Image Denoising and Its Applications

2010.4.22 @ NIMS

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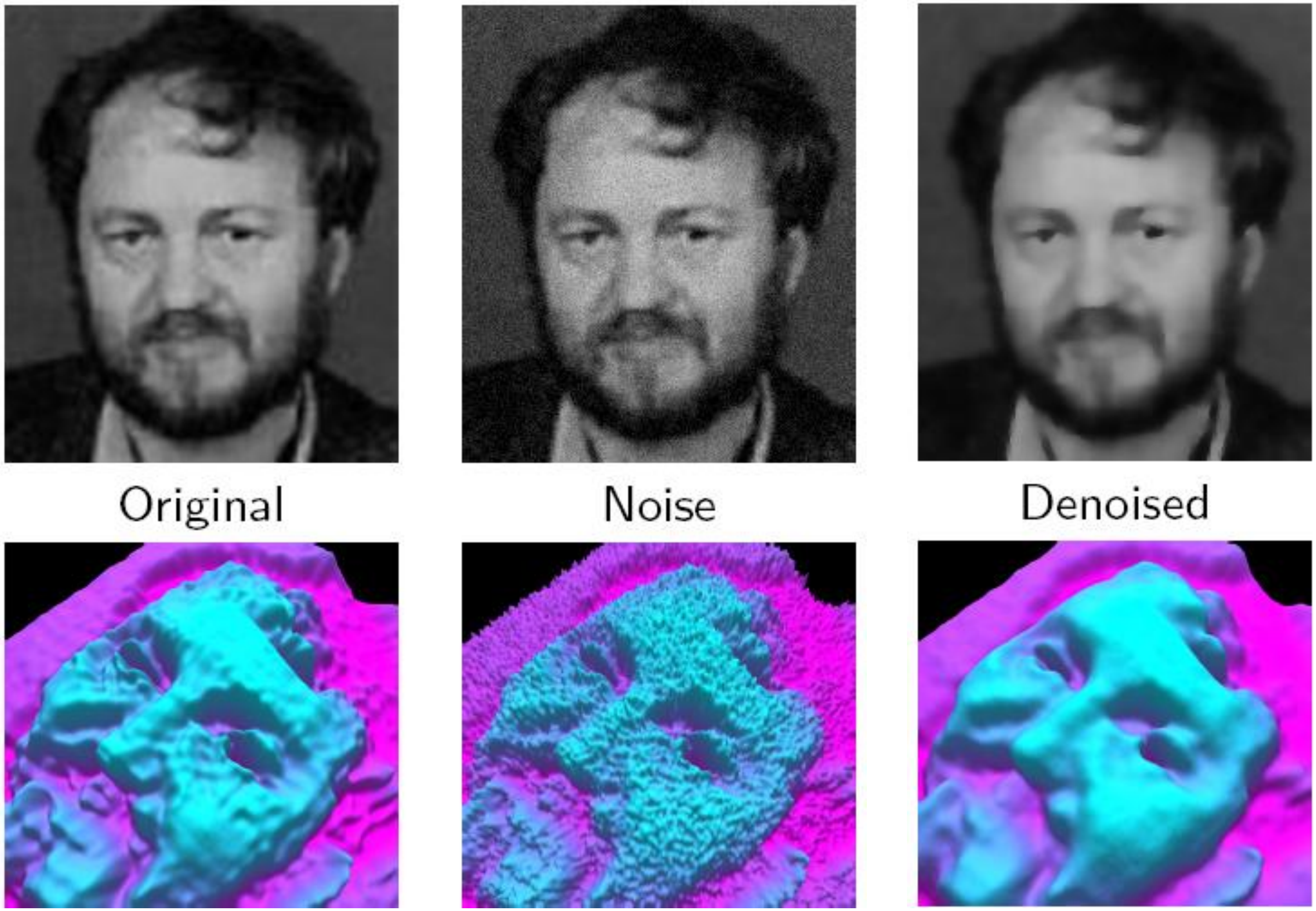
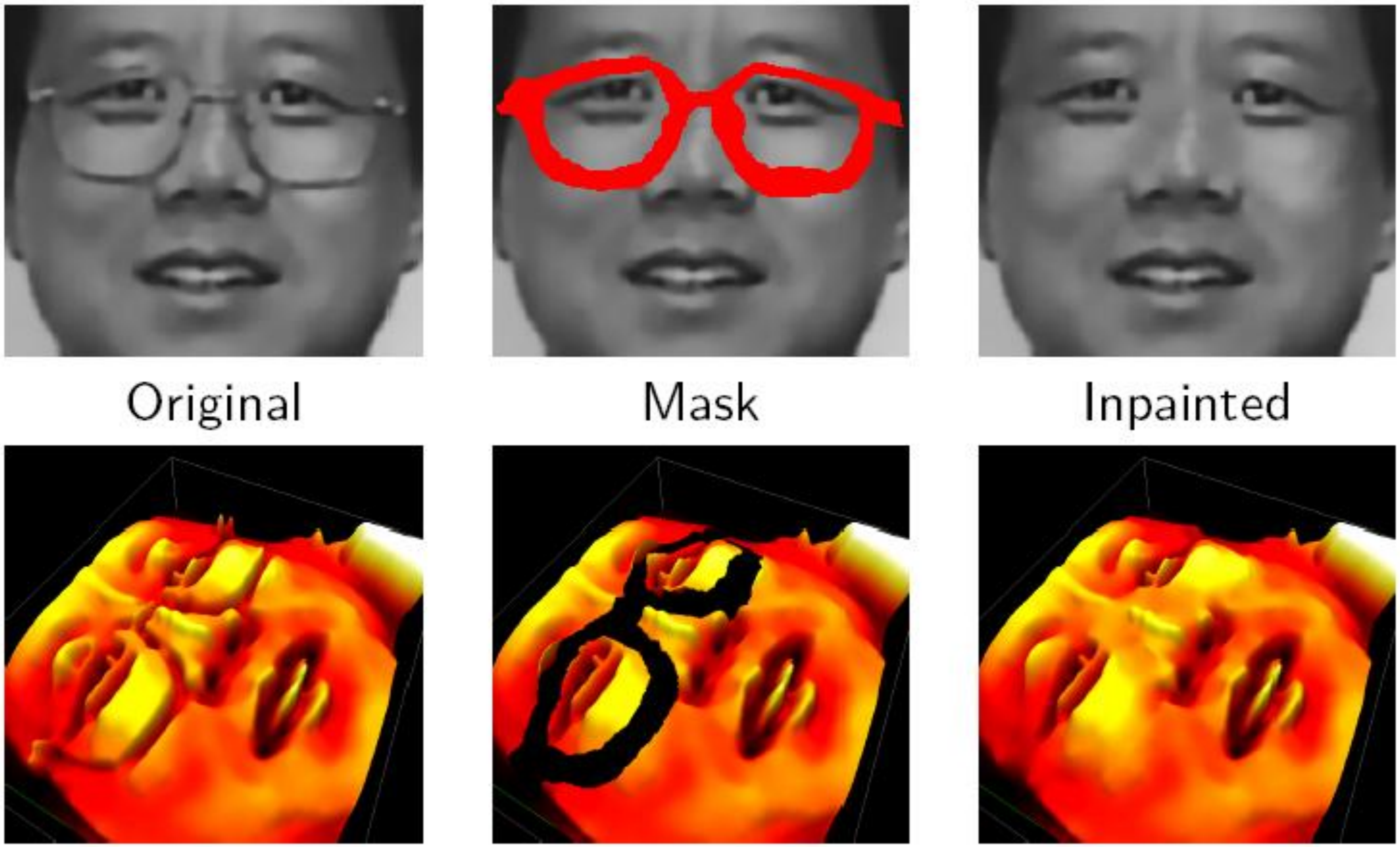
Denoising



Orientation-Matching Minimization with the TV-Stokes Equation, Jooyoung Hahn, Tai, Boroky, and Bruckstein

Inpainting



Orientation-Matching Minimization with the TV-Stokes Equation, Jooyoung Hahn, Tai, Boroky, and Bruckstein

Rudin-Osher-Fatemi(TV)

- for a given noisy image I^*

$$\text{true image } I : \Omega \subset R^2 \rightarrow [0,1], \text{ gaussian white noise } \eta$$

$$I^*(p) = I(p) + \eta(p), \; p = (x, y) \in \Omega$$

L.I. Rudin, S. Osher, and E. Fatemi, "Nonlinear total variation based noise removal algorithms," *Physica D, Vol. 60, pp. 259–268*, 1992.

