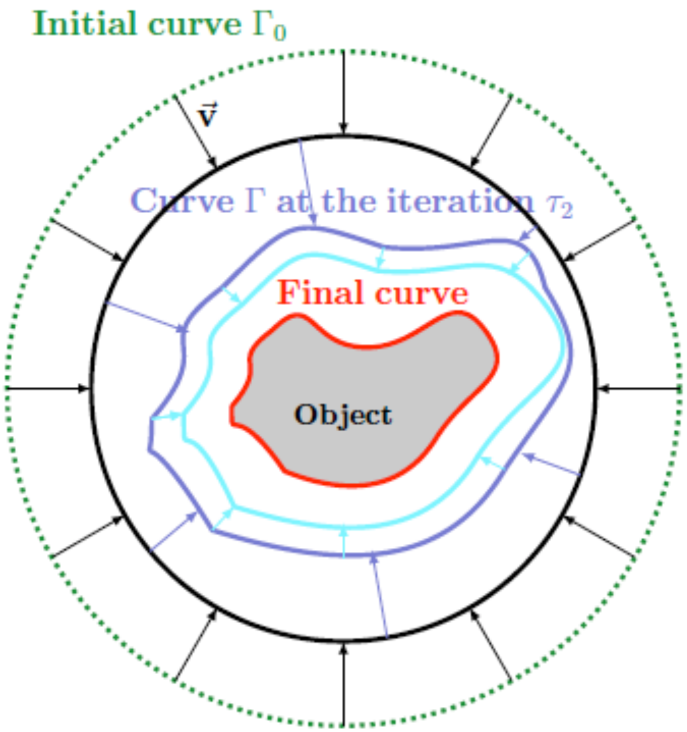
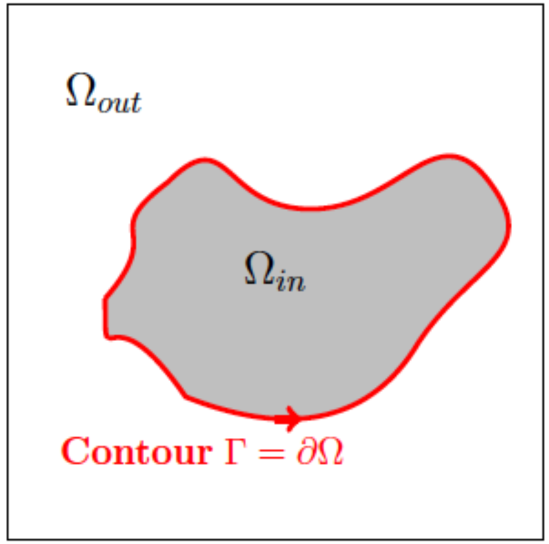
Active Contours

Principle



$$\min\left(E_{image} + E_{regularisation} + \ldots\right)$$

$$\Omega = \Omega_{in} \cup \Gamma \cup \Omega_{out}$$



Gradient-based approach:

$$E(\partial\Omega) = \int_{\partial\Omega} k_b(x,y)\,ds$$

Region-based approach:

$$E(\Omega_i) = \int_{\Omega} k_b(x,y,\Omega_i)\,ds$$

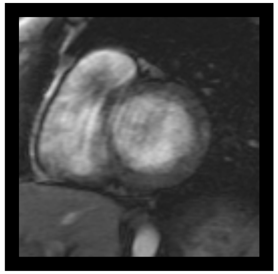
Shape Prior

Main Idea

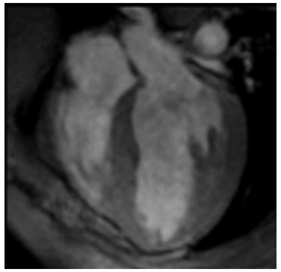
•In Medical Image, the shape of the structure to segment is often “known”

- ***Question:*** Knowing the “mean” shape of an object, can we integrate it in an AC segmentation process ?

