How fractal texture segmentation turns out to be a strongly convex optimization problem ?[†].

B. Pascal[1], N. Pustelnik[1], P. Abry[1]

Seminar "Image, Optimization, Probabilities"
IMB, Bordeaux, March, 12$^{\text{th}}$ 2020

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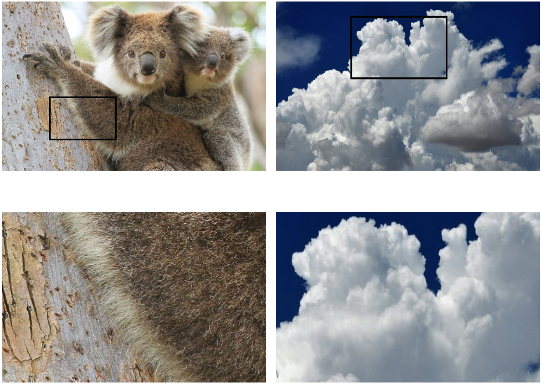
[†] Supported by Defi Imag'in SIROCCO and ANR-16-CE33-0020 MultiFracs, France.

Describing and interpreting real-world images

Texture as a discriminating feature

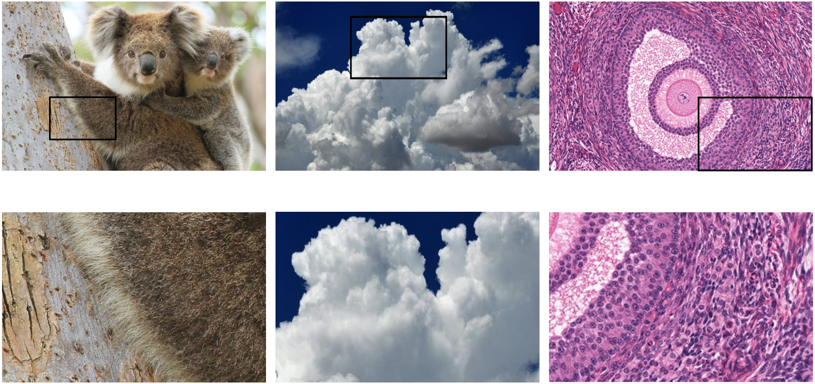
Describing and interpreting real-world images

Texture as a discriminating feature



Describing and interpreting real-world images

Texture as a discriminating feature



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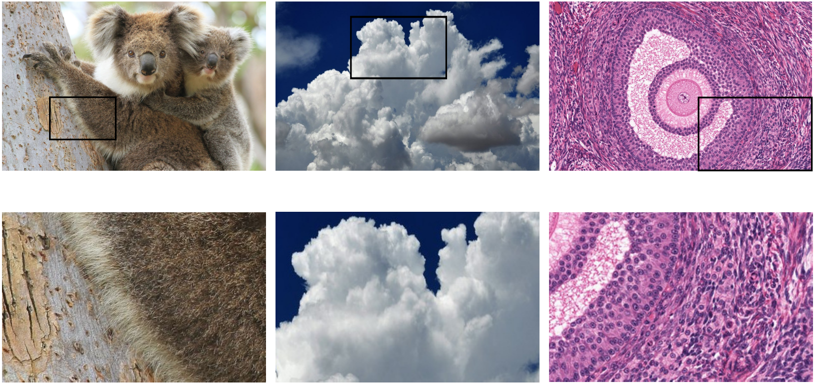
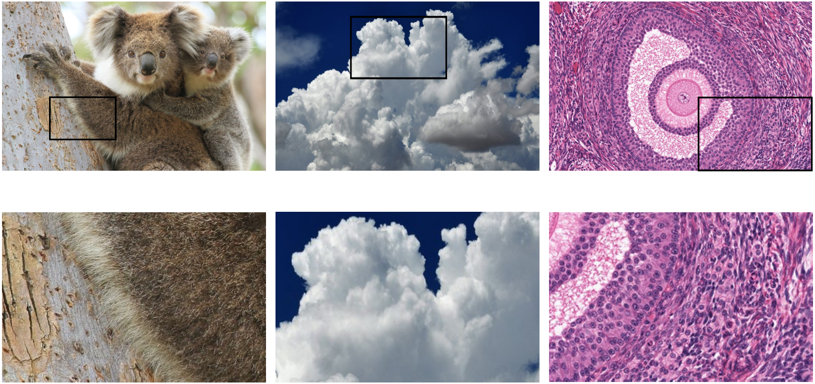


Texture is of utmost importance in complex computer vision tasks.

Describing and interpreting real-world images

Texture as a discriminating feature



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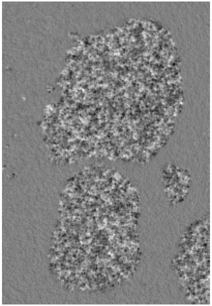
fractal segmentation

Formulation of the texture segmentation problem



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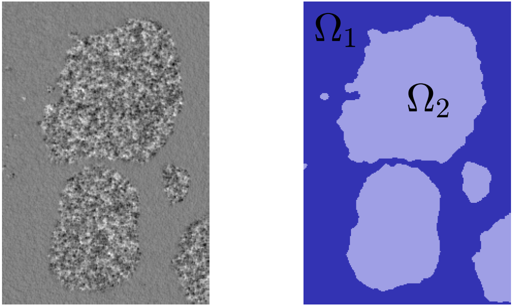


Purpose: obtaining a partition of the image into κ homogeneous regions

$$\Omega = \Omega_1 \bigsqcup \ldots \bigsqcup \Omega_\kappa$$

Ω_k: pixels corresponding to texture k.

Outline – Fractal texture segmentation

1. Fractal texture model

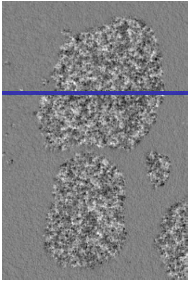
2. Attributes estimation and segmentation

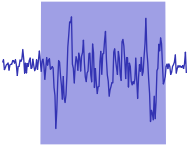
3. Multiphasic flow segmentation

4. Regularization parameters tuning

Texture's attributes definition

Piecewise monofractal model





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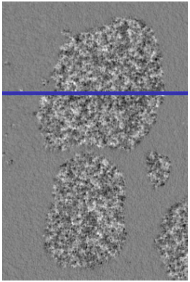

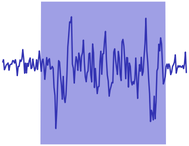

Variance σ^2 *amplitude of variations*

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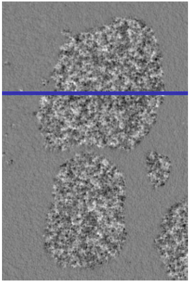
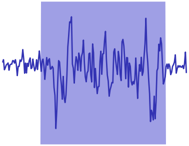
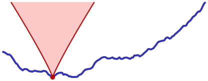
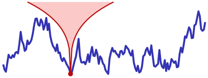




<u>Variance σ^2</u> *amplitude of variations*

<u>Local regularity h</u> *scale-free behavior*





$h(x) \equiv h_1 = 0.9$ $h(x) \equiv h_2 = 0.3$

Fit local behavior with power law functions

$$|f(x) - f(y)| \leq C|x - y|^{h(x)}$$

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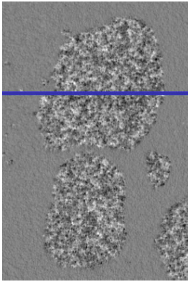

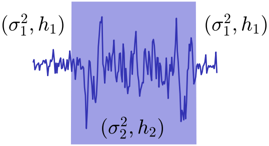

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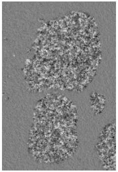
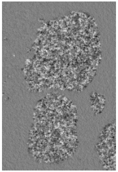
Segmentation requires local measurement of σ^2 and h.

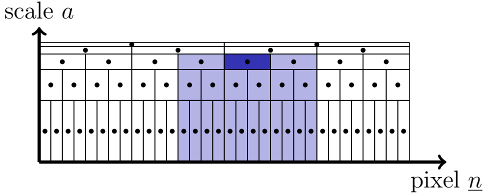
Textured image



Textured image

Local supremum of wavelet coefficients: *leaders* $\mathcal{L}_{a,\cdot}$

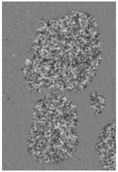




Texture's attributes estimation

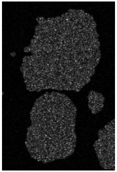
Multiscale analysis

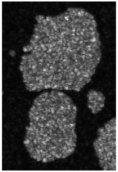
Textured image

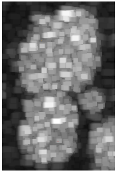


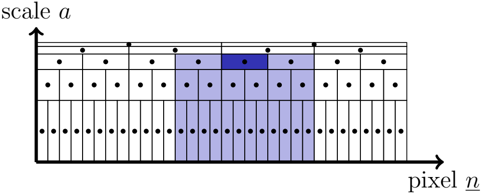
Local supremum of wavelet coefficients: *leaders* $\mathcal{L}_{a,\cdot}$

Scale $a = 2^1$ $a = 2^2$ … $a = 2^5$









Texture's attributes estimation

Multiscale analysis

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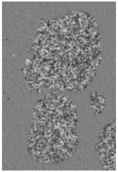

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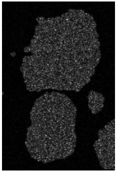

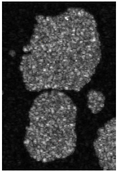

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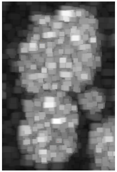

Log-log linear behavior

$$\log\left(\mathcal{L}_{a,\cdot}\right) \simeq \underbrace{\boldsymbol{v}}_{\substack{\sim\log(\boldsymbol{\sigma}^2)\\ \text{(variance)}}} + \log(a) \underbrace{\boldsymbol{h}}_{\textit{regularity}}$$

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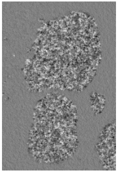

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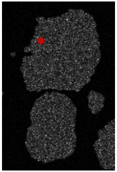
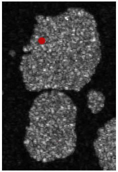
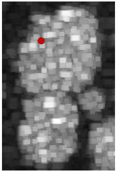


$a = 2^2$



...

$a = 2^5$



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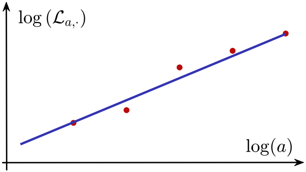

Texture's attributes estimation

Multiscale analysis

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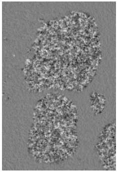

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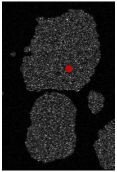

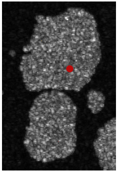

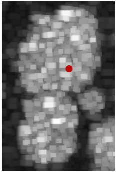

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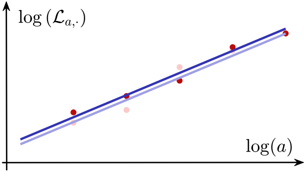
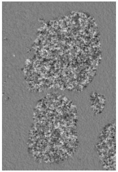


Texture's attributes estimation

Multiscale analysis

Textured image



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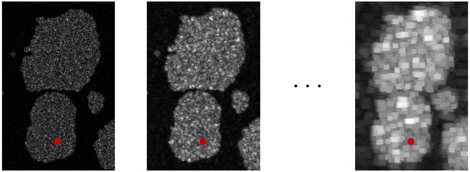

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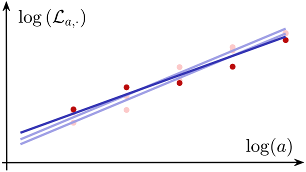

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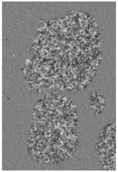

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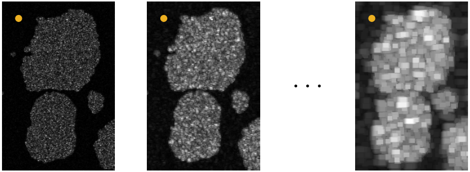

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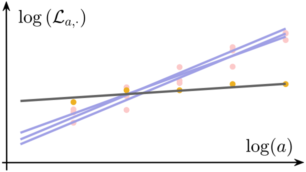

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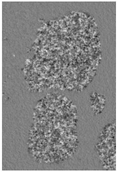

Local supremum of wavelet coefficients: *leaders* $\mathcal{L}_{a,\cdot}$

Scale

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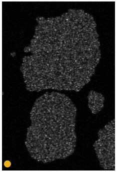
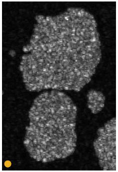


$a = 2^2$



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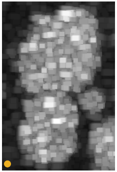

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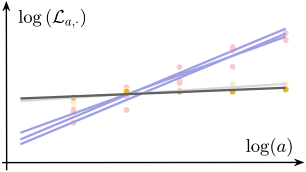

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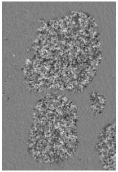
Multiscale analysis

Textured image



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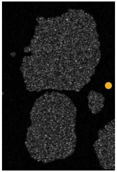

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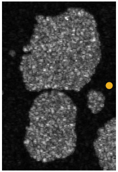

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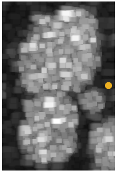

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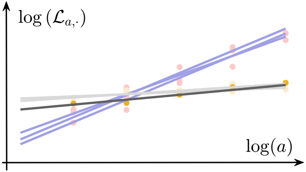

Texture's attributes estimation

Pointwise linear regression

$$\log\left(\mathcal{L}_{a,\cdot}\right) \simeq \underbrace{\boldsymbol{v}}_{\sim \log(\boldsymbol{\sigma}^2)} + \log(a) \underbrace{\boldsymbol{h}}_{regularity}$$

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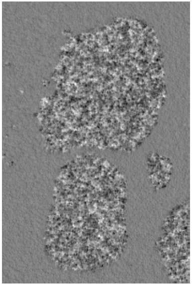
$$\underset{\boldsymbol{v},\boldsymbol{h}}{\text{minimize}} \sum_a \left\|\log\left(\mathcal{L}_{a,\cdot}\right) - \boldsymbol{v} - \log(a)\boldsymbol{h}\right\|^2$$

Textured image



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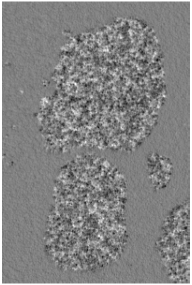
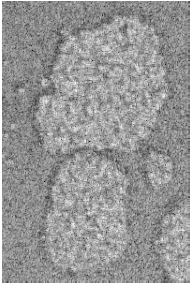


Local power $\widehat{\boldsymbol{v}}^{\mathrm{LR}}$



Local regularity $\widehat{\boldsymbol{h}}^{\mathrm{LR}}$

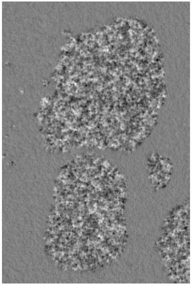
Texture's attributes estimation

Pointwise linear regression

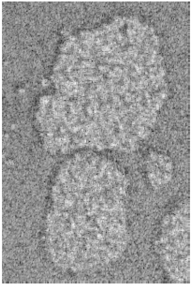
$$\underbrace{\mathbb{E}\log\left(\mathcal{L}_{a,\cdot}\right)}_{\text{expected value}} \simeq \underbrace{\boldsymbol{v}}_{\sim\log(\boldsymbol{\sigma}^2)} + \log(a)\underbrace{\boldsymbol{h}}_{\text{regularity}}$$

$$\underset{\boldsymbol{v},\boldsymbol{h}}{\text{minimize}} \sum_a \left\|\log\left(\mathcal{L}_{a,\cdot}\right) - \boldsymbol{v} - \log(a)\boldsymbol{h}\right\|^2$$

Textured image



Local power $\widehat{\boldsymbol{v}}^{\mathrm{LR}}$



Local regularity $\widehat{\boldsymbol{h}}^{\mathrm{LR}}$

Pointwise linear regression is an estimation from **one** sample!

