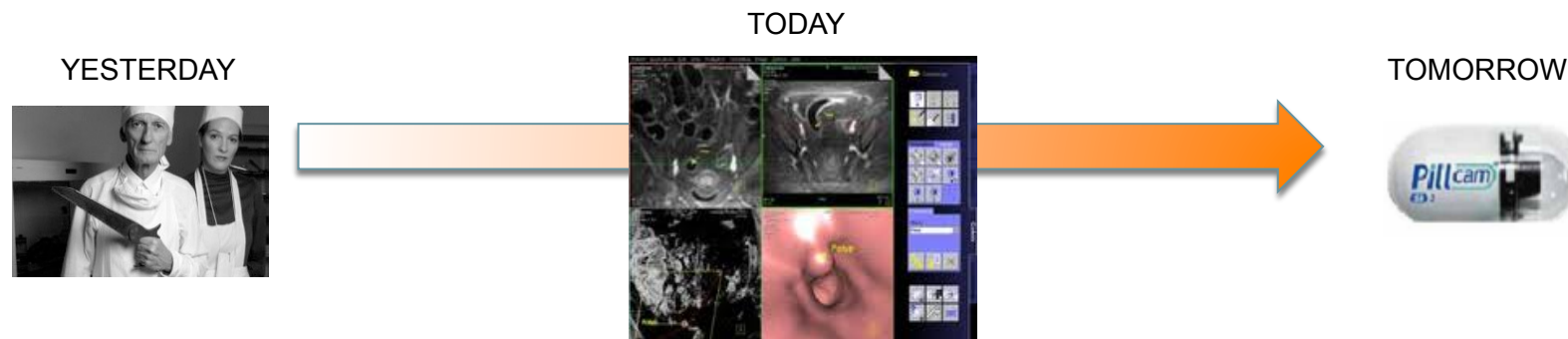


# Contributions to Image Processing For Medical Image Analysis

From Computer-Aided-Diagnosis to  
Embedded Systems For *In Situ*  
Diagnosis



Aymeric Histace  
HDR Defense



28-11-2014



# Roadmap

- **General Presentation**

- *Who am I?*



- **Research Activities**

- *What are my contributions?*



- **Perspectives**

- *What is my research project?*





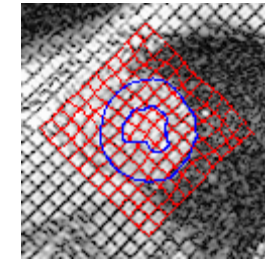


# CV

## Certificate of Birth

- 4th Sept. 1977, Lyon
- **Parents:** B. Histace and D. Ferreyre-Histace

1977



2001

2001

2004

## Master of Engineering

- EIGSI La Rochelle
- Industrial Systems Engineering

## MSc

- Signal and Image in Biology and Medicine
- University of Angers
- *Wavelet Compression of Thoravision images (X)*

## PhD

- *“Detection and tracking of structure in image sequences: application to tagged cardiac MR images”*
- **Mention:** “Très Honorable avec les félicitations du jury”
- University of Angers



Who am I?

# Professional Experience



**TODAY**



## Research

- Member of ASTRE team
- In charge of the "Embedded Systems for Health" axis
- Elected Member of the Laboratory Council

## Administrative

- **Co-Head** of MSc MADOCS (Methods for Complex Data Analysis)

## Teaching

- Institute of Technology
- Dpt of Electrical Engineering and Industrial Informatic (GEII)
- Member of the "Commission de choix"