Rudin-Osher-Fatemi(TV)

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$$I^*(p) = I(p) + \eta(p),\ p = (x, y) \in \Omega$$

$$\min_I \int_\Omega |\nabla I|\, dp \text{ subject to } \int_\Omega |I - I^*|^2\, dp = \sigma^2$$

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Rudin-Osher-Fatemi(TV)

- for a given noisy image I^*

$$\text{true image } I:\Omega\subset R^2\to[0,1],\ \text{gaussian white noise } \eta$$

$$I^*(p)=I(p)+\eta(p),\ p=(x,y)\in\Omega$$

$$\min_I \int_\Omega |\nabla I|\,dp \text{ subject to } \int_\Omega |I-I^*|^2\,dp=\sigma^2$$

$$\nabla f=\left\langle \frac{\partial f}{\partial x},\frac{\partial f}{\partial y}\right\rangle \begin{bmatrix}-1 & 0 & 1\\ -2 & 0 & 2\\ -1 & 0 & 1\end{bmatrix}\begin{bmatrix}1 & 2 & 1\\ 0 & 0 & 0\\ -1 & -2 & -1\end{bmatrix}$$

L.I. Rudin, S. Osher, and E. Fatemi, "Nonlinear total variation based noise removal algorithms," *Physica D, Vol. 60, pp. 259–268*, 1992.

Rudin-Osher-Fatemi(TV)

- using Lagrange multiplier

$$\min_I \int_\Omega |\nabla I| + \frac{\lambda}{2}\int_\Omega |I - I^*|^2$$

$$-\nabla \cdot \left(\frac{\nabla I}{|\nabla I|} \right) + \lambda (I - I^*) = 0$$

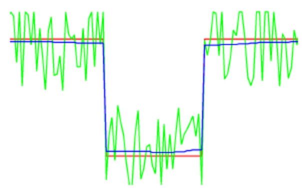
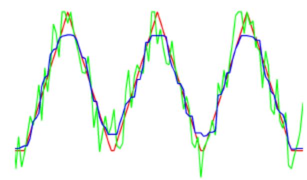
$$I_t = \nabla \cdot \left(\frac{\nabla I}{|\nabla I|} \right) - \lambda (I - I^*),\ I^0 = I^*$$

$$\frac{I^{n+1} - I^n}{\Delta t} = \nabla \cdot \left(\frac{\nabla I^n}{|\nabla I^n|} \right) - \lambda (I^n - I^0),\ I^0 = I^*$$

Rudin-Osher-Fatemi(TV)

- Property

$$\min_{I} \int_{\Omega} |\nabla I| + \frac{\lambda}{2} \int_{\Omega} |I - I^*|^2$$

- preserve locations of discontinuities of data
- dislocate locations of discontinuities of data gradient

Lysaker-Lundervold-Tai

- using fourth-order partial differential equation

$$\min_I \int_\Omega (\nabla(\partial_1 I)\cdot\nabla(\partial_1 I)+\nabla(\partial_2 I)\cdot\nabla(\partial_2 I))^{\frac{1}{2}} + \frac{\lambda}{2}\int_\Omega \left|I - I^*\right|^2$$

M. Lysaker, A. Lundervold, and X.-C. Tai. Noise Removal Using Fourth-Order Partial Differential Equation with Applications to Medical Magnetic Resonance Images in Space and Time. IEEE Transactions on Image Processing, 12(12):1579–1590, 2003.

Lysaker-Osher-Tai

- using smoothed normals

$$\min_{|n|=1} \int_\Omega |\nabla n| + \frac{\lambda}{2}\int_\Omega |n - n^*|^2 \quad n^* = \frac{\nabla I^*}{|\nabla I^*|}$$

$$\min_I \int_\Omega (|\nabla I| - \nabla I \cdot n) + \frac{\xi}{2}\int_\Omega |I - I^*|^2$$

Lysaker, M., Osher, S., Tai, X.C.: Noise removal using smoothed normals and surface fitting. IEEE Trans. Image Processing 13(10) (2004) 1345–1357

Tai-Osher-Holm (TV-Stokes)

- incompressibility condition

  For a given image I, the tangential vectors to the level curves of the image satisfies the incompressibility condition.

$$t = \nabla^{\perp} I = (\partial_2 I, -\partial_1 I)^t \Rightarrow \nabla \cdot t = 0$$

$$\min_{\nabla \cdot t = 0} \int_{\Omega} |\nabla t| + \frac{\eta}{2} \int_{\Omega \setminus R} |t - t^*|^2, t^* = n^{*\perp}, n = \nabla I$$

$$\min_{I} \int_{\Omega} (|\nabla I| - \nabla I \cdot \frac{n}{|n|}) + \frac{\xi}{2} \int_{\Omega \setminus R} |I - I^*|^2$$

S. Osher X.-C. Tai and R. Holm. Image Inpainting using a TV-Stokes Equation. "Image Processing based on partial differential equations" Tai, Lie, Chan and Osher eds; Springer., pages 3–22, 2007.

Image Denoising

$$\min_{I} \int_{\Omega} |\nabla I| + \frac{\lambda}{2} \int_{\Omega} |I - I^{*}|^{2}$$

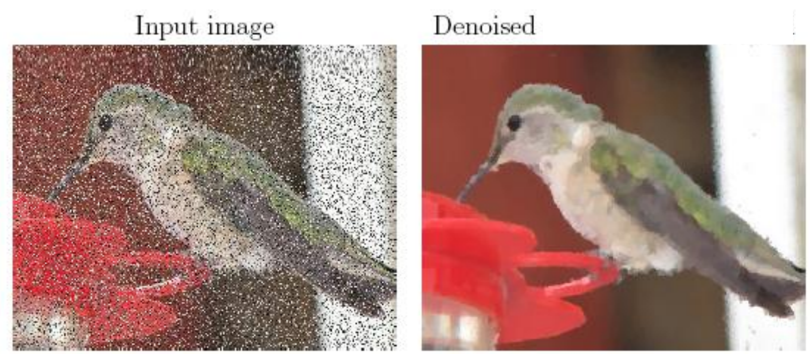
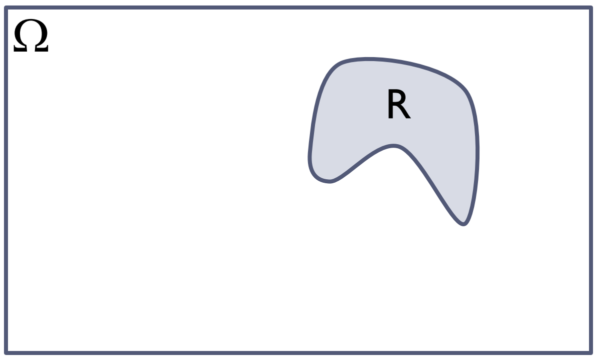


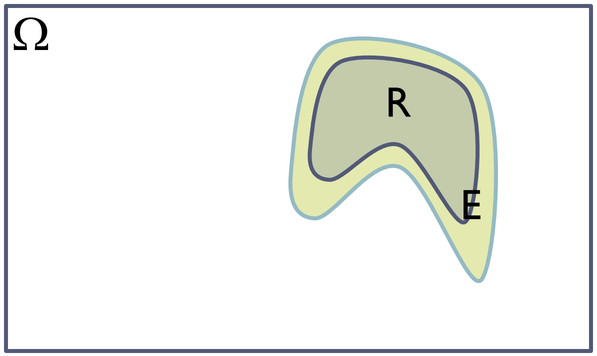
Image Denoising & Inpainting



R : Inpainting Domain

$$\min_I \int_\Omega |\nabla I| + \frac{\lambda}{2} \int_{\Omega \setminus R} |I - I^*|^2$$

Image Inpainting



R : Inpainting Domain
E : Extended Inpainting Domain

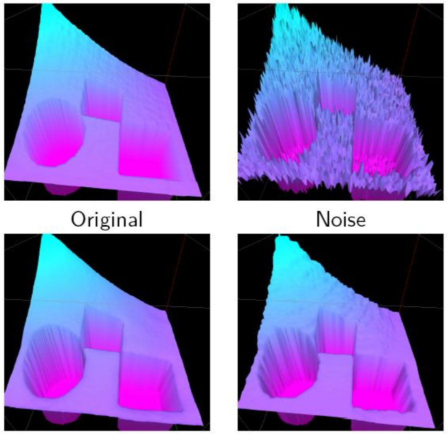
$$\min_{I} \int_{E} |\nabla I| + \frac{\lambda}{2} \int_{E \backslash R} |I - I^{*}|^{2}$$