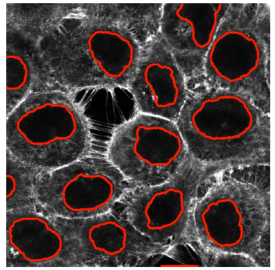
Cardiac MRI



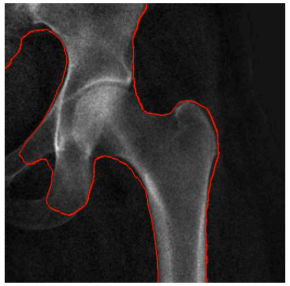
SA



LA



Microconfocal images



X-Ray Radiography
(hip bone)

Proposal

$$E(\lambda_r) = E_{prior}(\lambda_r) + E_{image}(\lambda_r)$$

with λ_r a reduced shape descriptor (statistical learning)

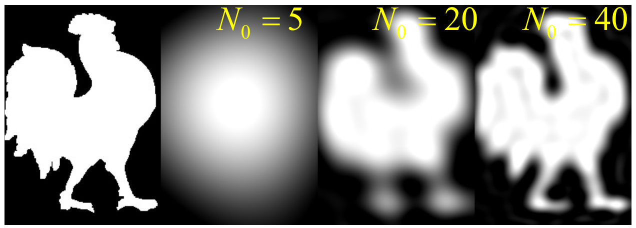
Shape Prior

Shape Space Representation

Shape descriptor

Shape Ω

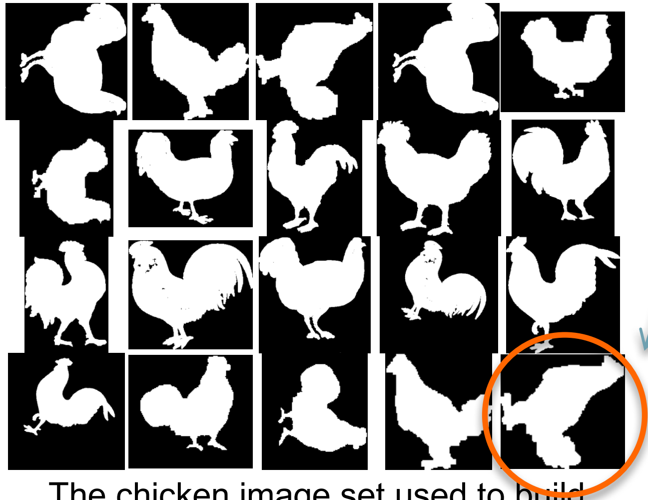
Moments λ_i such as $\sum_{i=1}^{N_0} \lambda_i$



Zernike moments

Legendre moments

Statistical Learning (PCA)



Test image

The chicken image set used to build the statistical shape model

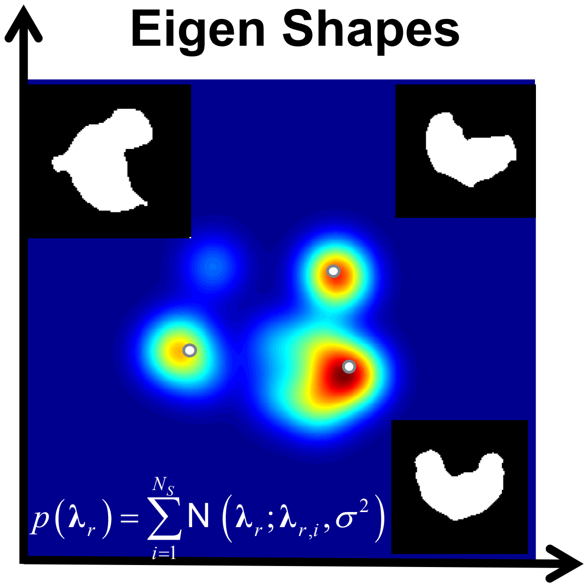
$$\bar{\boldsymbol{\lambda}} = \frac{1}{N_S}\sum_{i=1}^{N_S}\boldsymbol{\lambda}_i \quad \mathbf{Q} = \frac{1}{N_S}\sum_{i=1}^{N_S}\left(\boldsymbol{\lambda}_i - \bar{\boldsymbol{\lambda}}\right)\left(\boldsymbol{\lambda}_i - \bar{\boldsymbol{\lambda}}\right)^T$$

$$\boldsymbol{\lambda}_{r,i} = \mathbf{P}^T\left(\boldsymbol{\lambda}_i - \bar{\boldsymbol{\lambda}}\right)$$