Outline – Fractal texture segmentation

1. Fractal texture model

$$\log\left(\mathcal{L}_{a,\cdot}\right) \simeq \underbrace{\boldsymbol{v}}_{\sim\log(\boldsymbol{\sigma}^2)} + \log(a)\underbrace{\boldsymbol{h}}_{regularity}$$

2. Attributes estimation and segmentation

3. Multiphasic flow segmentation

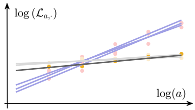
4. Regularization parameters tuning

Texture's attributes estimation

One-step joint and coupled segmentation as a convex minimization

$$\sum_a \underbrace{\|\log \mathcal{L}_{a,\cdot} - \boldsymbol{v} - \log(a)\boldsymbol{h}\|^2}_{\textbf{Least-Squares}}$$

$\rightarrow$ fidelity to log-linear model

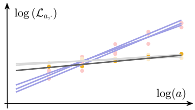


Texture's attributes estimation

One-step joint and coupled segmentation as a convex minimization

$$\underbrace{\sum_a \|\log \mathcal{L}_{a,\cdot} - \boldsymbol{v} - \log(a)\boldsymbol{h}\|^2}_{\textbf{Least-Squares}} + \underbrace{\lambda\, \mathcal{N}(\mathbf{D}\boldsymbol{v}, \mathbf{D}\boldsymbol{h}; \alpha)}_{\textbf{Total Variation}}$$

$\rightarrow$ fidelity to log-linear model



$\rightarrow$ enforce piecewise constancy

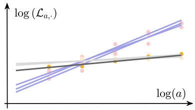
Texture's attributes estimation

One-step joint and coupled segmentation as a convex minimization

$$\underset{\boldsymbol{v},\boldsymbol{h}}{\text{minimize}} \; \underbrace{\sum_a \|\log \mathcal{L}_{a,\cdot} - \boldsymbol{v} - \log(a)\boldsymbol{h}\|^2}_{\textbf{Least-Squares}} + \underbrace{\lambda\, \mathcal{N}(\mathbf{D}\boldsymbol{v}, \mathbf{D}\boldsymbol{h}; \alpha)}_{\textbf{Total Variation}}$$

$\rightarrow$ fidelity to log-linear model

$\rightarrow$ enforce piecewise constancy



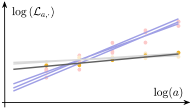
Texture's attributes estimation

One-step joint and coupled segmentation as a convex minimization

$$\underset{\boldsymbol{v},\boldsymbol{h}}{\text{minimize}} \sum_a \underbrace{\|\log \mathcal{L}_{a,\cdot} - \boldsymbol{v} - \log(a)\boldsymbol{h}\|^2}_{\textbf{Least-Squares}} + \lambda \underbrace{\mathcal{N}(\mathbf{D}\boldsymbol{v}, \mathbf{D}\boldsymbol{h}; \alpha)}_{\textbf{Total Variation}}$$

$\rightarrow$ fidelity to log-linear model

$\rightarrow$ enforce piecewise constancy



joint: $\boldsymbol{v}$, $\boldsymbol{h}$ are **independently** piecewise constant

coupled: $\boldsymbol{v}$, $\boldsymbol{h}$ are **concomitantly** piecewise constant

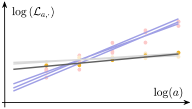
Texture's attributes estimation

One-step joint and coupled segmentation as a convex minimization

$$\underset{\boldsymbol{v},\boldsymbol{h}}{\text{minimize}} \; \underbrace{\sum_a \|\log \mathcal{L}_{a,\cdot} - \boldsymbol{v} - \log(a)\boldsymbol{h}\|^2}_{\textbf{Least-Squares}} + \lambda \underbrace{\mathcal{N}(\mathbf{D}\boldsymbol{v}, \mathbf{D}\boldsymbol{h}; \alpha)}_{\textbf{Total Variation}}$$

Least-Squares → fidelity to log-linear model

Total Variation → enforce piecewise constancy



Discrete differences $\mathbf{H}\boldsymbol{x}$ (horizontal), $\mathbf{V}\boldsymbol{x}$ (vertical) at each pixel

joint: $\boldsymbol{v}$, $\boldsymbol{h}$ are **independently** piecewise constant

$$\mathcal{N}_{\mathrm{J}}(\mathbf{D}\boldsymbol{v}, \mathbf{D}\boldsymbol{h}; \alpha) = \left(\sum_{\text{pixels}} \sqrt{(\mathbf{H}\boldsymbol{v})^2 + (\mathbf{V}\boldsymbol{v})^2} + \alpha \sum_{\text{pixels}} \sqrt{(\mathbf{H}\boldsymbol{h})^2 + (\mathbf{V}\boldsymbol{h})^2} \right)$$

coupled: $\boldsymbol{v}$, $\boldsymbol{h}$ are **concomitantly** piecewise constant

$$\mathcal{N}_{\mathrm{C}}(\mathbf{D}\boldsymbol{v}, \mathbf{D}\boldsymbol{h}; \alpha) = \sum_{\text{pixels}} \sqrt{(\mathbf{H}\boldsymbol{v})^2 + (\mathbf{V}\boldsymbol{v})^2 + \alpha^2(\mathbf{H}\boldsymbol{h})^2 + \alpha^2(\mathbf{V}\boldsymbol{h})^2}$$

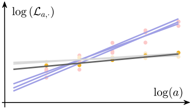
Texture's attributes estimation

One-step joint and coupled segmentation as a convex minimization

$$\underset{\boldsymbol{v},\boldsymbol{h}}{\text{minimize}} \ \underbrace{\sum_a \|\log \mathcal{L}_{a,\cdot} - \boldsymbol{v} - \log(a)\boldsymbol{h}\|^2}_{\textbf{Least-Squares}} + \lambda \underbrace{\mathcal{N}(\mathbf{D}\boldsymbol{v}, \mathbf{D}\boldsymbol{h}; \alpha)}_{\textbf{Total Variation}}$$

→ fidelity to log-linear model

→ enforce piecewise constancy



Discrete differences $\mathbf{D}\boldsymbol{x} = [\mathbf{H}\boldsymbol{x}, \mathbf{V}\boldsymbol{x}]$

joint: $\boldsymbol{v}$, $\boldsymbol{h}$ are **independently** piecewise constant

$$\mathcal{N}_{\mathrm{J}}(\mathbf{D}\boldsymbol{v}, \mathbf{D}\boldsymbol{h}; \alpha) = \|\mathbf{D}\boldsymbol{v}\|_{2,1} + \alpha\|\mathbf{D}\boldsymbol{h}\|_{2,1}$$

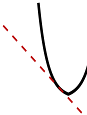
coupled: $\boldsymbol{v}$, $\boldsymbol{h}$ are **concomitantly** piecewise constant

$$\mathcal{N}_{\mathrm{C}}(\mathbf{D}\boldsymbol{v}, \mathbf{D}\boldsymbol{h}; \alpha) = \|[\mathbf{D}\boldsymbol{v}, \alpha\mathbf{D}\boldsymbol{h}]\|_{2,1}$$

Texture's attributes estimation

One-step joint and coupled segmentation as a convex minimization

$$\underset{\boldsymbol{v},\boldsymbol{h}}{\text{minimize}} \sum_a \underbrace{\|\log \boldsymbol{\mathcal{L}}_{a,.} - \boldsymbol{v} - \log(a)\boldsymbol{h}\|^2}_{\textbf{Least-Squares}} + \lambda \underbrace{\mathcal{N}(\mathbf{D}\boldsymbol{v}, \mathbf{D}\boldsymbol{h}; \alpha)}_{\textbf{Total Variation}}$$

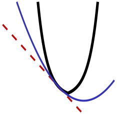


convex

Texture's attributes estimation

One-step joint and coupled segmentation as a convex minimization

$$\underset{\boldsymbol{v},\boldsymbol{h}}{\text{minimize}} \; \underbrace{\sum_a \|\log \mathcal{L}_{a,\cdot} - \boldsymbol{v} - \log(a)\boldsymbol{h}\|^2}_{\textbf{Least-Squares}} \; + \; \lambda \underbrace{\mathcal{N}(\mathbf{D}\boldsymbol{v}, \mathbf{D}\boldsymbol{h}; \alpha)}_{\textbf{Total Variation}}$$



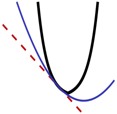
μ-strongly convex

convex

Texture's attributes estimation

One-step joint and coupled segmentation as a convex minimization

$$\underset{\boldsymbol{v},\boldsymbol{h}}{\text{minimize}} \; \underbrace{\sum_a \|\log \mathcal{L}_{a,\cdot} - \boldsymbol{v} - \log(a)\boldsymbol{h}\|^2}_{\textbf{Least-Squares}} \; + \; \lambda \underbrace{\mathcal{N}(\mathbf{D}\boldsymbol{v}, \mathbf{D}\boldsymbol{h}; \alpha)}_{\textbf{Total Variation}}$$



$\boldsymbol{\mu}$-strongly convex

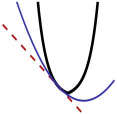
convex

φ is $\boldsymbol{\mu}$-strongly convex iff $\varphi - \frac{\boldsymbol{\mu}}{2}\|\cdot\|^2$ is convex.

Texture's attributes estimation

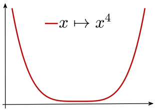
One-step joint and coupled segmentation as a convex minimization

$$\underset{\boldsymbol{v},\boldsymbol{h}}{\text{minimize}} \quad \underbrace{\sum_a \|\log \mathcal{L}_{a,\cdot} - \boldsymbol{v} - \log(a)\boldsymbol{h}\|^2}_{\textbf{Least-Squares}} \quad + \quad \lambda \underbrace{\mathcal{N}(\mathbf{D}\boldsymbol{v}, \mathbf{D}\boldsymbol{h}; \alpha)}_{\textbf{Total Variation}}$$

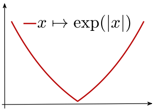


μ-strongly convex — convex

φ is μ-strongly convex iff $\varphi - \frac{\mu}{2}\|\cdot\|^2$ is convex.



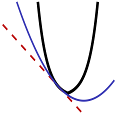
✓ strictly convex
✗ not strongly convex



✓ strictly convex
✓ 1-strongly convex

One-step joint and coupled segmentation as a convex minimization

$$\underset{\boldsymbol{v},\boldsymbol{h}}{\text{minimize}} \; \underbrace{\sum_a \|\log \boldsymbol{\mathcal{L}}_{a,.} - \boldsymbol{v} - \log(a)\boldsymbol{h}\|^2}_{\textbf{Least-Squares}} \;+\; \lambda \underbrace{\mathcal{N}(\mathbf{D}\boldsymbol{v}, \mathbf{D}\boldsymbol{h}; \alpha)}_{\textbf{Total Variation}}$$



$\boldsymbol{\mu}$-strongly convex — convex

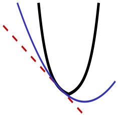
φ is $\boldsymbol{\mu}$-strongly convex iff $\varphi - \frac{\boldsymbol{\mu}}{2}\|\cdot\|^2$ is convex.

If φ is $\mathcal{C}^2$ with Hessian $\boldsymbol{H}\varphi$, φ is $\min \mathrm{Sp}(\boldsymbol{H}\varphi)$-strongly convex.

Texture's attributes estimation

One-step joint and coupled segmentation as a convex minimization

$$\underset{\boldsymbol{v},\boldsymbol{h}}{\text{minimize}} \; \underbrace{\sum_a \|\log \mathcal{L}_{a,.} - \boldsymbol{v} - \log(a)\boldsymbol{h}\|^2}_{\textbf{Least-Squares}} \; + \; \lambda \underbrace{\mathcal{N}(\mathbf{D}\boldsymbol{v}, \mathbf{D}\boldsymbol{h}; \alpha)}_{\textbf{Total Variation}}$$



μ-strongly convex — convex

φ is μ-strongly convex iff $\varphi - \frac{\mu}{2}\|\cdot\|^2$ is convex.

If φ is $\mathcal{C}^2$ with Hessian $\boldsymbol{H}\varphi$, φ is $\min \mathrm{Sp}(\boldsymbol{H}\varphi)$-strongly convex.

$$\mathrm{LS}(\boldsymbol{v}, \boldsymbol{h}) = \sum_{a=a_{\min}}^{a_{\max}} \|\log \mathcal{L}_{a,.} - \boldsymbol{v} - \log(a)\boldsymbol{h}\|^2 = \|\log \mathcal{L} - \mathbf{A}(\boldsymbol{v}, \boldsymbol{h})\|^2$$

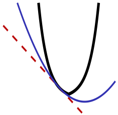
$$\boldsymbol{H}\mathrm{LS} = 2\mathbf{A}^*\mathbf{A}, \quad \text{with} \quad \mathbf{A} : (\boldsymbol{v}, \boldsymbol{h}) \mapsto \{\boldsymbol{v} + \log(a)\boldsymbol{h}\}_{a=a_{\min}}^{a_{\max}}$$

$\mathrm{LS}(\boldsymbol{v}, \boldsymbol{h})$ is μ-strongly convex, μ the smallest eigenvalue of $2\mathbf{A}^*\mathbf{A}$

Texture's attributes estimation

One-step joint and coupled segmentation as a convex minimization

$$\underset{\boldsymbol{v},\boldsymbol{h}}{\text{minimize}} \quad \underbrace{\sum_a \|\log \mathcal{L}_{a,.} - \boldsymbol{v} - \log(a)\boldsymbol{h}\|^2}_{\textbf{Least-Squares}} \quad + \quad \lambda \underbrace{\mathcal{N}(\mathbf{D}\boldsymbol{v}, \mathbf{D}\boldsymbol{h}; \alpha)}_{\textbf{Total Variation}}$$

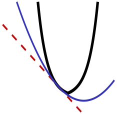


μ-strongly convex

Texture's attributes estimation

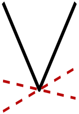
One-step joint and coupled segmentation as a convex minimization

$$\underset{\boldsymbol{v},\boldsymbol{h}}{\text{minimize}} \ \sum_a \underbrace{\|\log \mathcal{L}_{a,.} - \boldsymbol{v} - \log(a)\boldsymbol{h}\|^2}_{\textbf{Least-Squares}} + \lambda \underbrace{\mathcal{N}(\mathbf{D}\boldsymbol{v}, \mathbf{D}\boldsymbol{h}; \alpha)}_{\textbf{Total Variation}}$$



μ-strongly convex

nonsmooth

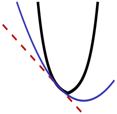


$$\text{prox}_{\tau\varphi} \triangleq (\mathbf{I} - \tau\partial\varphi)^{-1}$$

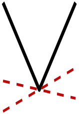
Texture's attributes estimation

One-step joint and coupled segmentation as a convex minimization

$$\underset{\boldsymbol{v},\boldsymbol{h}}{\text{minimize}} \quad \underbrace{\sum_a \|\log \mathcal{L}_{a,.} - \boldsymbol{v} - \log(a)\boldsymbol{h}\|^2}_{\textbf{Least-Squares}} \quad + \quad \lambda \underbrace{\mathcal{N}(\mathbf{D}\boldsymbol{v}, \mathbf{D}\boldsymbol{h}; \alpha)}_{\textbf{Total Variation}}$$



μ-strongly convex nonsmooth



Accelerated primal-dual algorithm (Chambolle, Pock 11')

$$\boldsymbol{x}^n = (\boldsymbol{v}^n, \boldsymbol{h}^n), \quad \boldsymbol{y}^n = (\boldsymbol{u}^n, \boldsymbol{\ell}^n)$$

$$\boldsymbol{y}^{n+1} = \text{prox}_{\sigma_n \lambda \mathcal{N}} (\boldsymbol{y}^n + \sigma_n \mathbf{D}\bar{\boldsymbol{x}}^n)$$

$$\boldsymbol{x}^{n+1} = \text{prox}_{\tau_n \text{LS}} \left(\boldsymbol{x}^n - \tau_n \mathbf{D}^* \boldsymbol{y}^{n+1}\right)$$

$$\theta_n = \sqrt{1 + 2\mu\tau_n}, \quad \tau_{n+1} = \tau_n/\theta_n, \quad \sigma_{n+1} = \theta_n \sigma_n$$