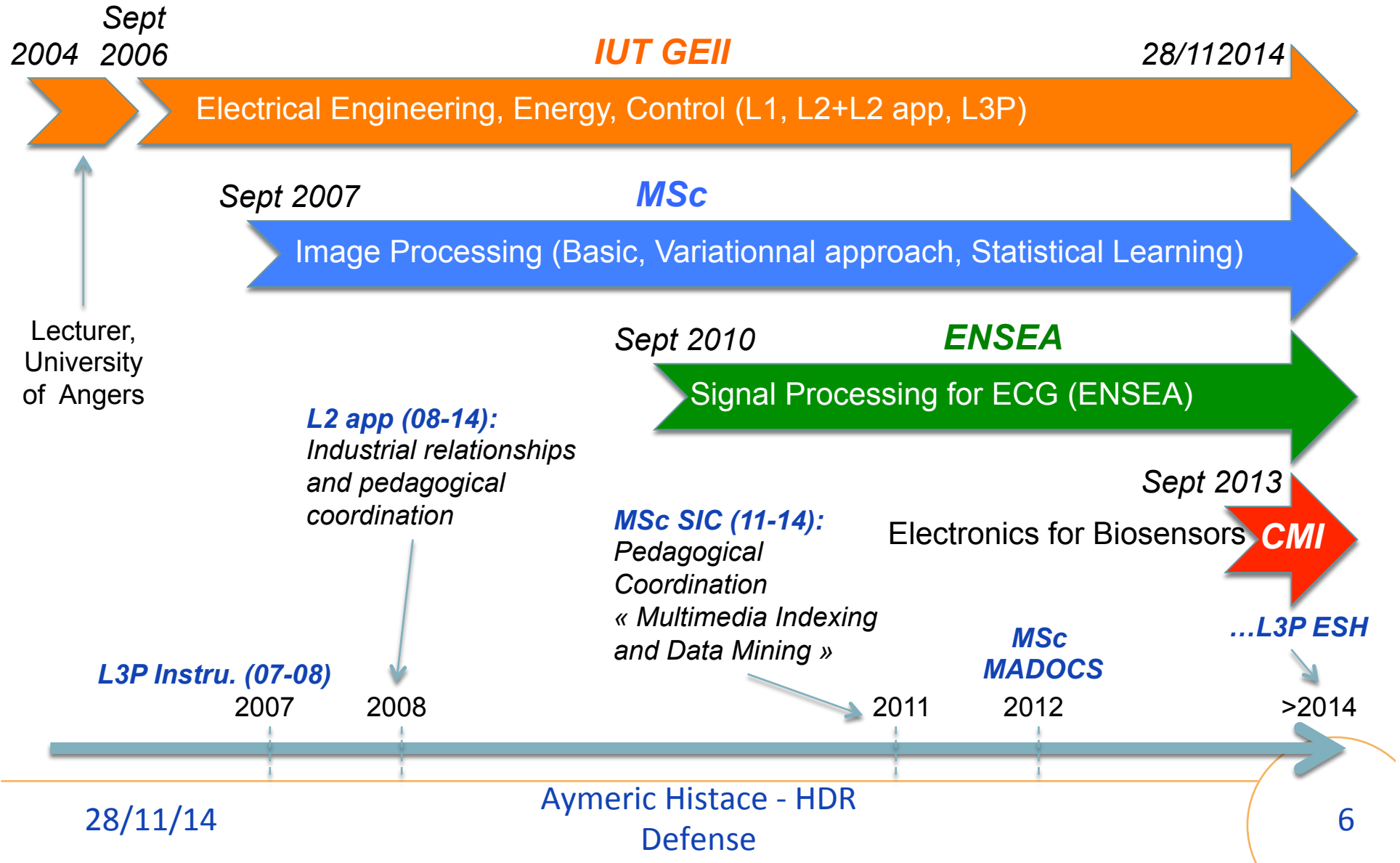
28/11/14

Aymeric Histace - HDR  
Defense



Who am I?

