

BLOCK-COORDINATE PROXIMAL ALGORITHMS FOR SCALE-FREE TEXTURE SEGMENTATION[†]

B. Pascal¹, N. Pustelnik¹, P. Abry¹, J.-C. Pesquet²

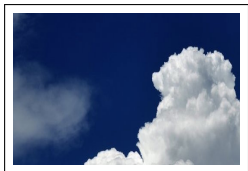
April, 28th 2018

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9 rue Joliot Curie, 91190 Gif sur Yvette, France, jean-christophe.pesquet@centralesupelec.fr

TEXTURE SEGMENTATION

Segmentation task



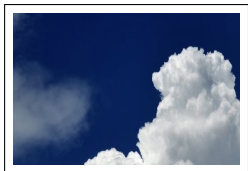
k-means



Piecewise constant image

TEXTURE SEGMENTATION

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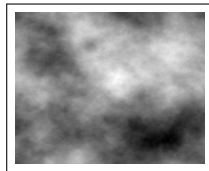


k-means

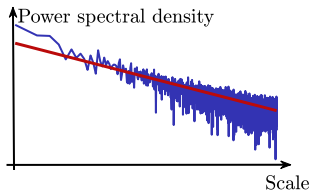


Piecewise constant image

Monofractal scale invariant texture



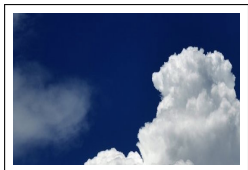
Slope : fractal parameter h [Abry1995]



High resolution necessary

TEXTURE SEGMENTATION

Segmentation task

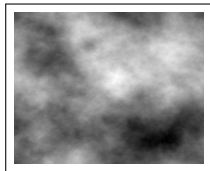


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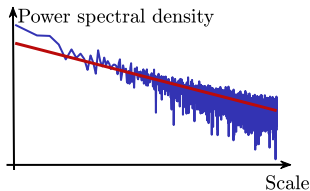


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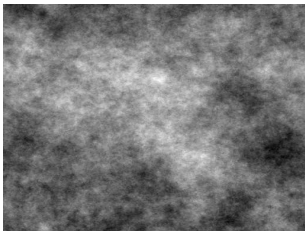
High resolution necessary

I) **Detect constant h areas**
Estimation of local h

II) **Effective implementation**
Block-coordinate algorithm

MONOFRACTAL TEXTURES

SYNTHETIC TEXTURE WITH CONSTANT LOCAL REGULARITY



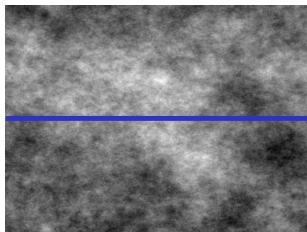
$h = 0.3$



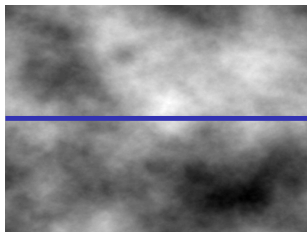
$h = 0.9$

MONOFRACTAL TEXTURES

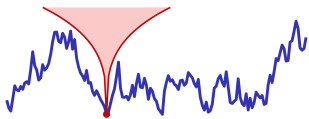
SYNTHETIC TEXTURE WITH CONSTANT LOCAL REGULARITY



$h = 0.3$



$h = 0.9$



IDEA : fit local behavior with power law functions

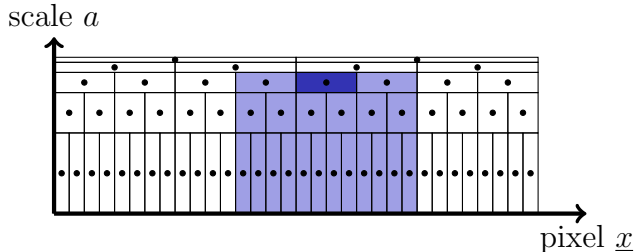
$$|f(x) - f(y)| \leq C|x - y|^{h(x)}, \quad h(x) \equiv 0.3 \text{ (left), } 0.9 \text{ (right)}$$