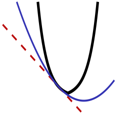
$$\bar{\boldsymbol{x}}^{n+1} = \boldsymbol{x}^{n+1} + \theta_n^{-1}\left(\boldsymbol{x}^{n+1} - \boldsymbol{x}^n\right)$$

$$\text{prox}_{\tau\varphi} \triangleq (\mathbf{I} - \tau\partial\varphi)^{-1}$$

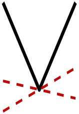
Texture's attributes estimation

One-step joint and coupled segmentation as a convex minimization

$$\underset{\boldsymbol{v},\boldsymbol{h}}{\text{minimize}} \; \sum_a \underbrace{\|\log \boldsymbol{\mathcal{L}}_{a,.} - \boldsymbol{v} - \log(a)\boldsymbol{h}\|^2}_{\textbf{Least-Squares}} \; + \; \lambda \underbrace{\mathcal{N}(\mathbf{D}\boldsymbol{v}, \mathbf{D}\boldsymbol{h}; \alpha)}_{\textbf{Total Variation}}$$



μ-strongly convex   nonsmooth



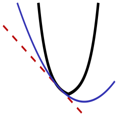
Accelerated primal-dual algorithm (Chambolle, Pock 11')

$$\boldsymbol{x}^n = (\boldsymbol{v}^n, \boldsymbol{h}^n), \quad \boldsymbol{y}^n = (\boldsymbol{u}^n, \boldsymbol{\ell}^n)$$

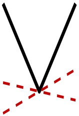
Texture's attributes estimation

One-step joint and coupled segmentation as a convex minimization

$$\underset{\boldsymbol{v},\boldsymbol{h}}{\text{minimize}} \underbrace{\sum_a \|\log \mathcal{L}_{a,.} - \boldsymbol{v} - \log(a)\boldsymbol{h}\|^2}_{\textbf{Least-Squares}} + \lambda \underbrace{\mathcal{N}(\mathbf{D}\boldsymbol{v}, \mathbf{D}\boldsymbol{h}; \alpha)}_{\textbf{Total Variation}}$$



μ-strongly convex   nonsmooth



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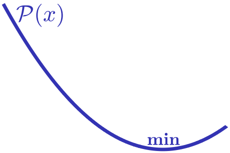
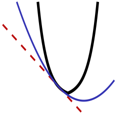


$$\min_{\boldsymbol{x}} \mathrm{LS}(\boldsymbol{x}) + \lambda \mathcal{N}(\mathbf{D}\boldsymbol{x})$$

Texture's attributes estimation

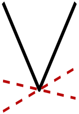
One-step joint and coupled segmentation as a convex minimization

$$\underset{\boldsymbol{v},\boldsymbol{h}}{\text{minimize}} \; \sum_a \underbrace{\|\log \boldsymbol{\mathcal{L}}_{a,.} - \boldsymbol{v} - \log(a)\boldsymbol{h}\|^2}_{\textbf{Least-Squares}} \; + \; \lambda \underbrace{\mathcal{N}(\mathbf{D}\boldsymbol{v}, \mathbf{D}\boldsymbol{h}; \alpha)}_{\textbf{Total Variation}}$$



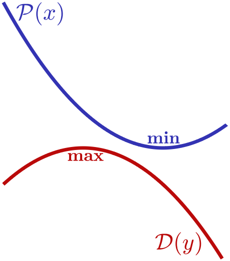
μ-strongly convex

nonsmooth



Accelerated primal-dual algorithm (Chambolle, Pock 11')

$$\boldsymbol{x}^n = (\boldsymbol{v}^n, \boldsymbol{h}^n), \quad \boldsymbol{y}^n = (\boldsymbol{u}^n, \boldsymbol{\ell}^n)$$



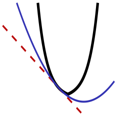
$$\min_{\boldsymbol{x}} \mathrm{LS}(\boldsymbol{x}) + \lambda \mathcal{N}(\mathbf{D}\boldsymbol{x})$$

$$\max_{\boldsymbol{y}} \; -\mathrm{LS}^*(-\mathbf{D}^*\boldsymbol{y}) - (\lambda\mathcal{N})^*(\boldsymbol{y})$$

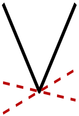
Texture's attributes estimation

One-step joint and coupled segmentation as a convex minimization

$$\underset{\boldsymbol{v},\boldsymbol{h}}{\text{minimize}} \sum_a \underbrace{\|\log \boldsymbol{\mathcal{L}}_{a,.} - \boldsymbol{v} - \log(a)\boldsymbol{h}\|^2}_{\textbf{Least-Squares}} + \lambda \underbrace{\mathcal{N}(\mathbf{D}\boldsymbol{v}, \mathbf{D}\boldsymbol{h}; \alpha)}_{\textbf{Total Variation}}$$



μ-strongly convex nonsmooth



Accelerated primal-dual algorithm (Chambolle, Pock 11')

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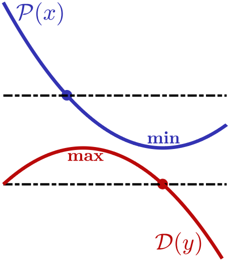


$$\min_{\boldsymbol{x}} \mathrm{LS}(\boldsymbol{x}) + \lambda\mathcal{N}(\mathbf{D}\boldsymbol{x})$$

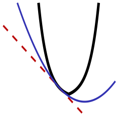
$$\max_{\boldsymbol{y}} -\mathrm{LS}^*(-\mathbf{D}^*\boldsymbol{y}) - (\lambda\mathcal{N})^*(\boldsymbol{y})$$

$$\delta(\boldsymbol{x}; \boldsymbol{y}) \triangleq \mathcal{P}(\boldsymbol{x}) - \mathcal{D}(\boldsymbol{y})$$

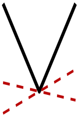
Texture's attributes estimation

One-step joint and coupled segmentation as a convex minimization

$$\underset{\boldsymbol{v},\boldsymbol{h}}{\text{minimize}} \sum_a \underbrace{\|\log \boldsymbol{\mathcal{L}}_{a,.} - \boldsymbol{v} - \log(a)\boldsymbol{h}\|^2}_{\textbf{Least-Squares}} \;+\; \lambda \underbrace{\mathcal{N}(\mathbf{D}\boldsymbol{v}, \mathbf{D}\boldsymbol{h}; \alpha)}_{\textbf{Total Variation}}$$

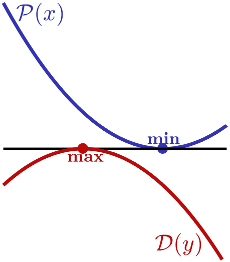


μ-strongly convex nonsmooth



Accelerated primal-dual algorithm (Chambolle, Pock 11')

$$\boldsymbol{x}^n = (\boldsymbol{v}^n, \boldsymbol{h}^n), \quad \boldsymbol{y}^n = (\boldsymbol{u}^n, \boldsymbol{\ell}^n)$$



$$\min_{\boldsymbol{x}} \mathrm{LS}(\boldsymbol{x}) + \lambda \mathcal{N}(\mathbf{D}\boldsymbol{x})$$

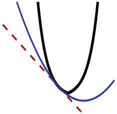
$$\max_{\boldsymbol{y}} \; -\mathrm{LS}^*(-\mathbf{D}^*\boldsymbol{y}) - (\lambda\mathcal{N})^*(\boldsymbol{y})$$

$$\delta(\widehat{\boldsymbol{x}}; \widehat{\boldsymbol{y}}) = \mathcal{P}(\widehat{\boldsymbol{x}}) - \mathcal{D}(\widehat{\boldsymbol{y}}) = 0$$

Texture's attributes estimation

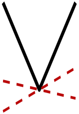
One-step joint and coupled segmentation as a convex minimization

$$\underset{\boldsymbol{v},\boldsymbol{h}}{\text{minimize}} \;\; \underbrace{\sum_a \|\log \boldsymbol{\mathcal{L}}_{a,\cdot} - \boldsymbol{v} - \log(a)\boldsymbol{h}\|^2}_{\textbf{Least-Squares}} \;\; + \;\; \lambda \underbrace{\mathcal{N}(\mathbf{D}\boldsymbol{v}, \mathbf{D}\boldsymbol{h}; \alpha)}_{\textbf{Total Variation}}$$



μ-strongly convex

nonsmooth



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Texture's attributes estimation

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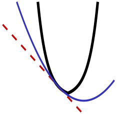

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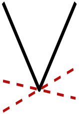

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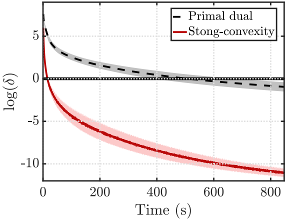
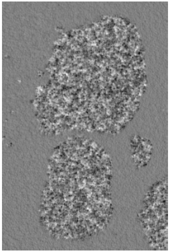


Texture's attributes estimation

Iterated thresholding for segmentation

$$\underset{\boldsymbol{v},\boldsymbol{h}}{\text{minimize}} \quad \underbrace{\sum_a \|\log \boldsymbol{\mathcal{L}}_{a,\cdot} - \boldsymbol{v} - \log(a)\boldsymbol{h}\|^2}_{\textbf{Least-Squares}} \quad + \quad \lambda \underbrace{\mathcal{N}(\mathbf{D}\boldsymbol{v}, \mathbf{D}\boldsymbol{h}; \alpha)}_{\textbf{Total Variation}}$$

Textured image



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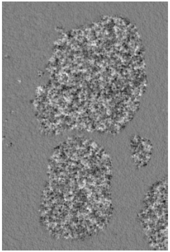
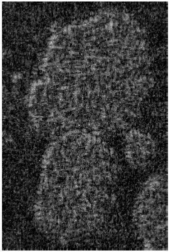
Textured image



Lin. Reg. $\widehat{\boldsymbol{h}}^{\mathrm{LR}}$



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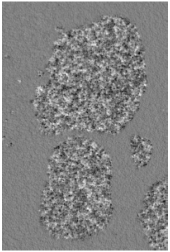
Textured image



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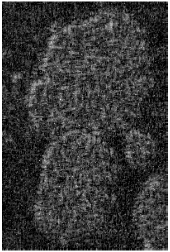
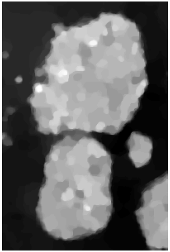


Coupled $\widehat{\boldsymbol{h}}^{\mathrm{C}}$

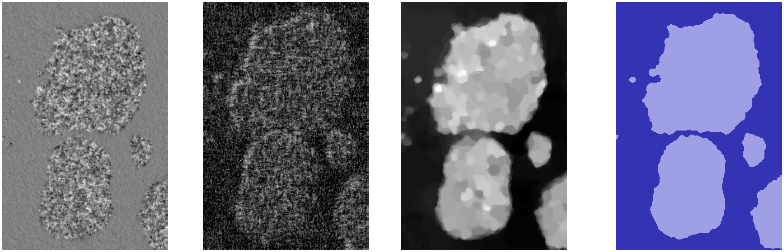


Texture's attributes estimation

Iterated thresholding for segmentation

$$\underset{\boldsymbol{v},\boldsymbol{h}}{\text{minimize}} \ \sum_a \underbrace{\|\log \boldsymbol{\mathcal{L}}_{a,\cdot} - \boldsymbol{v} - \log(a)\boldsymbol{h}\|^2}_{\textbf{Least-Squares}} \ + \ \lambda \underbrace{\mathcal{N}(\mathbf{D}\boldsymbol{v}, \mathbf{D}\boldsymbol{h}; \alpha)}_{\textbf{Total Variation}}$$

Textured image | Lin. Reg. $\widehat{\boldsymbol{h}}^{\mathrm{LR}}$ | Coupled $\widehat{\boldsymbol{h}}^{\mathrm{C}}$ | Thresholded $T\widehat{\boldsymbol{h}}^{\mathrm{C}}$

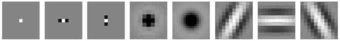


X.Cai, *et al.*, *Multiclass segmentation by iterated ROF thresholding* (2013)

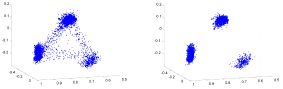
State-of-the-art two-step texture segmentation

Factorization-based segmentation [Yuan *et al.* 15']†

(i) local spectral histograms



(ii) matrix factorization



(a) (b)

Fig. 2. Scatterplot of features in subspace. (a) Scatterplot of features projected onto the 3-d subspace. (b) Scatterplot after removing features with high edgeness.

†https://sites.google.com/site/factorizationsegmentation/

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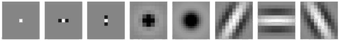
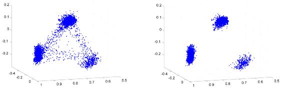


(ii) matrix factorization



(a) (b)

Fig. 2. Scatterplot of features in subspace. (a) Scatterplot of features projected onto the 3-d subspace. (b) Scatterplot after removing features with high edgeness.

Threshold-ROF on $\widehat{\boldsymbol{h}}^{\mathrm{LR}}$ [Pustelnik 16']

$$\min_{\boldsymbol{h}} \|\boldsymbol{h} - \widehat{\boldsymbol{h}}^{\mathrm{LR}}\|^2 + \lambda \|\mathbf{D}\boldsymbol{h}\|_{2,1}$$

Lin. Reg.

ROF

Threshold

Based on regularity $\boldsymbol{h}$ only.

†https://sites.google.com/site/factorizationsegmentation/

Outline – Fractal texture segmentation

1. Fractal texture model

$$\log\left(\mathcal{L}_{a,\cdot}\right) \simeq \underbrace{\boldsymbol{v}}_{\sim\log(\boldsymbol{\sigma}^2)} + \log(a) \underbrace{\boldsymbol{h}}_{regularity}$$

2. Attributes estimation and segmentation

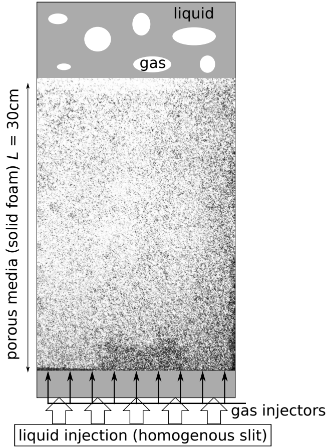
$$\underset{\boldsymbol{v},\boldsymbol{h}}{\text{minimize}} \sum_a \underbrace{\|\log \mathcal{L}_{a,\cdot} - \boldsymbol{v} - \log(a)\boldsymbol{h}\|^2}_{\textbf{Least-Squares}} + \lambda \underbrace{\mathcal{N}(\mathbf{D}\boldsymbol{v}, \mathbf{D}\boldsymbol{h}; \alpha)}_{\textbf{Total Variation}}$$

3. Multiphasic flow segmentation

4. Regularization parameters tuning

Multiphasic (quasi 2D) flow in a porous media

Laboratoire de Physique, ENS Lyon, V. Vidal, T. Busser, (M. Serres, IFPEN)



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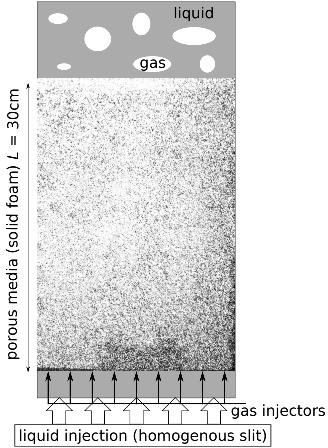

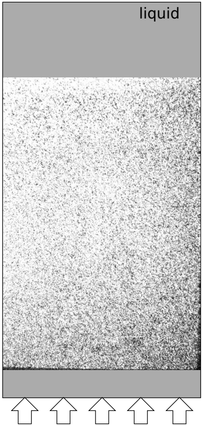

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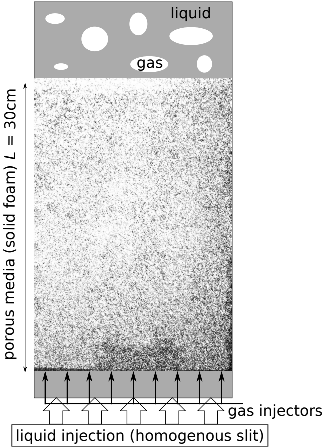
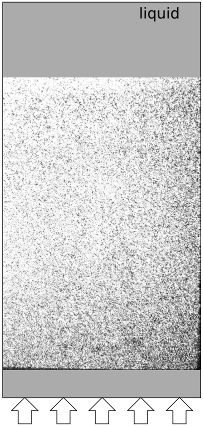
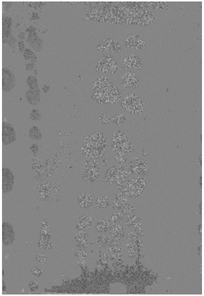




Normalized image



Textured

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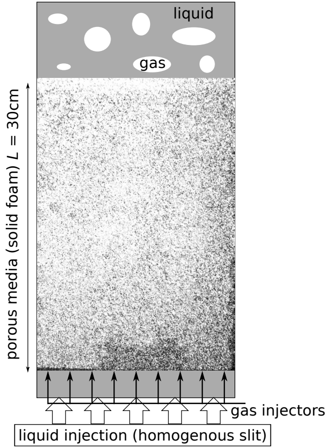

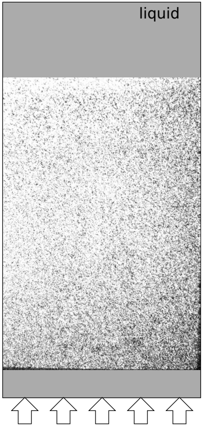

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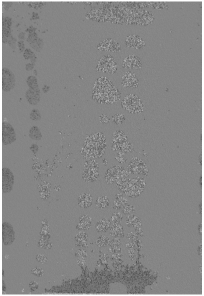
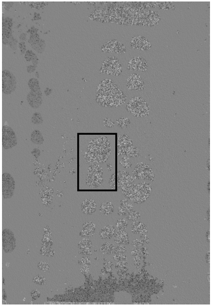


Textured

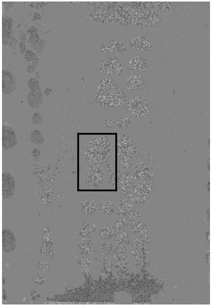
Physical quantities: gas volume & contact surface.