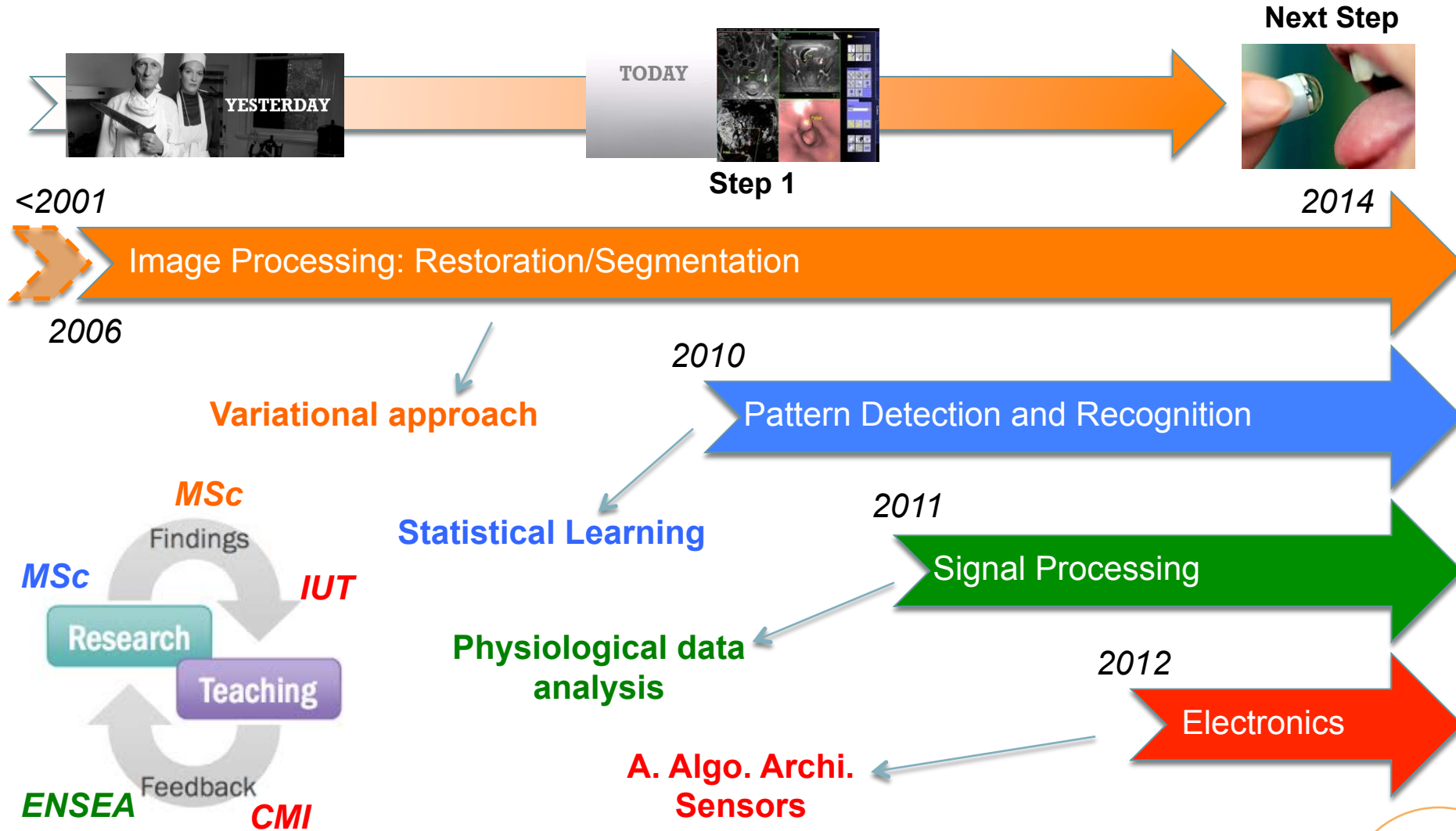
# Teaching and Responsibilities





Who am I?

# Research Overview





Who am I?

# Involvement on Projects

## Leader

**TERAFS (09-11)** ●  
Laser Confocal Imaging of Cells for Study of Radiotherapy Insult

**SIMBAD (08-...)** ●  
Biomedical Image Segmentation for CAD

**Cyclope (11-...)** ●●  
Smart Videoendoscopy for CRC early-diagnosis

**TRAPIL (10-14)** ●  
Automatic Detection of Defect in Pipelines Using Ultrasonic Images

● *International (EPSRC, AUF)*

● *National (CNRS)*

● *Regional, Local (FUI, ENSEA, UCP)*

● *Industrial (SATT, CIFRE, Subcontract)*

## Partner

**ECSON (07-09)** ●  
Oncology Network of Competences

**FibroSES, iFib (2013-...)** ●●  
In Vivo and In Vitro Electric Characterization of Fibrosis Induced by Electronic Implant

**SmartEEG (13-...)** ●●  
Smart Mobile System for ExG Signals Acquisition and Analysis

**PAPILLON (14-...)** ●●  
On-line Characterization of Dypters using Image Processing

**Technological Transfer**

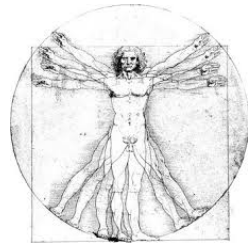




Who am I?

