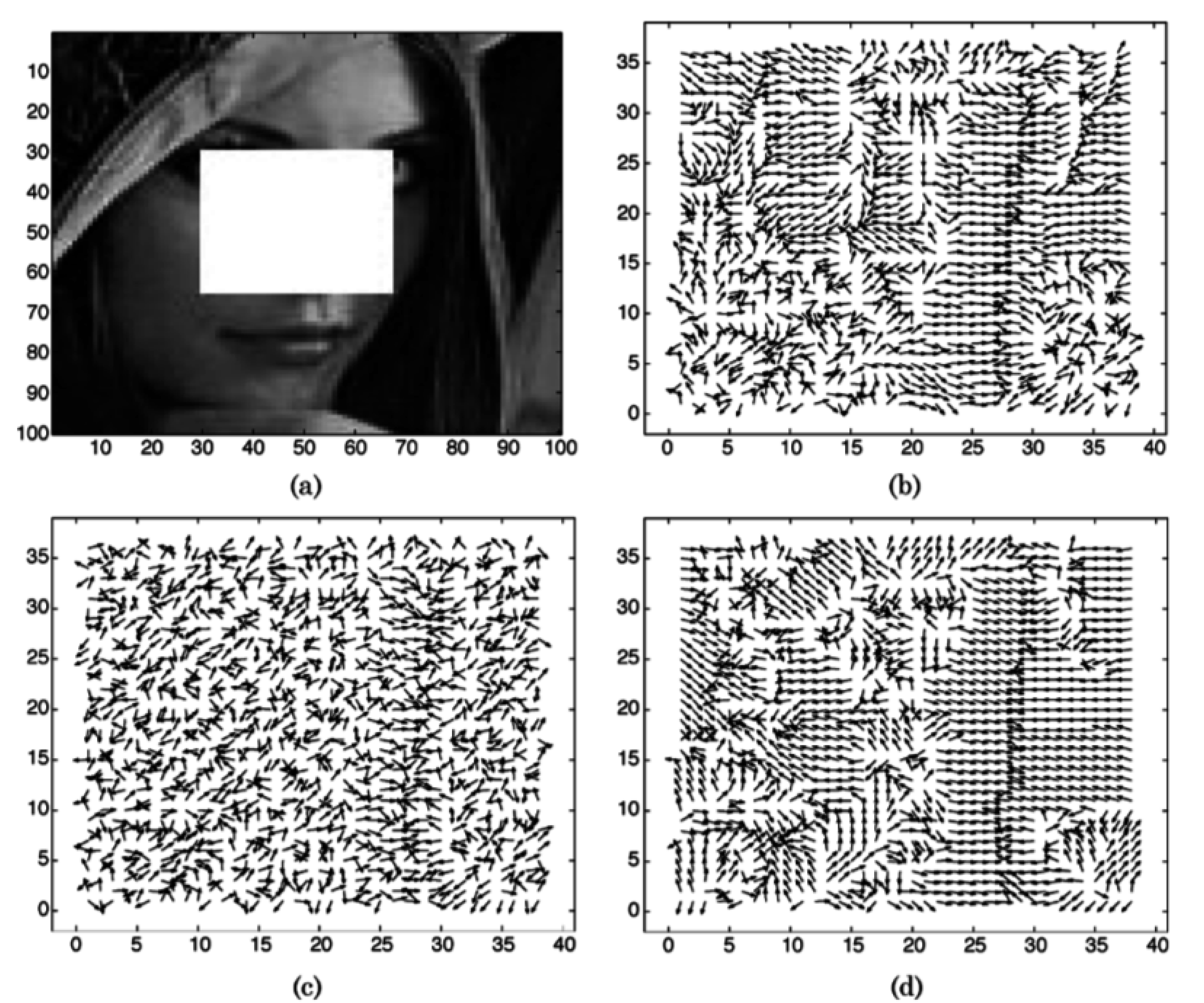
IEEE TRANSACTIONS ON IMAGE PROCESSING, VOL. 13, NO. 10, OCTOBER 2004

Noise Removal Using Smoothed Normals and Surface Fitting

Marius Lysaker, Stanley Osher, and Xue-Cheng Tai

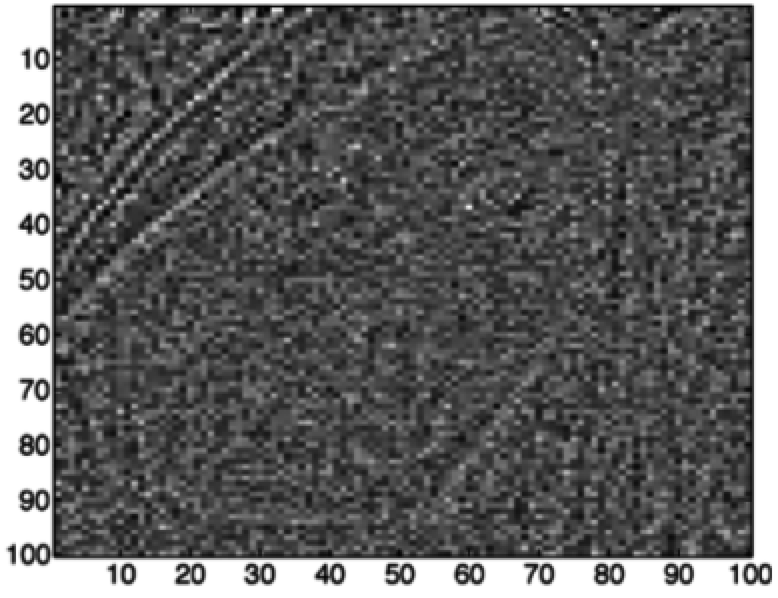
$$\min_{|\vec{n}|=1} \left\{ \int_{\Omega} |\nabla \vec{n}| dx + \frac{\lambda}{2} \int_{\Omega} |\vec{n} - \vec{n}_0|^2 dx \right\}.$$

$$\min_{\int_{\Omega} |d-d_0|^2 dx = \sigma^2} \int_{\Omega} \left(|\nabla d| - \nabla d \cdot \vec{n} \right) dx$$


(a)
(b)
(c)
(d)


10 20 30 40 50 60 70 80 90 100
10 20 30 40 50 60 70 80 90 100

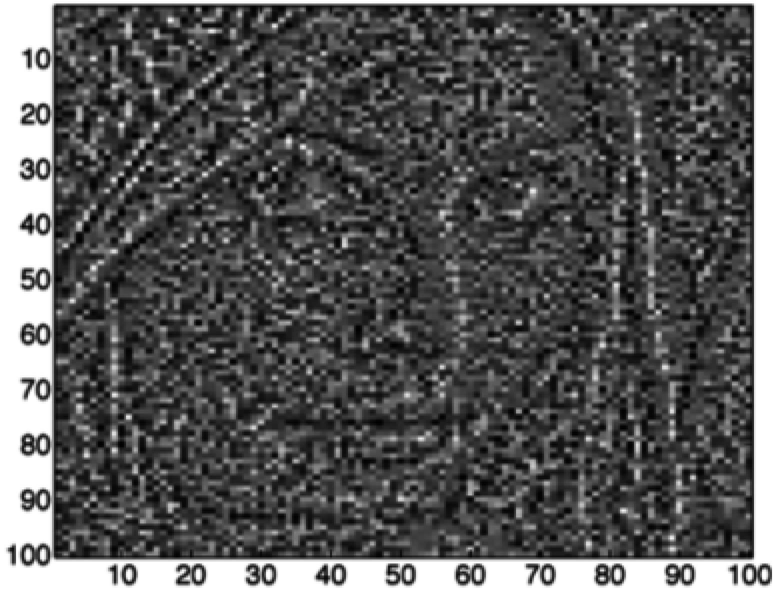
(a)


10 20 30 40 50 60 70 80 90 100
10 20 30 40 50 60 70 80 90 100

(b)


10 20 30 40 50 60 70 80 90 100
10 20 30 40 50 60 70 80 90 100

(c)


10 20 30 40 50 60 70 80 90 100
10 20 30 40 50 60 70 80 90 100

(d)

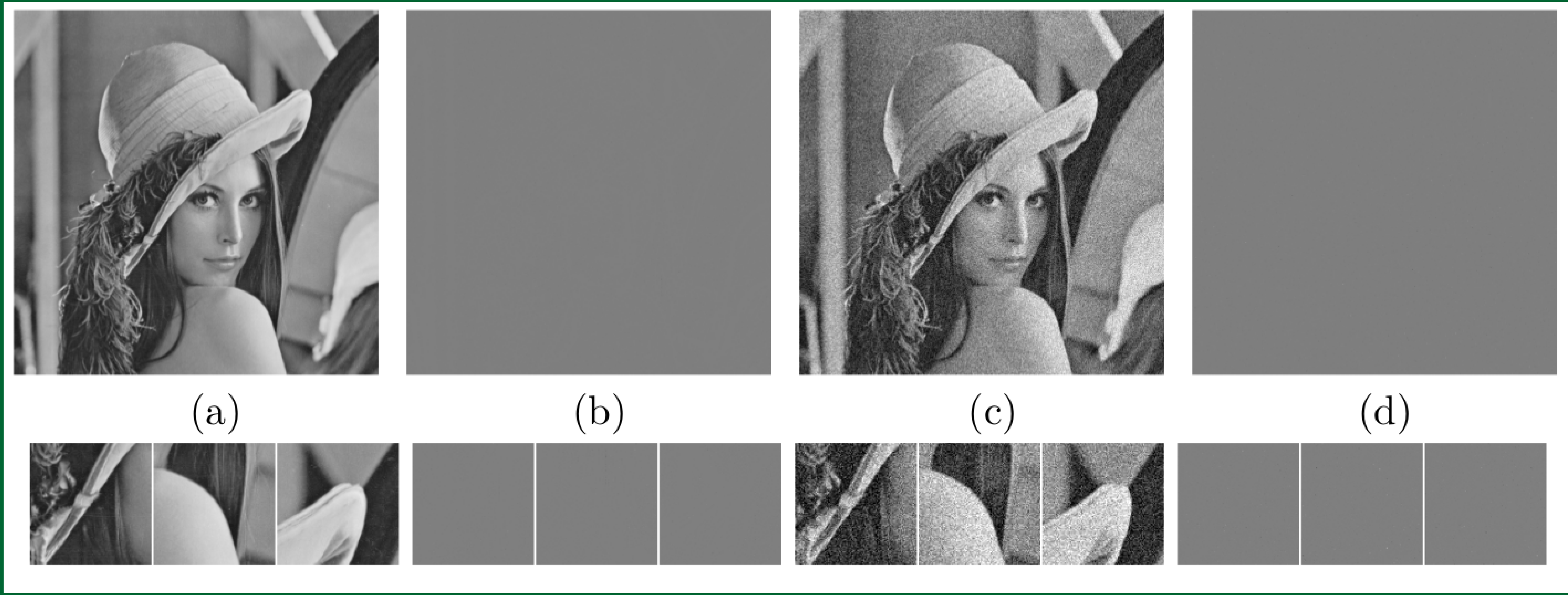
SIAM J. Imaging Sci., 7(1), 187–211. (25 pages)

