Textured image segmentation in high dimension.

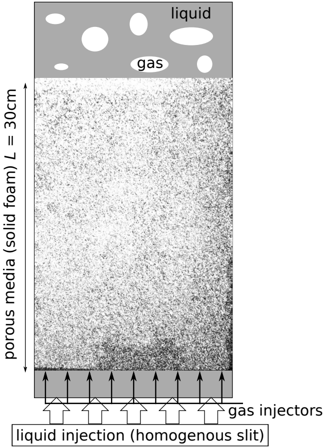
Application to multiphasic flows analysis.

B. Pascal, T. Busser, N. Pustelnik, P. Abry, V. Vidal

GRETSI 2019, Lille, France
August, 30th

Multiphasic (quasi 2D) flow in a porous media

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



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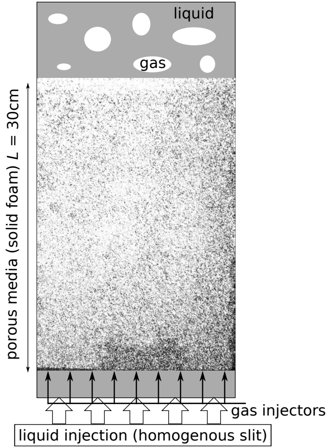

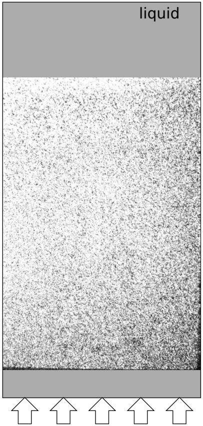

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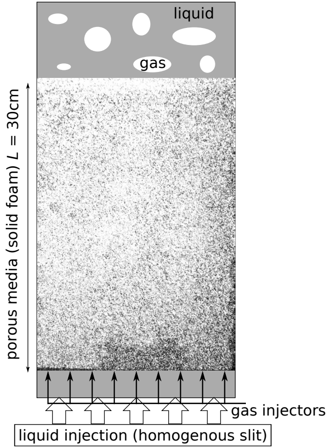
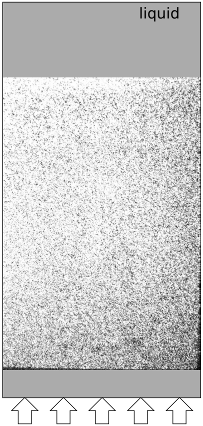
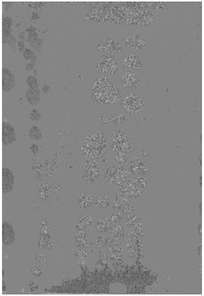




Normalized image



Textured

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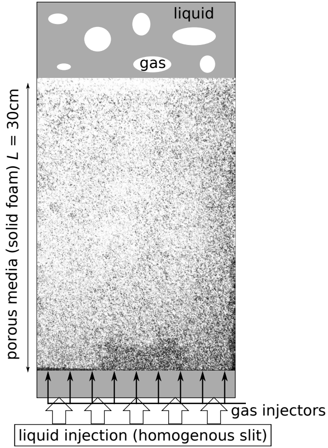

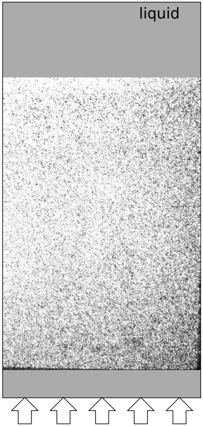

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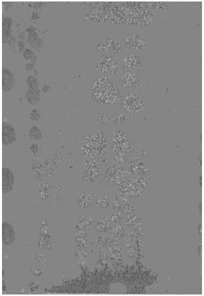
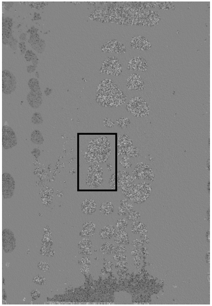


Textured

Physical quantities: $\underbrace{\text{gas volume}}_{\text{area}}$ & $\underbrace{\text{contact surface}}_{\text{perimeter}}$.