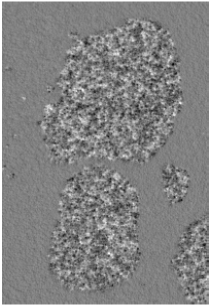
area perimeter

Texture segmentation

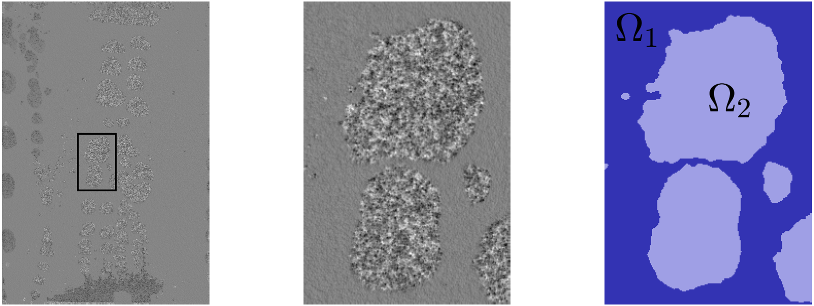


Texture segmentation





Texture segmentation

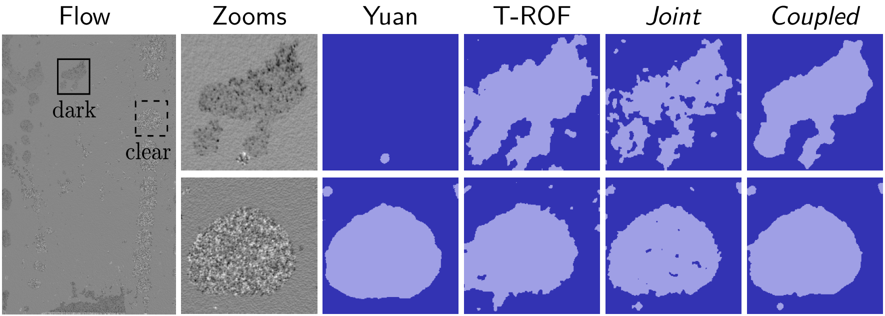


Purpose: obtaining a partition of the image into two regions

$$\Omega = \Omega_1 \bigsqcup \Omega_2$$

Ω_1: liquid, Ω_2: gas.

Multiphasic flow. $Q_{\mathrm{G}} = 300$mL/min - $Q_{\mathrm{L}} = 300$mL/min: low activity



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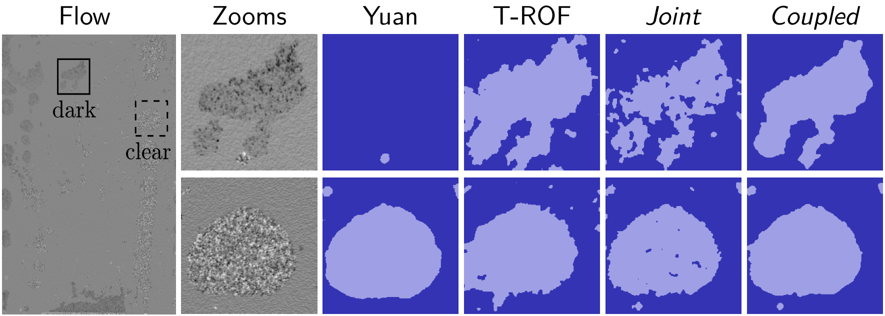

Liquid: $h_{\mathrm{L}} = 0.4$

Gas: $h_{\mathrm{G}} = 0.9$

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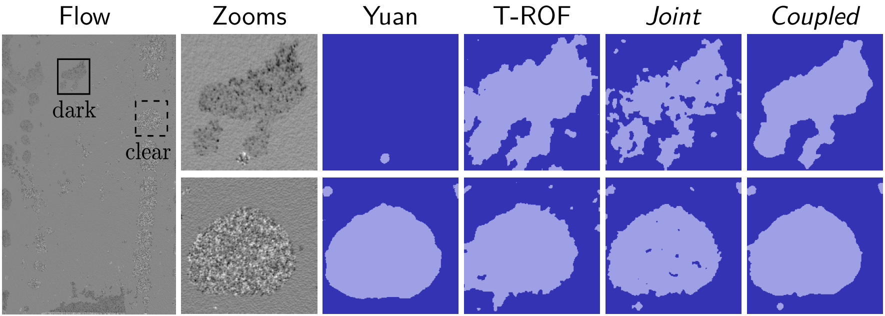
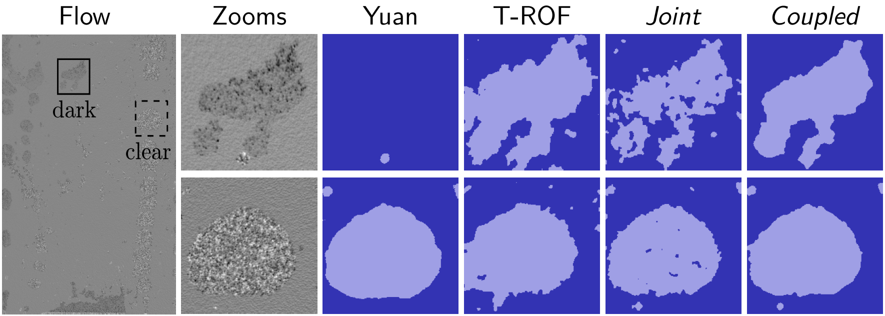


Liquid: $h_{\mathrm{L}} = 0.4$ $\quad \sigma^2_{\mathrm{dark}} = 10^{-2}$

Gas: $h_{\mathrm{G}} = 0.9$ $\quad \sigma^2_{\mathrm{dark}} = 10^{-2}$(dark bubbles)

Multiphasic flow. $Q_{\mathrm{G}} = 300$mL/min - $Q_{\mathrm{L}} = 300$mL/min: low activity



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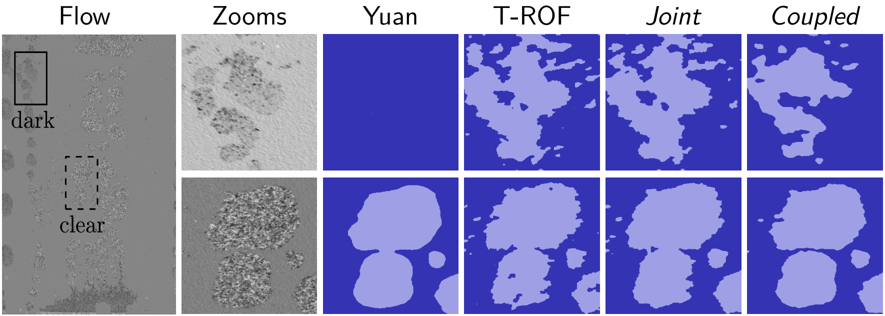
$\sigma^2_{\mathrm{dark}} = 10^{-2}$

$\sigma^2_{\mathrm{dark}} = 10^{-2}$(dark bubbles)

$\sigma^2_{\mathrm{clear}} = 10^{-1}$(clear bubbles)

Multiphasic flow. $Q_{\mathrm{G}} = 400$mL/min - $Q_{\mathrm{L}} = 700$mL/min: transition



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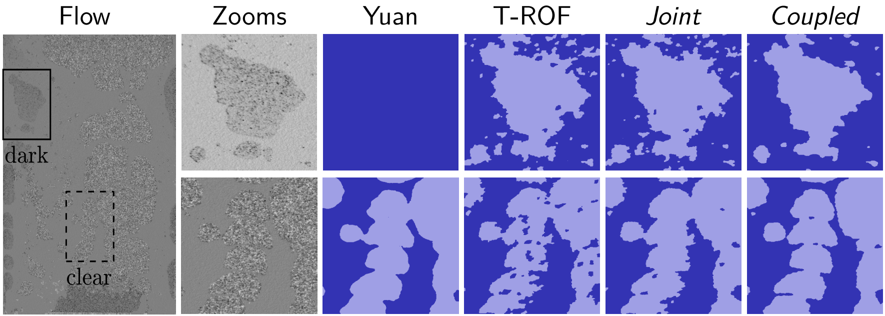
Multiphasic flow. $Q_{\mathrm{G}} = 1200$mL/min - $Q_{\mathrm{L}} = 300$mL/min: high activity

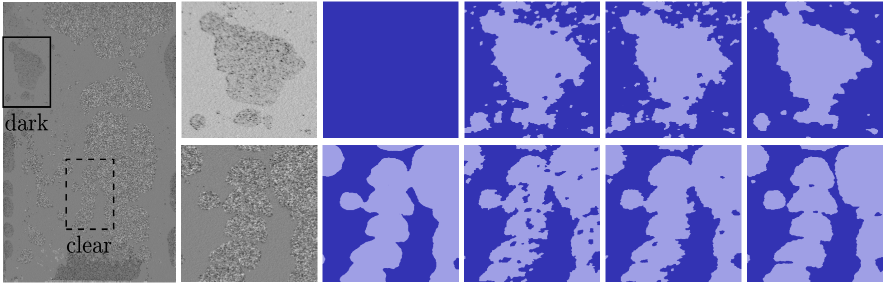


Liquid: $h_{\mathrm{L}} = 0.4$ $\quad \sigma^2_{\mathrm{dark}} = 10^{-2}$

Gas: $h_{\mathrm{G}} = 0.9$ $\quad \left| \begin{array}{l} \sigma^2_{\mathrm{dark}} = 10^{-2} \text{(dark bubbles)} \\ \sigma^2_{\mathrm{clear}} = 10^{-1} \text{(clear bubbles)} \end{array} \right.$

Multiphasic flow. $Q_{\mathrm{G}} = 1200$mL/min - $Q_{\mathrm{L}} = 300$mL/min: high activity

Flow	Zooms	Yuan	T-ROF	*Joint*	*Coupled*



Computational time	1s	12s	700s	**2100s**

Liquid: $h_{\mathrm{L}} = 0.4$ $\quad \sigma^2_{\mathrm{dark}} = 10^{-2}$

Gas: $h_{\mathrm{G}} = 0.9$ $\quad \Big| \; \sigma^2_{\mathrm{dark}} = 10^{-2}$(dark bubbles), $\sigma^2_{\mathrm{clear}} = 10^{-1}$(clear bubbles)

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Texture's attributes estimation

Hyperparameters tuning

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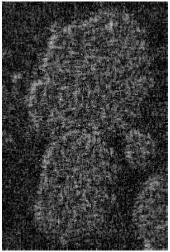
Lin. Reg. $\widehat{\boldsymbol{h}}^{\mathrm{LR}}$



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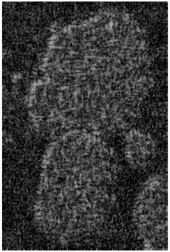
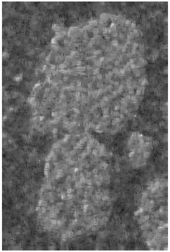
Lin. Reg. $\widehat{\boldsymbol{h}}^{\mathrm{LR}}$



Too small



Texture's attributes estimation

Hyperparameters tuning

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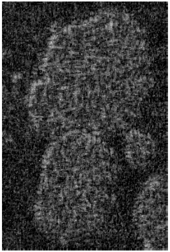

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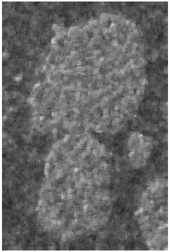
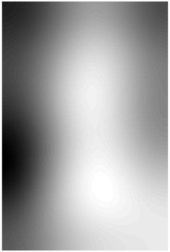


Too large

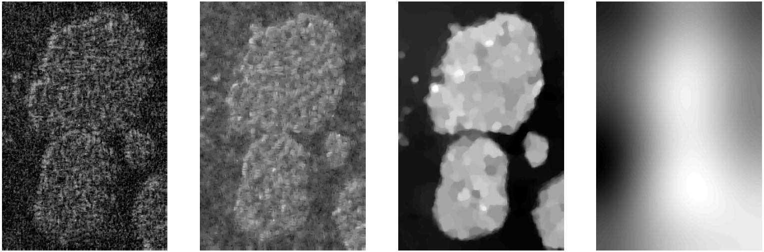


Texture's attributes estimation

Hyperparameters tuning

$$\underset{\boldsymbol{v},\boldsymbol{h}}{\text{minimize}} \quad \underbrace{\sum_a \|\log \mathcal{L}_{a,\cdot} - \boldsymbol{v} - \log(a)\boldsymbol{h}\|^2}_{\textbf{Least-Squares}} \quad + \quad \lambda \underbrace{\mathcal{N}(\mathbf{D}\boldsymbol{v}, \mathbf{D}\boldsymbol{h}; \alpha)}_{\textbf{Total Variation}}$$

Lin. Reg. $\widehat{\boldsymbol{h}}^{\mathrm{LR}}$ | Too small | Optimal | Too large



Texture's attributes estimation

Hyperparameters tuning

$$\underset{\boldsymbol{v},\boldsymbol{h}}{\text{minimize}} \quad \underbrace{\sum_a \|\log \mathcal{L}_{a,.} - \boldsymbol{v} - \log(a)\boldsymbol{h}\|^2}_{\textbf{Least-Squares}} \quad + \quad \lambda \underbrace{\mathcal{N}(\mathbf{D}\boldsymbol{v}, \mathbf{D}\boldsymbol{h}; \alpha)}_{\textbf{Total Variation}}$$

$\bar{\boldsymbol{h}}$: true regularity

$$R(\lambda, \alpha) = \left\| \widehat{\boldsymbol{h}}_{\lambda,\alpha} - \bar{\boldsymbol{h}} \right\|^2$$

Texture's attributes estimation

Hyperparameters tuning

$$\underset{\boldsymbol{v},\boldsymbol{h}}{\text{minimize}} \; \sum_a \underbrace{\|\log \mathcal{L}_{a,\cdot} - \boldsymbol{v} - \log(a)\boldsymbol{h}\|^2}_{\textbf{Least-Squares}} \; + \; \lambda \underbrace{\mathcal{N}(\mathbf{D}\boldsymbol{v}, \mathbf{D}\boldsymbol{h}; \alpha)}_{\textbf{Total Variation}}$$

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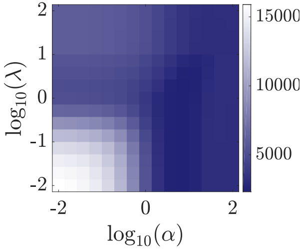


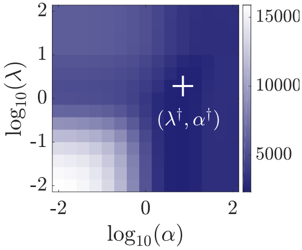
Texture's attributes estimation

Hyperparameters tuning

$$\underset{\boldsymbol{v},\boldsymbol{h}}{\text{minimize}} \sum_a \underbrace{\|\log \boldsymbol{\mathcal{L}}_{a,\cdot} - \boldsymbol{v} - \log(a)\boldsymbol{h}\|^2}_{\textbf{Least-Squares}} + \lambda \underbrace{\mathcal{N}(\mathbf{D}\boldsymbol{v}, \mathbf{D}\boldsymbol{h}; \alpha)}_{\textbf{Total Variation}}$$

$\bar{\boldsymbol{h}}$: true regularity

$$R(\lambda,\alpha) = \left\| \widehat{\boldsymbol{h}}_{\lambda,\alpha} - \bar{\boldsymbol{h}} \right\|^2$$



Texture's attributes estimation

Hyperparameters tuning

$$\underset{\boldsymbol{v},\boldsymbol{h}}{\text{minimize}} \quad \underbrace{\sum_a \|\log \mathcal{L}_{a,\cdot} - \boldsymbol{v} - \log(a)\boldsymbol{h}\|^2}_{\textbf{Least-Squares}} \quad + \quad \lambda \underbrace{\mathcal{N}(\mathbf{D}\boldsymbol{v}, \mathbf{D}\boldsymbol{h}; \alpha)}_{\textbf{Total Variation}}$$

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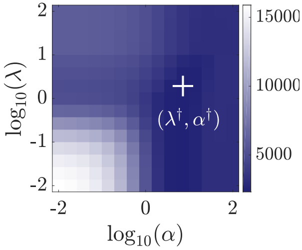


$\bar{\boldsymbol{h}}$: unknown!