MULTISCALE ANALYSIS

ESTIMATION OF LOCAL REGULARITY

Wavelet transform and leader coefficients

- (i) **WT** of image X : $w_{a,\underline{n}}(X)$ at scale a and pixel \underline{n} ,
- (ii) **Local supremum** of $|w_{a,\underline{n}}(X)|$: $\mathcal{L}_{a,\underline{n}}(X)$ (*leaders*)



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Linear regression [Wendt2009]

$$\log(\mathcal{L}_{a,\underline{n}}) \simeq \log(\eta(\underline{n})) + \log(a)h(\underline{n})$$

MULTISCALE ANALYSIS

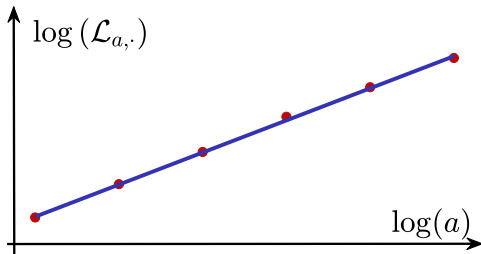
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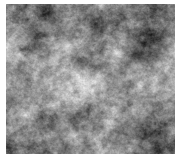
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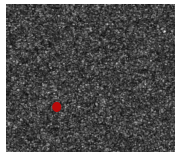
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Texture X

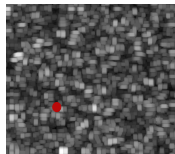


Scale $a = 2^1$



⋮

Scale $a = 2^6$



MULTISCALE ANALYSIS

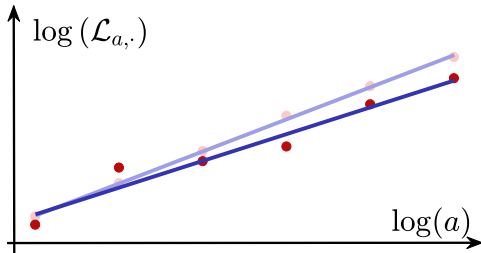
ESTIMATION OF LOCAL REGULARITY

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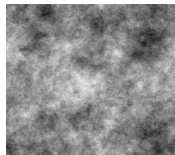
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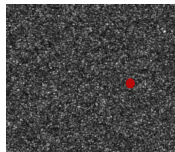
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Texture X

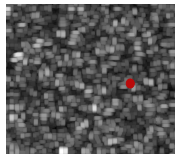


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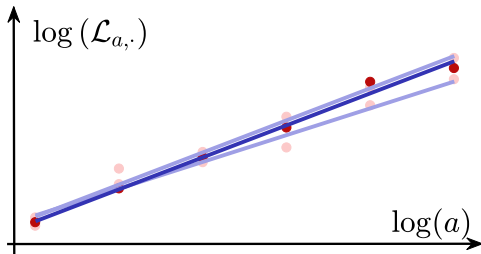
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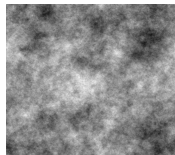
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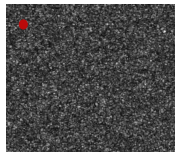
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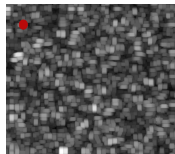


Scale $a = 2^1$



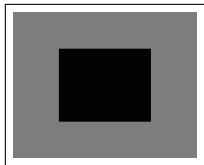
⋮

Scale $a = 2^6$



PIECEWISE MONOFRACTAL TEXTURES

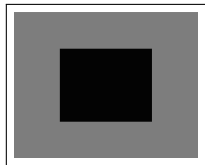
SYNTHETIC DATA



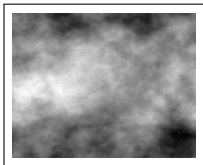
Piecewise constant h

PIECEWISE MONOFRACTAL TEXTURES

SYNTHETIC DATA



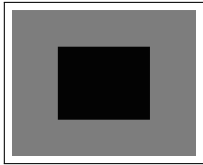
Piecewise constant h



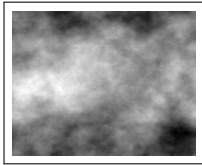
Texture sample X

PIECEWISE MONOFRACTAL TEXTURES

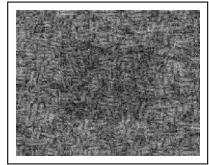
SYNTHETIC DATA



Piecewise constant h



Texture sample X



Linear fit \hat{h}

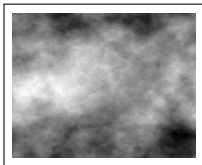
Linear fit is not satisfactory !