Texture segmentation



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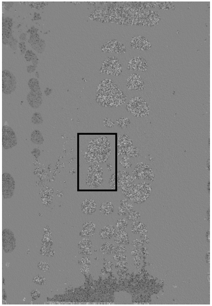

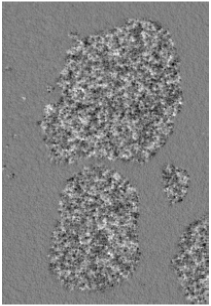

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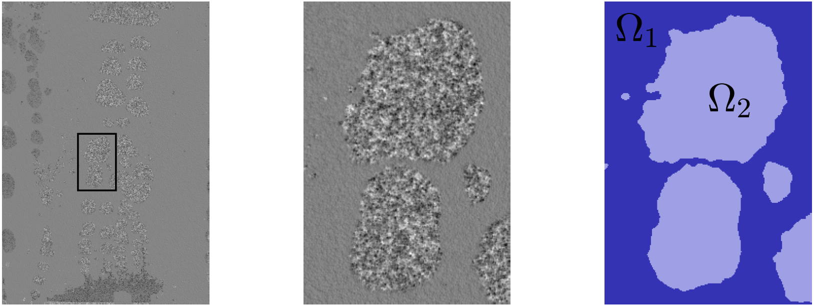


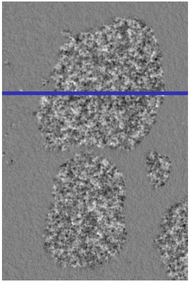
Purpose: obtaining a partition of the image into two regions

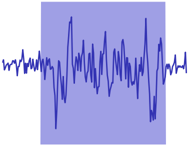
$$\Omega = \Omega_1 \bigsqcup \Omega_2$$

Ω_1: liquid, Ω_2: gas.

Piecewise monofractal textures

Local characterization





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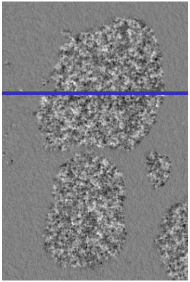

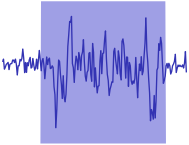

Texture's attributes
(mathematical model)

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

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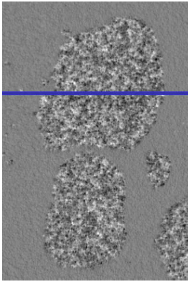
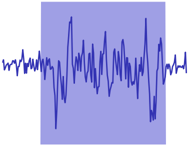
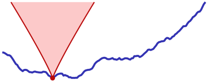




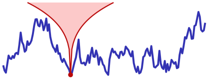
Texture's attributes
(mathematical model)

Variance σ^2 — *amplitude of variations*

Local regularity h — *scale-free behavior*



$h(x) \equiv h_1 = 0.9$



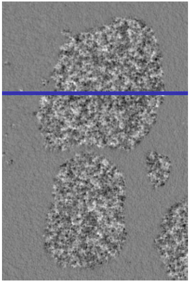
$h(x) \equiv h_2 = 0.3$

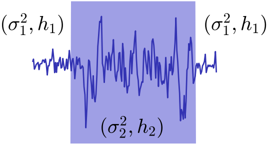
Fit local behavior with power law functions

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

Piecewise monofractal textures

Local characterization





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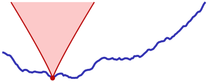

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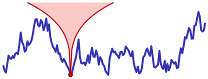

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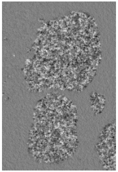
Segmentation requires local measurement of σ^2 and h.