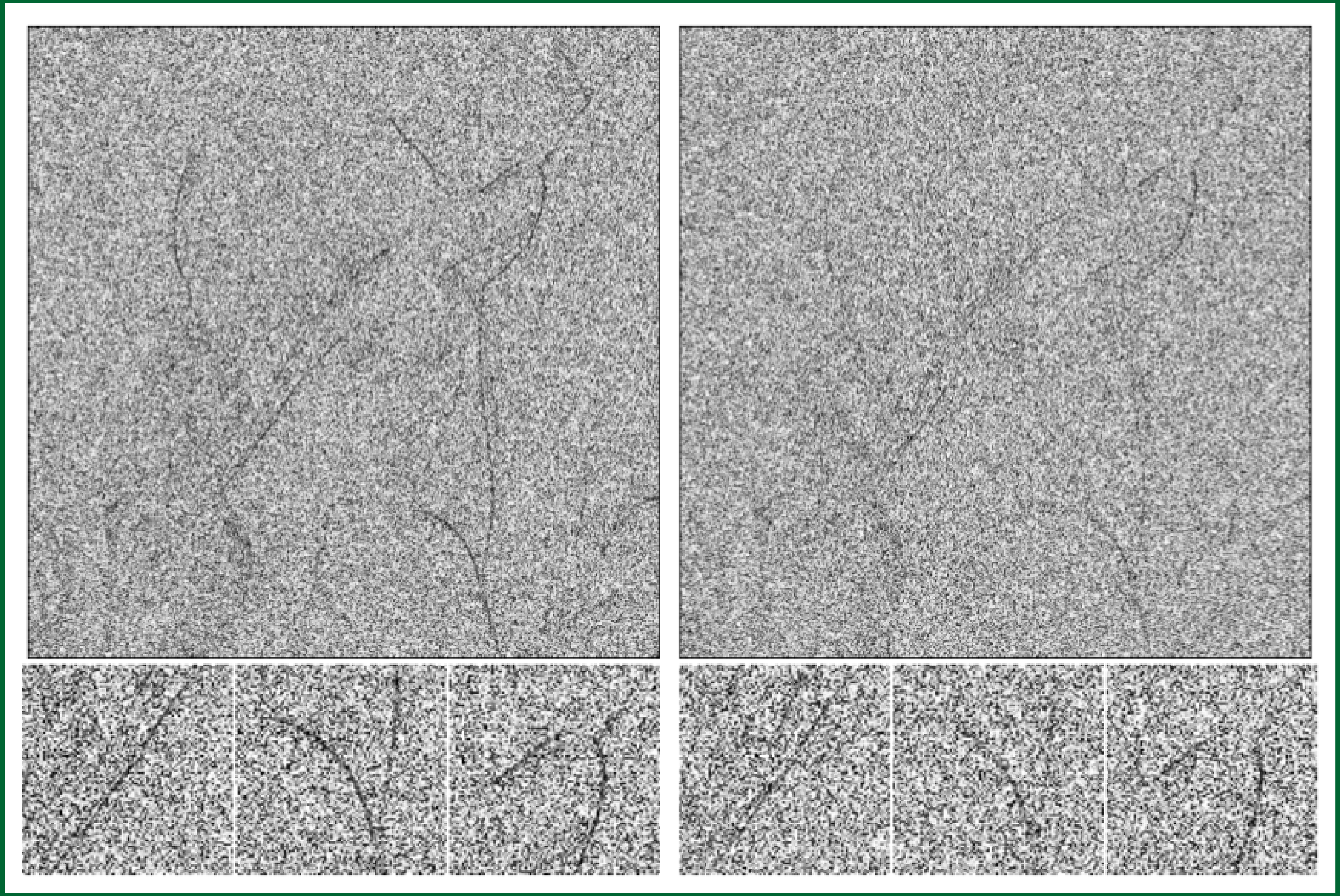
Denoising an Image by Denoising Its Curvature Image

Marcelo Bertalmío and Stacey Levine

DOI:10.1137/120901246

Published in SIAM SIIMS, January 2014


(a)
(b)
(c)
(d)



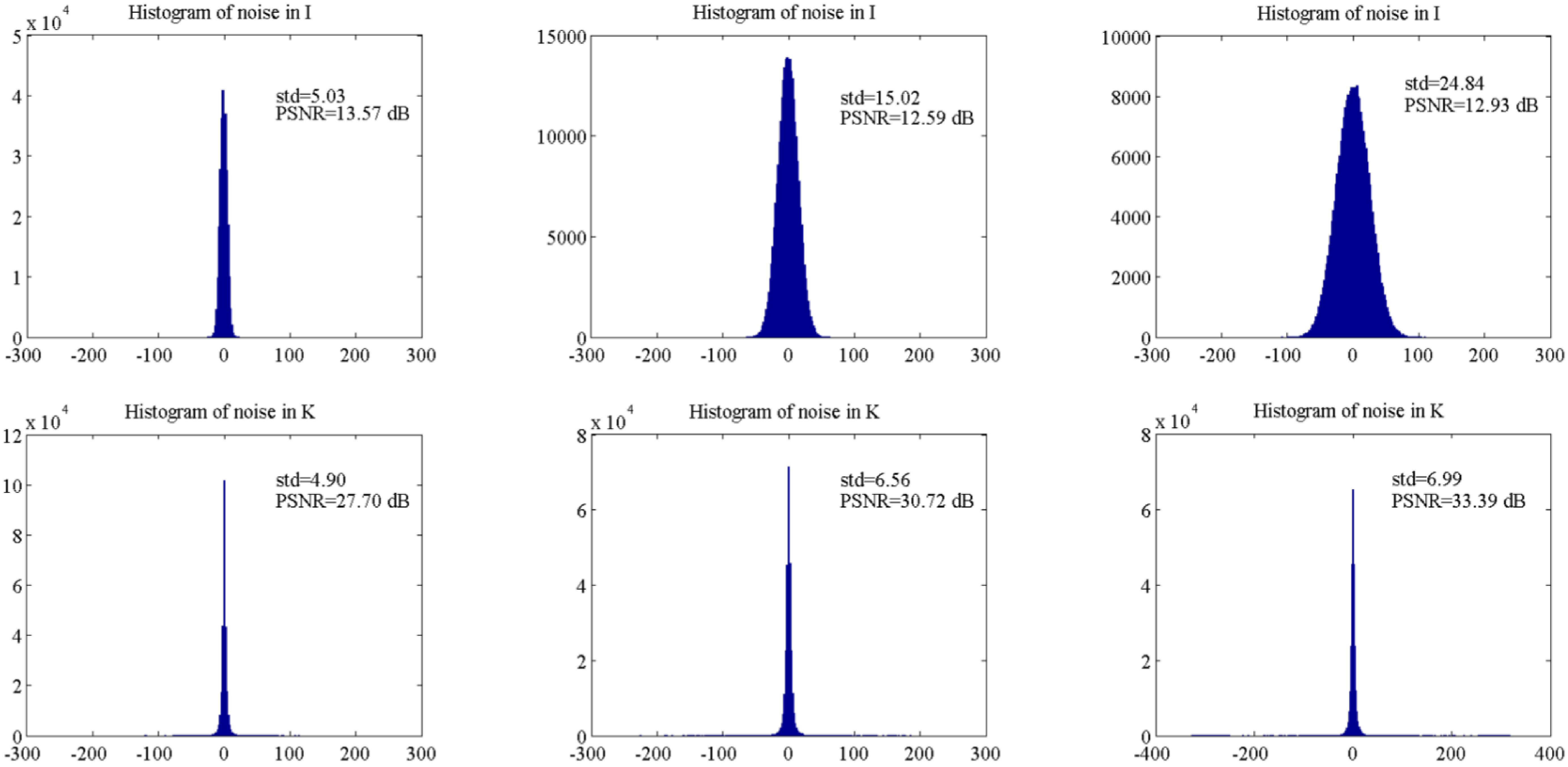


FIG. 1.3. *Noise histograms for I (top) and $\kappa(I)$ (bottom). From left to right:* $\sigma = 5, 15, 25$.