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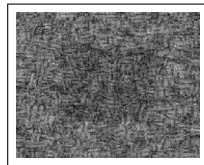
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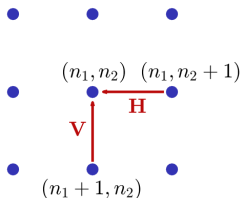
Objective function enforcing piecewise constancy [Pustelnik2016]

$$\hat{h} \in \underset{h}{\text{Argmin}} \quad \underbrace{\mathbf{DF}(h, X)}_{\text{Data Fidelity}} + \underbrace{\lambda \mathbf{TV}(h)}_{\text{Total Variation}}$$

TOTAL VARIATION DENOISING

CONVEX OPTIMIZATION

AIM : enforce piecewise behavior of estimate



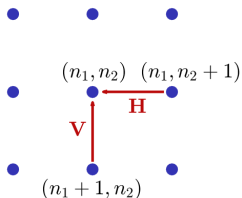
Discrete difference operator

$$(\mathbf{D}h)_{n_1, n_2} = \frac{1}{2} \begin{pmatrix} h_{n_1, n_2+1} - h_{n_1, n_2} \\ h_{n_1+1, n_2} - h_{n_1, n_2} \end{pmatrix}$$

TOTAL VARIATION DENOISING

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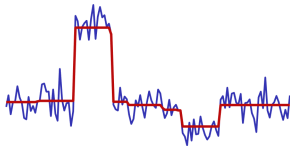


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Total variation penalization

$$\|\mathbf{D}h\|_{2,1} = \sum_{n_1=1}^{N-1} \sum_{n_2=1}^{N-1} \sqrt{(\mathbf{H}h)_{n_1, n_2}^2 + (\mathbf{V}h)_{n_1, n_2}^2}$$



TOTAL VARIATION DENOISING

CONVEX OPTIMIZATION

TV denoising (\hat{h} piecewise constant estimate)

$$\hat{h} \in \underset{h}{\operatorname{Argmin}} \frac{1}{2} \|h - \hat{h}\|_2^2 + \lambda \|\mathbf{D}h\|_{2,1}$$

Reminder : \hat{h} linear fit estimate.

TOTAL VARIATION DENOISING

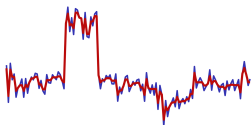
CONVEX OPTIMIZATION

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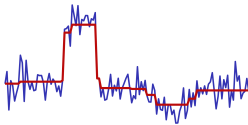
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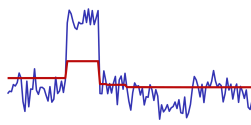
Regularization parameter (fine tuning of λ)



Too small



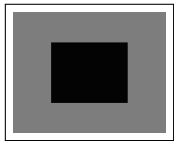
Optimal



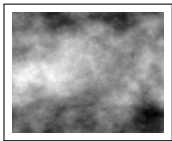
Too large

RESULTS ON SYNTHETIC DATA

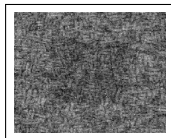
LINEAR REGRESSION THEN TV DENOISING



Mask



Texture sample



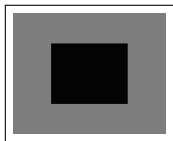
Linear fit \hat{h} ~~X~~



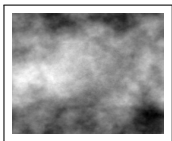
TV denoised $\hat{\hat{h}}$ ✓

RESULTS ON SYNTHETIC DATA

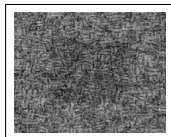
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Texture sample



Linear fit \hat{h} ✗



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Issues/Difficulties :