Multiscale analysis for features extraction

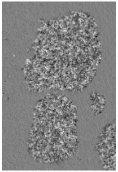
Textured image



Multiscale analysis for features extraction

Textured image

Non-linear transform of wavelet coefficients: $\mathcal{L}_{a,\cdot}$



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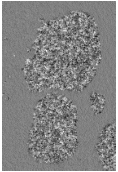

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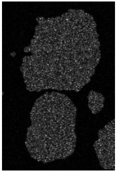
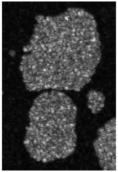
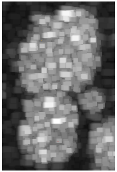




$\ldots$



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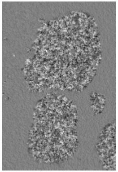

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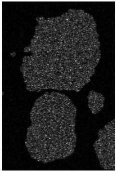

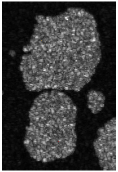

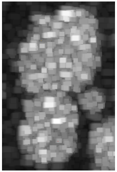

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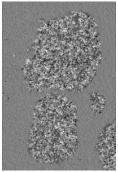

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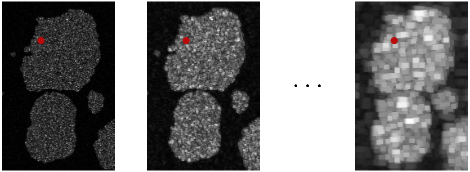

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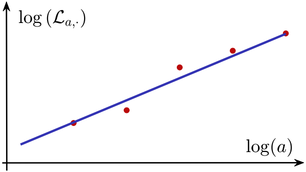

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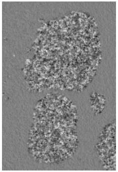

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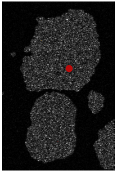

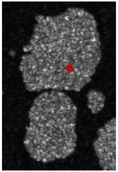

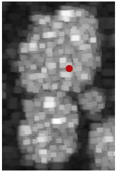

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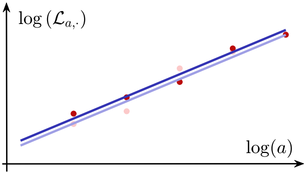

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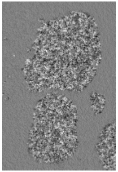

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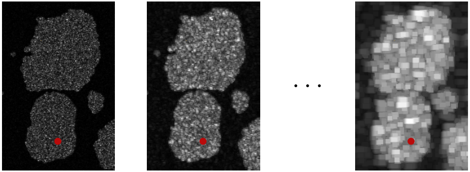

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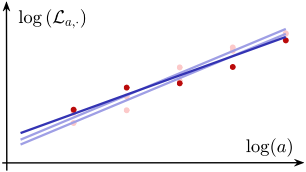

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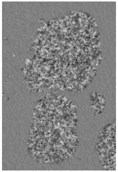

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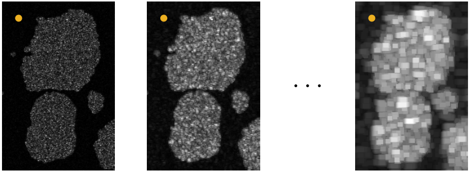

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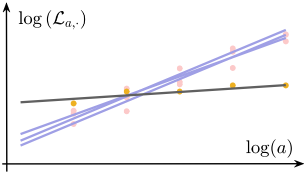

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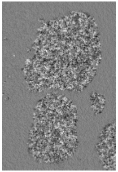

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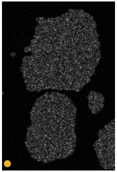

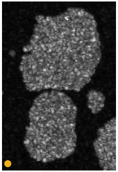

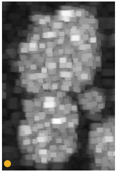

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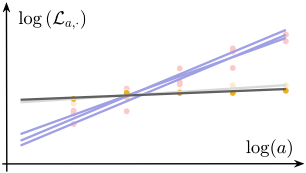

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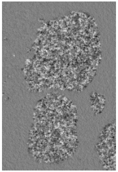

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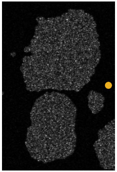

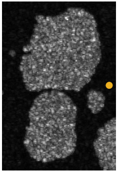

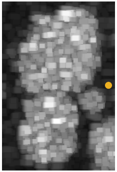

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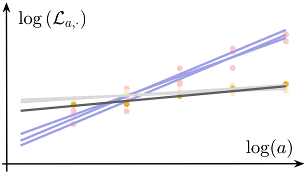
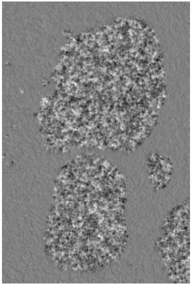