$$u_t = \kappa(u) - \kappa(a) + \lambda(I - u),\ u(0,\cdot) = I$$

Proposed Approach

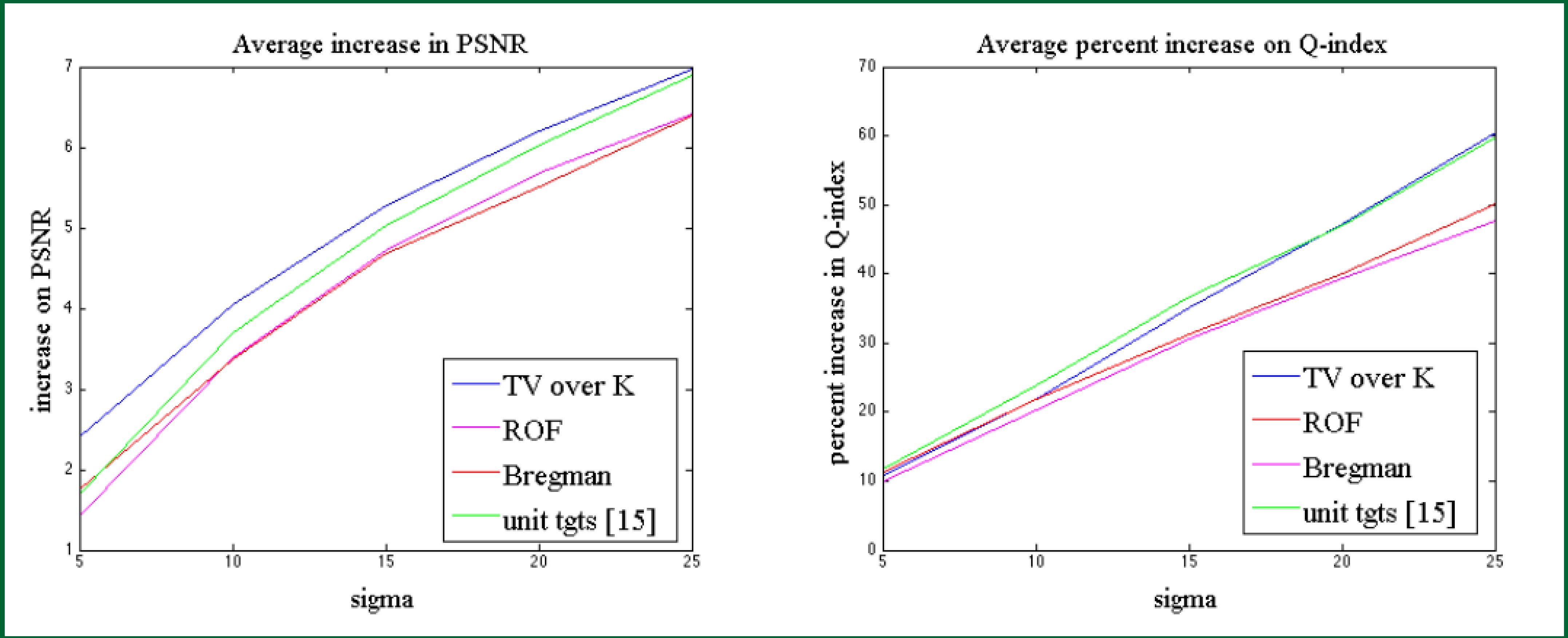
Step 1: Given a noisy image, I, denoise $\kappa(I)$ with method $\mathcal{F}$ to obtain $\kappa_{\mathcal{F}} = \mathcal{F}(\kappa(I))$.

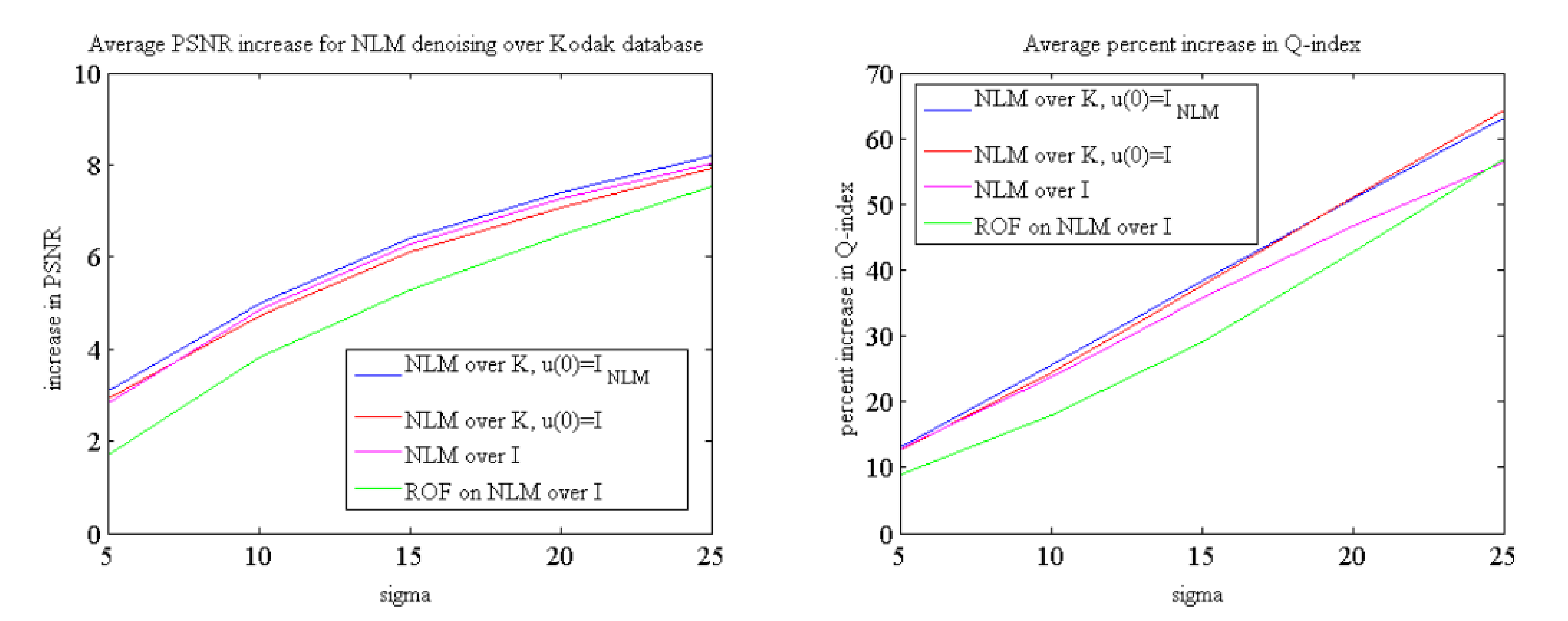
Step 2: Generate an image $\hat{I}_{\mathcal{F}}$ that satisfies the following criteria:

1. $\kappa(\hat{I}_{\mathcal{F}}) \simeq \kappa_{\mathcal{F}}$; that is, the level lines of $\hat{I}_{\mathcal{F}}$ are well described by $\kappa_{\mathcal{F}}$.
2. The overall contrast of $\hat{I}_{\mathcal{F}}$ matches that of the given data $I = a+n$ in the sense that the intensity of any given level line of $\hat{I}_{\mathcal{F}}$ is close to the average value of I along that contour.

$$u_t = \kappa(u) - \kappa_{\mathcal{F}} + 2\lambda(I - u)$$

$$\hat{I}_{\mathcal{F}} = \arg\min_u \int_\Omega |\kappa(u) - \kappa_{\mathcal{F}}| + \frac{\lambda}{2} \int_\Omega (I - u)^2$$


Average increase in PSNR
increase on PSNR
sigma
TV over K
ROF
Bregman
unit tgts [15]
Average percent increase on Q-index
percent increase in Q-index
sigma
TV over K
ROF
Bregman
unit tgts [15]



Average PSNR increase for NLM denoising over Kodak database
increase in PSNR
sigma
NLM over K, u(0)=I NLM
NLM over K, u(0)=I
NLM over I
ROF on NLM over I
Average percent increase in Q-index
percent increase in Q-index
sigma

IEEE TRANSACTIONS ON IMAGE PROCESSING, VOL. 25, NO. 1, JANUARY 2016

A Decomposition Framework for Image Denoising Algorithms

Gabriela Ghimpeţeanu, Thomas Batard, Marcelo Bertalmío, and Stacey Levine

1. Given a denoising method, it's better to project the noisy image into a moving frame and to denoise these components, than to denoise the image directly

2. Along contours, the PSNR of the components is higher than that of the image

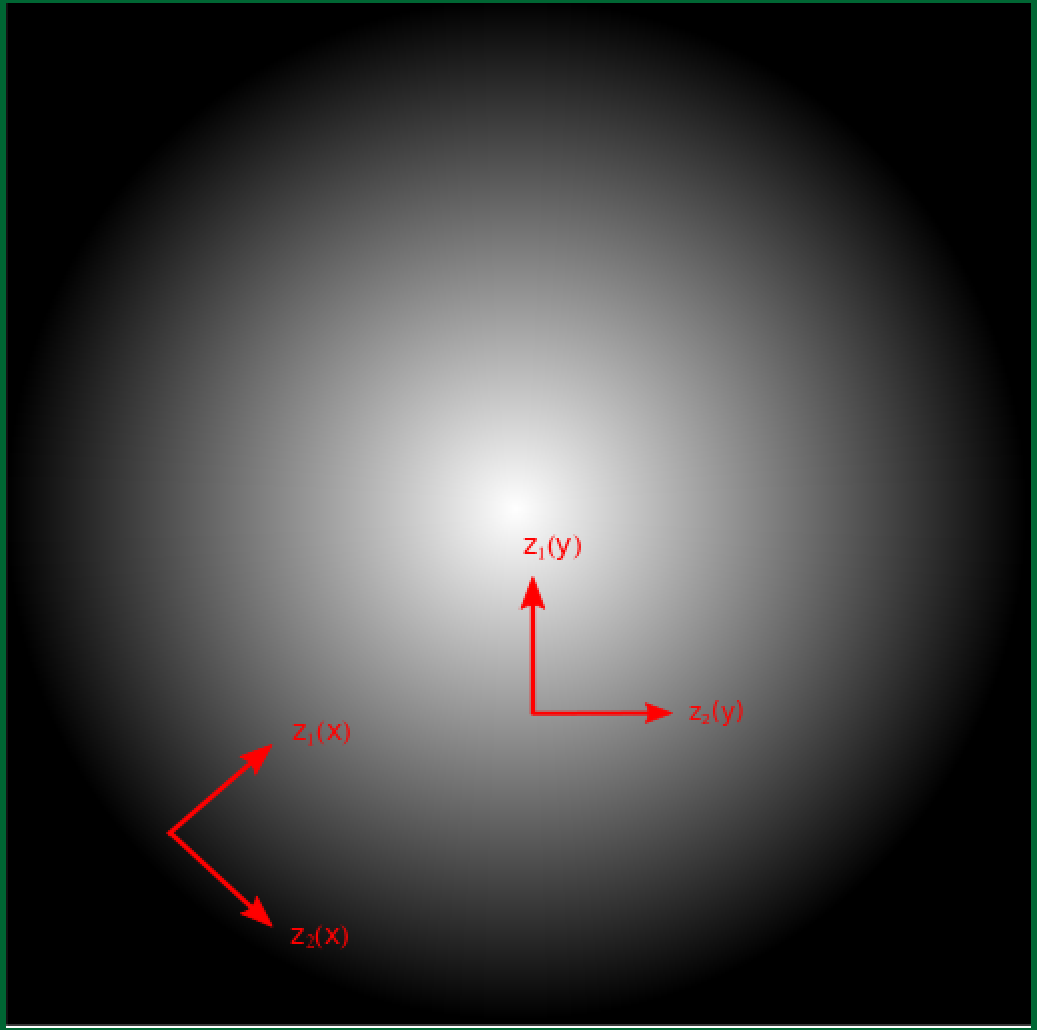
3. Reconstruction (denoised components → denoised image) is extremely simple