Image Inpainting

Original Mask TV

Tai-Borok-Hahn (Orientation-Matching)

- incompressibility condition



$$t = \nabla^{\perp} I = (\partial_2 I, -\partial_1 I)^t \Rightarrow \nabla \cdot t = 0$$

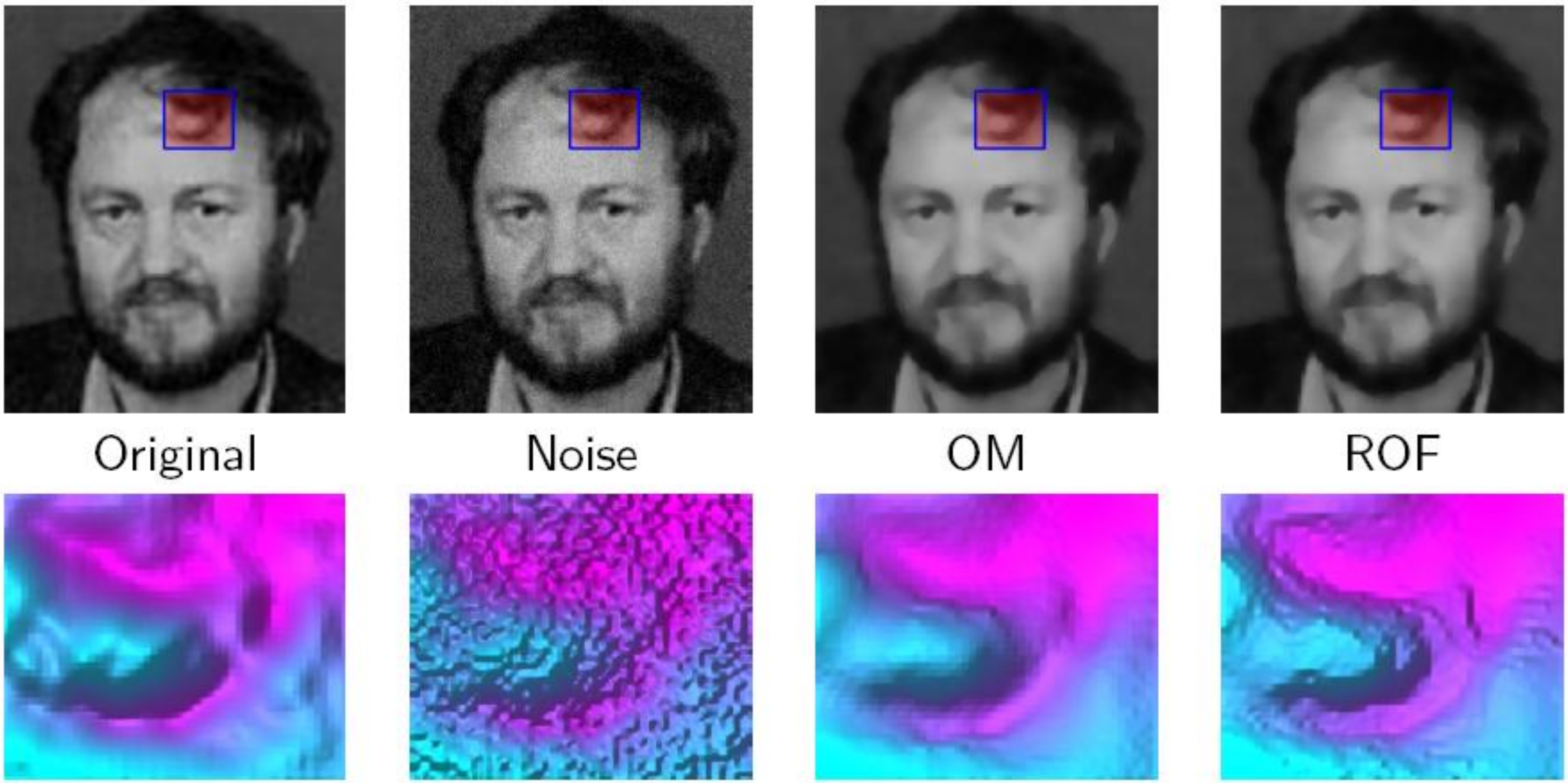
$$\min_{\nabla \cdot t = 0} \int_{\Omega} |\nabla t| + \frac{\eta}{2} \int_{\Omega \setminus R} |t - t^*|^2, t^* = n^{*\perp}$$

$$\min_{I} \int_{\Omega} (-\mu_1 \left| \frac{\nabla I \cdot n}{|\nabla I||n|} \right| + \mu_2 |\nabla I - n|) + \frac{\xi}{2} \int_{\Omega \setminus R} |I - I^*|^2$$

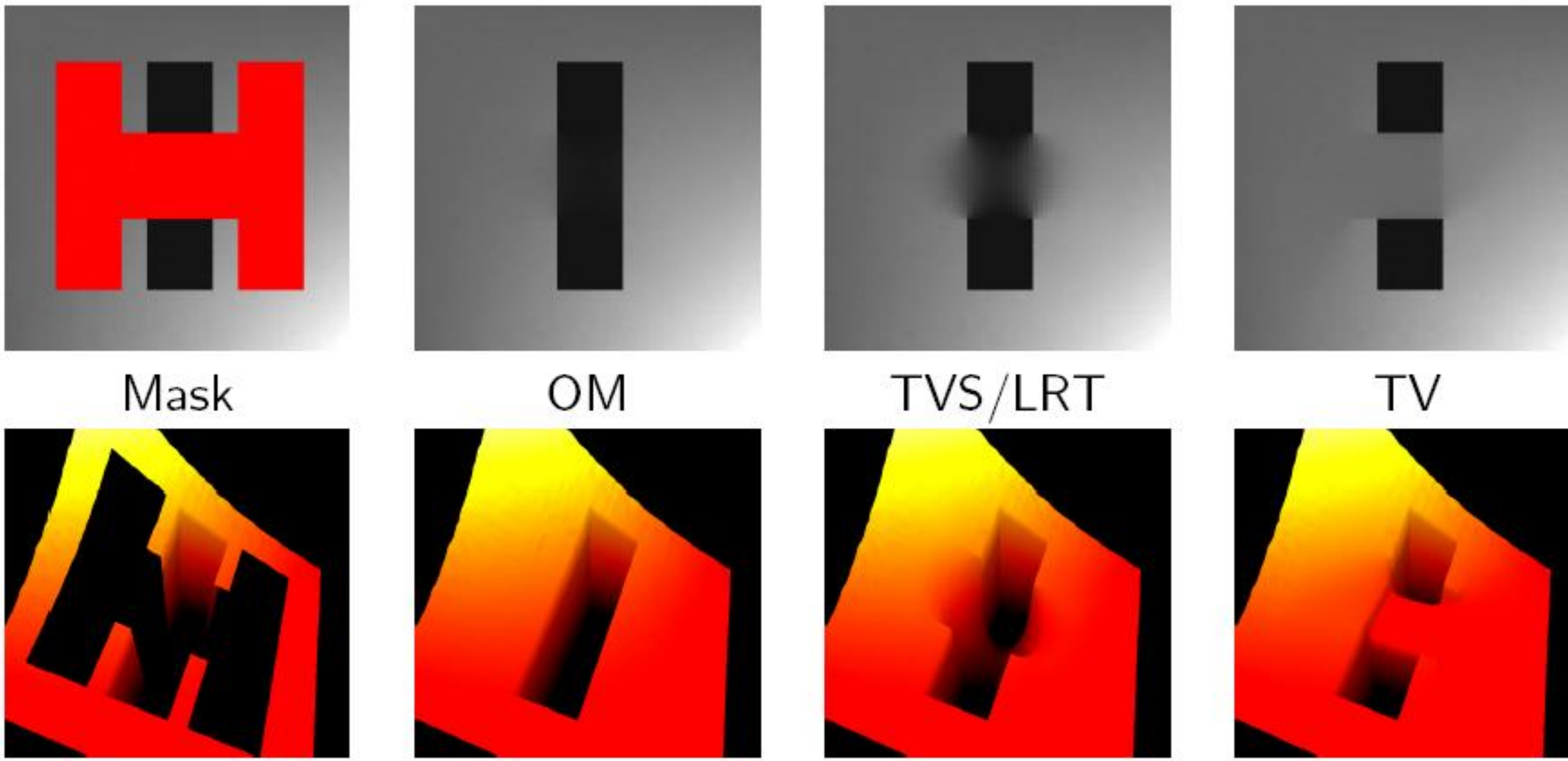
Image Denoising : $\mu_1 = 1, \mu_2 = 0,$ and $R = \phi$