Linear regression
Pointwise estimates

Textured image



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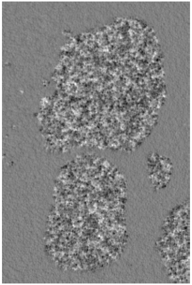
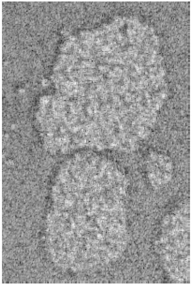


Local power $\widehat{\boldsymbol{v}}^{\mathrm{LR}}$

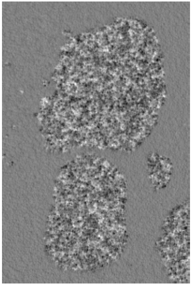


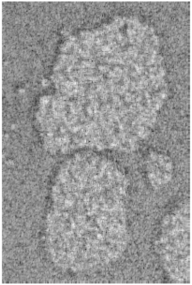
Local regularity $\widehat{\boldsymbol{h}}^{\mathrm{LR}}$

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

Linear regression
Pointwise estimates

Textured image | Local power $\widehat{\boldsymbol{v}}^{\mathrm{LR}}$ | Local regularity $\widehat{\boldsymbol{h}}^{\mathrm{LR}}$





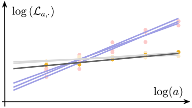
$$\underbrace{\mathbb{E}\log\left(\mathcal{L}_{a,\cdot}\right)}_{\text{expected value}} \simeq \underbrace{\boldsymbol{v}}_{\sim\log(\boldsymbol{\sigma}^2)} + \log(a)\underbrace{\boldsymbol{h}}_{\textit{regularity}}$$

Pointwise linear regression is an estimation from **<u>one</u>** sample!

Joint and coupled segmentation

$$\sum_a \underbrace{\|\log \mathcal{L}_{a,.} - \boldsymbol{v} - \log(a)\boldsymbol{h}\|^2}_{\textbf{least-squares}}$$

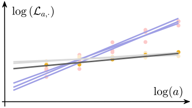
$\rightarrow$ fidelity to log-linear model



Joint and coupled segmentation

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

$\rightarrow$ fidelity to log-linear model



$$\underbrace{\lambda\, \mathcal{R}(\boldsymbol{v}, \boldsymbol{h}; \alpha)}_{\textbf{total variation}}$$

$\rightarrow$ enforce piecewise constancy

Joint and coupled segmentation

$$\underset{\boldsymbol{v},\boldsymbol{h}}{\text{minimize}} \quad \underbrace{\sum_a \|\log \boldsymbol{\mathcal{L}}_{a,\cdot} - \boldsymbol{v} - \log(a)\boldsymbol{h}\|^2}_{\textbf{least-squares}} \quad + \quad \underbrace{\lambda\, \mathcal{R}(\boldsymbol{v},\boldsymbol{h};\alpha)}_{\textbf{total variation}}$$

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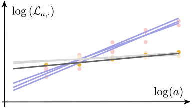
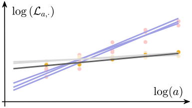


Joint and coupled segmentation

$$\underset{\boldsymbol{v},\boldsymbol{h}}{\text{minimize}} \quad \underbrace{\sum_a \|\log \mathcal{L}_{a,\cdot} - \boldsymbol{v} - \log(a)\boldsymbol{h}\|^2}_{\substack{\textbf{least-squares} \\ \to \text{ fidelity to log-linear model}}} + \underbrace{\lambda\, \mathcal{R}(\boldsymbol{v}, \boldsymbol{h}; \alpha)}_{\substack{\textbf{total variation} \\ \to \text{ enforce piecewise constancy}}}$$

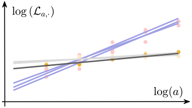


joint: $\boldsymbol{v}$, $\boldsymbol{h}$ are **independently** piecewise constant