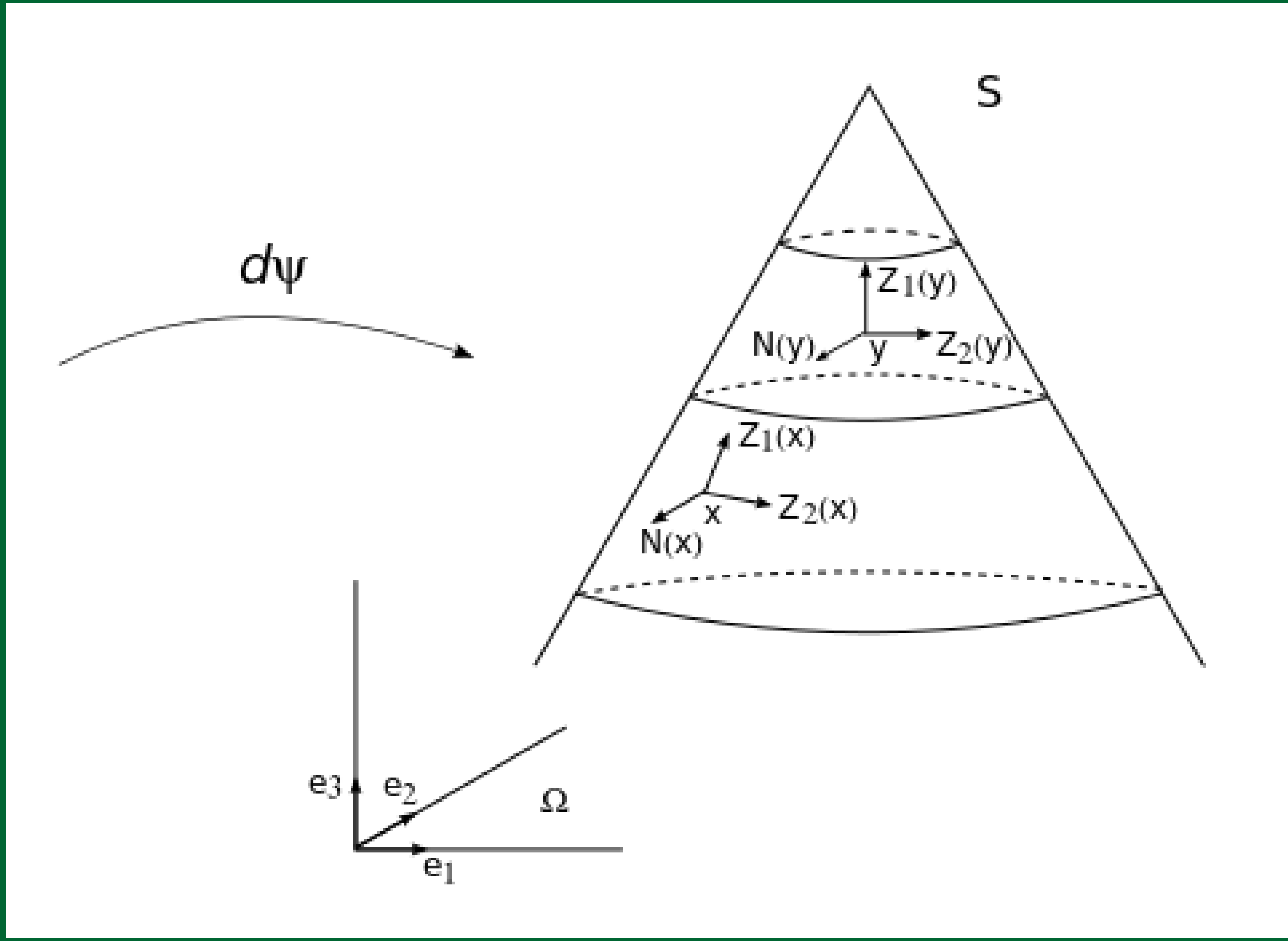
Image decomposition in a moving frame

ON COVARIANT DERIVATIVES AND THEIR APPLICATIONS TO IMAGE REGULARIZATION *

THOMAS BATARD AND MARCELO BERTALMÍO †

Published in SIAM SIIMS, 2014


z₁(y)
z₂(y)
z₁(x)
z₂(x)


S
dψ
Z1(y)
N(y)
y
Z2(y)
Z1(x)
x
Z2(x)
N(x)
e3
e2
e1
Ω

$$(\boldsymbol{Z_1}, \boldsymbol{Z_2}, \boldsymbol{N})$$

$$P = \begin{pmatrix} \frac{I_x}{\sqrt{|\nabla I|^2(1+\mu^2|\nabla I|^2)}} & \frac{-I_y}{|\nabla I|} & \frac{-\mu\, I_x}{\sqrt{1+\mu^2|\nabla I|^2}} \\ \frac{I_y}{\sqrt{|\nabla I|^2(1+\mu^2|\nabla I|^2)}} & \frac{I_x}{|\nabla I|} & \frac{-\mu\, I_y}{\sqrt{1+\mu^2|\nabla I|^2}} \\ \frac{\mu|\nabla I|^2}{\sqrt{|\nabla I|^2(1+\mu^2|\nabla I|^2)}} & 0 & \frac{1}{\sqrt{1+\mu^2|\nabla I|^2}} \end{pmatrix}, \tag{3}$$

$$\begin{pmatrix} J^1 \\ J^2 \\ J^3 \end{pmatrix} = P^{-1} \begin{pmatrix} 0 \\ 0 \\ I \end{pmatrix}$$

nt: gray-level image "Lena", component J^1, component J^3.

1) Process I with some denoising technique F and call the output image I_{den}.
2) Compute the components (J^1, J^2, J^3) of I in the moving frame (3), for some scalar μ, with formula (4). Apply the same denoising technique F to the components to obtain the processed components $(J^1_{den}, J^2_{den}, J^3_{den})$. Then, apply the inverse frame change matrix field to the processed components, i.e.

$$\begin{pmatrix} I^1_{denMF} \\ \\ I^2_{denMF} \\ \\ I^3_{denMF} \end{pmatrix} := P \begin{pmatrix} J^1_{den} \\ \\ J^2_{den} \\ \\ J^3_{den} \end{pmatrix} \tag{8}$$

and denote by I_{denMF} the third component I^3_{denMF}.
3) Compare I_{den} and I_{denMF} with the metrics PSNR and SSIM.

At image contours:

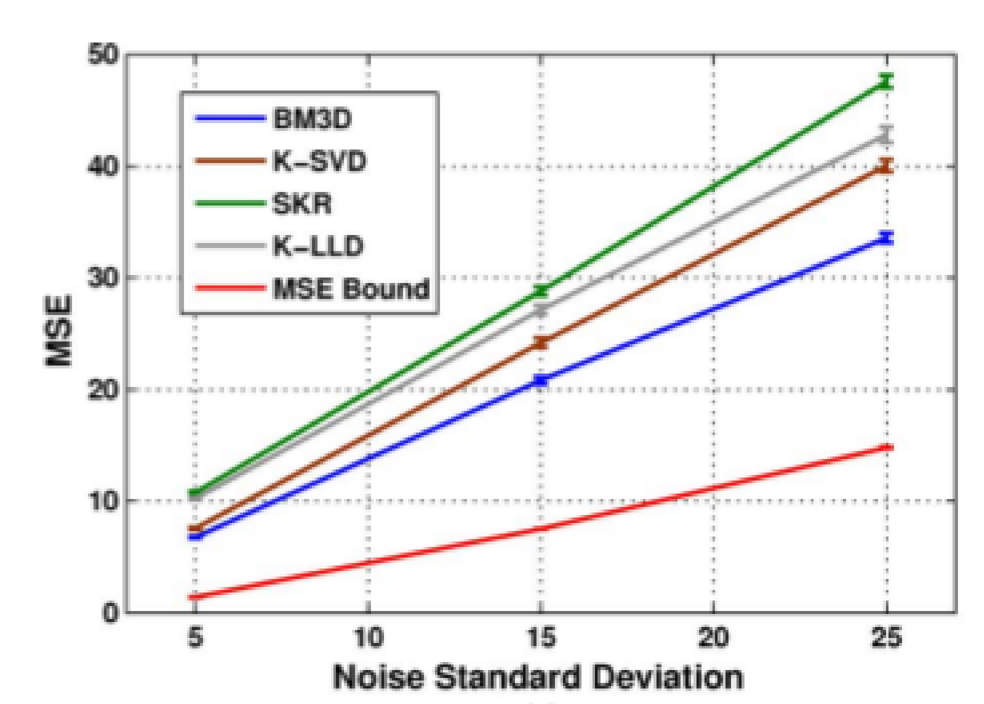
$$PSNR(J^1(I)) \geq PSNR(I)$$

$$PSNR(J^3(I)) > PSNR(I)$$

At homogeneous regions:

$$PSNR(J^1(I)) > PNSR(I).$$

$$PNSR(J^3(I)) \approx PNSR(I).$$



BM3D
K-SVD
SKR
K-LLD
MSE Bound
MSE
50
40
30
20
10
0
5
10
15
20
25
Noise Standard Deviation

Experiments

TABLE II

AVERAGE PSNR AND SSIM INDEX (X100), AND OPTIMAL PARAMETER OVER THE KODAK DATABASE: THE GRAY-LEVEL CASE. COMPARISON OF THE STANDARD AND OUR MOVING FRAME APPROACHES FOR THE VTV-BASED DENOISING METHOD, AT DIFFERENT NOISE LEVELS.