Image Inpainting : $\mu_1 = \mu, \mu_2 = 1,$ and $\phi \neq R \subset \Omega$

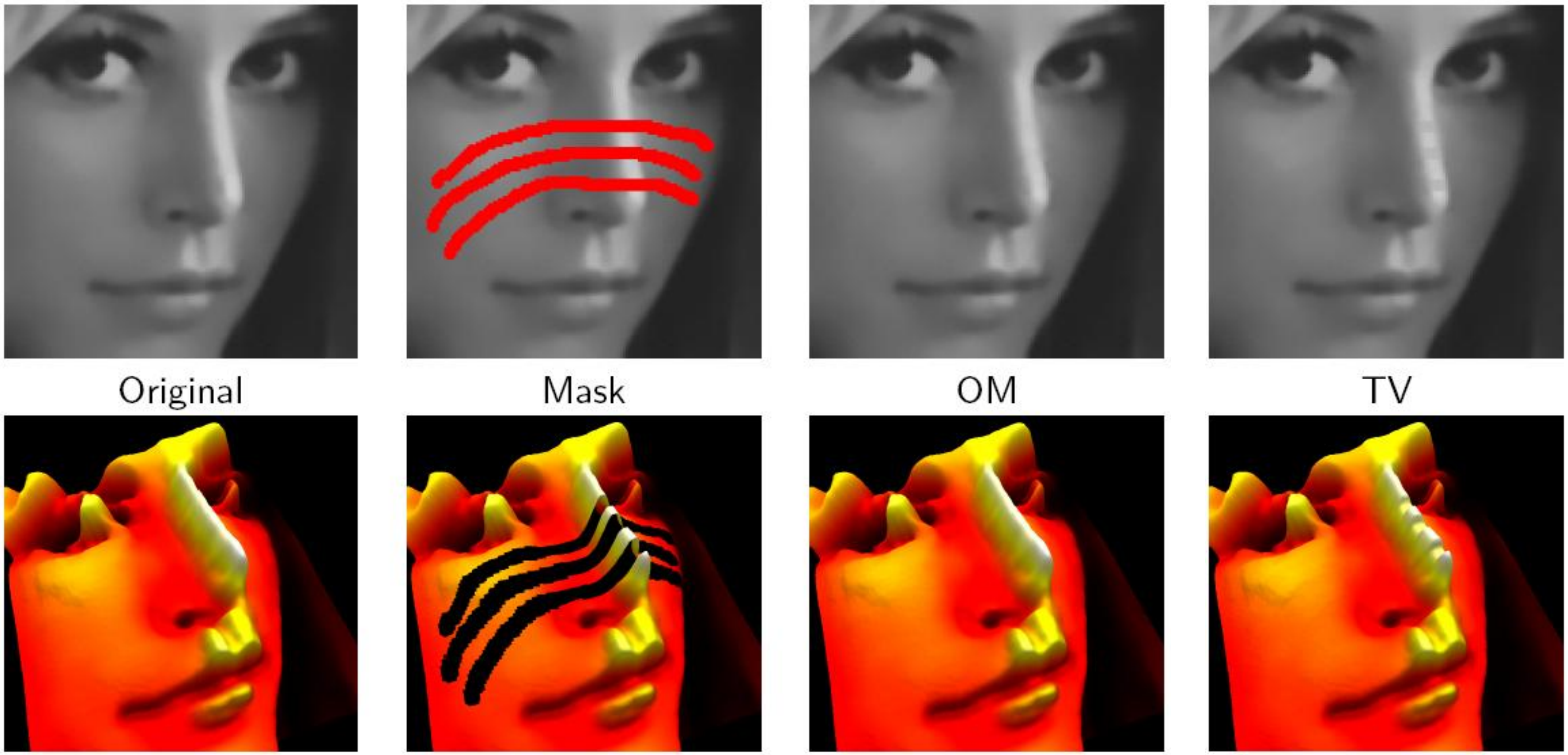
Xue-Cheng Tai1, Sofia Borok, and Jooyoung Hahn, Image denoising using TV-Stokes equation with an orientation-matching minimization, 2009



Orientation-Matching Minimization with the TV-Stokes Equation, Jooyoung Hahn, Tai, Boroky, and Bruckstein

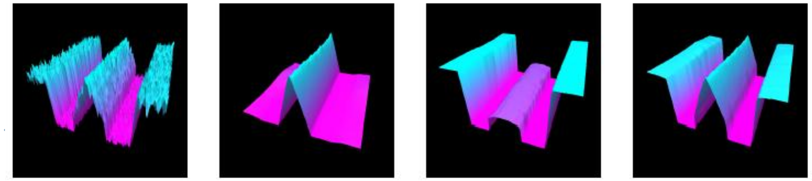


Orientation-Matching Minimization with the TV-Stokes Equation, Jooyoung Hahn, Tai, Boroky, and Bruckstein



Orientation-Matching Minimization with the TV-Stokes Equation, Jooyoung Hahn, Tai, Boroky, and Bruckstein

Litvinov-Raham-Tai



noise　　g　　f　　$I = f + g$

- there exist an image g such that $\nabla g = n$

$$\min_I \int_\Omega |\nabla I - n| + \frac{\xi}{2}\int_\Omega |I - I^*|^2$$

$$= \min_I \int_\Omega |\nabla I - \nabla g| + \frac{\xi}{2}\int_\Omega |(I-g)-(I^*-g)|^2$$

$$= \min_f \int_\Omega |\nabla f| + \frac{\xi}{2}\int_\Omega |f - f^*|^2 \text{ where } f^* = I^* - g$$

- the image f preserves discontinuities of images as the ROF model does
- the image g preserves discontinuities of image gradient and recovers smooth features of image surfaces as LLT model does

Algorithm for Image Denoising

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tvreg by getreuer@gmail.com

- variational imaging methods for denoising, deconvolution, inpainting, and segmentation

$$\min_{u} \int_{\Omega} |\nabla u(x)| dx + \lambda \int_{\Omega \setminus D} F(Ku(x), f(x)) dx$$

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- variational imaging methods for denoising, deconvolution, inpainting, and segmentation

$$\min_u \int_\Omega |\nabla u(x)| dx + \lambda \int_{\Omega \backslash D} F(Ku(x), f(x)) dx$$

- Denoising $f = u + \eta$ (η:Gaussian noise) $D=\phi$
- Deblurring $f = Ku + \eta$ (K:blur operator) $D=\phi$
- Inpainting $f = u + \eta$ (η:Gaussian noise) $D \neq \phi$

$$F(Ku(x), f(x)) = \begin{cases} (Ku(x) - f(x))^2 / 2 \text{ Gaussian noise} \\ |Ku(x) - f(x)| \text{ Laplacian noise} \end{cases}$$

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- solution with split bregman

$$\min_{\vec{d},z,u} \int_\Omega \left|\vec{d}(x)\right| dx + \lambda \int_{\Omega\setminus D} F(z(x), f(x))dx$$

$$\text{subject to } \vec{d} = \nabla u, z = Ku$$

$$\min_{\vec{d},z,u} \int_\Omega \left|\vec{d}\right| dx + \lambda \int_{\Omega\setminus D} F(z, f)dx$$

$$+\frac{\gamma_1}{2}\left\|\vec{d} - \nabla u - \vec{b}_1\right\|_2^2 + \frac{\gamma_2}{2}\left\|z - Ku - b_2\right\|_2^2$$

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- d subproblem with z and u fixed

$$\min_{\vec{d}} \int_\Omega \left|\vec{d}\right| dx + \frac{\gamma_1}{2}\left\|\vec{d} - \nabla u - \vec{b}_1\right\|_2^2$$

$$\vec{d}(x) = \frac{\nabla u(x) - \vec{b}_1(x)}{\left|\nabla u(x) - \vec{b}_1(x)\right|} \max\{\left|\nabla u(x) + \vec{b}_1(x)\right| - \frac{1}{\gamma_1}, 0\}$$