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

Joint and coupled segmentation

$$\underset{\boldsymbol{v},\boldsymbol{h}}{\text{minimize}} \quad \underbrace{\sum_{a} \|\log \boldsymbol{\mathcal{L}}_{a,\cdot} - \boldsymbol{v} - \log(a)\boldsymbol{h}\|^2}_{\substack{\textbf{least-squares} \\ \rightarrow \text{ fidelity to log-linear model}}} \quad + \quad \underbrace{\lambda\, \mathcal{R}(\boldsymbol{v}, \boldsymbol{h}; \alpha)}_{\substack{\textbf{total variation} \\ \rightarrow \text{ enforce piecewise constancy}}}$$



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

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

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

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

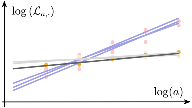
$$\mathcal{R}_{\mathsf{C}}(\boldsymbol{v}, \boldsymbol{h}; \alpha) = \sum_{\text{pixels}} \sqrt{(\mathbf{H}\boldsymbol{v})^2 + (\mathbf{V}\boldsymbol{v})^2 + \alpha^2(\mathbf{H}\boldsymbol{h})^2 + \alpha^2(\mathbf{V}\boldsymbol{h})^2}$$

Joint and coupled segmentation

$$\underset{\boldsymbol{v},\boldsymbol{h}}{\text{minimize}} \quad \underbrace{\sum_a \|\log \boldsymbol{\mathcal{L}}_{a,\cdot} - \boldsymbol{v} - \log(a)\boldsymbol{h}\|^2}_{\textbf{least-squares}} \quad + \quad \lambda\, \underbrace{\mathcal{R}(\boldsymbol{v}, \boldsymbol{h}; \alpha)}_{\textbf{total variation}}$$

→ fidelity to log-linear model

→ enforce piecewise constancy



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

$$\mathcal{R}_{\mathrm{J}}(\boldsymbol{v}, \boldsymbol{h}; \alpha) = \mathcal{R}(\boldsymbol{v}) + \alpha\mathcal{R}(\boldsymbol{h})$$

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

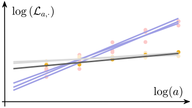
$$\mathcal{R}_{\mathrm{C}}(\boldsymbol{v}, \boldsymbol{h}; \alpha) = \mathcal{R}(\boldsymbol{v}, \alpha\boldsymbol{h})$$

Regularization parameters

$$\underset{\boldsymbol{v},\boldsymbol{h}}{\text{minimize}} \quad \sum_a \underbrace{\|\log \mathcal{L}_{a,\cdot} - \boldsymbol{v} - \log(a)\boldsymbol{h}\|^2}_{\textbf{least-squares}} \quad + \quad \underbrace{\lambda\, \mathcal{R}(\boldsymbol{v}, \boldsymbol{h}; \alpha)}_{\textbf{total variation}}$$

$\rightarrow$ fidelity to log-linear model

$\rightarrow$ enforce piecewise constancy



Regularization parameters

$$\underset{\boldsymbol{v},\boldsymbol{h}}{\text{minimize}} \sum_a \underbrace{\|\log \boldsymbol{\mathcal{L}}_{a,\cdot} - \boldsymbol{v} - \log(a)\boldsymbol{h}\|^2}_{\textbf{least-squares}} + \underbrace{\lambda\, \mathcal{R}(\boldsymbol{v},\boldsymbol{h};\alpha)}_{\textbf{total variation}}$$

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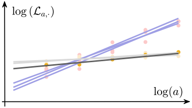
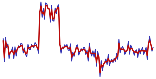
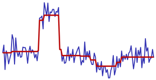


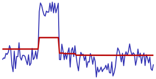
Fine tuning of regularization parameters (λ, α) is necessary ...



too small



optimal



too large

Regularization parameters

$$\underset{\boldsymbol{v},\boldsymbol{h}}{\text{minimize}} \; \underbrace{\sum_{a} \|\log \boldsymbol{\mathcal{L}}_{a,\cdot} - \boldsymbol{v} - \log(a)\boldsymbol{h}\|^2}_{\textbf{least-squares}} + \underbrace{\lambda \, \mathcal{R}(\boldsymbol{v}, \boldsymbol{h}; \alpha)}_{\textbf{total variation}}$$

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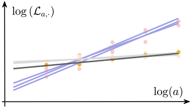
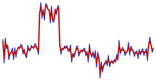
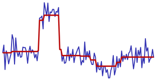


Fine tuning of regularization parameters (λ, α) is necessary ... but **costly**!



too small



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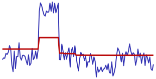


too large

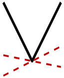
In practice, we explore a log-spaced grid of $15 \times 15 = \mathbf{225}$ hyperparameters (λ, α).