Approach \ Noise variance	5	10	15	20	25
PSNR Standard	35.39	31.51	29.48	28.15	27.17
PSNR Moving frame	36.36	32.23	30.04	28.60	27.49
Approach \ Noise variance	5	10	15	20	25
SSIM Index Standard	93.76	87.07	81.91	77.63	74.12
SSIM Index Moving frame	94.61	88.37	83.22	78.71	74.78

Parameters \ Noise variance	5	10	15	20	25
μ	0.008	0.005	0.005	0.004	0.004

TABLE VI

COMPARISON OF THE STANDARD APPROACH AND OUR MOVING FRAME APPROACH WITH $\mu = 0.001$ FOR NLM, AT DIFFERENT NOISE LEVELS. AVERAGE PSNR AND SSIM INDEX (X100), AND OPTIMAL PARAMETER σ_3 OVER THE KODAK DATABASE: THE GRAY-LEVEL CASE.

Approach \ Noise variance	5	10	15	20	25
PSNR Standard	37.41	33.38	31.05	30.04	28.91
PSNR Moving frame	37.52	33.59	31.57	30.12	29.00

Approach \ Noise variance	5	10	15	20	25
SSIM Index Standard	94.96	88.71	82.17	80.34	75.94
SSIM Index Moving frame	95.11	89.54	85.37	81.03	76.95

Parameter \ Noise variance	5	10	15	20	25
σ_3	5.6	11	16	21	26

TABLE VIII

COMPARISON OF THE STANDARD APPROACH AND OUR MOVING FRAME APPROACH WITH $\mu = 0.001$ FOR $BM3D$, AT DIFFERENT NOISE LEVELS. AVERAGE PSNR AND SSIM INDEX (X100), AND OPTIMAL PARAMETER σ_3 OVER THE KODAK DATABASE: THE GRAY-LEVEL CASE.

Approach \ Noise variance	5	10	15	20	25
PSNR Standard	38.23	34.34	32.26	30.89	29.88
PSNR Moving frame	38.25	34.38	32.31	30.93	29.92

Approach \ Noise variance	5	10	15	20	25
SSIM Index Standard	95.71	91.38	87.52	84.19	81.32
SSIM Index Moving frame	95.74	91.49	87.71	84.38	81.44

Parameter \ Noise variance	5	10	15	20	25
σ_3	4.9	9.7	14.4	19.1	23.9

How to improve your denoising result
without changing your denoising algorithm:

2. Ensure the image follows noise model assumed by denoising algorithm

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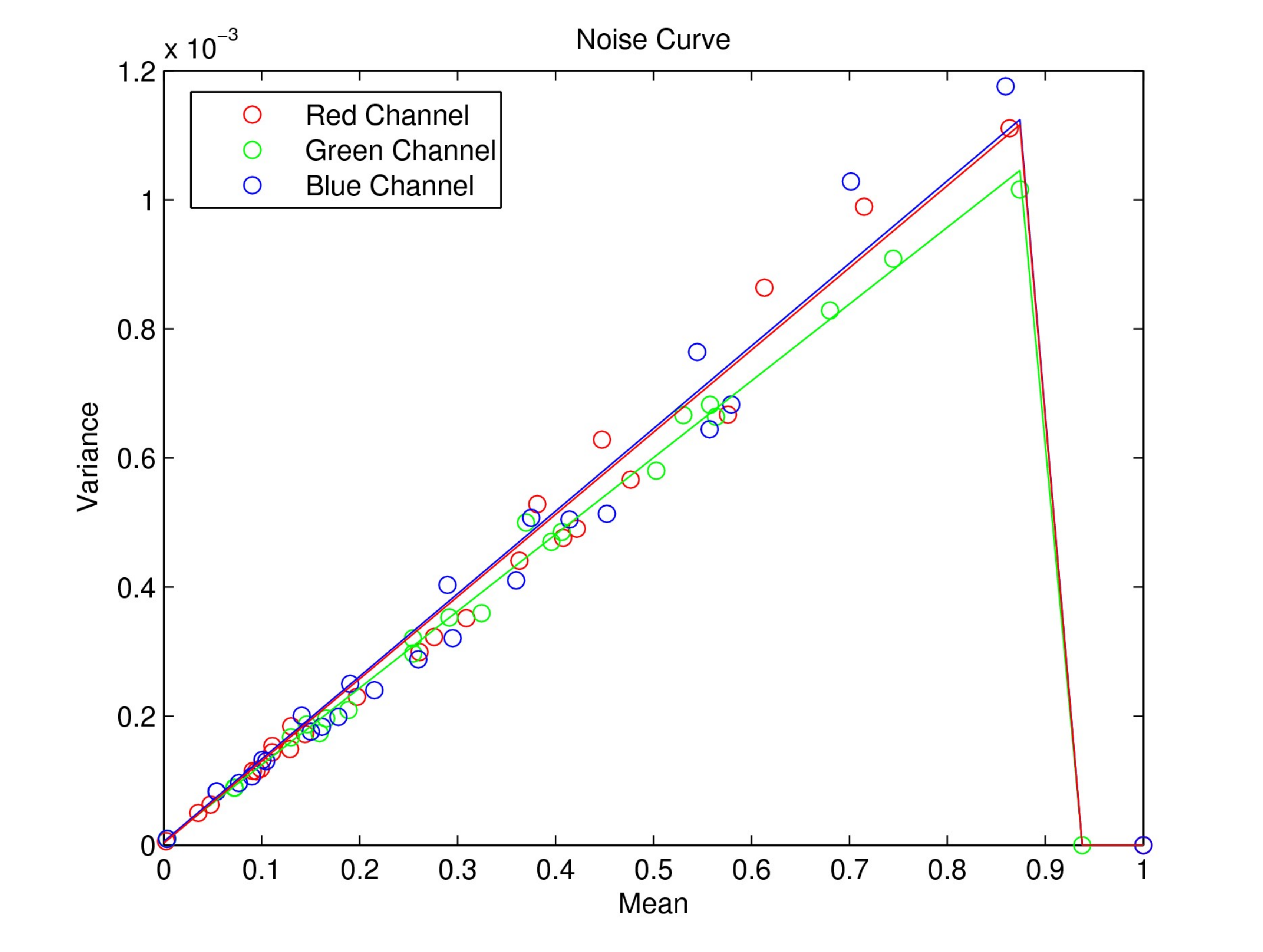
Local denoising applied to RAW images may outperform non-local patch-based methods applied to the camera output

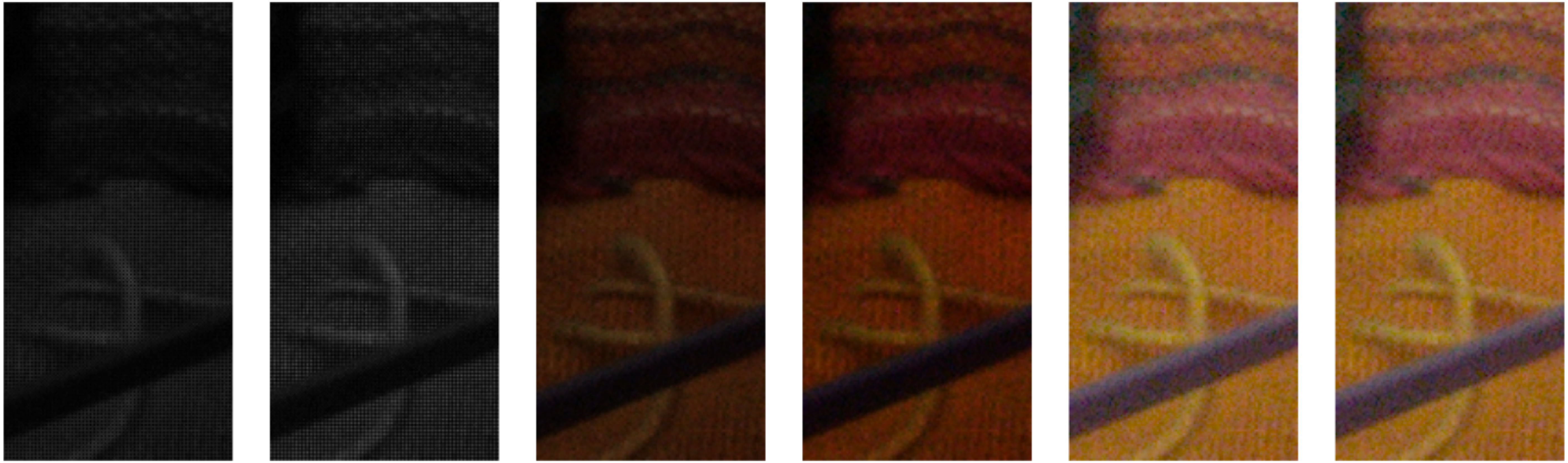
Gabriela Ghimpețeanu[1], *Thomas Batard*[1], *Tamara Seybold*[2] *and Marcelo Bertalmío*[1] *;*
[1] *Information and Communication Technologies Department, Universitat Pompeu Fabra, Barcelona, Spain*
[2] *Arnold & Richter Cine Technik (ARRI), München, Germany*

Published in Proc. Electronic Imaging (2016)

$$I = a + n$$


colorchecker CLASSIC
x-rite


Noise Curve
x 10^-3
Red Channel
Green Channel
Blue Channel
Variance
Mean
0
0.2
0.4
0.6
0.8
1
1.2
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1



(a) (b) (c) (d) (e) (f)

Fig. 1. Image example to illustrate the camera processing pipeline. From left to right: RAW original image (a), result after applying white-balance (b), demosaicking (c), color correction (d), gamma correction (e) and quantizing (f).