?

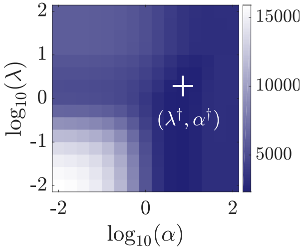
Texture's attributes estimation

Hyperparameters tuning

$$\underset{\boldsymbol{v},\boldsymbol{h}}{\text{minimize}} \; \sum_a \underbrace{\|\log \boldsymbol{\mathcal{L}}_{a,\cdot} - \boldsymbol{v} - \log(a)\boldsymbol{h}\|^2}_{\textbf{Least-Squares}} \; + \; \lambda \underbrace{\mathcal{N}(\mathbf{D}\boldsymbol{v}, \mathbf{D}\boldsymbol{h}; \alpha)}_{\textbf{Total Variation}}$$

$\bar{\boldsymbol{h}}$: true regularity

$$R(\lambda, \alpha) = \left\| \widehat{\boldsymbol{h}}_{\lambda,\alpha} - \bar{\boldsymbol{h}} \right\|^2$$



$\bar{\boldsymbol{h}}$: unknown!

?

Stein Unbiased Risk Estimate (SURE)

Stein Unbiased Risk Estimate

i.i.d. Gaussian noise

Observation model $\quad \boldsymbol{y} = \underset{\text{truth}}{\bar{\boldsymbol{x}}} + \underset{\text{noise}}{\boldsymbol{\varepsilon}} \in \mathbb{R}^N$

Stein Unbiased Risk Estimate

i.i.d. Gaussian noise

Observation model $\boldsymbol{y} = \underset{\text{truth}}{\bar{\boldsymbol{x}}} + \underset{\text{noise}}{\boldsymbol{\varepsilon}} \in \mathbb{R}^N$

Estimator $\widehat{\boldsymbol{x}}_\lambda(\boldsymbol{y})$

Stein Unbiased Risk Estimate

i.i.d. Gaussian noise

Observation model $\quad \boldsymbol{y} = \underset{\text{truth}}{\bar{\boldsymbol{x}}} + \underset{\text{noise}}{\boldsymbol{\varepsilon}} \in \mathbb{R}^N$

Estimator $\quad \widehat{\boldsymbol{x}}_\lambda(\boldsymbol{y}) = \begin{cases} (\mathbf{I} + \lambda \mathbf{D}^* \mathbf{D})^{-1} \boldsymbol{y} & \text{(linear)} \\ \operatorname*{arg\,min}_{\boldsymbol{x}} \|\boldsymbol{y} - \boldsymbol{x}\|^2 + \lambda \mathcal{N}(\mathbf{D}\boldsymbol{x}) & \text{(nonlinear)} \end{cases}$

Stein Unbiased Risk Estimate

i.i.d. Gaussian noise

$$\text{Observation model} \quad \boldsymbol{y} = \underset{\text{truth}}{\bar{\boldsymbol{x}}} + \underset{\text{noise}}{\boldsymbol{\varepsilon}} \in \mathbb{R}^N$$

$$\text{Estimator} \quad \widehat{\boldsymbol{x}}_\lambda(\boldsymbol{y}) = \begin{cases} (\mathbf{I} + \lambda \mathbf{D}^* \mathbf{D})^{-1} \boldsymbol{y} & \text{(linear)} \\ \underset{\boldsymbol{x}}{\arg\min} \|\boldsymbol{y} - \boldsymbol{x}\|^2 + \lambda \mathcal{N}(\mathbf{D}\boldsymbol{x}) & \text{(nonlinear)} \end{cases}$$

If $\boldsymbol{\varepsilon}$ is i.i.d. Gaussian noise of variance ρ^2

Stein Unbiased Risk Estimate

i.i.d. Gaussian noise

Observation model $\boldsymbol{y} = \underset{\text{truth}}{\bar{\boldsymbol{x}}} + \underset{\text{noise}}{\boldsymbol{\varepsilon}} \in \mathbb{R}^N$

Estimator $\widehat{\boldsymbol{x}}_\lambda(\boldsymbol{y}) = \begin{cases} (\mathbf{I} + \lambda \mathbf{D}^* \mathbf{D})^{-1} \boldsymbol{y} & \text{(linear)} \\ \arg\min_{\boldsymbol{x}} \|\boldsymbol{y} - \boldsymbol{x}\|^2 + \lambda \mathcal{N}(\mathbf{D}\boldsymbol{x}) & \text{(nonlinear)} \end{cases}$

If $\boldsymbol{\varepsilon}$ is i.i.d. Gaussian noise of variance ρ^2

$$R(\lambda) \triangleq \mathbb{E} \left\| \widehat{\boldsymbol{x}}_\lambda(\boldsymbol{y}) - \bar{\boldsymbol{x}} \right\|^2$$

Stein Unbiased Risk Estimate

i.i.d. Gaussian noise

$$\text{Observation model} \quad \boldsymbol{y} = \underset{\text{truth}}{\bar{\boldsymbol{x}}} + \underset{\text{noise}}{\boldsymbol{\varepsilon}} \in \mathbb{R}^N$$

$$\text{Estimator} \quad \widehat{\boldsymbol{x}}_\lambda(\boldsymbol{y}) = \begin{cases} (\mathbf{I} + \lambda \mathbf{D}^* \mathbf{D})^{-1} \boldsymbol{y} & \text{(linear)} \\ \underset{\boldsymbol{x}}{\arg\min} \|\boldsymbol{y} - \boldsymbol{x}\|^2 + \lambda \mathcal{N}(\mathbf{D}\boldsymbol{x}) & \text{(nonlinear)} \end{cases}$$

If ε is i.i.d. Gaussian noise of variance ρ^2

$$R(\lambda) \triangleq \mathbb{E} \left\| \widehat{\boldsymbol{x}}_\lambda(\boldsymbol{y}) - \bar{\boldsymbol{x}} \right\|^2 = \mathbb{E} \left\| \widehat{\boldsymbol{x}}_\lambda(\boldsymbol{y}) - \boldsymbol{y} + \boldsymbol{y} - \bar{\boldsymbol{x}} \right\|^2$$

Stein Unbiased Risk Estimate

i.i.d. Gaussian noise

Observation model $\quad \boldsymbol{y} = \underset{\text{truth}}{\bar{\boldsymbol{x}}} + \underset{\text{noise}}{\boldsymbol{\varepsilon}} \in \mathbb{R}^N$

Estimator $\quad \widehat{\boldsymbol{x}}_\lambda(\boldsymbol{y}) = \begin{cases} (\mathbf{I} + \lambda \mathbf{D}^*\mathbf{D})^{-1}\boldsymbol{y} & \text{(linear)} \\ \arg\min_{\boldsymbol{x}} \|\boldsymbol{y} - \boldsymbol{x}\|^2 + \lambda \mathcal{N}(\mathbf{D}\boldsymbol{x}) & \text{(nonlinear)} \end{cases}$

If ε is i.i.d. Gaussian noise of variance ρ^2

$$R(\lambda) \triangleq \mathbb{E}\,\|\widehat{\boldsymbol{x}}_\lambda(\boldsymbol{y}) - \bar{\boldsymbol{x}}\|^2 = \mathbb{E}\,\|\widehat{\boldsymbol{x}}_\lambda(\boldsymbol{y}) - \boldsymbol{y} + \boldsymbol{y} - \bar{\boldsymbol{x}}\|^2$$
$$= \mathbb{E}\,\|\widehat{\boldsymbol{x}}_\lambda(\boldsymbol{y}) - \boldsymbol{y}\|^2 + 2\mathbb{E}\,\langle \widehat{\boldsymbol{x}}_\lambda(\boldsymbol{y}) - \boldsymbol{y}, \boldsymbol{y} - \bar{\boldsymbol{x}} \rangle + \mathbb{E}\,\|\boldsymbol{y} - \bar{\boldsymbol{x}}\|^2$$

Stein Unbiased Risk Estimate

i.i.d. Gaussian noise

Observation model $\quad \boldsymbol{y} = \underset{\text{truth}}{\bar{\boldsymbol{x}}} + \underset{\text{noise}}{\boldsymbol{\varepsilon}} \in \mathbb{R}^N$

$$\text{Estimator} \quad \widehat{\boldsymbol{x}}_\lambda(\boldsymbol{y}) = \begin{cases} (\mathbf{I} + \lambda \mathbf{D}^* \mathbf{D})^{-1} \boldsymbol{y} & \text{(linear)} \\ \arg\min_{\boldsymbol{x}} \|\boldsymbol{y} - \boldsymbol{x}\|^2 + \lambda \mathcal{N}(\mathbf{D}\boldsymbol{x}) & \text{(nonlinear)} \end{cases}$$

If ε is i.i.d. Gaussian noise of variance ρ^2

$$\begin{aligned} R(\lambda) &\triangleq \mathbb{E}\,\|\widehat{\boldsymbol{x}}_\lambda(\boldsymbol{y}) - \bar{\boldsymbol{x}}\|^2 = \mathbb{E}\,\|\widehat{\boldsymbol{x}}_\lambda(\boldsymbol{y}) - \boldsymbol{y} + \boldsymbol{y} - \bar{\boldsymbol{x}}\|^2 \\ &= \mathbb{E}\,\|\widehat{\boldsymbol{x}}_\lambda(\boldsymbol{y}) - \boldsymbol{y}\|^2 + 2\mathbb{E}\,\langle \widehat{\boldsymbol{x}}_\lambda(\boldsymbol{y}) - \boldsymbol{y}, \boldsymbol{y} - \bar{\boldsymbol{x}} \rangle + \mathbb{E}\,\|\boldsymbol{y} - \bar{\boldsymbol{x}}\|^2 \\ &= \underline{\mathbb{E}\,\|\widehat{\boldsymbol{x}}_\lambda(\boldsymbol{y}) - \boldsymbol{y}\|^2} + 2 \quad \underline{\mathbb{E}\,\langle \widehat{\boldsymbol{x}}_\lambda(\boldsymbol{y}), \boldsymbol{\varepsilon} \rangle} \quad - \underline{\mathbb{E}\,\|\boldsymbol{\varepsilon}\|^2} \end{aligned}$$

Stein Unbiased Risk Estimate

i.i.d. Gaussian noise

Observation model $\quad \boldsymbol{y} = \underset{\text{truth}}{\bar{\boldsymbol{x}}} + \underset{\text{noise}}{\boldsymbol{\varepsilon}} \in \mathbb{R}^N$

Estimator $\quad \widehat{\boldsymbol{x}}_\lambda(\boldsymbol{y}) = \begin{cases} \left(\mathbf{I} + \lambda \mathbf{D}^* \mathbf{D}\right)^{-1} \boldsymbol{y} & \text{(linear)} \\ \underset{\boldsymbol{x}}{\arg\min} \, \|\boldsymbol{y} - \boldsymbol{x}\|^2 + \lambda \mathcal{N}(\mathbf{D}\boldsymbol{x}) & \text{(nonlinear)} \end{cases}$

If $\boldsymbol{\varepsilon}$ is i.i.d. Gaussian noise of variance ρ^2

$$\begin{aligned} R(\lambda) &\triangleq \mathbb{E}\left\|\widehat{\boldsymbol{x}}_\lambda(\boldsymbol{y}) - \bar{\boldsymbol{x}}\right\|^2 = \mathbb{E}\left\|\widehat{\boldsymbol{x}}_\lambda(\boldsymbol{y}) - \boldsymbol{y} + \boldsymbol{y} - \bar{\boldsymbol{x}}\right\|^2 \\ &= \mathbb{E}\left\|\widehat{\boldsymbol{x}}_\lambda(\boldsymbol{y}) - \boldsymbol{y}\right\|^2 + 2\mathbb{E}\left\langle \widehat{\boldsymbol{x}}_\lambda(\boldsymbol{y}) - \boldsymbol{y}, \boldsymbol{y} - \bar{\boldsymbol{x}} \right\rangle + \mathbb{E}\left\|\boldsymbol{y} - \bar{\boldsymbol{x}}\right\|^2 \\ &= \underbrace{\mathbb{E}\left\|\widehat{\boldsymbol{x}}_\lambda(\boldsymbol{y}) - \boldsymbol{y}\right\|^2}_{\text{known}} + 2 \quad \underline{\mathbb{E}\left\langle \widehat{\boldsymbol{x}}_\lambda(\boldsymbol{y}), \boldsymbol{\varepsilon} \right\rangle} \quad - \underline{\mathbb{E}\left\|\boldsymbol{\varepsilon}\right\|^2} \end{aligned}$$

Stein Unbiased Risk Estimate

i.i.d. Gaussian noise

Observation model $\boldsymbol{y} = \underset{\text{truth}}{\bar{\boldsymbol{x}}} + \underset{\text{noise}}{\boldsymbol{\varepsilon}} \in \mathbb{R}^N$

Estimator $\widehat{\boldsymbol{x}}_\lambda(\boldsymbol{y}) = \begin{cases} (\mathbf{I} + \lambda \mathbf{D}^* \mathbf{D})^{-1} \boldsymbol{y} & \text{(linear)} \\ \arg\min_{\boldsymbol{x}} \|\boldsymbol{y} - \boldsymbol{x}\|^2 + \lambda \mathcal{N}(\mathbf{D}\boldsymbol{x}) & \text{(nonlinear)} \end{cases}$

If ε is i.i.d. Gaussian noise of variance ρ^2

$$\begin{aligned} R(\lambda) &\triangleq \mathbb{E}\left\|\widehat{\boldsymbol{x}}_\lambda(\boldsymbol{y}) - \bar{\boldsymbol{x}}\right\|^2 = \mathbb{E}\left\|\widehat{\boldsymbol{x}}_\lambda(\boldsymbol{y}) - \boldsymbol{y} + \boldsymbol{y} - \bar{\boldsymbol{x}}\right\|^2 \\ &= \mathbb{E}\left\|\widehat{\boldsymbol{x}}_\lambda(\boldsymbol{y}) - \boldsymbol{y}\right\|^2 + 2\mathbb{E}\left\langle \widehat{\boldsymbol{x}}_\lambda(\boldsymbol{y}) - \boldsymbol{y}, \boldsymbol{y} - \bar{\boldsymbol{x}} \right\rangle + \mathbb{E}\left\|\boldsymbol{y} - \bar{\boldsymbol{x}}\right\|^2 \\ &= \underbrace{\mathbb{E}\left\|\widehat{\boldsymbol{x}}_\lambda(\boldsymbol{y}) - \boldsymbol{y}\right\|^2}_{\text{known}} + 2 \quad \underline{\mathbb{E}\left\langle \widehat{\boldsymbol{x}}_\lambda(\boldsymbol{y}), \boldsymbol{\varepsilon} \right\rangle} \quad - \underbrace{\mathbb{E}\left\|\boldsymbol{\varepsilon}\right\|^2}_{\rho^2 N} \end{aligned}$$