Algorithmic minimization of joint and coupled functionals

$$\underset{\boldsymbol{v},\boldsymbol{h}}{\text{minimize}} \;\; \sum_{a} \underbrace{\|\log \boldsymbol{\mathcal{L}}_{a,.} - \boldsymbol{v} - \log(a)\boldsymbol{h}\|^2}_{\textbf{least-squares}} \;\; + \;\; \lambda \underbrace{\mathcal{R}(\boldsymbol{v}, \boldsymbol{h}; \alpha)}_{\textbf{total variation}}$$

Algorithmic minimization of joint and coupled functionals

$$\underset{\boldsymbol{v},\boldsymbol{h}}{\text{minimize}} \ \sum_a \underset{\textbf{least-squares}}{\underline{\|\log \boldsymbol{\mathcal{L}}_{a,\cdot} - \boldsymbol{v} - \log(a)\boldsymbol{h}\|^2}} \ + \ \lambda \underset{\substack{\textbf{total variation} \\ \to \text{ non-smooth}}}{\underline{\mathcal{R}(\boldsymbol{v},\boldsymbol{h};\alpha)}}$$

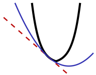


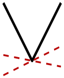
primal-dual algorithm (Chambolle, Pock 11')

Algorithmic minimization of joint and coupled functionals

$$\underset{\boldsymbol{v},\boldsymbol{h}}{\text{minimize}} \;\; \sum_a \underbrace{\|\log \boldsymbol{\mathcal{L}}_{a,.} - \boldsymbol{v} - \log(a)\boldsymbol{h}\|^2}_{\substack{\textbf{least-squares}\\ \to \text{ strongly convex}}} \;+\; \lambda \underbrace{\mathcal{R}(\boldsymbol{v},\boldsymbol{h};\alpha)}_{\substack{\textbf{total variation}\\ \to \text{ non-smooth}}}$$

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





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

Algorithmic minimization of joint and coupled functionals

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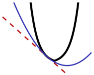
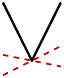




Accelerated primal-dual algorithm (Chambolle, Pock 11')

$$\boldsymbol{y}^{n+1} = \operatorname{prox}_{\sigma_n\|\cdot\|_{2,1}}\left(\boldsymbol{y}^n + \sigma_n \boldsymbol{\nabla}\bar{\boldsymbol{x}}^n\right)$$

$$\boldsymbol{x}^{n+1} = \operatorname{prox}_{\tau_n\|\boldsymbol{A}\cdot - \boldsymbol{b}\|_2^2}\left(\boldsymbol{x}^n - \tau_n \boldsymbol{\nabla}^* \boldsymbol{y}^{n+1}\right)$$

$$\theta_n = \sqrt{1 + 2\boldsymbol{\alpha}\tau_n}, \qquad \tau_{n+1} = \tau_n/\theta_n, \qquad \sigma_{n+1} = \theta_n\sigma_n$$

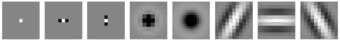
$$\bar{\boldsymbol{x}}^{n+1} = \boldsymbol{x}^{n+1} + \theta_n^{-1}\left(\boldsymbol{x}^{n+1} - \boldsymbol{x}^n\right)$$

Segmentation of multiphasic flow images.

Comparison of joint and coupled methods to state-of-the-art and previous work.

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

(i) local spectral histograms



(ii) matrix factorization

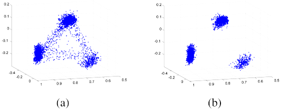


Fig. 2. Scatterplot of features in subspace. (a) Scatterplot of features projected onto the 3-d subspace. (b) Scatterplot after removing features with high edgeness.