$I = f\,(a\,,\,n)$

$f = ?$

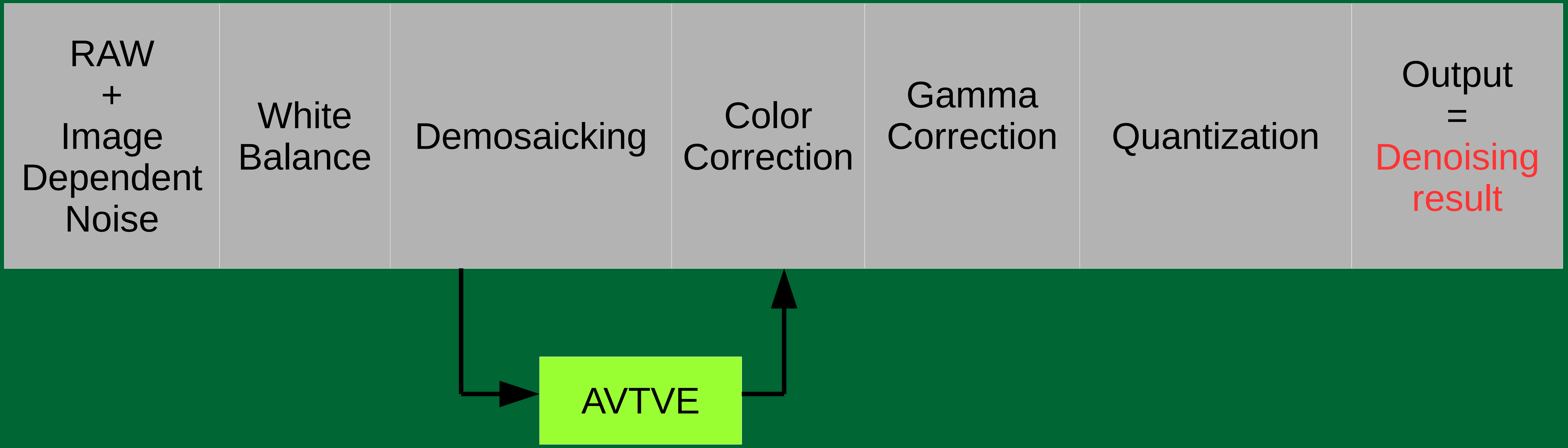
$$I_{RAW} = a + n(a)$$
$$\text{Anscombe}(I_{RAW}) = A + N$$

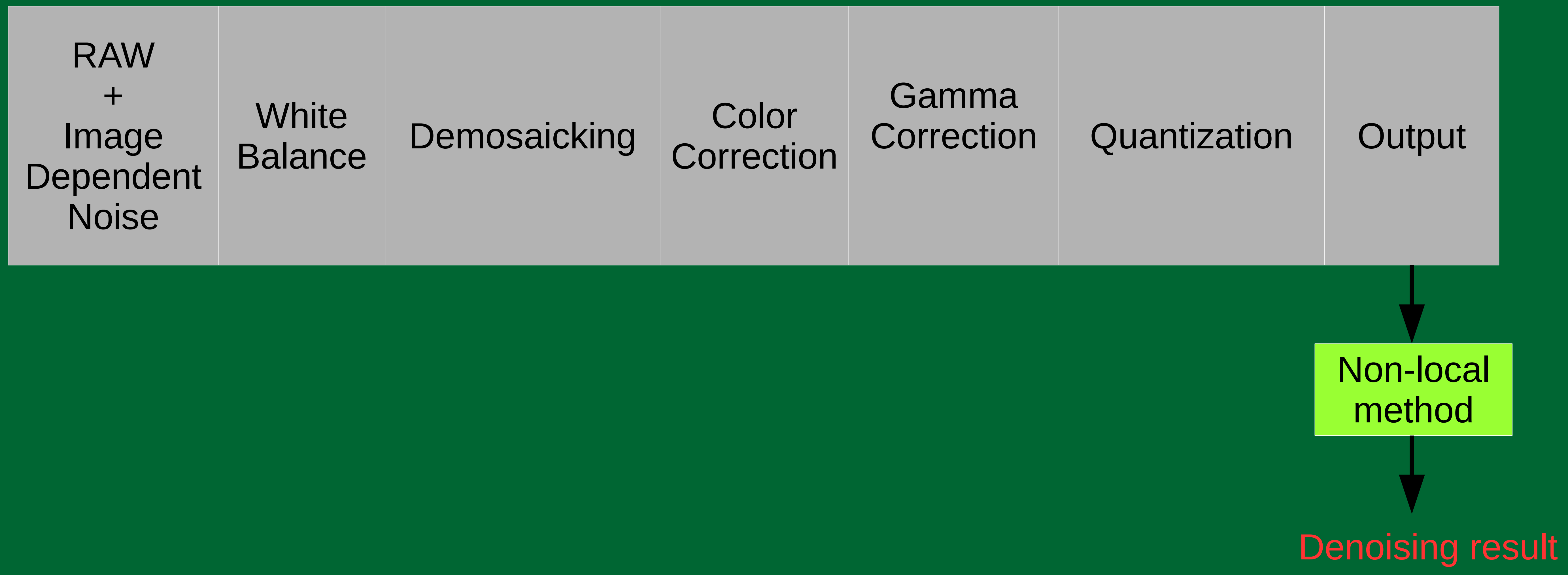
Donoho (1993), Mäkitalo and Foi (2011)

Local denoising method AVTVE:

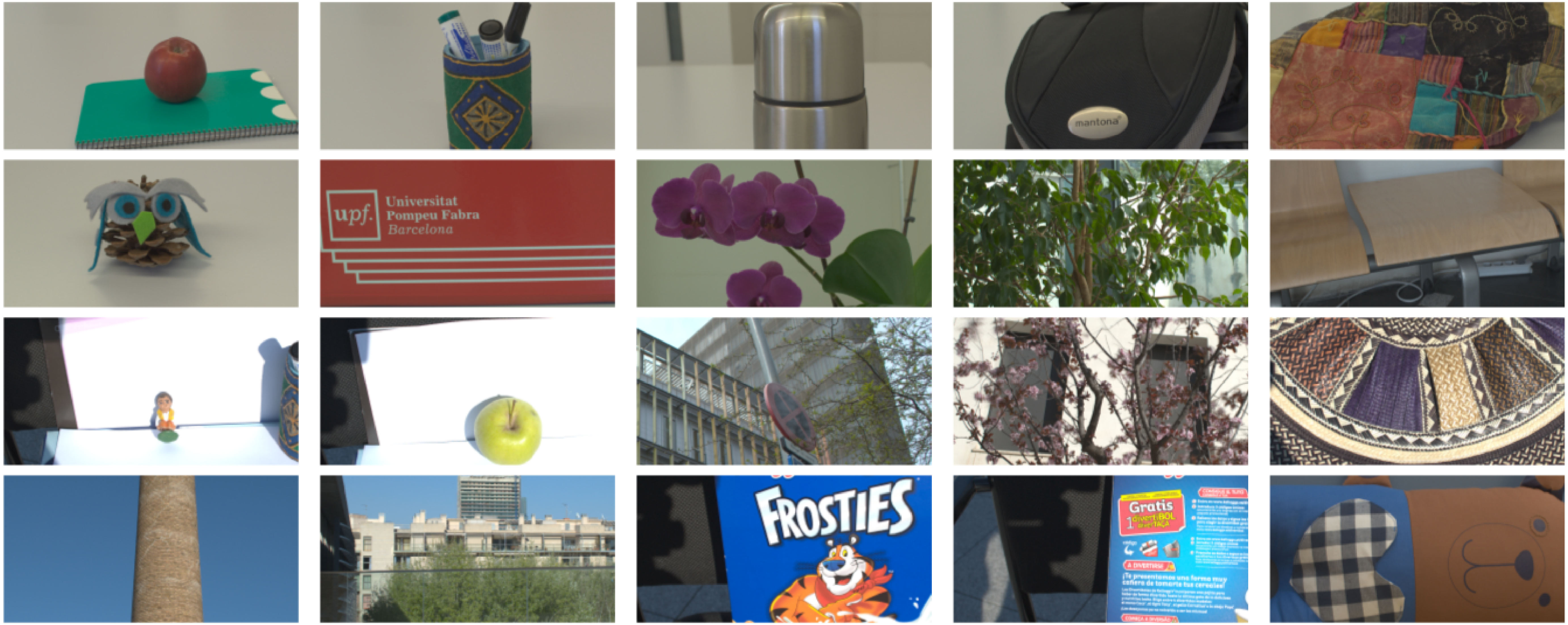
$$I_0 = \text{Anscombe}(\ I_{DRAW}\ )$$
$$I_1 = \text{VTV}(\ I_0\ )$$
$$I_2 = \text{Anscombe}^{-1}(\ I_{DRAW}\ )$$
$$I_d = (1\text{-}a)\ I_{DRAW} + a\ I_2$$