# Collaborations (National)

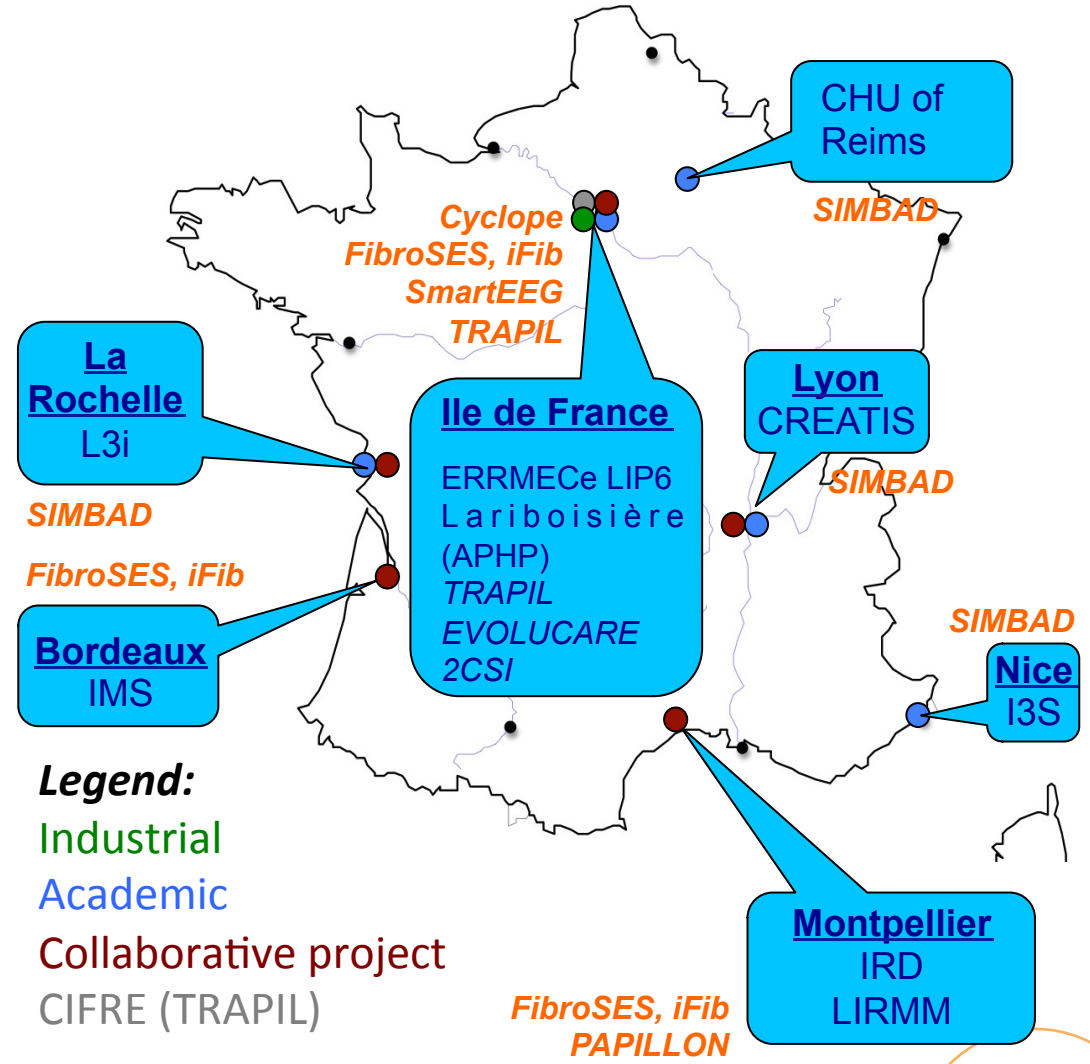
8 Labs  
 2 Hospitals  
 3 Companies  
 6 Projects



**GDR ISIS/SOC-SIP:**

- Sensors and SIP (2012)
- Statistical and Variational approaches in Medical Image Analysis (2013)

**BioniCamp 2012 (DEFISENS)**  
**DCIS'12 (Special Session)**  
**GEODIFF Workshop (2013)**





Who am I?