[†] `https://sites.google.com/site/factorizationsegmentation/`

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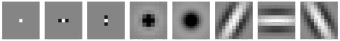

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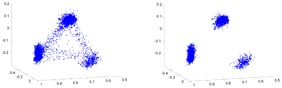


(a) (b)

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']

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

Lin. reg.

ROF

Threshold

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

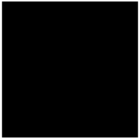
†`https://sites.google.com/site/factorizationsegmentation/`

Gas/liquid flow modeled by piecewise monofractal textures

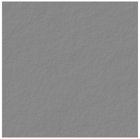
Synthetic textures

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

Mask



Texture



Gas/liquid flow modeled by piecewise monofractal textures

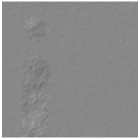
Synthetic textures

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

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

Mask

Texture

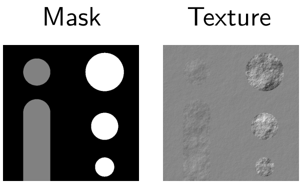


Gas/liquid flow modeled by piecewise monofractal textures

Synthetic textures

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

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



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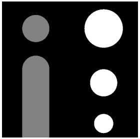

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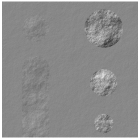
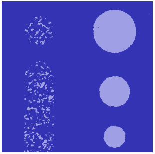


Segmentation performance

'Gas/Liquid'

Yuan 88%

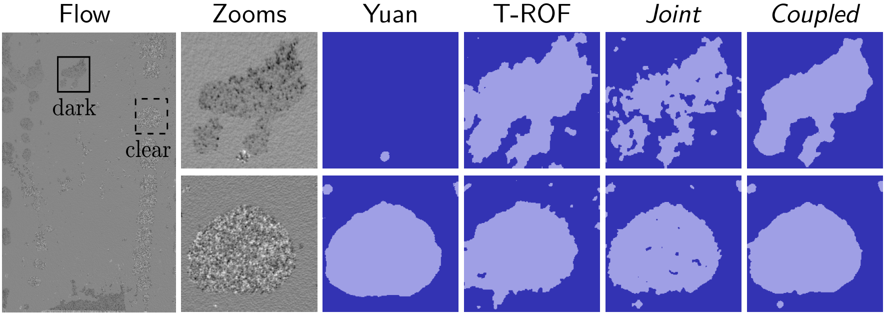


T-ROF 88%

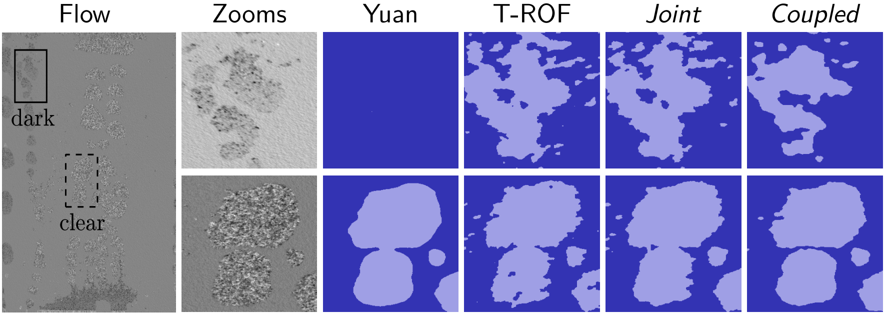
Joint 95%

Coupled 95%

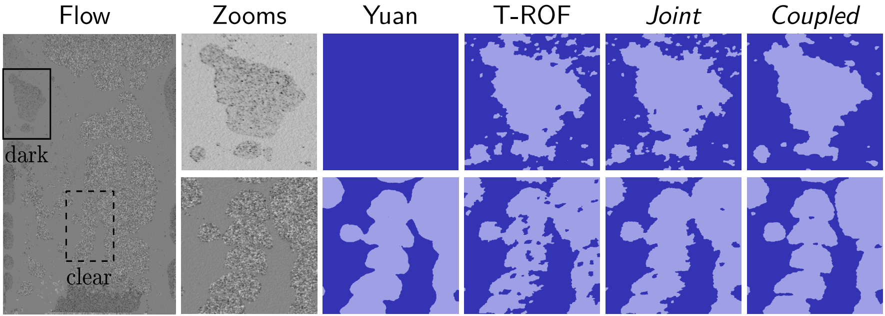
Multiphasic flow. $Q_{\mathrm{G}} = 300\text{mL/min}$ - $Q_{\mathrm{L}} = 300\text{mL/min}$: low activity