RAW + Image Dependent Noise	White Balance	Demosaicking	Color Correction	Gamma Correction	Quantization	Output


RAW
+
Image
Dependent
Noise
White
Balance
Demosaicking
Color
Correction
Gamma
Correction
Quantization
Output
=
Denoising
result
AVTVE


RAW
+
Image
Dependent
Noise
White
Balance
Demosaicking
Color
Correction
Gamma
Correction
Quantization
Output
Non-local
method
Denoising result

RAW No noise	White Balance	Demosaicking	Color Correction	Gamma Correction	Quantization	Output = Clean Ground Truth


mantona
upf.
Universitat
Pompeu Fabra
Barcelona
FROSTIES
Gratis

Original image

ISO 100

ISO 400

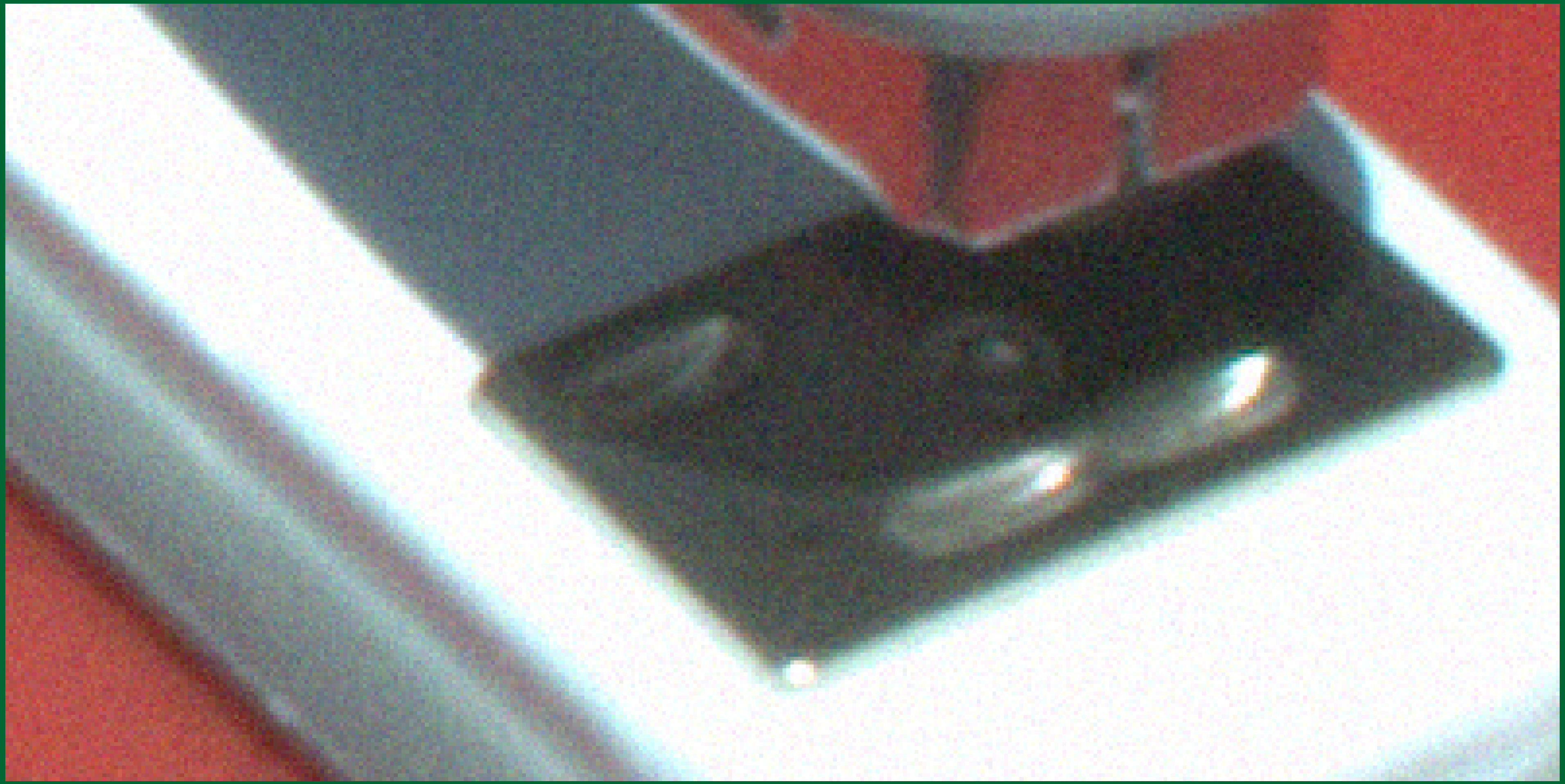
ISO 800

ISO 1600

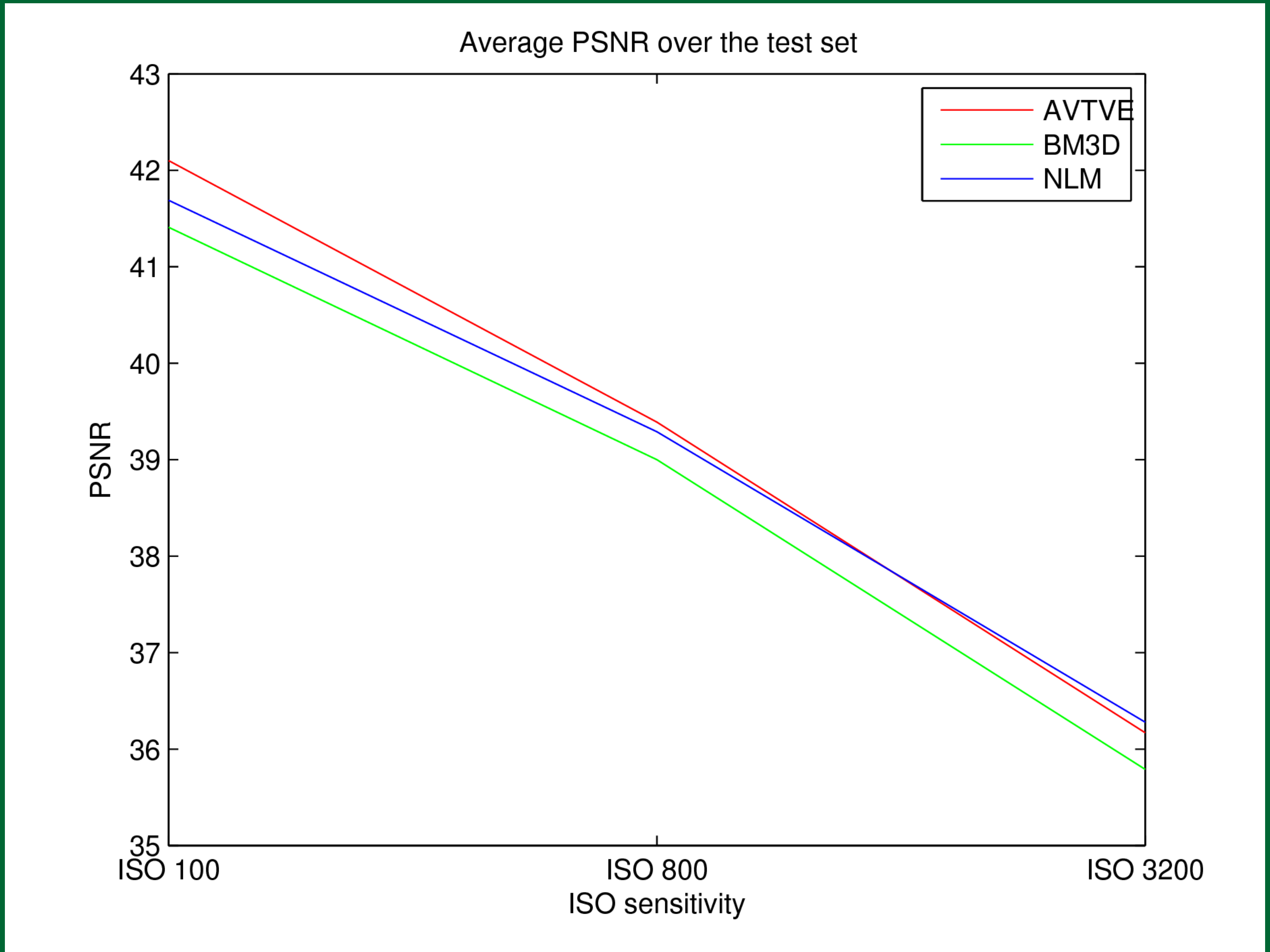
ISO 3200

Actual noisy image

Emulated with our model
(clean original + signal-dependent noise at RAW level)



Emulated adding Gaussian noise
to clean original


Average PSNR over the test set
AVTVE
BM3D
NLM
PSNR
43
42
41
40
39
38
37
36
35
ISO 100
ISO 800
ISO 3200
ISO sensitivity

Additive White Gaussian noise model:
TV-based (at output) < NLM < BM3D

Realistic noise model:
TV-based (at RAW) > NLM > BM3D

How to improve your denoising result
without changing your denoising algorithm:

3. Optimize parameters according to visual appearance, not PSNR (or SSIM)

LOCAL DENOISING BASED ON CURVATURE SMOOTHING CAN VISUALLY OUTPERFORM NON-LOCAL METHODS ON PHOTOGRAPHS WITH ACTUAL NOISE

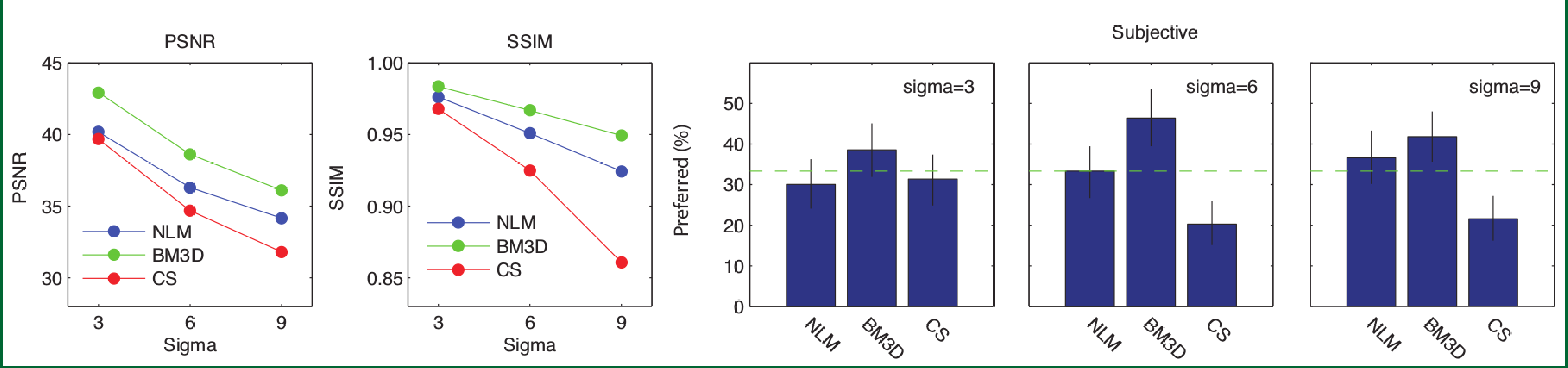
Gabriela Ghimpeteanu⋆*, David Kane*⋆*, Thomas Batard*⋆*, Stacey Levine*† *and Marcelo Bertalmío*⋆

Published in Proc. IEEE-ICIP (2016)

Proposed local denoising method: CS (curvature smoothing)

$$I^{n+1} = I^n + \Delta t \left[\nabla^- \cdot \left(\frac{\nabla^+ I^n}{\sqrt{\|\nabla^+ I^n\|^2 + \epsilon_1}} \right) - \kappa_{\epsilon_2}(I_0) \right]$$

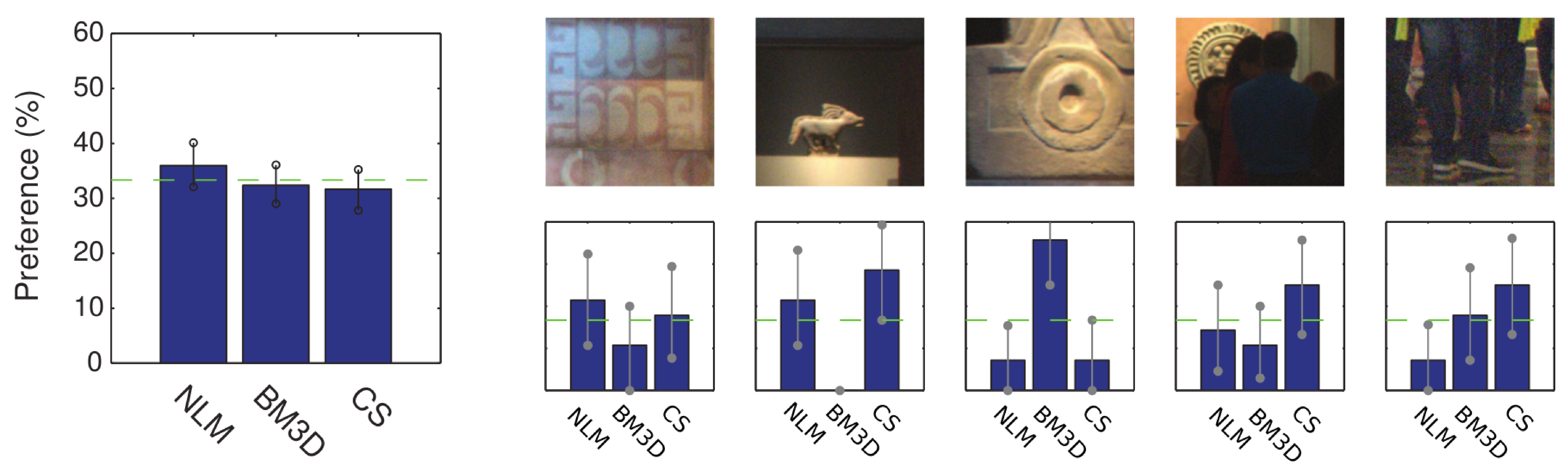
Experiment 1: AWG noise



PSNR
45
40
35
30
PSNR
NLM
BM3D
CS
3
6
9
Sigma
SSIM
1.00
0.95
0.90
0.85
SSIM
NLM
BM3D
CS
3
6
9
Sigma
Subjective
Preferred (%)
50
40
30
20
10
0
sigma=3
sigma=6
sigma=9
NLM
BM3D
CS
NLM
BM3D
CS
NLM
BM3D
CS


Subjective
100
50
0
Preferred (%)
NLM
BM3D
CS
Metrics
1.00
0.95
0.90
SSIM
50
45
40
PSNR
NLM
BM3D
CS
Original
NLM
BM3D
CS

Experiment 2: Real pictures with actual noise



Preference (%)
60
50
40
30
20
10
0
NLM
BM3D
CS

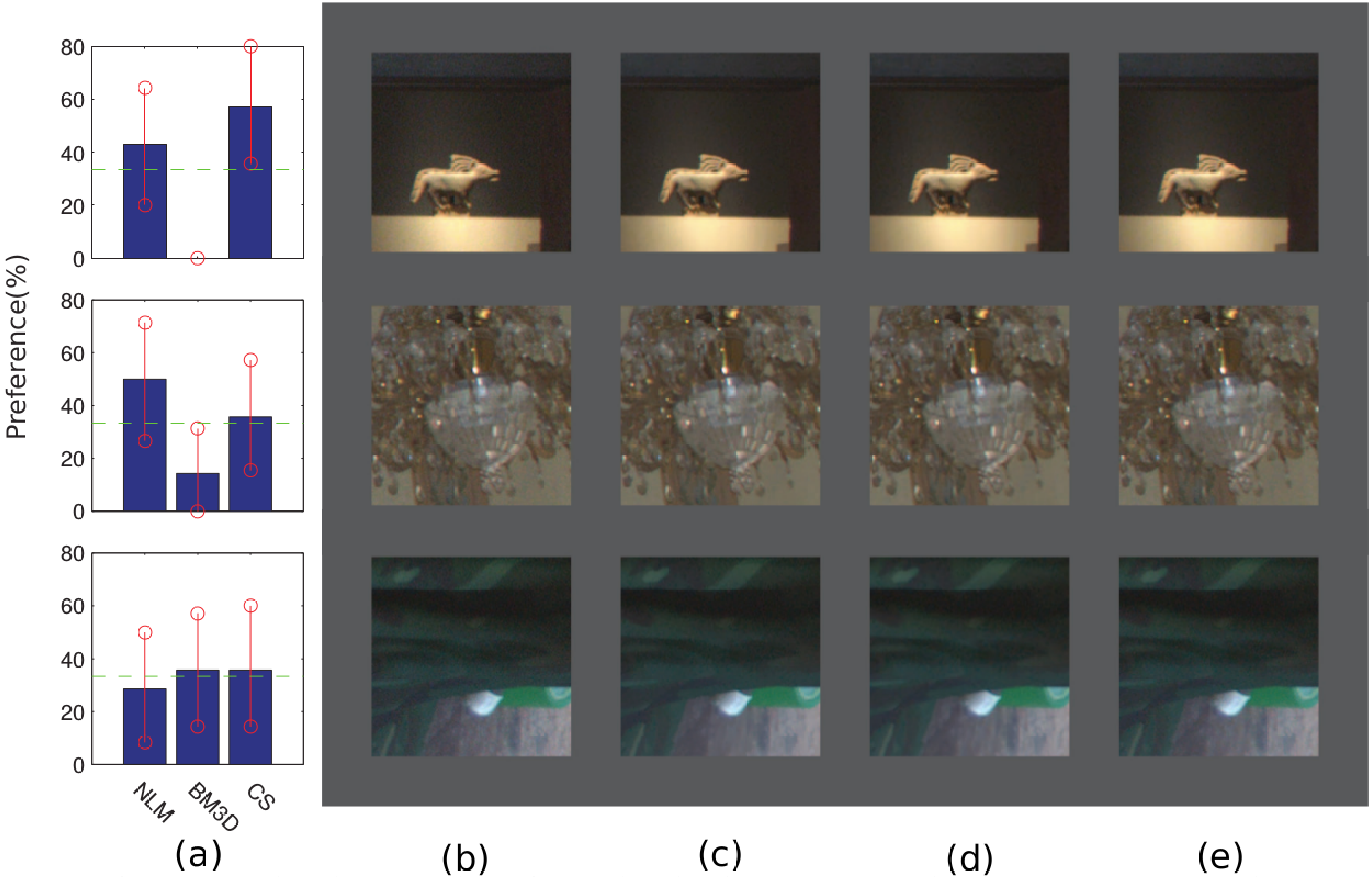


Fig. 5: (a) User preferences. Visual comparison for real-noise images: (b) noisy image, (c) NLM, (d) BM3D and (e) CS.

AWG noise: PSNR+SSIM consistent with subjective results on average, not image by image

Real noise: PSNR+SSIM not consistent with subjective results, neither on average nor image by image

Conclusion

How to improve your denoising result
without changing your denoising algorithm:

1. Apply denoising algorithm to <u>transform</u> of image, not to image itself

How to improve your denoising result
without changing your denoising algorithm:

2. Ensure the image follows noise model assumed by denoising algorithm

How to improve your denoising result
without changing your denoising algorithm:

3. Optimize parameters according to visual appearance, not PSNR (or SSIM)

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erc
European Research Council
Established by the European Commission

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Thank you

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