Amir Beck and Marc Teboulle, A Fast Iterative Shrinkage-Thresholding Algorithm for Linear Inverse Problems, SIAM J. IMAGING SCIENCES, Vol. 2, No. 1, pp. 183–202, 2009

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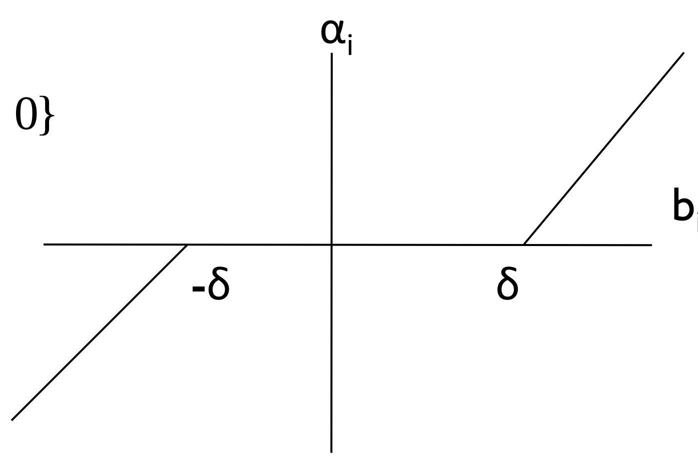
- given by soft thresholding

$$\vec{\alpha}^{opt} = \arg\min_{\vec{\alpha}} \left\|\vec{\alpha}\right\|_1 + \lambda\left\|\vec{\alpha} - \vec{b}\right\|_2^2$$

$$\alpha_i^{opt} = \text{soft\_threshold}(b_i,\ \delta)$$
$$= sign(b_i)\max\{|b_i| - \delta,\ 0\}$$



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- z subproblem with d and u fixed

$$\min_z \lambda \int_{\Omega \setminus D} F(z, f)dx + \frac{\gamma_2}{2}\|z - Ku - b_2\|_2^2$$

$$\lambda \partial_z F(z, f) + \gamma_2 (z - Ku - b_2) = 0$$

- for Gaussian noise

$$z(x) = \frac{Ku(x) + b_2(x) + \lambda / \gamma_2 f(x)}{1 + \lambda / \gamma_2} \text{ for } x \in \Omega \setminus D$$

- for Laplacian noise

$$z(x) = f(x) + \frac{s(x)}{|s(x)|} \max\{|s(x)| - \frac{\lambda}{\gamma_2}, 0\}, s = Ku - f + b_2 \text{ for } x \in \Omega \setminus D$$

- for Poisson model

$$z(x) = s(x)/2 + \sqrt{(s(x)/2)^2 + \frac{\lambda}{\gamma_2} f(x)}, s = Ku - \frac{\lambda}{\gamma_2} + b_2 \text{ for } x \in \Omega \setminus D$$

- inpainting domain D

$$z(x) = Ku(x) + b_2(x) \text{ for } x \in D$$

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- u subproblem with d and z fixed

$$\min_u \frac{\gamma_1}{2}\left\|\nabla u - \vec{d} + \vec{b}_1\right\|_2^2 + \frac{\gamma_2}{2}\left\|Ku - z + b_2\right\|_2^2$$

- For denoising and inpainting, K is identity

$$\frac{\gamma_2}{\gamma_1}u - \Delta u = \frac{\gamma_2}{\gamma_1}(z - b_2) - div(\vec{d} - \vec{b}_1)$$

- For general K

$$(\frac{\gamma_2}{\gamma_1}K^*K - \Delta)u = \frac{\gamma_2}{\gamma_1}K^*(z - b_2) - div(\vec{d} - \vec{b}_1) \text{ where } K^* \text{ is the adjoint of } K$$

Amir Beck and Marc Teboulle, A Fast Iterative Shrinkage-Thresholding Algorithm for Linear Inverse Problems, SIAM J. IMAGING SCIENCES, Vol. 2, No. 1, pp. 183–202, 2009

Regularization & Linear Programming

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$Y_k : m \times n$ *low resolution gray image*
$\underline{Y_k} : mn \times 1$ *gray image with lexicographic order*
$\underline{Y_k} = vec(Y_k)$

$H : (2p+1)\times(2p+1)$ *gaussian blur mask*

$$H = \begin{bmatrix} h_{1-1} & h_{01} & h_{02} \\ h_{10} & h_{11} & h_{12} \\ h_{20} & h_{21} & h_{11} \end{bmatrix}$$

$$\begin{bmatrix} 0.0751 & 0.1238 & 0.0751 \\ 0.1238 & 0.2042 & 0.1238 \\ 0.0751 & 0.1238 & 0.0751 \end{bmatrix}$$

3x3 Gaussian blur mask

$\mathbf{H} : r^2mn \times r^2mn$ *gaussian blur matrix*
$vec(H * X) = \mathbf{H}\,\underline{X}$

$$\begin{bmatrix} g_{11} \\ g_{21} \\ g_{31} \\ g_{41} \\ g_{12} \\ g_{22} \\ g_{32} \\ g_{42} \\ g_{13} \\ g_{23} \\ g_{33} \\ g_{43} \\ g_{14} \\ g_{24} \\ g_{34} \\ g_{44} \end{bmatrix} = \left[\begin{array}{cccc|cccc|cccc|cccc}
k_{22}&k_{12}&&&k_{21}&k_{11}&&&&&&&&&& \\
k_{32}&k_{22}&k_{12}&&k_{31}&k_{21}&k_{11}&&&&&&&&& \\
&k_{32}&k_{22}&k_{12}&&k_{31}&k_{21}&k_{11}&&&&&&&& \\
&&k_{32}&k_{22}&&&k_{31}&k_{21}&&&&&&&& \\ \hline
k_{23}&k_{13}&&&k_{22}&k_{12}&&&k_{21}&k_{11}&&&&&& \\
k_{33}&k_{23}&k_{13}&&k_{32}&k_{22}&k_{12}&&k_{31}&k_{21}&k_{11}&&&&& \\
&k_{33}&k_{23}&k_{13}&&k_{32}&k_{22}&k_{12}&&k_{31}&k_{21}&k_{11}&&&& \\
&&k_{33}&k_{23}&&&k_{32}&k_{22}&&&k_{31}&k_{21}&&&& \\ \hline
&&&&k_{23}&k_{13}&&&k_{22}&k_{12}&&&k_{21}&k_{11}&& \\
&&&&k_{33}&k_{23}&k_{13}&&k_{32}&k_{22}&k_{12}&&k_{31}&k_{21}&k_{11}& \\
&&&&&k_{33}&k_{23}&k_{13}&&k_{32}&k_{22}&k_{12}&&k_{31}&k_{21}&k_{11} \\
&&&&&&k_{33}&k_{23}&&&k_{32}&k_{22}&&&k_{31}&k_{21} \\ \hline
&&&&&&&&k_{23}&k_{13}&&&k_{22}&k_{12}&& \\
&&&&&&&&k_{33}&k_{23}&k_{13}&&k_{32}&k_{22}&k_{12}& \\
&&&&&&&&&k_{33}&k_{23}&k_{13}&&k_{32}&k_{22}&k_{12} \\
&&&&&&&&&&k_{33}&k_{23}&&&k_{32}&k_{22}
\end{array}\right] \begin{bmatrix} f_{11} \\ f_{21} \\ f_{31} \\ f_{41} \\ f_{12} \\ f_{22} \\ f_{32} \\ f_{42} \\ f_{13} \\ f_{23} \\ f_{33} \\ f_{43} \\ f_{14} \\ f_{24} \\ f_{34} \\ f_{44} \end{bmatrix}$$

Gradient Operator $\nabla f = \left\langle \frac{\partial f}{\partial x}, \frac{\partial f}{\partial y} \right\rangle$ $\begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix}$ $\begin{bmatrix} 1 & 0 & -1 \\ 2 & 0 & -2 \\ 1 & 0 & -1 \end{bmatrix}$

horizontal and vertical derivative mask

Laplace Operator $\Delta f = \nabla^2 f = \nabla \cdot \nabla f = \frac{\partial^2 f}{\partial x^2} + \frac{\partial^2 f}{\partial y^2}$ $\begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix}$ $\begin{bmatrix} 1 & 1 & 1 \\ 1 & -8 & 1 \\ 1 & 1 & 1 \end{bmatrix}$