Stein Unbiased Risk Estimate

i.i.d. Gaussian noise

Observation model $\quad \boldsymbol{y} = \underset{\text{truth}}{\bar{\boldsymbol{x}}} + \underset{\text{noise}}{\boldsymbol{\varepsilon}} \in \mathbb{R}^N$

$$\text{Estimator} \quad \widehat{\boldsymbol{x}}_\lambda(\boldsymbol{y}) = \begin{cases} \left(\mathbf{I} + \lambda \mathbf{D}^* \mathbf{D}\right)^{-1} \boldsymbol{y} & \text{(linear)} \\ \arg\min_{\boldsymbol{x}} \|\boldsymbol{y} - \boldsymbol{x}\|^2 + \lambda \mathcal{N}(\mathbf{D}\boldsymbol{x}) & \text{(nonlinear)} \end{cases}$$

If ε is i.i.d. Gaussian noise of variance ρ^2

$$\begin{aligned} R(\lambda) &\triangleq \mathbb{E}\left\|\widehat{\boldsymbol{x}}_\lambda(\boldsymbol{y}) - \bar{\boldsymbol{x}}\right\|^2 = \mathbb{E}\left\|\widehat{\boldsymbol{x}}_\lambda(\boldsymbol{y}) - \boldsymbol{y} + \boldsymbol{y} - \bar{\boldsymbol{x}}\right\|^2 \\ &= \mathbb{E}\left\|\widehat{\boldsymbol{x}}_\lambda(\boldsymbol{y}) - \boldsymbol{y}\right\|^2 + 2\mathbb{E}\left\langle \widehat{\boldsymbol{x}}_\lambda(\boldsymbol{y}) - \boldsymbol{y}, \boldsymbol{y} - \bar{\boldsymbol{x}}\right\rangle + \mathbb{E}\left\|\boldsymbol{y} - \bar{\boldsymbol{x}}\right\|^2 \\ &= \underbrace{\mathbb{E}\left\|\widehat{\boldsymbol{x}}_\lambda(\boldsymbol{y}) - \boldsymbol{y}\right\|^2}_{\text{known}} + 2 \underbrace{\mathbb{E}\left\langle \widehat{\boldsymbol{x}}_\lambda(\boldsymbol{y}), \boldsymbol{\varepsilon}\right\rangle}_{\int \widehat{\boldsymbol{x}}_\lambda(\boldsymbol{\varepsilon})\, \boldsymbol{\varepsilon} \exp(-\|\boldsymbol{\varepsilon}\|^2/2\rho^2)} - \underbrace{\mathbb{E}\left\|\boldsymbol{\varepsilon}\right\|^2}_{\rho^2 N} \end{aligned}$$

Stein Unbiased Risk Estimate

i.i.d. Gaussian noise

$$\text{Observation model} \quad \boldsymbol{y} = \underset{\text{truth}}{\bar{\boldsymbol{x}}} + \underset{\text{noise}}{\boldsymbol{\varepsilon}} \in \mathbb{R}^N$$

$$\text{Estimator} \quad \widehat{\boldsymbol{x}}_\lambda(\boldsymbol{y}) = \begin{cases} (\mathbf{I} + \lambda \mathbf{D}^* \mathbf{D})^{-1} \boldsymbol{y} & \text{(linear)} \\ \operatorname*{arg\,min}_{\boldsymbol{x}} \|\boldsymbol{y} - \boldsymbol{x}\|^2 + \lambda \mathcal{N}(\mathbf{D}\boldsymbol{x}) & \text{(nonlinear)} \end{cases}$$

If ε is i.i.d. Gaussian noise of variance ρ^2

$$\begin{aligned} R(\lambda) &\triangleq \mathbb{E}\,\|\widehat{\boldsymbol{x}}_\lambda(\boldsymbol{y}) - \bar{\boldsymbol{x}}\|^2 = \mathbb{E}\,\|\widehat{\boldsymbol{x}}_\lambda(\boldsymbol{y}) - \boldsymbol{y} + \boldsymbol{y} - \bar{\boldsymbol{x}}\|^2 \\ &= \mathbb{E}\,\|\widehat{\boldsymbol{x}}_\lambda(\boldsymbol{y}) - \boldsymbol{y}\|^2 + 2\mathbb{E}\,\langle \widehat{\boldsymbol{x}}_\lambda(\boldsymbol{y}) - \boldsymbol{y}, \boldsymbol{y} - \bar{\boldsymbol{x}} \rangle + \mathbb{E}\,\|\boldsymbol{y} - \bar{\boldsymbol{x}}\|^2 \\ &= \underbrace{\mathbb{E}\,\|\widehat{\boldsymbol{x}}_\lambda(\boldsymbol{y}) - \boldsymbol{y}\|^2}_{\text{known}} + 2 \underbrace{\mathbb{E}\,\langle \widehat{\boldsymbol{x}}_\lambda(\boldsymbol{y}), \boldsymbol{\varepsilon} \rangle}_{\int \widehat{\boldsymbol{x}}_\lambda(\boldsymbol{\varepsilon})\, \boldsymbol{\varepsilon} \exp(-\|\boldsymbol{\varepsilon}\|^2/2\rho^2)} - \underbrace{\mathbb{E}\,\|\boldsymbol{\varepsilon}\|^2}_{\rho^2 N} \end{aligned}$$

$$\widehat{R}(\lambda|\rho^2) \triangleq \|\widehat{\boldsymbol{x}}_\lambda(\boldsymbol{y}) - \boldsymbol{y}\|^2 + 2\rho^2 \operatorname{tr}\left(\frac{\partial \widehat{\boldsymbol{x}}}{\partial \boldsymbol{y}}(\boldsymbol{y};\lambda)\right) - \rho^2 N$$

Texture's attributes estimation

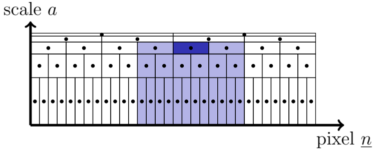
Hyperparameters tuning

$$\underset{\boldsymbol{v},\boldsymbol{h}}{\text{minimize}} \sum_a \underbrace{\|\log \boldsymbol{\mathcal{L}}_{a,\cdot} - \boldsymbol{v} - \log(a)\boldsymbol{h}\|^2}_{\textbf{Least-Squares}} + \lambda \underbrace{\mathcal{N}(\mathbf{D}\boldsymbol{v}, \mathbf{D}\boldsymbol{h}; \alpha)}_{\textbf{Total Variation}}$$

Fractal model $\log \boldsymbol{\mathcal{L}}_{a,\cdot} = \bar{\boldsymbol{v}} + \log(a)\bar{\boldsymbol{h}} + \boldsymbol{\varepsilon}_{a,\cdot}$

Correlated Gaussian noise $\boldsymbol{\varepsilon}$

$\rho^2 \longleftrightarrow \boldsymbol{\mathcal{S}}$



Texture's attributes estimation

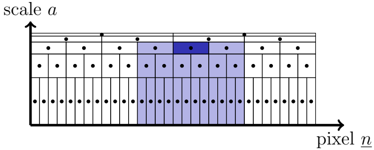
Hyperparameters tuning

$$\underset{\boldsymbol{v},\boldsymbol{h}}{\text{minimize}} \quad \underbrace{\sum_a \|\log \boldsymbol{\mathcal{L}}_{a,\cdot} - \boldsymbol{v} - \log(a)\boldsymbol{h}\|^2}_{\textbf{Least-Squares}} \quad + \quad \lambda \underbrace{\mathcal{N}(\mathbf{D}\boldsymbol{v}, \mathbf{D}\boldsymbol{h}; \alpha)}_{\textbf{Total Variation}}$$

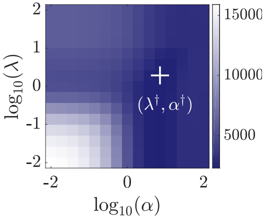
Fractal model $\log \boldsymbol{\mathcal{L}}_{a,\cdot} = \bar{\boldsymbol{v}} + \log(a)\bar{\boldsymbol{h}} + \boldsymbol{\varepsilon}_{a,\cdot}$

Correlated Gaussian noise $\boldsymbol{\varepsilon}$

$\rho^2 \longleftrightarrow \boldsymbol{\mathcal{S}}$



$R(\lambda)$



Texture's attributes estimation

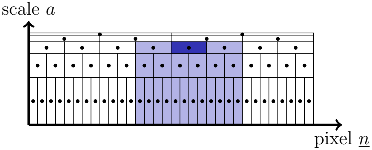
Hyperparameters tuning

$$\underset{\boldsymbol{v},\boldsymbol{h}}{\text{minimize}} \quad \sum_a \underbrace{\|\log \boldsymbol{\mathcal{L}}_{a,.} - \boldsymbol{v} - \log(a)\boldsymbol{h}\|^2}_{\textbf{Least-Squares}} \quad + \quad \lambda \underbrace{\mathcal{N}(\mathbf{D}\boldsymbol{v}, \mathbf{D}\boldsymbol{h}; \alpha)}_{\textbf{Total Variation}}$$

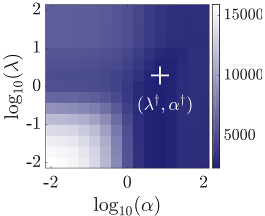
Fractal model $\quad \log \boldsymbol{\mathcal{L}}_{a,.} = \bar{\boldsymbol{v}} + \log(a)\bar{\boldsymbol{h}} + \boldsymbol{\varepsilon}_{a,.}$

Correlated Gaussian noise $\boldsymbol{\varepsilon}$

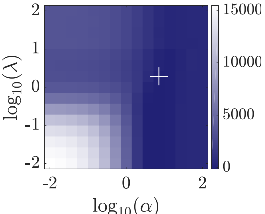
$\rho^2 \longleftrightarrow \boldsymbol{\mathcal{S}}$



$R(\lambda)$



$\widehat{R}(\lambda|\boldsymbol{\mathcal{S}})$



Texture's attributes estimation

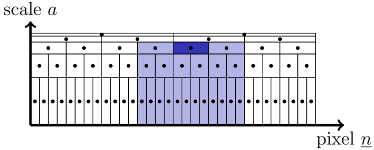
Hyperparameters tuning

$$\underset{\boldsymbol{v},\boldsymbol{h}}{\text{minimize}} \quad \sum_a \underbrace{\|\log \boldsymbol{\mathcal{L}}_{a,\cdot} - \boldsymbol{v} - \log(a)\boldsymbol{h}\|^2}_{\textbf{Least-Squares}} \quad + \quad \lambda \underbrace{\mathcal{N}(\mathbf{D}\boldsymbol{v}, \mathbf{D}\boldsymbol{h}; \alpha)}_{\textbf{Total Variation}}$$

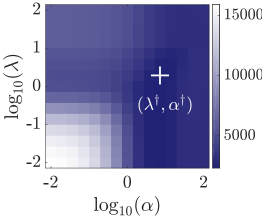
Fractal model $\quad \log \boldsymbol{\mathcal{L}}_{a,\cdot} = \bar{\boldsymbol{v}} + \log(a)\bar{\boldsymbol{h}} + \boldsymbol{\varepsilon}_{a,\cdot}$

Correlated Gaussian noise $\boldsymbol{\varepsilon}$

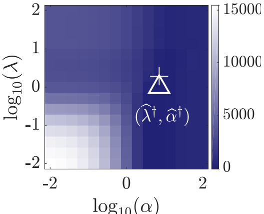
$\rho^2 \longleftrightarrow \boldsymbol{\mathcal{S}}$



$R(\lambda)$



$\widehat{R}(\lambda|\boldsymbol{\mathcal{S}})$



Texture's attributes estimation

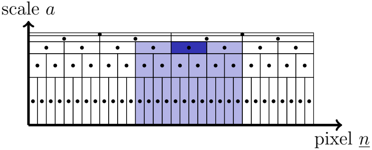
Hyperparameters tuning

$$\underset{\boldsymbol{v},\boldsymbol{h}}{\text{minimize}} \quad \sum_a \underbrace{\|\log \boldsymbol{\mathcal{L}}_{a,\cdot} - \boldsymbol{v} - \log(a)\boldsymbol{h}\|^2}_{\textbf{Least-Squares}} \quad + \quad \lambda \underbrace{\mathcal{N}(\mathbf{D}\boldsymbol{v}, \mathbf{D}\boldsymbol{h}; \alpha)}_{\textbf{Total Variation}}$$

Fractal model $\quad \log \boldsymbol{\mathcal{L}}_{a,\cdot} = \bar{\boldsymbol{v}} + \log(a)\bar{\boldsymbol{h}} + \boldsymbol{\varepsilon}_{a,\cdot}$

Correlated Gaussian noise $\boldsymbol{\varepsilon}$

$\rho^2 \longleftrightarrow \boldsymbol{\mathcal{S}}$



Mask

100%

Texture's attributes estimation

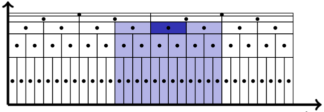
Hyperparameters tuning

$$\underset{\boldsymbol{v},\boldsymbol{h}}{\text{minimize}} \sum_a \underbrace{\|\log \boldsymbol{\mathcal{L}}_{a,\cdot} - \boldsymbol{v} - \log(a)\boldsymbol{h}\|^2}_{\textbf{Least-Squares}} + \lambda \underbrace{\mathcal{N}(\mathbf{D}\boldsymbol{v}, \mathbf{D}\boldsymbol{h}; \alpha)}_{\textbf{Total Variation}}$$

Fractal model $\log \boldsymbol{\mathcal{L}}_{a,\cdot} = \bar{\boldsymbol{v}} + \log(a)\bar{\boldsymbol{h}} + \boldsymbol{\varepsilon}_{a,\cdot}$

Correlated Gaussian noise $\boldsymbol{\varepsilon}$

$\rho^2 \longleftrightarrow \boldsymbol{\mathcal{S}}$



Mask	Min. R
	
100%	92%

Texture's attributes estimation

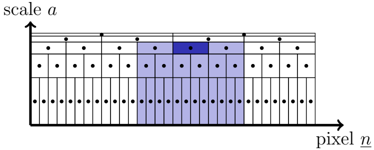
Hyperparameters tuning

$$\underset{\boldsymbol{v},\boldsymbol{h}}{\text{minimize}} \quad \underbrace{\sum_a \|\log \boldsymbol{\mathcal{L}}_{a,\cdot} - \boldsymbol{v} - \log(a)\boldsymbol{h}\|^2}_{\textbf{Least-Squares}} \quad + \quad \lambda \underbrace{\mathcal{N}(\mathbf{D}\boldsymbol{v}, \mathbf{D}\boldsymbol{h}; \alpha)}_{\textbf{Total Variation}}$$

Fractal model $\quad \log \boldsymbol{\mathcal{L}}_{a,\cdot} = \bar{\boldsymbol{v}} + \log(a)\bar{\boldsymbol{h}} + \boldsymbol{\varepsilon}_{a,\cdot}$

Correlated Gaussian noise $\boldsymbol{\varepsilon}$

$\rho^2 \longleftrightarrow \boldsymbol{\mathcal{S}}$



Mask	Min. R	Min. $\widehat{R}$
		
100%	92%	95%

Texture's attributes estimation

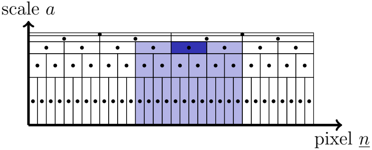
Hyperparameters tuning

$$\underset{\boldsymbol{v},\boldsymbol{h}}{\text{minimize}} \quad \sum_a \underbrace{\|\log \boldsymbol{\mathcal{L}}_{a,\cdot} - \boldsymbol{v} - \log(a)\boldsymbol{h}\|^2}_{\textbf{Least-Squares}} \quad + \quad \lambda \underbrace{\mathcal{N}(\mathbf{D}\boldsymbol{v}, \mathbf{D}\boldsymbol{h}; \alpha)}_{\textbf{Total Variation}}$$

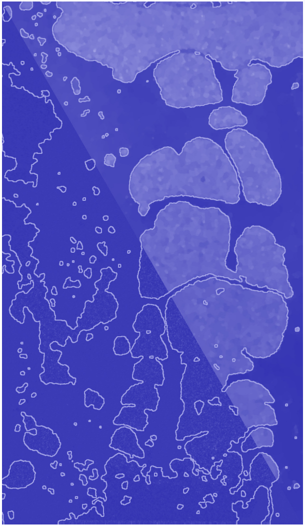
Fractal model $\quad \log \boldsymbol{\mathcal{L}}_{a,\cdot} = \bar{\boldsymbol{v}} + \log(a)\bar{\boldsymbol{h}} + \boldsymbol{\varepsilon}_{a,\cdot}$

Correlated Gaussian noise $\boldsymbol{\varepsilon}$

$\rho^2 \longleftrightarrow \boldsymbol{\mathcal{S}}$



Mask	Min. R	Min. $\widehat{R}$	Automatic
			
100%	92%	95%	94%



Thank you for your attention!