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



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



Conclusion

Comparison of the different methods

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

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Yuan	✗	✓	✓

Conclusion

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

Conclusion

Comparison of the different methods

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

Conclusion

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Yuan	✗	✓	✓
T-ROF	✓	✓	✗
Joint	✓	✓	∼
Coupled	✓	✓	✓

Conclusion

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

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Yuan	✗	✓	✓
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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)

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

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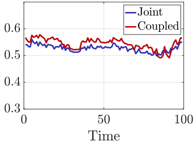
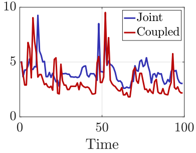
Intership of L. Helmlinger

✓ 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*



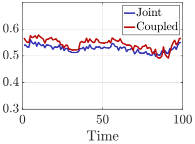
Ongoing work and perspectives

- Video analysis (temporal series of hundreds of images)

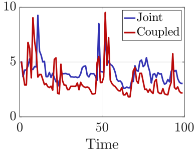
Intership of *L. Helmlinger*

✓ 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)*



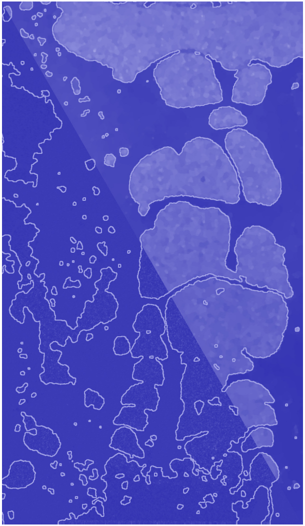
Liquid/gas contact *perimeter*



- Automatic tuning of hyperparameters

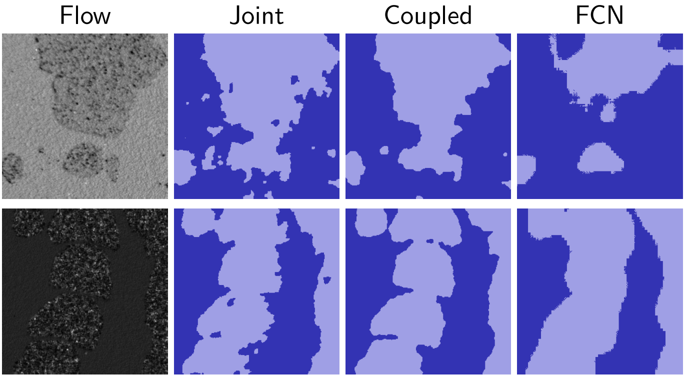
Stein's **U**nbiased **R**isk **E**stimate $\widehat{R}(\lambda, \alpha)$

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



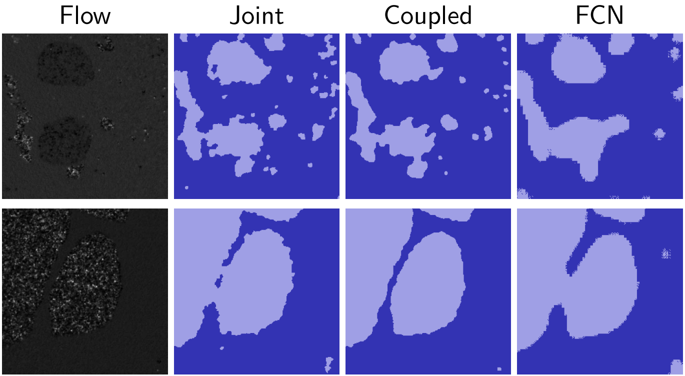
Thank you for your attention!

Fully Convolutional Neural Networks†



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

Fully Convolutional Neural Networks†



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