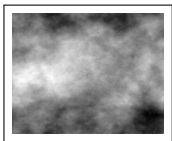
- (i) fine tuning of the regularization parameter : $\lambda \in [\lambda_{\min}, \dots, \lambda_{\max}]$

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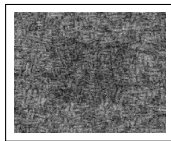
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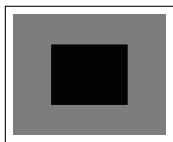
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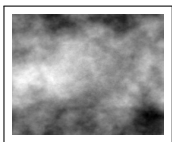
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- (ii) $\lambda_{\text{opt}} \sim 10$ (compared to $\lambda_{\text{opt}} \sim 10^{-2}$ for image denoising)
 - ↪ needs large number of iterations

RESULTS ON SYNTHETIC DATA

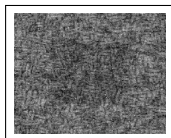
LINEAR REGRESSION THEN TV DENOISING



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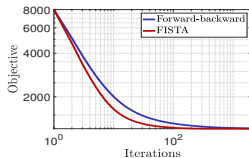
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- (ii) $\lambda_{\text{opt}} \sim 10$ (compared to $\lambda_{\text{opt}} \sim 10^{-2}$ for image denoising)
 ↪ needs large number of iterations
- (iii) computational cost (time & memory) :

Image size	256 × 256	512 × 512	1024 × 1024
Computational time	3 min	16 min	86 min

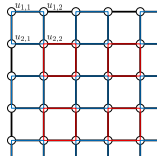
PROXIMAL ALGORITHMS ACCELERATION

STATE OF THE ART

Over-relaxation : FISTA [Dossal2014]
Fast Iterative Shrinkage Thresholding Algorithm



Alternating methods : ADMM [Chambolle2015]
Proximal Alternating Descent



Block-coordinate approaches : (Random) block selection

- Stochastic gradient (*machine learning*) [Le Roux2012]
- Primal and/or dual splitting (*image processing*) [Repetti2015, Feriel2017, Chambolle2017]

PROXIMAL ALGORITHMS

TV denoising

$$\hat{h} \in \underset{h}{\text{Argmin}} \frac{1}{2} \|h - \hat{h}\|_2^2 + \lambda \|\mathbf{D}h\|_{2,1}$$

for $k \in \mathbb{N}$ **do**

$$y^{[k+1]} = \text{prox}_{\gamma \lambda \|\cdot\|_{2,1}^*} \left(y^{[k]} + \gamma \mathbf{D} h^{[k]} \right)$$
$$h^{[k+1]} = h^{[k]} - \mathbf{D}^* \left(y^{[k+1]} - y^{[k]} \right)$$

end

Dual forward-backward algorithm [Ferial2017]

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Dual forward-backward algorithm [Ferial2017]

Convergence of the iterates

$$\gamma < 1 / \|\mathbf{D}\|^2$$

PROXIMAL ALGORITHMS

TV denoising

$$\hat{h} \in \underset{h}{\operatorname{Argmin}} \frac{1}{2} \|h - \hat{h}\|_2^2 + \lambda \sum_{\ell=1}^L \|\mathbf{D}_\ell h\|_{2,1}$$

Block strategies

$$\mathbf{D} = [\mathbf{D}_1, \dots, \mathbf{D}_\ell, \dots, \mathbf{D}_L]^\top$$

$$\|\mathbf{D}h\|_{2,1} = \sum_{\ell=1}^L \|\mathbf{D}_\ell h\|_{2,1}$$

for $k \in \mathbb{N}$ do

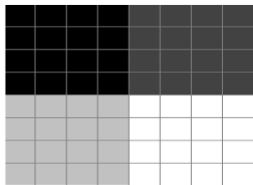
 for $\ell \in \{1, \dots, L\}$ do

$$y_\ell^{[k+1]} = \operatorname{prox}_{\gamma_\ell \lambda \|\cdot\|_{2,1}^*} \left(y_\ell^{[k]} + \gamma_\ell \mathbf{D}_\ell h^{[k]} \right)$$

$$h^{[k+1]} = h^{[k]} - \mathbf{D}_\ell^* \left(y_\ell^{[k+1]} - y_\ell^{[k]} \right)$$

 end

end



Block dual forward-backward algorithm [Friel2017]