# Collaborations (International)

**3 Countries**

**4 Universities**

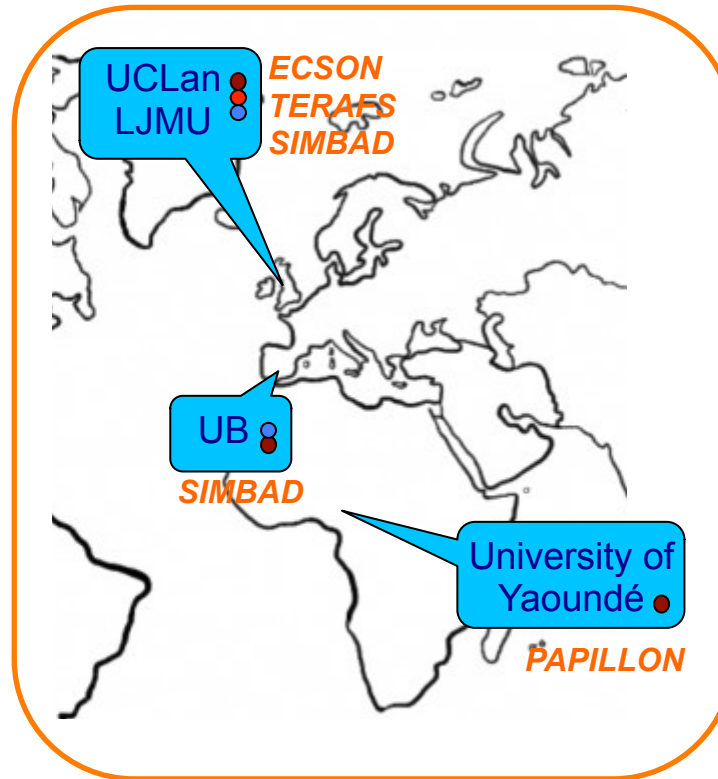
**4 Projects**

- ECSON
- TERAFS
- SIMBAD
- PAPILLON

**3 Student Exchanges**

**2 Special Sessions**  
(ECSMIO10, ICIP11)

**1 Workshop**  
(BioSan14)



**1 joint PhD**

**Legend:**

- Collaborative projects
- Guest
- Host



# Supervising



## 4 PhD students: 120%+80%

- 2 *Defended* (11/2013, 06/2014)
- 2 *just started*
  - Cyclope (50%, 2014-2017)
  - PAPILLON (30%, Yaounde, 2014-2017)

## 7 MSc students: 400%

- MSc SIC
- MSc ESA), SESI (UPMC)

## Others:

- 1 *Post-doc* (50%-1 year)
- 1 *Research Engineer* (50%)
- *Several Initiation-to-Research projects*

# Roadmap

- **General Presentation**

- *Who am I?*



- **Research Activities**

- *What are my contributions?*



- **Perspectives**

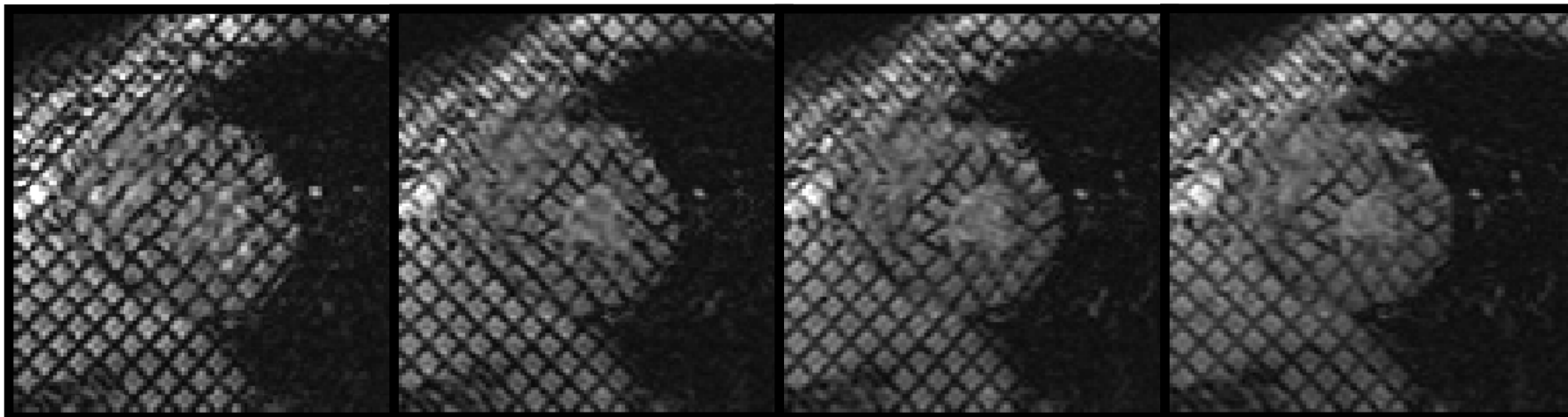
- *What is my research project?*





# PhD

(Tagged Cardiac MRI)



Quantification of LV contraction



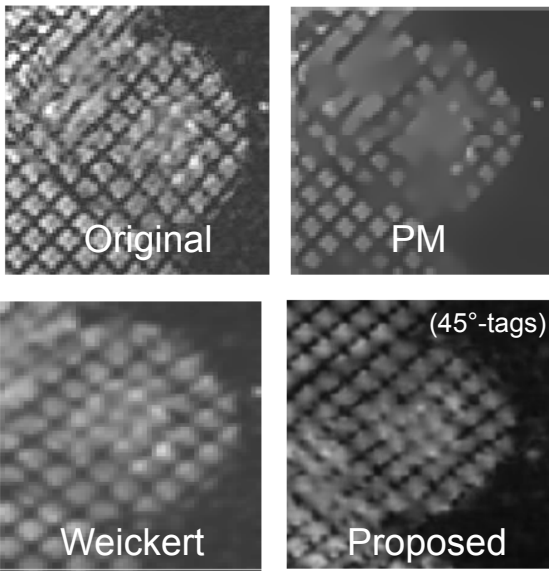
# PhD

(Tagged Cardiac MRI)