Shape Prior

Shape Space of Moments

Eigen Shapes



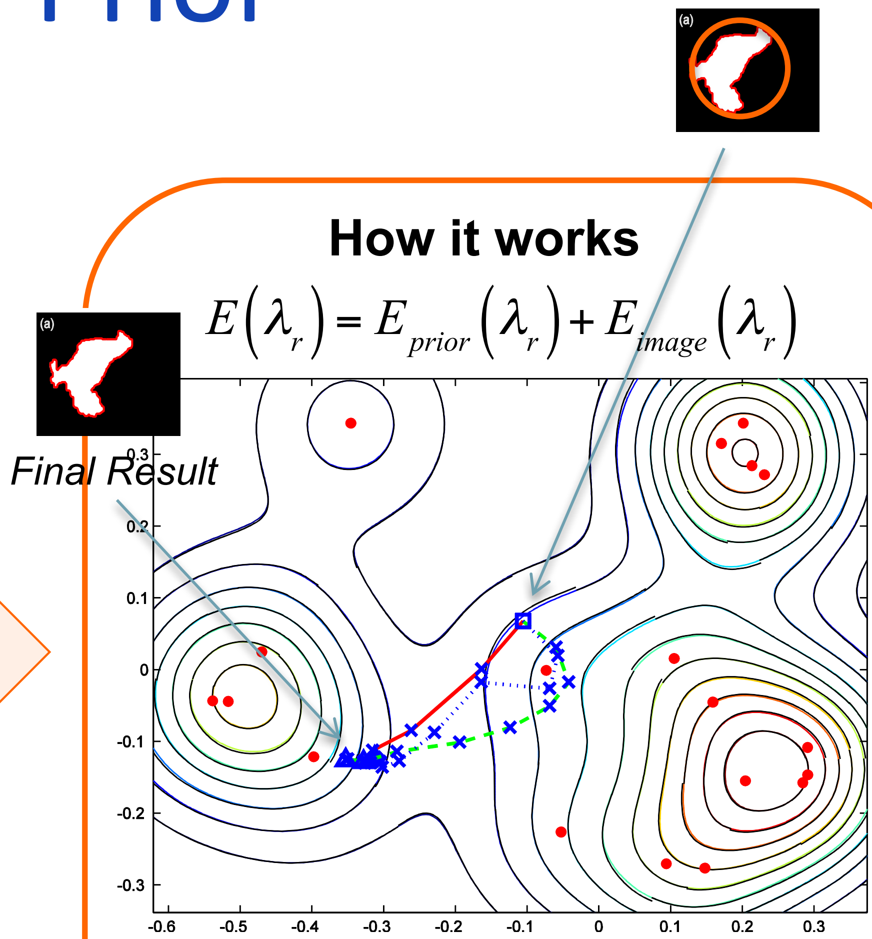
$$p(\boldsymbol{\lambda}_r) = \sum_{i=1}^{N_S} \mathrm{N}\left(\boldsymbol{\lambda}_r;\boldsymbol{\lambda}_{r,i},\sigma^2\right)$$

$$\boldsymbol{\lambda} = \lambda_{r,1}\cdot\mathbf{p}_1 + \lambda_{r,2}\cdot\mathbf{p}_2 + \overline{\boldsymbol{\lambda}}$$

$$E_{prior}(\boldsymbol{\lambda}_r) = -\ln\left(\sum_{i=1}^{N_S} \mathrm{N}\left(\boldsymbol{\lambda}_r;\boldsymbol{\lambda}_{r,i},\sigma^2\right)\right)$$