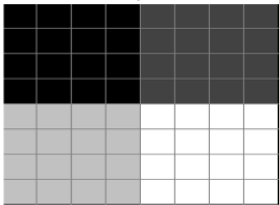
Convergence of the iterates

$$\gamma_\ell < 1 / \|\mathbf{D}_\ell\|^2$$

CHOICE OF THE BLOCKS

REGIONS AND LATTICES

Hh or **Vh**

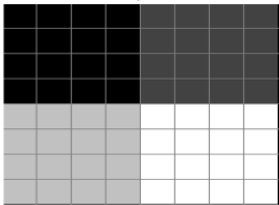


Regions

CHOICE OF THE BLOCKS

REGIONS AND LATTICES

Hh or Vh



Regions

$$\forall l \in \{1, \dots, 4\},$$

$$\|\mathbf{D}_l\| = \sqrt{2} \simeq 1.4142$$

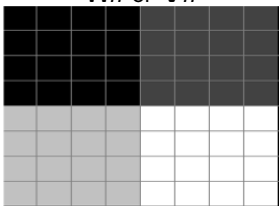
$$= \|\mathbf{D}\|$$

no gain !

CHOICE OF THE BLOCKS

REGIONS AND LATTICES

Hh or Vh



Regions

$$\forall \ell \in \{1, \dots, 4\},$$

$$\|\mathbf{D}_\ell\| = \sqrt{2} \simeq 1.4142$$

$$= \|\mathbf{D}\|$$

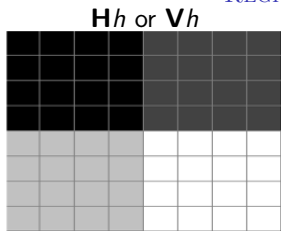
no gain !

Descent steps

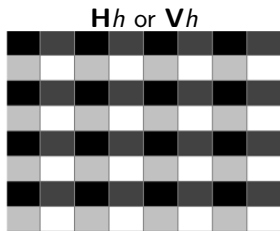
$$\gamma_\ell < 1$$

CHOICE OF THE BLOCKS

REGIONS AND LATTICES



Regions



Lattices

$$\forall l \in \{1, \dots, 4\},$$

$$\|\mathbf{D}_l\| = \sqrt{2} \simeq 1.4142$$

$$= \|\mathbf{D}\|$$

no gain !

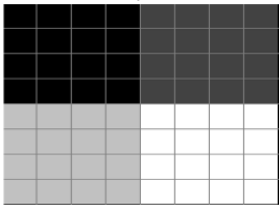
Descent steps

$$\gamma_l < 1$$

CHOICE OF THE BLOCKS

REGIONS AND LATTICES

Hh or Vh



Regions

Hh or Vh



Lattices

$$\forall \ell \in \{1, \dots, 4\},$$

$$\begin{aligned}\|\mathbf{D}_\ell\| &= \sqrt{2} \simeq 1.4142 \\ &= \|\mathbf{D}\|\end{aligned}$$

no gain !

$$\forall \ell \in \{1, \dots, 4\},$$

$$\begin{aligned}\|\mathbf{D}_\ell\| &= \sqrt{3}/2 \simeq 0.8660 \\ &< \|\mathbf{D}\|\end{aligned}$$

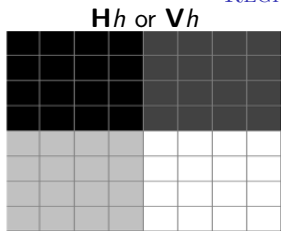
gain of factor $\simeq 1.6$

Descent steps

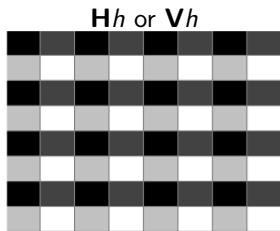
$$\gamma_\ell < 1$$

CHOICE OF THE BLOCKS

REGIONS AND LATTICES



Regions



Lattices

$$\begin{aligned}\forall \ell \in \{1, \dots, 4\}, \\ \|\mathbf{D}_\ell\| &= \sqrt{2} \simeq 1.4142 \\ &= \|\mathbf{D}\| \\ &\text{no gain!}\end{aligned}$$

$$\begin{aligned}\forall \ell \in \{1, \dots, 4\}, \\ \|\mathbf{D}_\ell\| &= \sqrt{3}/2 \simeq 0.8660 \\ &< \|\mathbf{D}\| \\ &\text{gain of factor } \simeq 1.6\end{aligned}$$