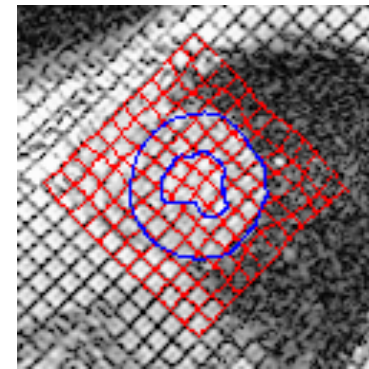
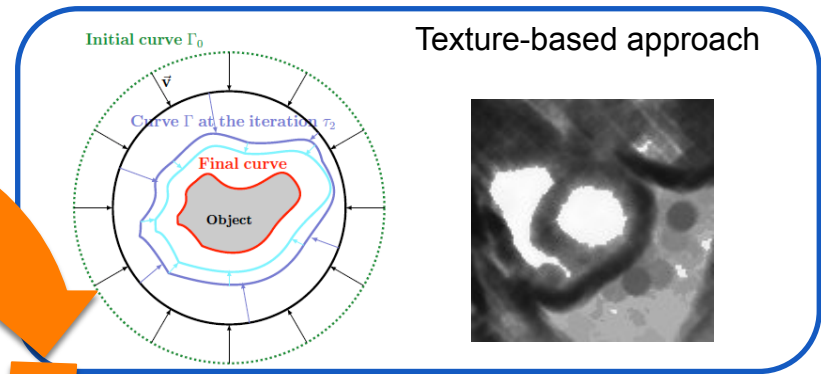
## PDE-based Image Restoration

$$\frac{\partial I}{\partial t} = (\nabla - A) \cdot (\nabla - A) I$$

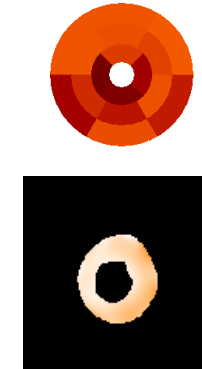
A is a prior vector field taking into account the gradient orientation to restore or not



## Active Contour Segmentation



Movement Estimation



Quantification



# Main Questions



## Question 1

Can we profit in an original way from the **non-linearity** of the usual **divergence-based PDE**?

$$\frac{\partial I}{\partial t} = \text{div}(g(\|\nabla I\|)\nabla I)$$

## Question 2

Can we profit from the **prior knowledge** we have in medical image analysis (shape, texture, noise, etc.)?

## Question 3

Can we propose **CAD methods compatible with embedding constraints**?

# CAD: Main Contributions

## Stochastic Resonance Non-Linear PDE

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



$$g_\eta(u) = g(u + \eta(x, y)) \rightarrow \text{Gaussian Noise}$$

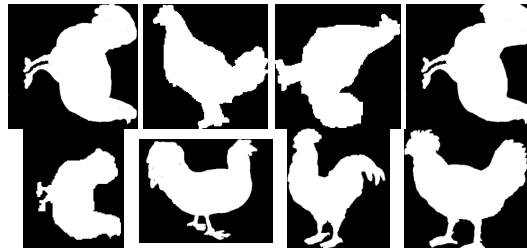
Coll. CREATIS  
David Rousseau

## Active Contour With Shape Prior

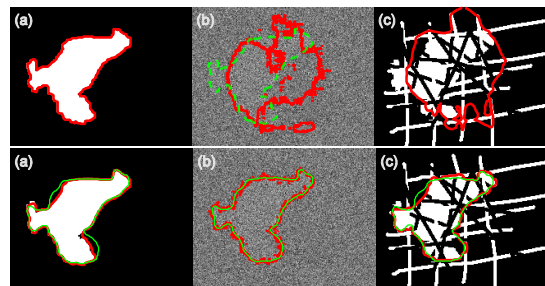
$$E = E_{\text{prior}} + E_{\text{image}} \rightarrow \text{ChanVese}$$



Shape learning



Shape descriptor (Legendre)

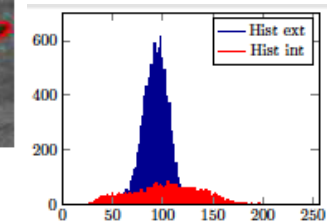
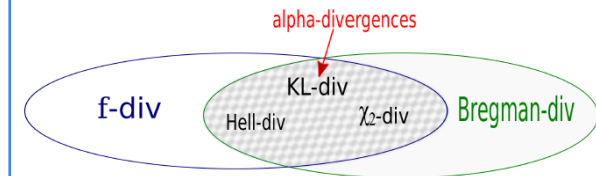