How it works

$$E(\lambda_r) = E_{prior}(\lambda_r) + E_{image}(\lambda_r)$$

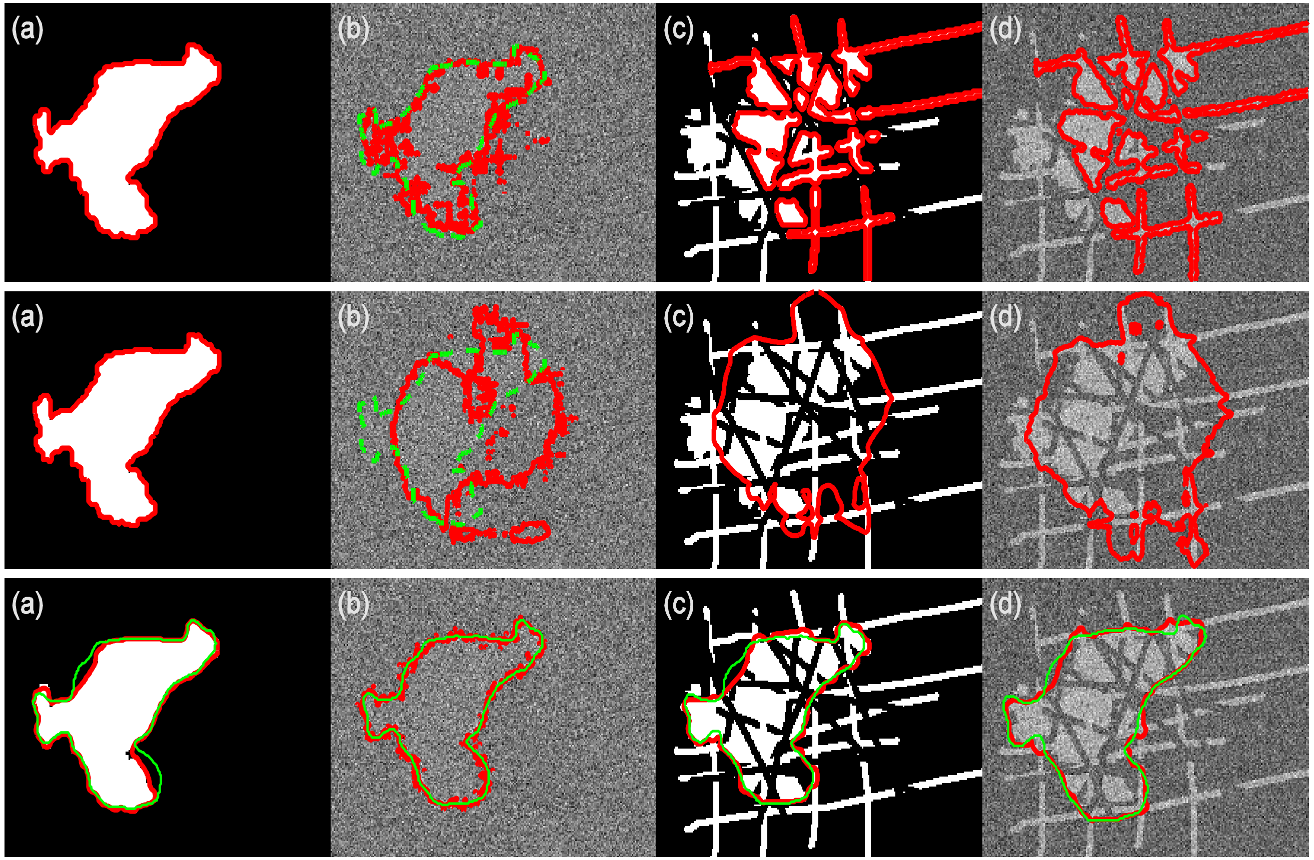


Iterations shown in the feature space spanned by the first two principal axes

Different from Template Matching

Shape Prior

Results 1 (Legendre Moments)



Chan-Vese method

Multi-reference shape prior method (Foulonneau 09)