Descent steps

$$\gamma_\ell < 1$$

$$\gamma_\ell < 8/3$$

FORWARD-BACKWARD ALGORITHMS CONVERGENCE

REGION VS LATTICE STRATEGIES

Duality gap

$$\delta(h, y) = \underbrace{\frac{1}{2} \|h - \hat{h}\|_2^2 + \lambda \|Dh\|_{2,1}}_{\text{primal functional}} + \underbrace{\frac{1}{2} \|-D^*y + \hat{h}\|_2^2 - \frac{1}{2} \|\hat{h}\|_2^2 + \iota_{2,\infty(\lambda)}(y)}_{\text{dual functional}}$$

FORWARD-BACKWARD ALGORITHMS CONVERGENCE

REGION VS LATTICE STRATEGIES

Duality gap

$$\delta(h, y) = \underbrace{\frac{1}{2}\|h - \hat{h}\|_2^2 + \lambda\|\mathbf{D}h\|_{2,1}}_{\text{primal functional}} + \underbrace{\frac{1}{2}\|-\mathbf{D}^*y + \hat{h}\|_2^2 - \frac{1}{2}\|\hat{h}\|_2^2 + \iota_{2,\infty(\lambda)}(y)}_{\text{dual functional}}$$

Convergence

$$\log \delta(h^{[k]}, y^{[k]}) \xrightarrow[k \rightarrow \infty]{} -\infty$$

FORWARD-BACKWARD ALGORITHMS CONVERGENCE

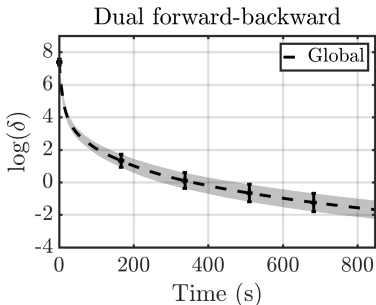
REGION VS LATTICE STRATEGIES

Duality gap

$$\delta(h, y) = \underbrace{\frac{1}{2} \|h - \hat{h}\|_2^2 + \lambda \|Dh\|_{2,1}}_{\text{primal functional}} + \underbrace{\frac{1}{2} \|-D^*y + \hat{h}\|_2^2 - \frac{1}{2} \|\hat{h}\|_2^2 + \iota_{2,\infty(\lambda)}(y)}_{\text{dual functional}}$$

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FORWARD-BACKWARD ALGORITHMS CONVERGENCE

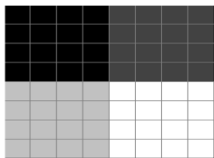
REGION VS LATTICE STRATEGIES

Duality gap

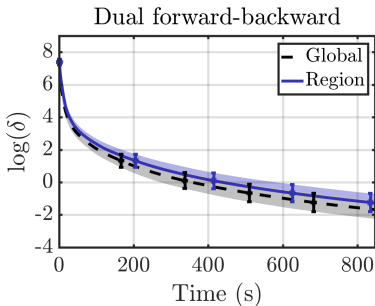
$$\delta(h, y) = \underbrace{\frac{1}{2} \|h - \hat{h}\|_2^2 + \lambda \|Dh\|_{2,1}}_{\text{primal functional}} + \underbrace{\frac{1}{2} \|-D^*y + \hat{h}\|_2^2 - \frac{1}{2} \|\hat{h}\|_2^2 + \iota_{2,\infty(\lambda)}(y)}_{\text{dual functional}}$$