Up : Foulonneau, Down : Our Approach

Coll. UCLan  
B. Matuszewski

## Alpha-Divergence Based Active Contour

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



### Joint Optimization:

- Segmentation Process
- Metric of the divergence

Coll. I3S  
PhD Leila Meziou



# CAD: Main Contributions

## Stochastic Resonance Non-Linear PDE

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



$$g_\eta(u) = g(u + \eta(x, y)) \rightarrow \text{Gaussian Noise}$$

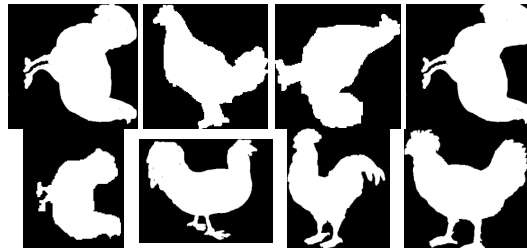
Coll. CREATIS  
David Rousseau

## Active Contour With Shape Prior

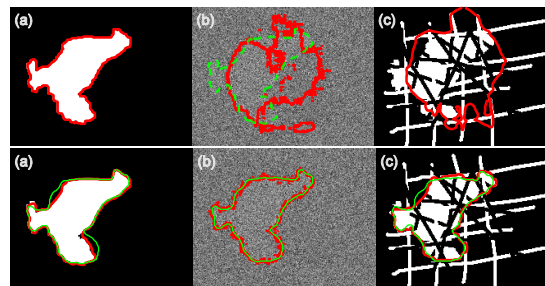
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Shape learning



Shape descriptor (Legendre)

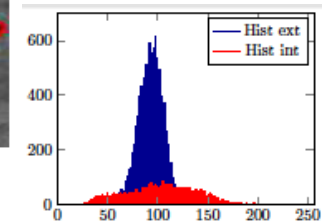
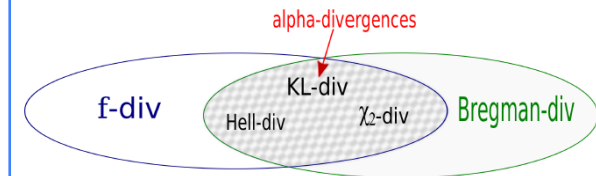


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### Joint Optimization:

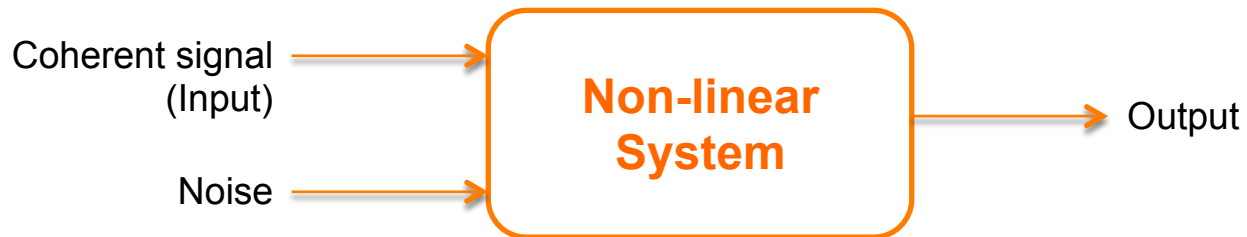
- Segmentation Process
- Metric of the divergence

Coll. I3S  
PhD Leila Meziou

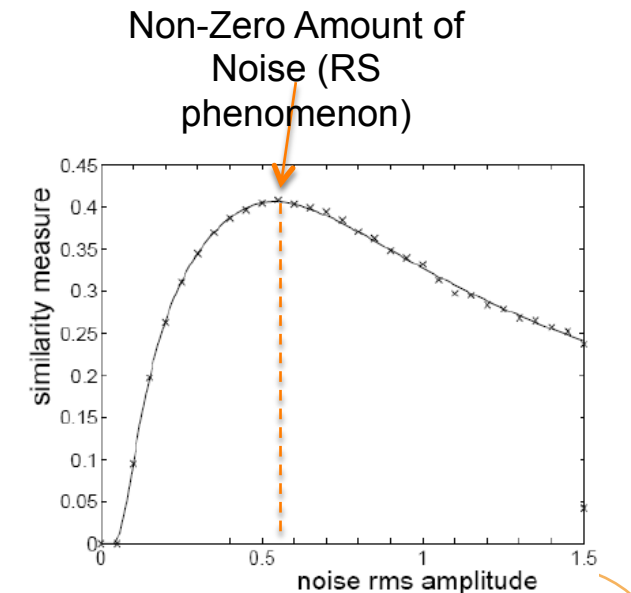
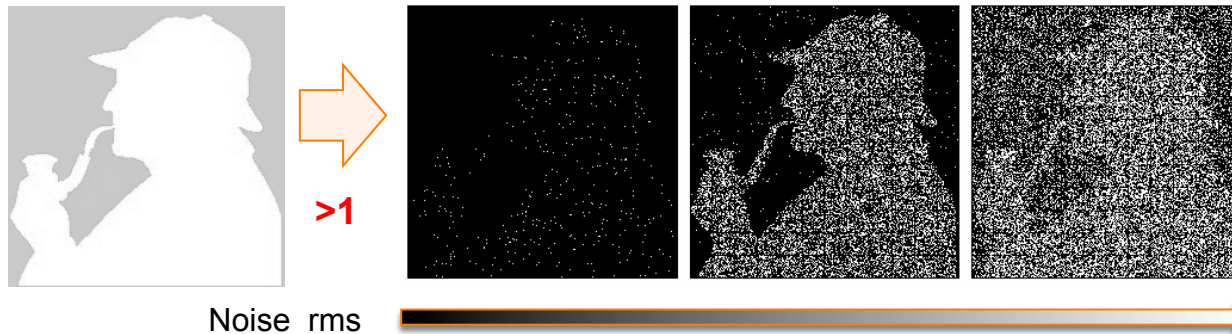