Outline – Fractal texture segmentation

1. Fractal texture model

$$\log\left(\mathcal{L}_{a,\cdot}\right) \simeq \underset{\sim\log(\boldsymbol{\sigma}^2)}{\underline{\boldsymbol{v}}} + \log(a)\, \underset{\textit{regularity}}{\underline{\boldsymbol{h}}}$$

2. Attributes estimation and segmentation

$$\underset{\boldsymbol{v},\boldsymbol{h}}{\text{minimize}} \sum_a \underbrace{\|\log \mathcal{L}_{a,\cdot} - \boldsymbol{v} - \log(a)\boldsymbol{h}\|^2}_{\textbf{Least-Squares}} + \lambda \underbrace{\mathcal{N}(\mathbf{D}\boldsymbol{v}, \mathbf{D}\boldsymbol{h}; \alpha)}_{\textbf{Total Variation}}$$

3. Multiphasic flow segmentation

4. Regularization parameters tuning

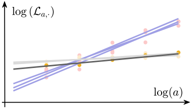
Texture's attributes estimation

Fine tuning of regularization parameters

$$\underset{\boldsymbol{v},\boldsymbol{h}}{\text{minimize}} \sum_a \underbrace{\|\log \boldsymbol{\mathcal{L}}_{a,\cdot} - \boldsymbol{v} - \log(a)\boldsymbol{h}\|^2}_{\textbf{Least-Squares}} + \lambda \underbrace{\mathcal{N}(\boldsymbol{v}, \boldsymbol{h}; \alpha)}_{\textbf{Total Variation}}$$

→ fidelity to log-linear model

→ enforce piecewise constancy



Texture's attributes estimation

Fine tuning of regularization parameters

$$\underset{\boldsymbol{v},\boldsymbol{h}}{\text{minimize}} \; \underbrace{\sum_a \|\log \mathcal{L}_{a,\cdot} - \boldsymbol{v} - \log(a)\boldsymbol{h}\|^2}_{\textbf{Least-Squares}} \; + \; \lambda \, \underbrace{\mathcal{N}(\boldsymbol{v}, \boldsymbol{h}; \alpha)}_{\textbf{Total Variation}}$$

→ fidelity to log-linear model

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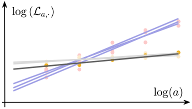
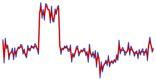
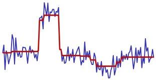


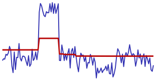
Fine tuning of regularization parameters (λ, α) is necessary ...



too small



optimal



too large

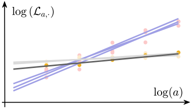
Texture's attributes estimation

Fine tuning of regularization parameters

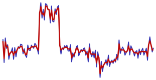
$$\underset{\boldsymbol{v},\boldsymbol{h}}{\text{minimize}} \sum_a \underbrace{\|\log \mathcal{L}_{a,\cdot} - \boldsymbol{v} - \log(a)\boldsymbol{h}\|^2}_{\textbf{Least-Squares}} + \underbrace{\lambda\, \mathcal{N}(\boldsymbol{v},\boldsymbol{h};\alpha)}_{\textbf{Total Variation}}$$

Least-Squares $\rightarrow$ fidelity to log-linear model

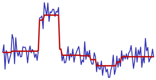
Total Variation $\rightarrow$ enforce piecewise constancy



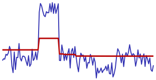
Fine tuning of regularization parameters (λ, α) is necessary ... but **costly**!



too small



optimal



too large

In practice, we explore a log-spaced grid of $15 \times 15 = \mathbf{225}$ hyperparameters (λ, α).

Ongoing work and perspectives

- Video analysis (temporal series of hundreds of images)

Intership of L. Helmlinger

Ongoing work and perspectives

- Video analysis (temporal series of hundreds of images)

  Intership of L. Helmlinger

  ✓ Best (λ, α) tuned on 1^{st} image is sufficiently robust for the entire series.

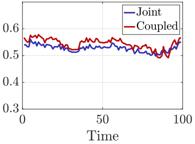
Ongoing work and perspectives

- Video analysis (temporal series of hundreds of images)

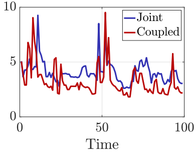
Intership of L. Helmlinger

✓ Best (λ, α) tuned on 1^{st} image is sufficiently robust for the entire series.
✓ Time evolution of physical quantities can be assessed.

Fraction of gas *(area)*



Liquid/gas contact *perimeter*



Ongoing work and perspectives

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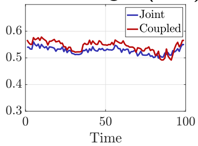
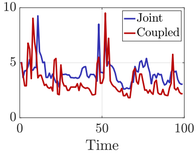


Liquid/gas contact *perimeter*

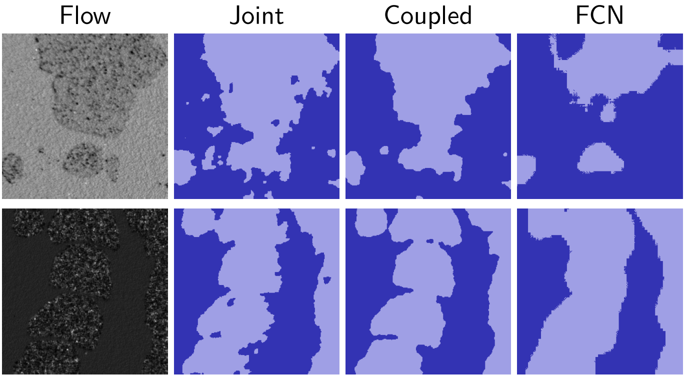


- Automatic tuning of hyperparameters

Stein's **U**nbiased **R**isk **E**stimate $\widehat{R}(\lambda, \alpha)$

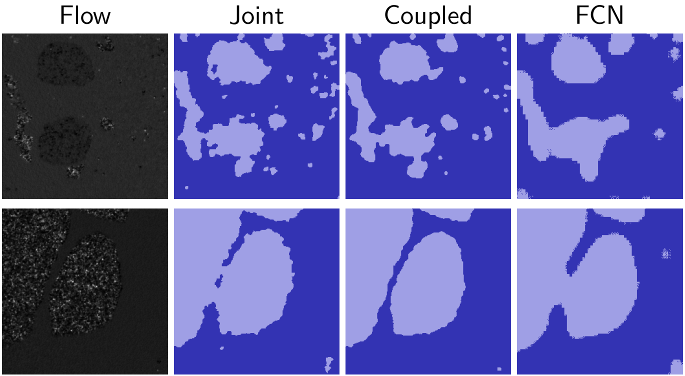
Stein **U**nbiased **GrA**dient estimator of the **R**isk $\nabla_\lambda \widehat{R}(\lambda, \alpha)$

Fully Convolutional Neural Networks[†]



[†] V. Andrearczyk, `https://arxiv.org/abs/1703.05230`

Fully Convolutional Neural Networks†



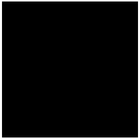
† V. Andrearczyk, `https://arxiv.org/abs/1703.05230`

Gas/liquid flow modeled by piecewise monofractal textures

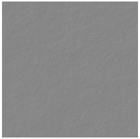
Synthetic textures

Liquid: $h_1 = 0.4$, $\sigma_1^2 = 10^{-2}$

Mask



Texture



Gas/liquid flow modeled by piecewise monofractal textures

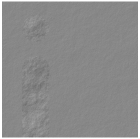
Synthetic textures

Liquid: $h_1 = 0.4$, $\sigma_1^2 = 10^{-2}$

Gas: $h_2 = 0.9$, $\sigma_1^2 = 10^{-2}$ (dark bubbles)

Mask

Texture

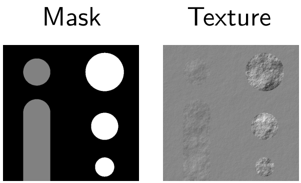


Gas/liquid flow modeled by piecewise monofractal textures

Synthetic textures

Liquid: $h_1 = 0.4,\ \sigma_1^2 = 10^{-2}$

Gas: $\left| \begin{array}{l} h_2 = 0.9,\ \sigma_1^2 = 10^{-2} \text{ (dark bubbles)} \\ h_2 = 0.9,\ \sigma_2^2 = 10^{-1} \text{ (clear bubbles)} \end{array} \right.$



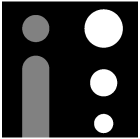
Gas/liquid flow modeled by piecewise monofractal textures

Synthetic textures

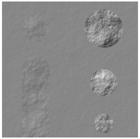
Liquid: $h_1 = 0.4,\ \sigma_1^2 = 10^{-2}$

Gas:
- $h_2 = 0.9,\ \sigma_1^2 = 10^{-2}$ (dark bubbles)
- $h_2 = 0.9,\ \sigma_2^2 = 10^{-1}$ (clear bubbles)

Mask



Texture



Segmentation performance

'Gas/Liquid' | Yuan 88% | T-ROF 88% | Joint 95% | Coupled 95%

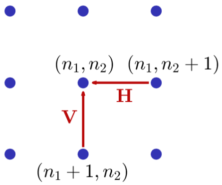
Optimization scheme - Monofractal model and piecewise constancy

$$\underset{\boldsymbol{v},\boldsymbol{h}}{\text{minimize}} \sum_a \|\log \boldsymbol{\mathcal{L}}_{a,.} - \boldsymbol{v} - \log(a)\boldsymbol{h}\|^2 + \lambda \mathcal{N}(\boldsymbol{v}, \boldsymbol{h}; \alpha)$$

Optimization scheme - Monofractal model and piecewise constancy

$$\underset{\boldsymbol{v},\boldsymbol{h}}{\text{minimize}} \sum_a \|\log \boldsymbol{\mathcal{L}}_{a,.} - \boldsymbol{v} - \log(a)\boldsymbol{h}\|^2 + \lambda\mathcal{N}(\boldsymbol{v},\boldsymbol{h};\alpha)$$

aim: enforce piecewise behavior of estimate

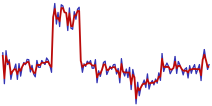


Discrete difference operator

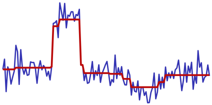
$$(\mathbf{D}x)_{n_1,n_2} := \begin{pmatrix} x_{n_1,n_2+1} - x_{n_1,n_2} \\ x_{n_1+1,n_2} - x_{n_1,n_2} \end{pmatrix} := \begin{bmatrix} \mathbf{H}\boldsymbol{x} \\ \mathbf{V}\boldsymbol{x} \end{bmatrix}_{n_1,n_2}$$

Total Variation penalization

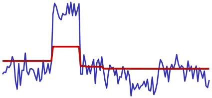
$$\mathcal{N}(\boldsymbol{x}) = \|\mathbf{D}\boldsymbol{x}\|_{2,1} = \sum_{n_1=1}^{N-1}\sum_{n_2=1}^{N-1}\sqrt{(\mathbf{H}\boldsymbol{x})^2_{n_1,n_2} + (\mathbf{V}\boldsymbol{x})^2_{n_1,n_2}}$$



Too small



Optimal



Too large

Optimization scheme - Monofractal model and piecewise constancy

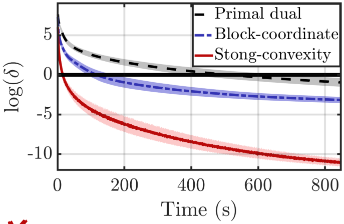
$$\underset{\boldsymbol{v},\boldsymbol{h}}{\text{minimize}} \sum_a \|\log \mathcal{L}_{a,.} - \boldsymbol{v} - \log(a)\boldsymbol{h}\|^2 + \lambda\mathcal{N}(\boldsymbol{v},\boldsymbol{h};\alpha)$$

State-of-the-art - Segmentation on h only

$$\underset{\boldsymbol{h}}{\text{minimize}} \|\boldsymbol{h} - \widehat{\boldsymbol{h}}^{\mathrm{LR}}\|_2^2 + \lambda\mathcal{N}(\boldsymbol{h})$$

✓ only one parameter λ

✓ fast algorithms **[Pascal2018]**



✗ poor segmentation performance

$$\underset{\boldsymbol{h},\boldsymbol{\omega}}{\text{minimize}} \|\boldsymbol{h} - \textstyle\sum_a \boldsymbol{\omega}_a \mathcal{L}_{a,.}\|_2^2 + \lambda\mathcal{N}(\boldsymbol{h},\boldsymbol{\omega};\alpha_a)$$

✗ additional constraints on $\{\omega\}_a$

✗ time and memory consuming

✓ very good accuracy **[Pustelnik2016]**

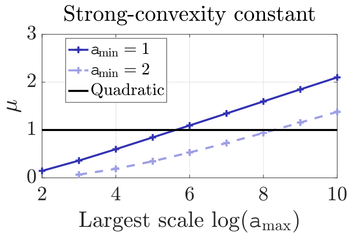
Strong convexity of data fidelity term

$$\mathrm{LS}(\boldsymbol{v}, \boldsymbol{h}) = \sum_{a=a_{\min}}^{a_{\max}} \|\log \mathcal{L}_{a,\cdot} - \boldsymbol{v} - \log(a)\boldsymbol{h}\|^2 = \|\log \mathcal{L} - \mathbf{A}(\boldsymbol{v}, \boldsymbol{h})\|^2$$

where $\mathbf{A} : (\boldsymbol{v}, \boldsymbol{h}) \mapsto \{\boldsymbol{v} + \log(a)\boldsymbol{h}\}_{a=a_{\min}}^{a_{\max}}$ is linear.

$$\boldsymbol{H}\mathrm{LS}\,(\boldsymbol{v}, \boldsymbol{h}) = \mathbf{A}^*\mathbf{A} = \begin{pmatrix} \mathrm{A}_0 \boldsymbol{I} & \mathrm{A}_1 \boldsymbol{I} \\ \mathrm{A}_1 \boldsymbol{I} & \mathrm{A}_2 \boldsymbol{I} \end{pmatrix}, \; \mathrm{A}_m = \sum_{a=a_{\min}}^{a_{\max}} (\log a)^m, \; \forall m \in \{0, 1, 2\}.$$

Prop: $\mathrm{LS}(\boldsymbol{v}, \boldsymbol{h})$ is μ-strongly convex, μ the smallest eigenvalue of $\mathbf{A}^*\mathbf{A}$.