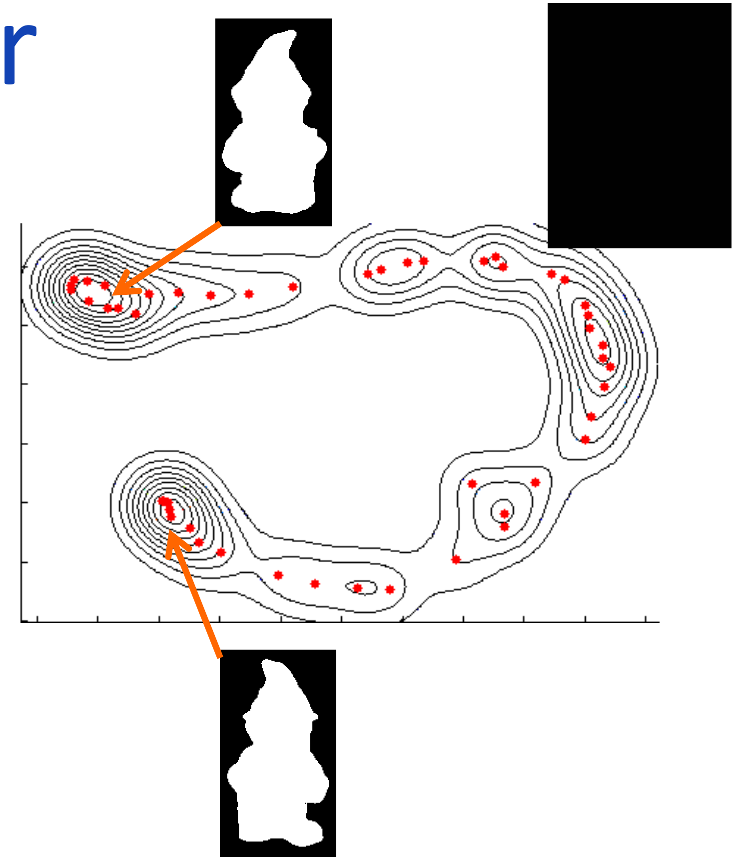
The proposed method

Original binary image | Image with Gaussian noise | Image with structural noise | Image with Gaussian and structural noise

Shape Prior

Results 2

CAIP 2011, Journal of Mathematical Imaging and Vision 2013



Question 2: Answer 1

Space Shape of Legendre Moments makes possible Shape Prior integration different from template matching

CAD: Main Contributions

Stochastic Resonance Non-Linear PDE

$$\frac{\partial I}{\partial t} = div\left(g_\eta\left(\|\nabla I\|\right)\nabla I\right)$$

$g_\eta(u) = g(u+\eta(x,y)) \longrightarrow$ Gaussian Noise

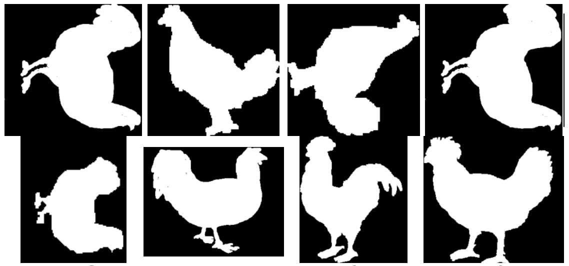
Coll. CREATIS
David Rousseau

Active Contour With Shape Prior

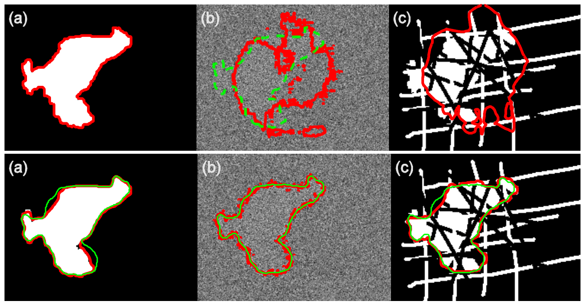
$E = E_{prior} + E_{image} \rightarrow$ ChanVese

$\downarrow$

Shape learning



Shape descriptor (Legendre)

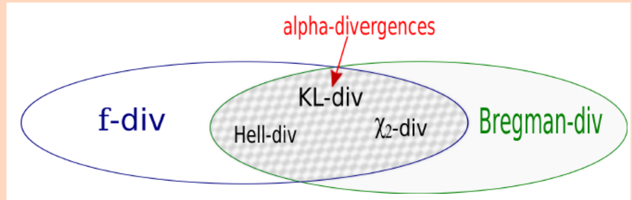


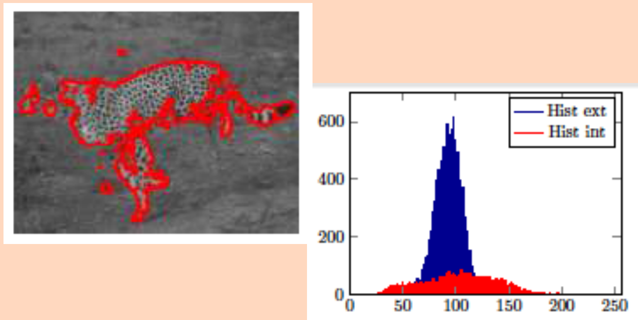
***Up** : Foulonneau, **Down** : Our Approach*