Convergence

$$\log \delta(h^{[k]}, y^{[k]}) \xrightarrow[k \rightarrow \infty]{} -\infty$$



Region



FORWARD-BACKWARD ALGORITHMS CONVERGENCE

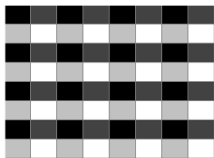
REGION VS LATTICE STRATEGIES

Duality gap

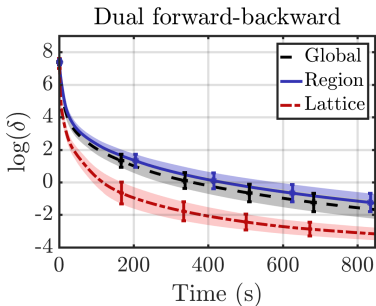
$$\delta(h, y) = \underbrace{\frac{1}{2} \|h - \hat{h}\|_2^2 + \lambda \|Dh\|_{2,1}}_{\text{primal functional}} + \underbrace{\frac{1}{2} \|-D^*y + \hat{h}\|_2^2 - \frac{1}{2} \|\hat{h}\|_2^2 + \iota_{2,\infty(\lambda)}(y)}_{\text{dual functional}}$$

Convergence

$$\log \delta(h^{[k]}, y^{[k]}) \xrightarrow[k \rightarrow \infty]{} -\infty$$



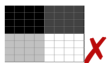
Lattice



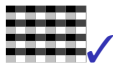
EXTENSION TO PRIMAL-DUAL ALGORITHMS

BLOCK FORWARD-BACKWARD

$$\gamma_\ell < \frac{1}{\|\mathbf{D}_\ell\|^2} \quad [\text{Ferial2017}]$$

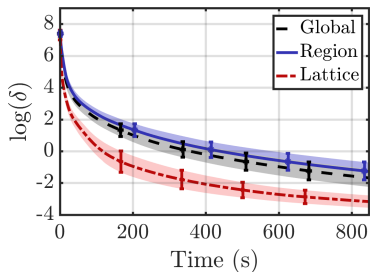


Region



Lattice

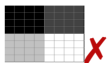
Dual forward-backward



EXTENSION TO PRIMAL-DUAL ALGORITHMS

BLOCK FORWARD-BACKWARD

$$\gamma_\ell < \frac{1}{\|\mathbf{D}_\ell\|^2} \quad [\text{Ferial2017}]$$



Region

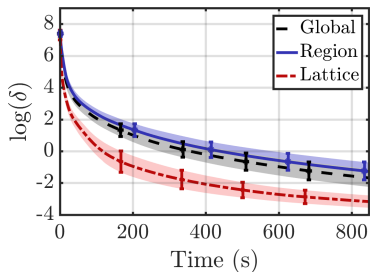


Lattice

BLOCK PRIMAL-DUAL

$$\sigma_\ell \tau < \frac{1}{L\|\mathbf{D}_\ell\|^2} \quad [\text{Chambolle2017}]$$

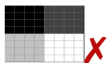
Dual forward-backward



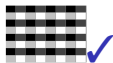
EXTENSION TO PRIMAL-DUAL ALGORITHMS

BLOCK FORWARD-BACKWARD

$$\gamma_\ell < \frac{1}{\|\mathbf{D}_\ell\|^2} \quad [\text{Ferial2017}]$$

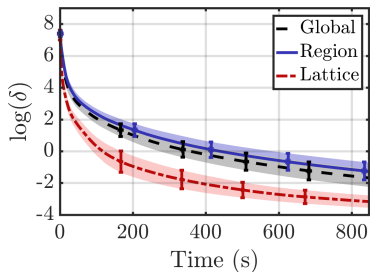


Region



Lattice

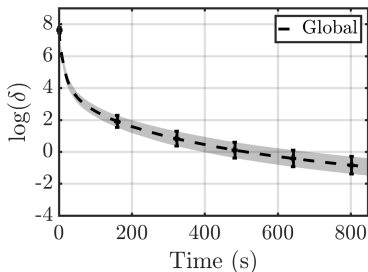
Dual forward-backward



BLOCK PRIMAL-DUAL

$$\sigma_\ell \tau < \frac{1}{L\|\mathbf{D}_\ell\|^2} \quad [\text{Chambolle2017}]$$