3x3 Laplacian mask

$$(H * X)(i,j) = \sum_{k=-p}^{p} \sum_{l=-p}^{p} h_{k,l} X(i-k, j-l)$$

$$\begin{aligned}(H * X)(i,j) = {} & h_{-1,-1}X(i+1,j+1) + h_{-1,0}X(i+1,j) + h_{-1,1}X(i+1,j-1) \\ & + h_{0,-1}X(i,j+1) + h_{0,0}X(i,j) + h_{0,1}X(i,j-1) \\ & + h_{1,-1}X(i-1,j+1) + h_{1,0}X(i-1,j) + h_{1,1}X(i-1,j-1)\end{aligned}$$

$$\mathbf{H}(irn + j, (i+k)rn + j + l) = h_{k,-l},\ i = 0,\cdots,rm,\ j = 0,\cdots,rn,\ k,l = -p,\cdots,p$$

Tikhonov cost function $\Upsilon_T(X) = \|\Gamma * X\|_2^2$

where Γ is usually a highpass operator such as derivative, Laplacian, or even identity matrix

$$\Gamma = I \qquad \Upsilon_T(X) = \|I * X\|_2^2 = \underline{X}^t \mathbf{I}^t \mathbf{I} \underline{X}$$

$$\Gamma = L = \begin{bmatrix} 1 & 1 & 1 \\ 1 & -8 & 1 \\ 1 & 1 & 1 \end{bmatrix} \qquad \Upsilon_T(X) = \|L * X\|_2^2 = \underline{X}^t \mathbf{L}^t \mathbf{L} \underline{X}$$

Laplace Operator $\Delta f = \nabla^2 f = \nabla \cdot \nabla f = \dfrac{\partial^2 f}{\partial x^2} + \dfrac{\partial^2 f}{\partial y^2}$

$$\begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix} \quad \begin{bmatrix} 1 & 1 & 1 \\ 1 & -8 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$

3x3 Laplacian mask

$$G_k = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & \\ -1 & -2 & -1 \end{bmatrix} \quad G_v = \begin{bmatrix} 1 & 0 & -1 \\ 2 & 0 & -2 \\ 1 & 0 & -1 \end{bmatrix} \qquad \Upsilon_T(X) = \|G_k * X\|_2^2 + \|G_v * X\|_2^2 = \underline{X}^t (\mathbf{G}_k^t \mathbf{G}_k + \mathbf{G}_v^t \mathbf{G}_v) \underline{X}$$

Gradient Operator $\nabla f = \left\langle \dfrac{\partial f}{\partial x}, \dfrac{\partial f}{\partial y} \right\rangle$

$$\begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix} \quad \begin{bmatrix} 1 & 0 & -1 \\ 2 & 0 & -2 \\ 1 & 0 & -1 \end{bmatrix}$$

horizontal and vertical derivative mask

Regularizers

- Convex Regularizers

$$f(x) = \frac{1}{2}\|x - y\|^2 + \lambda\Phi(x)$$

- regularizer $\Phi : \mathrm{X} \rightarrow \overline{\Re}$: it is convex, lower semi-continuous and proper
- denoising function

$$\Psi_\lambda(y) = \arg\min_x f(x)$$

Regularizers

- 1-Homogeneous Regularizers

$$f(x) = \frac{1}{2}\|x - y\|^2 + \lambda\Phi(x)$$

- positively homogeneous of degree 1 : $\Phi(\zeta x) = \zeta\Phi(x)$ for all $\zeta \geq 0$
- regularizer $\Phi : \mathrm{X} \to \overline{\Re}$: it is convex, lower semi-continuous, proper, and phd-1
- denoising function $\Psi_\lambda(y) = y - P_{\lambda C}(y)$

Regularizers

- Total Variation

$$\Phi_{iTV}(x) = \sum_i \sqrt{(\Delta_i^h x)^2 + (\Delta_i^v x)^2}$$

$$\Phi_{niTV}(x) = \sum_i \left|\Delta_i^h x\right| + \left|\Delta_i^v x\right|$$

- Isotropic
- Nonisotropic
- Horizontal and vertical first-order local difference operators

Regularizers

- Weighted lp norm

$$\Phi_{l_w^p}(x) = \|x\|_{p,w} = \left(\sum_i w_i |x_i|^p \right)^{1/p}$$

- The pth Power of a Weighted lp Norm

$$\Phi_{l_w^p}^p(x) = \|x\|_{p,w}^p = \sum_i w_i |x_i|^p$$

- Compressive sensing : k-sparse solution

$$\Phi_{l_0}(x) = \|x\|_{l_0} = \#\{i : x_i \neq 0\}$$

Exemplar-Based Inpainting

Criminisi, P. Perez, K. Toyama. Region filling and object removal by exemplar-based inpainting.
In *2004 IEEE Transactions on Image Processing 9 1200-1212*

Exemplar-Based Inpainting

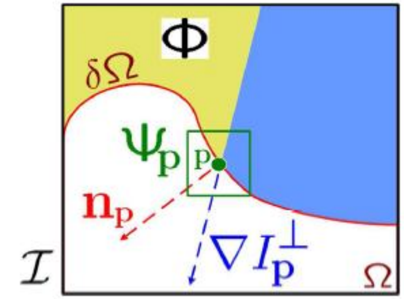
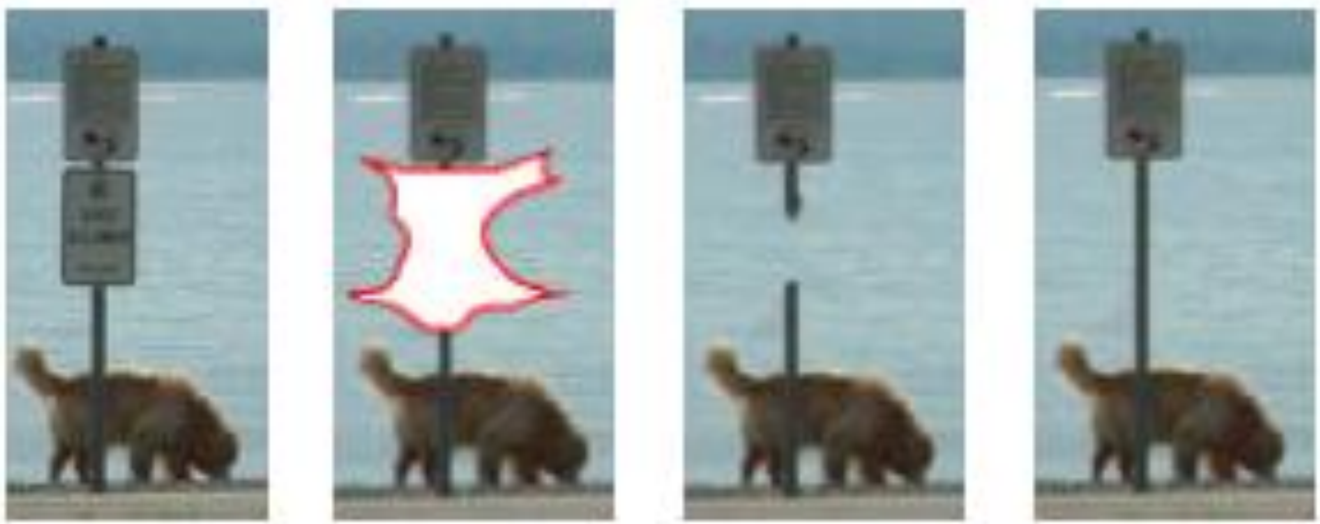


Fig. 5. **Notation diagram.** Given the patch Ψ_p, n_p is the normal to the contour $\delta\Omega$ of the target region Ω and $\nabla I_p^{\perp}$ is the isophote (direction and intensity) at point p. The entire image is denoted with $\mathcal{I}$.