Coll. UCLan
B. Matuszewski

Alpha-Divergence Based Active Contour

$$E = E_{histogram} + E_{regularisation}$$





Joint Optimization:
-Segmentation Process
-Metric of the divergence

Coll. I3S
PhD Leila Meziou

Alpha-divergence

Histogram-Based Active Contour

$$E = E_{histogram} + E_{regularisation}$$

Probability density function

Divergence

$$D\left(p_1 \,\|\, p_2, \Omega\right) = \int_{\Re^m} \varphi\left(p_1, p_2, \lambda\right) d\lambda$$

with

- φ a similarity function
- p_i the pdf of Ω_i
- λ the quantization level

Questions:

- How to model the pdf p_i (derivation constraints)?
- Which φ function?

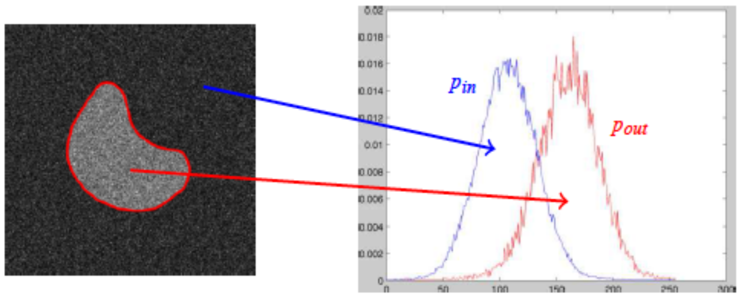
Alpha-divergence

Histogram-Based Active Contour

pdf modeling
(Parzen Window)

$$\hat{p}_i(\lambda,\Omega_i) = \frac{1}{|\Omega_i|}\int_{\Omega_i} g_\sigma\left(I(\mathrm{x})-\lambda\right)d\mathrm{x}$$

with g_σ a Gaussian kernel of variance σ



Divergence

Usually

- Kullback-Leibler $\alpha=\{0,1\}$
- Hellinger $\alpha=0.5$
- Ki² $\alpha=2$

Our proposal

- *Alpha-divergence*

$$\varphi_\alpha(p_1,p_2,\lambda) = \begin{cases} \dfrac{\alpha p_1 + (1-\alpha)p_2 - {p_1}^{\alpha}{p_2}^{1-\alpha}}{\alpha(1-\alpha)}\ , & \alpha \in \mathbb{R}\setminus\{0,1\} \\ p_2\, ln\left(\dfrac{p_2}{p_1}\right) + p_1 - p_2\ , & \alpha = 0 \\ p_1\, ln\left(\dfrac{p_1}{p_2}\right) - p_1 + p_2\ , & \alpha = 1 \end{cases}$$

Generalization

Alpha-divergence

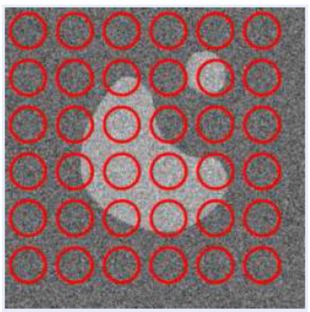
Joint Optimization

Maximization of the divergence

$$\mathrm{argmax}_{\Gamma}\left(D_{\alpha}\left(p_{in} \parallel p_{out},\Omega\right)\right)$$

Optimization of alpha-parameter

$$\mathrm{argmax}_{\alpha}\left(D_{\alpha}\left(p_{in} \parallel p_{out},\Omega\right)\right)$$



$$\begin{cases} \dfrac{\partial \alpha}{\partial t} = -\partial D_{\alpha}\left(p_{in} \parallel p_{out},\alpha\right) \\ \dfrac{\partial \Gamma}{\partial t} = -\partial_{p_{in},p_{out}} D_{\alpha}\left(p_{in} \parallel p_{out},\alpha\right) \end{cases}$$