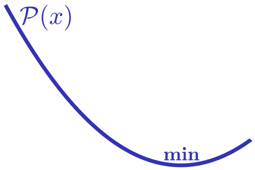


Convergence speed and stopping criterion

Duality gap

Primal problem

$$\widehat{x} = \underset{x}{\operatorname{argmin}}\ \mathrm{LS}(x) + \mathcal{N}(\mathbf{D}x)$$



Convergence speed and stopping criterion

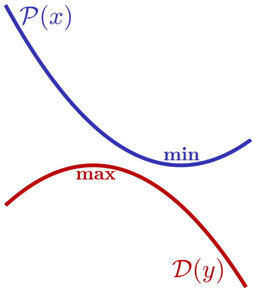
Duality gap

Primal problem

$$\widehat{x} = \underset{x}{\operatorname{argmin}} \; \mathrm{LS}(x) + \mathcal{N}(\mathbf{D}x)$$

Dual problem

$$\widehat{y} = \underset{y}{\operatorname{argmax}} \; -\mathrm{LS}^*(-\mathbf{D}^* y) - \mathcal{N}^*(y)$$



Convergence speed and stopping criterion

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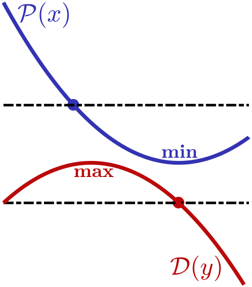
$$\widehat{y} = \underset{y}{\text{argmax}}\ -\mathrm{LS}^*(-\mathbf{D}^* y) - \mathcal{N}^*(y)$$

Duality gap $\delta(x; y)$

$$\underset{\text{def.}}{=} \mathrm{LS}(x) + \mathcal{N}(\mathbf{D}x) + \mathrm{LS}^*(-\mathbf{D}^* y) + \mathcal{N}^*(y)$$



Convergence speed and stopping criterion

Duality gap

Primal problem

$$\widehat{x} = \underset{x}{\operatorname{argmin}}\ \mathrm{LS}(x) + \mathcal{N}(\mathbf{D}x)$$

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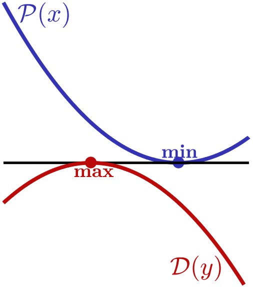
Duality gap $\delta(x; y)$

$$\underset{\text{def.}}{=} \mathrm{LS}(x) + \mathcal{N}(\mathbf{D}x) + \mathrm{LS}^*(-\mathbf{D}^*y) + \mathcal{N}^*(y)$$

Characterization of the solution

$$\delta(\widehat{x}; \widehat{y}) \underset{\text{prop.}}{=} 0$$



Computing the duality gap

For Joint penalization

$$\delta(\quad ; \quad)$$

$$= \qquad\qquad + $$

Computing the duality gap

For Joint penalization

$$\delta(\underbrace{\boldsymbol{v}, \boldsymbol{h}}_{\text{primal}}; \quad)$$

$$= \mathrm{LS}(\boldsymbol{v}, \boldsymbol{h}) + \mathcal{N}(\mathbf{D}\boldsymbol{v}, \mathbf{D}\boldsymbol{h}) +$$

Data fidelity

$$\mathrm{LS}(\boldsymbol{v}, \boldsymbol{h}) = \sum_{a} \|\boldsymbol{v} + \log(a)\boldsymbol{h} - \boldsymbol{\mathcal{L}}_{a,.}\|_2^2$$

Penalization

$$\mathcal{N}(\boldsymbol{u}, \boldsymbol{\ell}) = \lambda \left(\|\boldsymbol{u}\|_{2,1} + \alpha \|\boldsymbol{\ell}\|_{2,1} \right)$$

Computing the duality gap

For Joint penalization

$$\delta(\underbrace{\boldsymbol{v}, \boldsymbol{h}}_{\text{primal}}; \underbrace{\boldsymbol{u}, \boldsymbol{\ell}}_{\text{dual}})$$
$$= \mathrm{LS}(\boldsymbol{v}, \boldsymbol{h}) + \mathcal{N}(\mathbf{D}\boldsymbol{v}, \mathbf{D}\boldsymbol{h}) + \mathrm{LS}^*(-\mathbf{D}^*\boldsymbol{u}, -\mathbf{D}^*\boldsymbol{\ell}) + \mathcal{N}^*(\boldsymbol{u}, \boldsymbol{\ell})$$

Data fidelity

$$\mathrm{LS}(\boldsymbol{v}, \boldsymbol{h}) = \sum_a \|\boldsymbol{v} + \log(a)\boldsymbol{h} - \boldsymbol{\mathcal{L}}_{a,\cdot}\|_2^2$$

$$\mathrm{LS}^*(\boldsymbol{v}, \boldsymbol{h})$$
$$= \frac{1}{4}\langle(\boldsymbol{v}, \boldsymbol{h}), (\mathbf{A}^*\mathbf{A})^{-1}(\boldsymbol{v}, \boldsymbol{h})\rangle$$
$$+ \langle(\boldsymbol{\mathcal{S}}, \boldsymbol{\mathcal{T}}), (\mathbf{A}^*\mathbf{A})^{-1}(\boldsymbol{v}, \boldsymbol{h})\rangle$$
$$+ \mathcal{C}$$

where $\mathcal{C}$ constant term only depending on $\boldsymbol{\mathcal{L}}_{a,\cdot}$.

Penalization

$$\mathcal{N}(\boldsymbol{u}, \boldsymbol{\ell}) = \lambda\left(\|\boldsymbol{u}\|_{2,1} + \alpha\|\boldsymbol{\ell}\|_{2,1}\right)$$

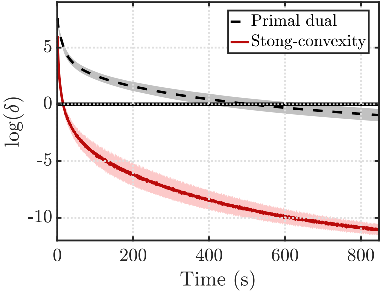
$$\mathcal{N}^*(\boldsymbol{u}, \boldsymbol{\ell}) = \iota_{\mathrm{B}_{2,\infty}(\lambda)}(\boldsymbol{u}) + \iota_{\mathrm{B}_{2,\infty}(\lambda\alpha)}(\boldsymbol{\ell})$$

$\mathrm{B}_{2,\infty}(\lambda)$: ball of radius λ w.r.t. $\|.\|_{2,\infty}$.

Computing the duality gap

For Joint penalization

$$\delta(\underbrace{\boldsymbol{v}, \boldsymbol{h}}_{\text{primal}} ; \underbrace{\boldsymbol{u}, \boldsymbol{\ell}}_{\text{dual}})$$
$$= \mathrm{LS}(\boldsymbol{v}, \boldsymbol{h}) + \mathcal{N}(\mathbf{D}\boldsymbol{v}, \mathbf{D}\boldsymbol{h}) + \mathrm{LS}^*(-\mathbf{D}^*\boldsymbol{u}, -\mathbf{D}^*\boldsymbol{\ell}) + \mathcal{N}^*(\boldsymbol{u}, \boldsymbol{\ell})$$



✓ Significant convergence acceleration

✓ Good stopping criterion: $\delta(\boldsymbol{v}^n, \boldsymbol{h}^n; \boldsymbol{u}^n, \boldsymbol{\ell}^n) \leq 10^{-3}$

Convex conjugate of data fidelity term

$$\mathrm{LS}^*(\boldsymbol{v},\boldsymbol{h}) = \sup_{\widetilde{\boldsymbol{v}},\widetilde{\boldsymbol{h}}\in\mathbb{R}^{|\Omega|}} \langle \widetilde{\boldsymbol{v}},\boldsymbol{v}\rangle + \langle \widetilde{\boldsymbol{h}},\boldsymbol{h}\rangle - \mathrm{LS}(\widetilde{\boldsymbol{v}},\widetilde{\boldsymbol{h}}) \underset{\text{(if sup is reached)}}{=} \langle \bar{\boldsymbol{v}},\boldsymbol{v}\rangle + \langle \bar{\boldsymbol{h}},\boldsymbol{h}\rangle - \mathrm{LS}(\bar{\boldsymbol{v}},\bar{\boldsymbol{h}}).$$

Convex conjugate of data fidelity term

$$\mathrm{LS}^*(\boldsymbol{v},\boldsymbol{h}) = \sup_{\widetilde{\boldsymbol{v}},\widetilde{\boldsymbol{h}}\in\mathbb{R}^{|\Omega|}} \langle \widetilde{\boldsymbol{v}}, \boldsymbol{v}\rangle + \langle \widetilde{\boldsymbol{h}}, \boldsymbol{h}\rangle - \mathrm{LS}(\widetilde{\boldsymbol{v}},\widetilde{\boldsymbol{h}}) \underset{\text{(if sup is reached)}}{=} \langle \bar{\boldsymbol{v}}, \boldsymbol{v}\rangle + \langle \bar{\boldsymbol{h}}, \boldsymbol{h}\rangle - \mathrm{LS}(\bar{\boldsymbol{v}},\bar{\boldsymbol{h}}).$$

Euler condition

$$\begin{cases} \boldsymbol{v} - 2\sum_a \left(\bar{\boldsymbol{v}} + \log(a)\bar{\boldsymbol{h}} - \log \boldsymbol{\mathcal{L}}_{a,.}\right) = 0 \\ \boldsymbol{h} - 2\sum_a \log(a)\left(\bar{\boldsymbol{v}} + \log(a)\bar{\boldsymbol{h}} - \log \boldsymbol{\mathcal{L}}_{a,.}\right) = 0 \end{cases}$$

Convex conjugate of data fidelity term

$$\mathrm{LS}^*(\boldsymbol{v},\boldsymbol{h}) = \sup_{\widetilde{\boldsymbol{v}},\widetilde{\boldsymbol{h}}\in\mathbb{R}^{|\Omega|}} \langle\widetilde{\boldsymbol{v}},\boldsymbol{v}\rangle + \langle\widetilde{\boldsymbol{h}},\boldsymbol{h}\rangle - \mathrm{LS}(\widetilde{\boldsymbol{v}},\widetilde{\boldsymbol{h}}) \underset{\text{(if sup is reached)}}{=} \langle\bar{\boldsymbol{v}},\boldsymbol{v}\rangle + \langle\bar{\boldsymbol{h}},\boldsymbol{h}\rangle - \mathrm{LS}(\bar{\boldsymbol{v}},\bar{\boldsymbol{h}}).$$

Euler condition

$$\begin{cases} \boldsymbol{v} - 2\sum_a \left(\bar{\boldsymbol{v}} + \log(a)\bar{\boldsymbol{h}} - \log\mathcal{L}_{a,.}\right) = 0 \\ \boldsymbol{h} - 2\sum_a \log(a)\left(\bar{\boldsymbol{v}} + \log(a)\bar{\boldsymbol{h}} - \log\mathcal{L}_{a,.}\right) = 0 \end{cases} \iff \mathbf{A}^*\mathbf{A}\begin{pmatrix}\bar{\boldsymbol{v}}\\ \bar{\boldsymbol{h}}\end{pmatrix} = \begin{pmatrix}\boldsymbol{v}/2+\mathcal{S}\\ \boldsymbol{h}/2+\mathcal{T}\end{pmatrix}$$

$$\mathcal{S} = \sum_a \log\mathcal{L}_{a,.} \quad \text{and} \quad \mathcal{T} = \sum_a \log(a)\log\mathcal{L}_{a,.},$$

Convex conjugate of data fidelity term

$$\mathrm{LS}^*(\boldsymbol{v},\boldsymbol{h}) = \sup_{\widetilde{\boldsymbol{v}},\widetilde{\boldsymbol{h}}\in\mathbb{R}^{|\Omega|}} \langle \widetilde{\boldsymbol{v}},\boldsymbol{v}\rangle + \langle \widetilde{\boldsymbol{h}},\boldsymbol{h}\rangle - \mathrm{LS}(\widetilde{\boldsymbol{v}},\widetilde{\boldsymbol{h}}) \underset{\text{(if sup is reached)}}{=} \langle \bar{\boldsymbol{v}},\boldsymbol{v}\rangle + \langle \bar{\boldsymbol{h}},\boldsymbol{h}\rangle - \mathrm{LS}(\bar{\boldsymbol{v}},\bar{\boldsymbol{h}}).$$

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$$\boldsymbol{\mathcal{S}} = \sum_a \log \boldsymbol{\mathcal{L}}_{a,.} \quad \text{and} \quad \boldsymbol{\mathcal{T}} = \sum_a \log(a) \log \boldsymbol{\mathcal{L}}_{a,.},$$

$$\forall m = \{0,1,2\},\ \mathrm{A}_m = \sum_a (\log a)^m, \quad \mathbf{A}^*\mathbf{A} = \begin{pmatrix}\mathrm{A}_0\boldsymbol{I} & \mathrm{A}_1\boldsymbol{I}\\ \mathrm{A}_1\boldsymbol{I} & \mathrm{A}_2\boldsymbol{I}\end{pmatrix}$$

Convex conjugate of data fidelity term

$$\mathrm{LS}^*(\boldsymbol{v},\boldsymbol{h}) = \sup_{\widetilde{\boldsymbol{v}},\widetilde{\boldsymbol{h}}\in\mathbb{R}^{|\Omega|}} \langle \widetilde{\boldsymbol{v}},\boldsymbol{v}\rangle + \langle \widetilde{\boldsymbol{h}},\boldsymbol{h}\rangle - \mathrm{LS}(\widetilde{\boldsymbol{v}},\widetilde{\boldsymbol{h}}) \underset{\text{(if sup is reached)}}{=} \langle \bar{\boldsymbol{v}},\boldsymbol{v}\rangle + \langle \bar{\boldsymbol{h}},\boldsymbol{h}\rangle - \mathrm{LS}(\bar{\boldsymbol{v}},\bar{\boldsymbol{h}}).$$

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$$\forall m = \{0,1,2\},\ \mathrm{A}_m = \sum_a (\log a)^m, \quad \mathbf{A}^*\mathbf{A} = \begin{pmatrix}\mathrm{A}_0\boldsymbol{I} & \mathrm{A}_1\boldsymbol{I}\\ \mathrm{A}_1\boldsymbol{I} & \mathrm{A}_2\boldsymbol{I}\end{pmatrix}$$

$$\mathrm{LS}^*(\boldsymbol{v},\boldsymbol{h}) = \frac{1}{4}\langle(\boldsymbol{v},\boldsymbol{h}),(\mathbf{A}^*\mathbf{A})^{-1}(\boldsymbol{v},\boldsymbol{h})\rangle + \langle(\boldsymbol{\mathcal{S}},\boldsymbol{\mathcal{T}}),(\mathbf{A}^*\mathbf{A})^{-1}(\boldsymbol{v},\boldsymbol{h})\rangle + \mathcal{C}$$

where $\mathcal{C}$ constant term only depending on $\boldsymbol{\mathcal{L}}(X)$.

Conclusion

Comparison of the different methods

	Liquid/Gas (regularity change)	Clear/Dark bubbles (variance change)	Smooth contours

Conclusion

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	Liquid/Gas (regularity change)	Clear/Dark bubbles (variance change)	Smooth contours
Yuan	✗	✓	✓

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T-ROF	✓	✓	✗

Conclusion

Comparison of the different methods

	Liquid/Gas (regularity change)	Clear/Dark bubbles (variance change)	Smooth contours
Yuan	✗	✓	✓
T-ROF	✓	✓	✗
Joint	✓	✓	∼

Conclusion

Comparison of the different methods

	Liquid/Gas (regularity change)	Clear/Dark bubbles (variance change)	Smooth contours
Yuan	✗	✓	✓
T-ROF	✓	✓	✗
Joint	✓	✓	∼
Coupled	✓	✓	✓

Conclusion

Comparison of the different methods

	Liquid/Gas (regularity change)	Clear/Dark bubbles (variance change)	Smooth contours
Yuan	✗	✓	✓
T-ROF	✓	✓	✗
Joint	✓	✓	$\sim$
Coupled	✓	✓	✓

Coupled is the most satisfactory in term of segmentation quality . . .

Conclusion

Comparison of the different methods

	Liquid/Gas (regularity change)	Clear/Dark bubbles (variance change)	Smooth contours
Yuan	✗	✓	✓
T-ROF	✓	✓	✗
Joint	✓	✓	∼
Coupled	✓	✓	✓

Coupled is the most satisfactory in term of segmentation quality . . .

. . . but it is the most time consuming (2100s)
Yuan(1s), T-ROF (12s), Joint (700s)