Criminisi, P. Perez, K. Toyama. Region filling and object removal by exemplar-based inpainting. In *2004 IEEE Transactions on Image Processing 9 1200-1212*

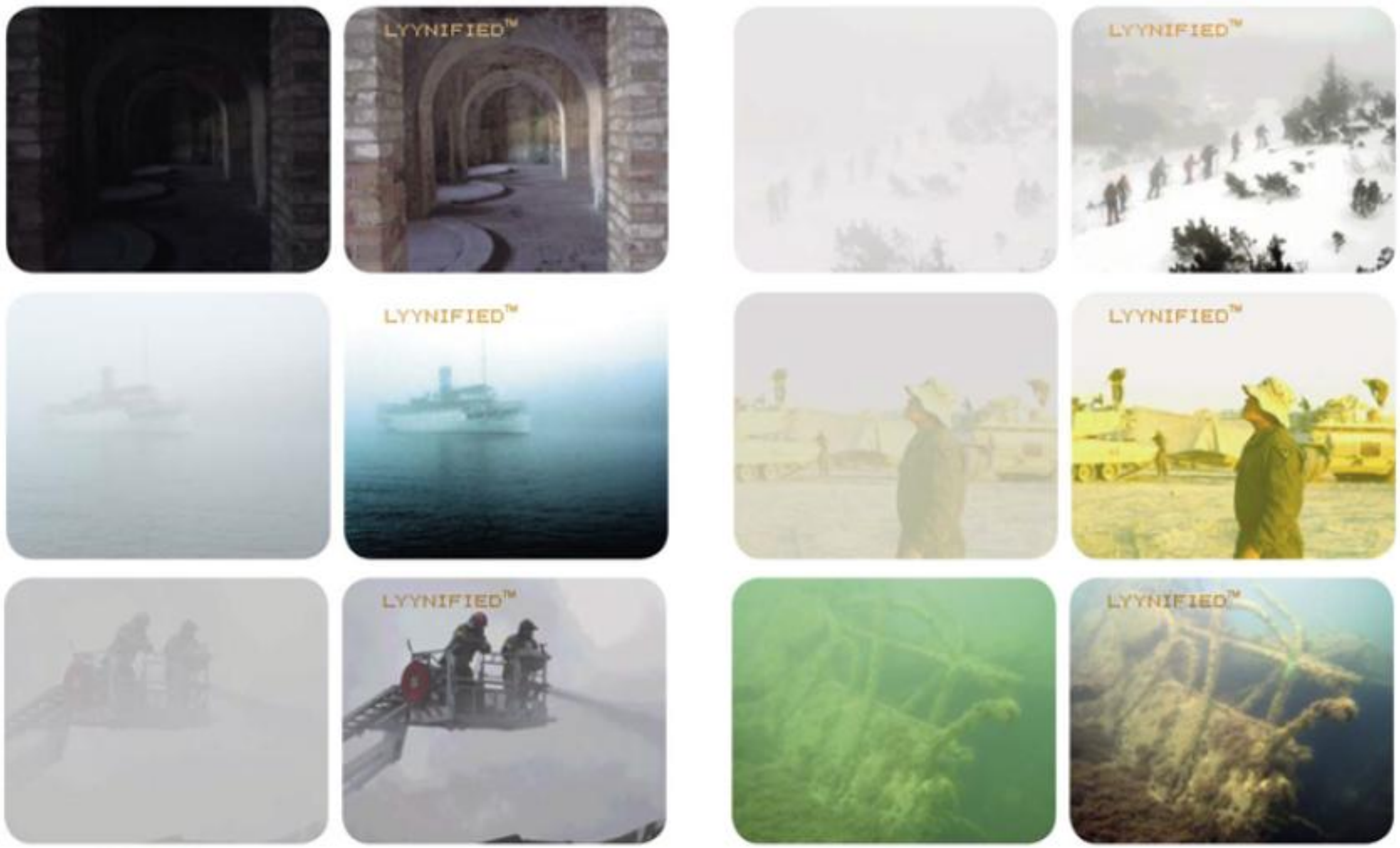
Exemplar-Based Inpainting

Criminisi, P. Perez, K. Toyama. Region filling and object removal by exemplar-based inpainting.
In *2004 IEEE Transactions on Image Processing 9 1200-1212*

Applications

- Clearer Vision

http://www.lyyn.com/



Applications

Bayesian Modeling of Dynamic Scenes for Object Detection

IEEE TRANSACTIONS ON PATTERN ANALYSIS AND MACHINE INTELLIGENCE, VOL. 27, NO. 11, NOVEMBER 2006
Yaser Sheikh, and Mubarak Shah
by lbg@dongseo.ac,kr 2009,02:25

Background $\varphi_b = \{y_1, y_2, \cdots, y_n\}, y = (r, g, b, x, y) \in \mathbb{R}^5$

$$P(x \mid \psi_b) = \frac{1}{n}\sum_{i=1}^{n} \varphi_H(x - y_i)$$

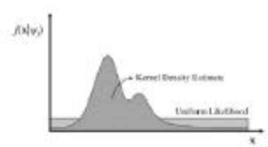
d−variate Gaussian density

$$\varphi_H^{(N)}(x) = |H|^{-1/2}(2\pi)^{-d/2}\exp(-\frac{1}{2}x^T H^{-1} x)$$

Foreground $\varphi_f = \{z_1, z_2, \cdots, z_m\}$

$$P(x \mid \psi_f) = \alpha\gamma + (1-\alpha)m^{-1}\sum_{i=1}^{m} \varphi_H(x - z_i)$$

Likelihood ratio classifier $\tau = -\ln\frac{P(x \mid \psi_b)}{P(x \mid \psi_f)}$



Algorithm

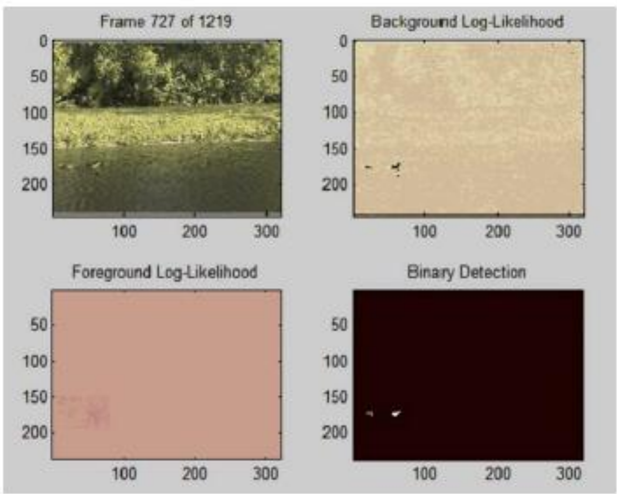
Initialize ψ_b using 1^{st} frame, $\psi_f = \emptyset$. At frame t, for each pixel,

Detection Step

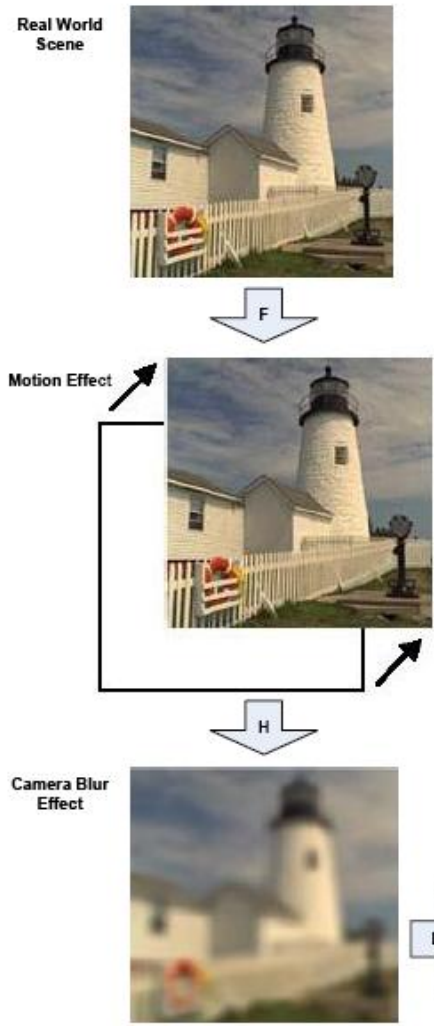
1) Find $P(\mathbf{x}_i|\psi_f)$ (Eq. 7) and $P(\mathbf{x}_i|\psi_b)$ (Eq. 1) and compute the Likelihood Ratio τ (Eq. 8).
2) Construct the graph to minimize Equation 13.

Model Update Step

1) Append all pixels detected as foreground to the foreground model ψ_f.
2) Remove all pixels in ψ_f from ρ_f frames ago.
3) Append all pixels of the image to the background model ψ_b.
4) Remove all pixels in ψ_b from ρ_b frames ago.