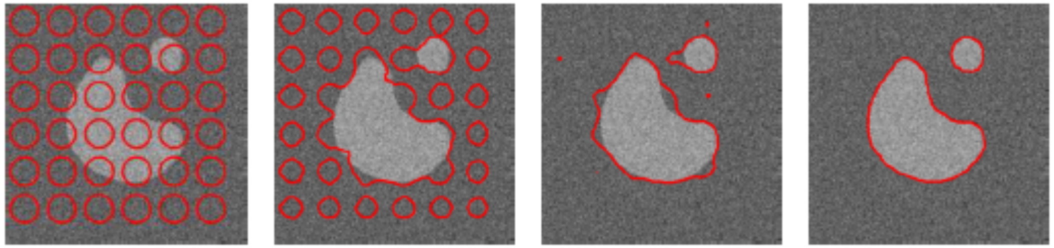
Algorithm

1.α_{t+1} (α_{init} = 1)

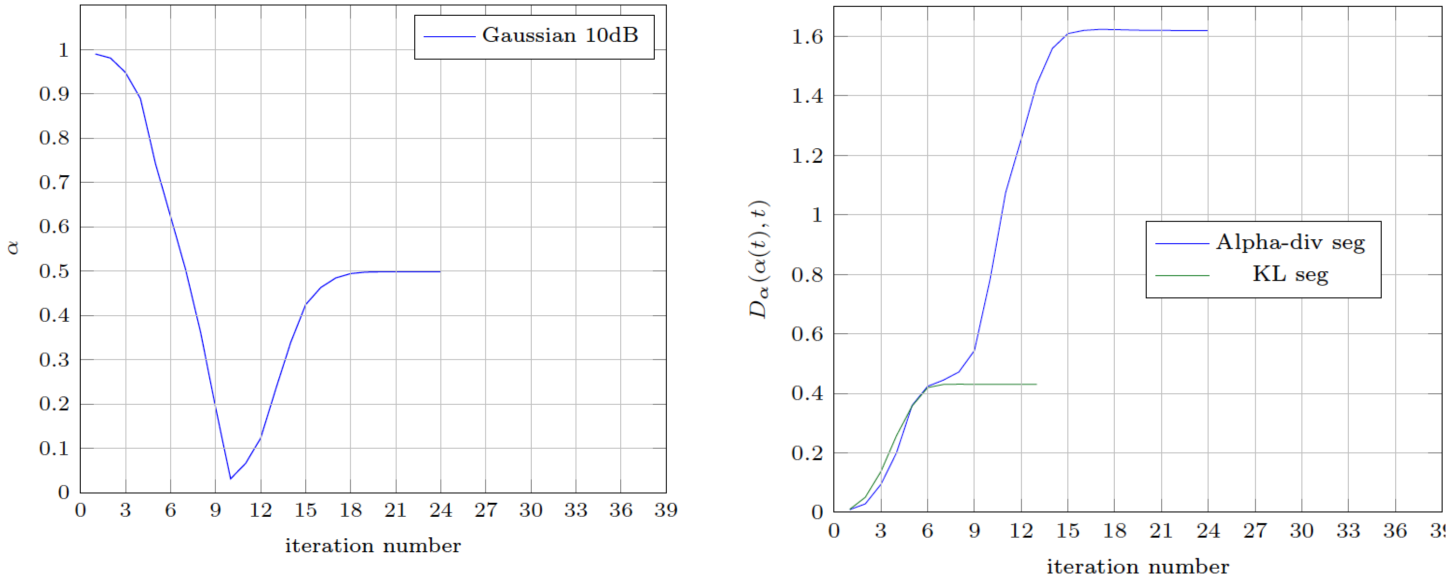
1.Γ_{t+1}

Alpha-divergence

Result 1 (Synthetic images)