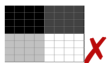
Primal dual



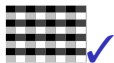
EXTENSION TO PRIMAL-DUAL ALGORITHMS

BLOCK FORWARD-BACKWARD

$$\gamma_\ell < \frac{1}{\|\mathbf{D}_\ell\|^2} \quad [\text{Ferial2017}]$$



Region



Lattice

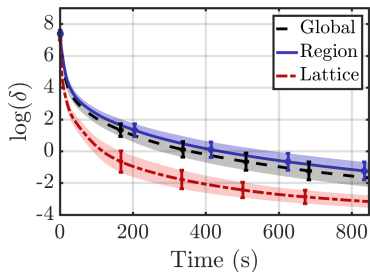
BLOCK PRIMAL-DUAL

$$\sigma_\ell \tau < \frac{1}{L\|\mathbf{D}_\ell\|^2} \quad [\text{Chambolle2017}]$$

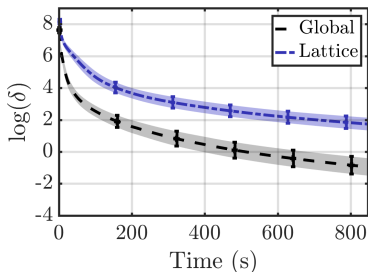


Lattice

Dual forward-backward



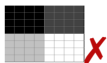
Primal dual



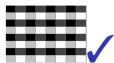
EXTENSION TO PRIMAL-DUAL ALGORITHMS

BLOCK FORWARD-BACKWARD

$$\gamma \ell < \frac{1}{\|\mathbf{D}_\ell\|^2} \quad [\text{Ferial2017}]$$



Region



Lattice

BLOCK PRIMAL-DUAL

$$\sigma \ell \tau < \frac{P\ell}{\|\mathbf{D}_\ell\|^2} \quad [\text{Chambolle2017}]$$

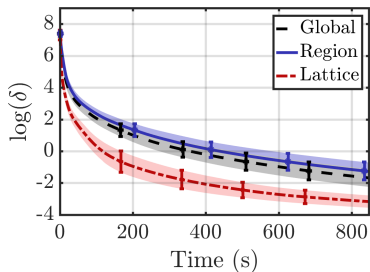


Lattice

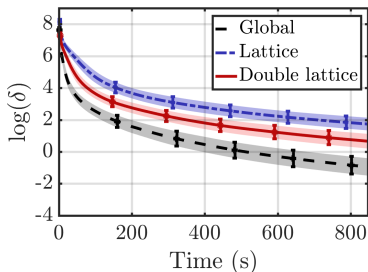


Double lattice

Dual forward-backward



Primal dual

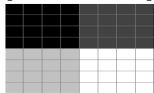


TAKE HOME MESSAGE

Block strategies

Lower memory requirements ✓

[Repetti2015]



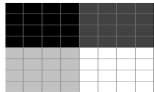
Larger computational time ✗

TAKE HOME MESSAGE

Block strategies

Lower memory requirements ✓

[Repetti2015]



Larger computational time ✗

Lattice splitting

Lower memory requirements ✓



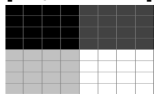
Reduced computational time ✓

TAKE HOME MESSAGE

Block strategies

Lower memory requirements ✓

[Repetti2015]



Larger computational time ✗

Lattice splitting

Lower memory requirements ✓



Reduced computational time ✓

Possibilities

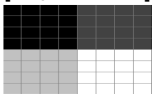
- explore large range of regularization parameter λ ,
- process high resolution images,
- analyze huge amount of data.

TAKE HOME MESSAGE

Block strategies

Lower memory requirements ✓

[Repetti2015]



Larger computational time ✗

Lattice splitting

Lower memory requirements ✓



Reduced computational time ✓

Possibilities

- explore large range of regularization parameter λ ,
- process high resolution images,
- analyze huge amount of data.

Applications

- medical imaging (cancer detection, ...) [Marin2017],
- meteorology (clouds characterization, ...) [Arrault1997],
- art (painting authentication, ...) [Abry2013].