Applications



Fast and Robust Multiframe Super Resolution

IEEE TRANSACTIONS ON IMAGE PROCESSING, VOL. 13, NO. 10, OCTOBER 2004
Sina Farsiu, M. Dirk Robinson, Michael Elad, and Peyman Milanfar
by lbg@dongseo.ac.kr 2009.02.23

$$\underline{Y}_k = D_k H_k F_k \underline{X} + \underline{V}_k$$

$$\underline{X} = \underset{\underline{X}}{ArgMin}\left[\sum_{k=1}^{N}\left\| D_k H_k F_k \underline{X} - \underline{Y}_k \right\|_p^p\right] \qquad \underline{X} = \underset{\underline{X}}{ArgMin}\left[\sum_{k=1}^{N}\left\| D_k H_k F_k \underline{X} - \underline{Y}_k \right\|_p^p + \lambda \Upsilon(\underline{X})\right]$$

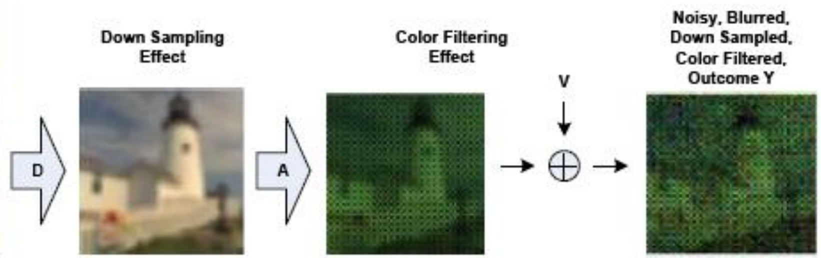
$$\Upsilon_T(\underline{X}) = \left\|\Gamma \underline{X}\right\|_2^2 \qquad \Upsilon_{TV}(\underline{X}) = \left\|\nabla \underline{X}\right\|_1 \qquad \Upsilon_{BTV}(\underline{X}) = \underbrace{\sum_{l=-p}^{p}\sum_{m=0}^{p}}_{l+m\geq 0} \alpha^{|m|+|l|}\left\| \underline{X} - S_x^l S_y^m \underline{X} \right\|_1$$

Robust Method

$$\underline{X}_{n+1} = \underline{X}_n - \beta\{\sum_{k=1}^{N} F_k^T H_k^T D_k^T sign(D_k H_k F_k \underline{X}_n - \underline{Y}_k) + \lambda \underbrace{\sum_{l=-P}^{P}\sum_{m=0}^{P}}_{l+m\geq 0} \alpha^{|m|+|l|}[I - S_y^{-m} S_x^{-l}] sign(\underline{X}_n - S_x^l S_y^m \underline{X}_n)\}$$

Fast Robust Method

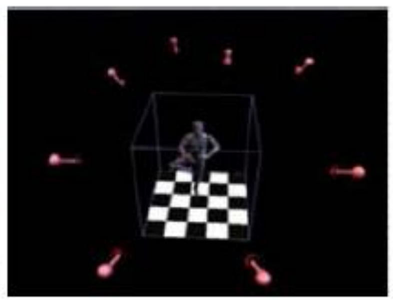
$$\underline{X}_{n+1} = \underline{X}_n - \beta\{H^T A^T sign(AH\underline{X}_n - A\underline{Z}) + \lambda \underbrace{\sum_{l=-P}^{P}\sum_{m=0}^{P}}_{l+m\geq 0} \alpha^{|m|+|l|}[I - S_y^{-m} S_x^{-l}] sign(\underline{X}_n - S_x^l S_y^m \underline{X}_n)\}$$

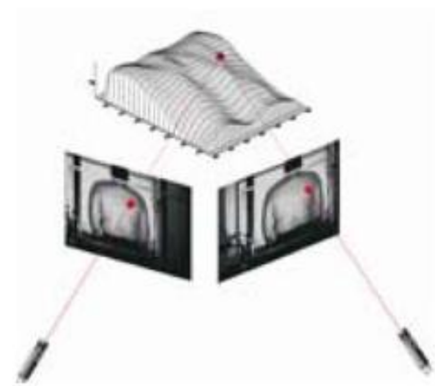


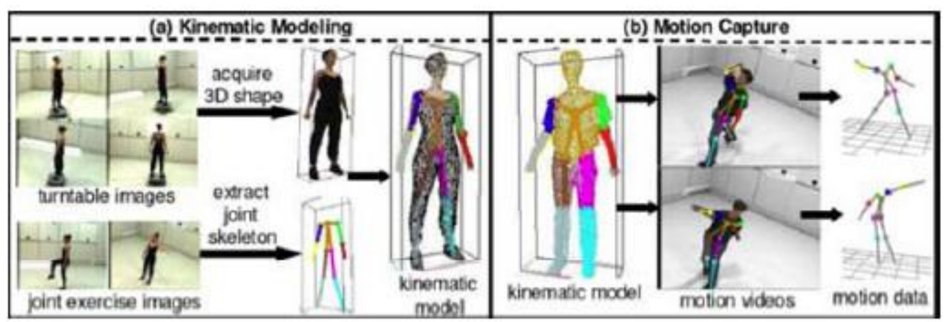
Applications

Image based Human Shape Digitization – Multi Camera Approach

Symposium On 3D Analysis Of Human Movement – *Videogrammetry for human movement analysis* – Fabio Remondino
Institute of Geodesy and Photogrammetry ETH Zurich, Switzerland
http://www.photogrammetry.ethz.ch
by lbg@dongseo.ac.kr 2009 02.25

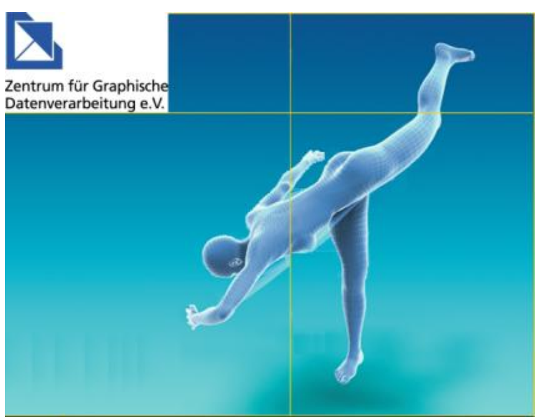


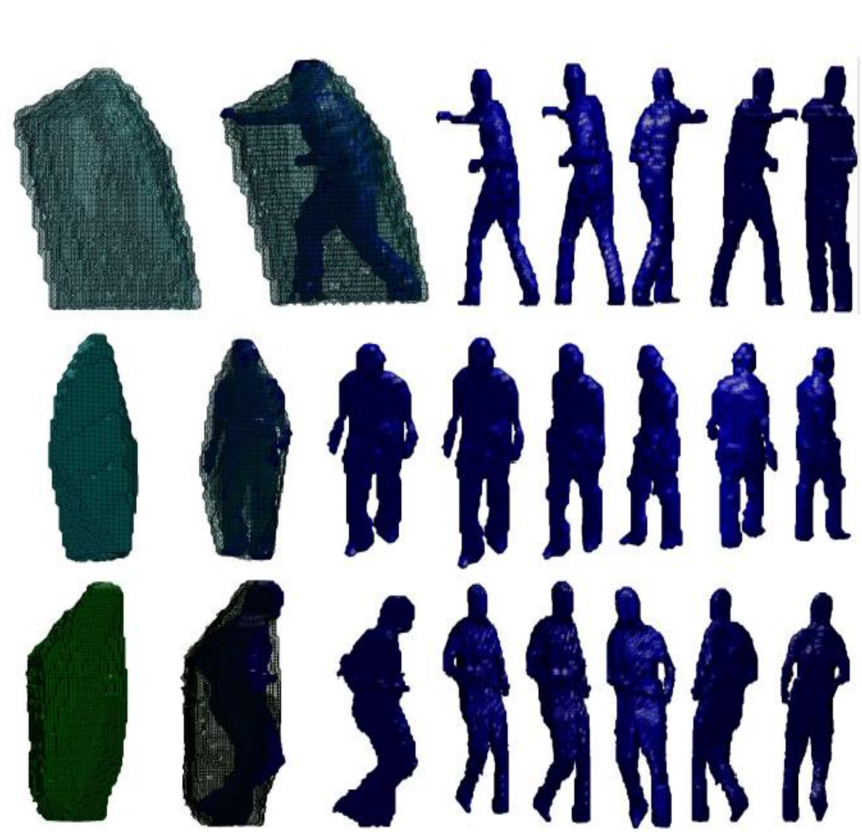




http://www.youtube.com/watch?v=R-it7qdgE7g

Applications





Applications

- Multiple View Geometry
- http://www.cs.unc.edu/~marc/
- http://www.cs.unc.edu/~marc/mvg/slides.html