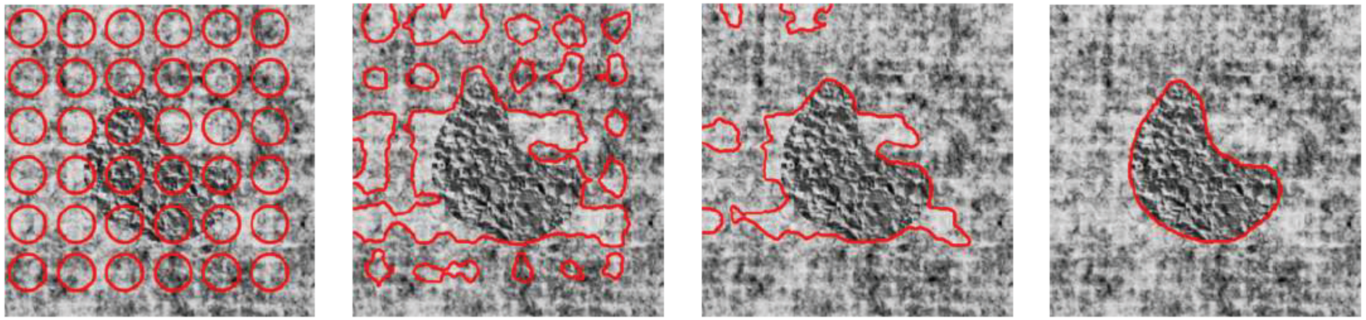


(a) $t = 0$ (b) $t = 5$ (c) $t = 10$ (d) $t = 24$

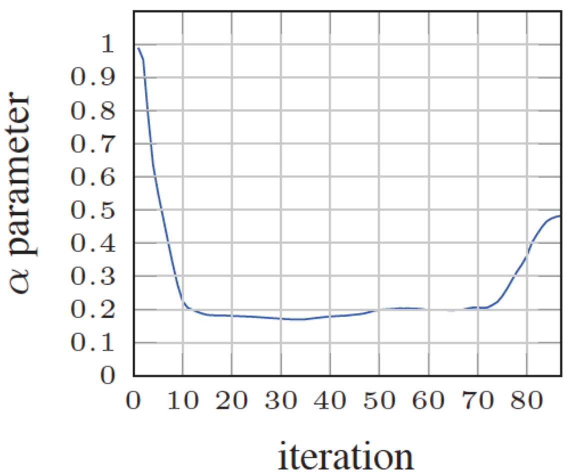


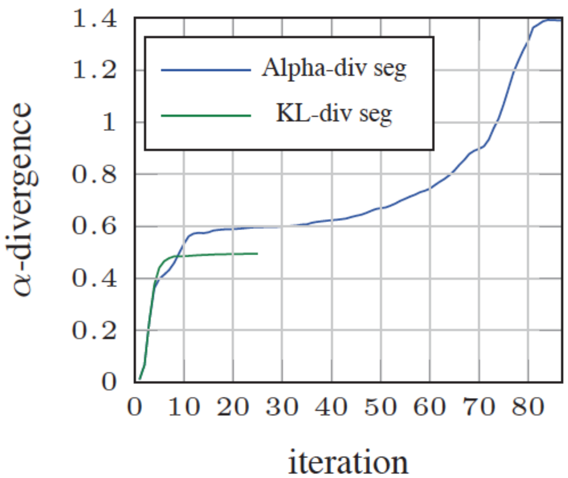
Alpha-divergence

Result 2 (Synthetic images)



(a) Initialization (b) $\tau = 5$, KL (c) $\tau = 50$ (d) Final contour

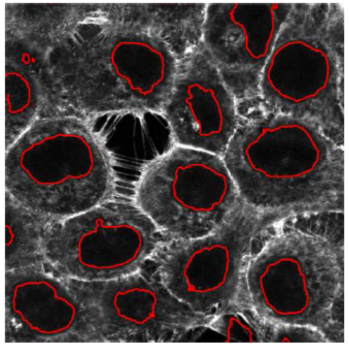




Alpha-divergence

Result 3 (Natural Images)

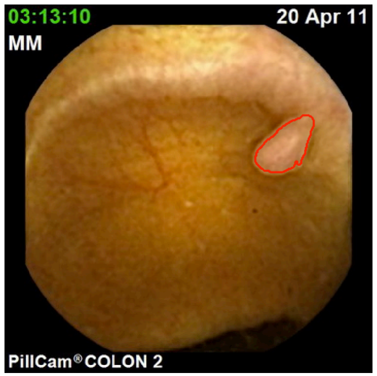
Microconfocal images of cells



Question 2: Answer 2

Alpha-divergence are a flexible tool to cop with different noise scenarios in medical image analysis (but not only)

Videocapsule (coloscopy)



X-Ray images

ICIP 2011, ICASSP 2012, MIUA 2012 (Best Student Paper Award), Annals of BMVA 2013, ICIP 2014, IJBI 2014