# Useful Noise Effect

## Stochastic Resonance



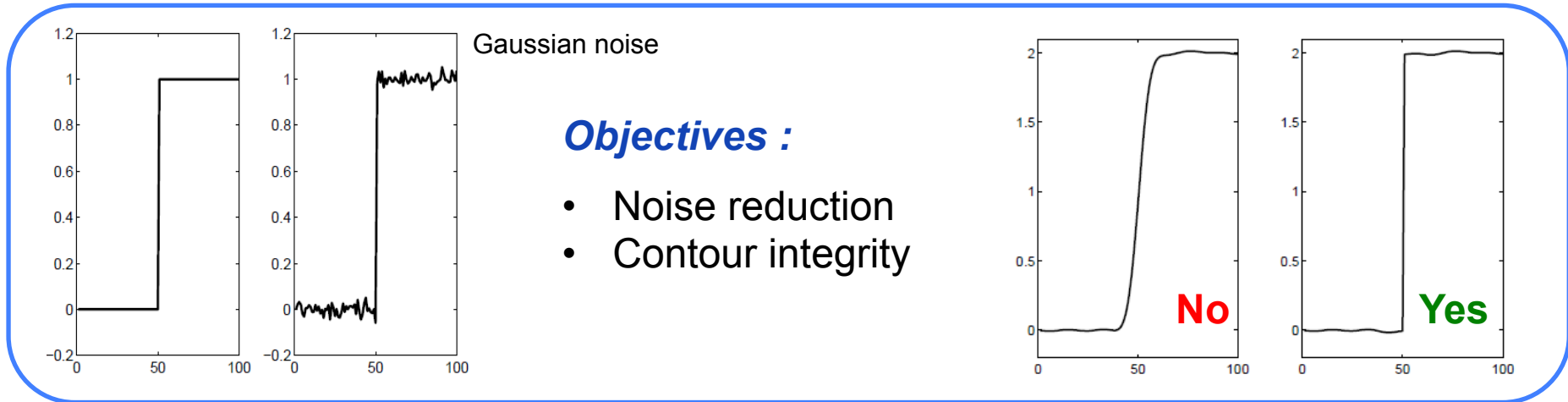
### Illustration: Binary Transmission Aided by Noise





# Useful Noise Effect

## Application to Image Restoration



### Method

$$\begin{cases} I(x, y, 0) = I_0 \\ \frac{\partial I}{\partial t} = \text{div}(g_\eta(\|\nabla I\|)\nabla I) \end{cases}$$

with

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

**Stochastic Variant of Perona-Malik process**

- $\eta$  a noise assumed independent and identically distributed (rms amplitude  $\sigma_\eta$ )
- $g$  a decreasing monotonic function



# Useful Noise Effect

## Experiment 1

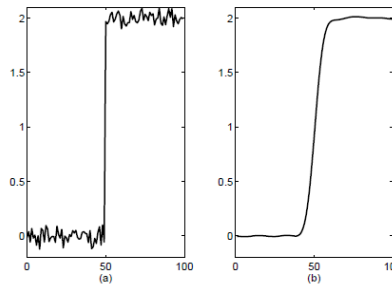
$$g_{\eta}(u) = g(u + \eta(x))$$

with

$$g(s) = \begin{cases} 1 & \text{if } s \geq k \\ 0 & \text{if } s < k \end{cases}$$

Hard-threshold

We consider a case where  $k$  parameter is badly tuned regarding PM approach :

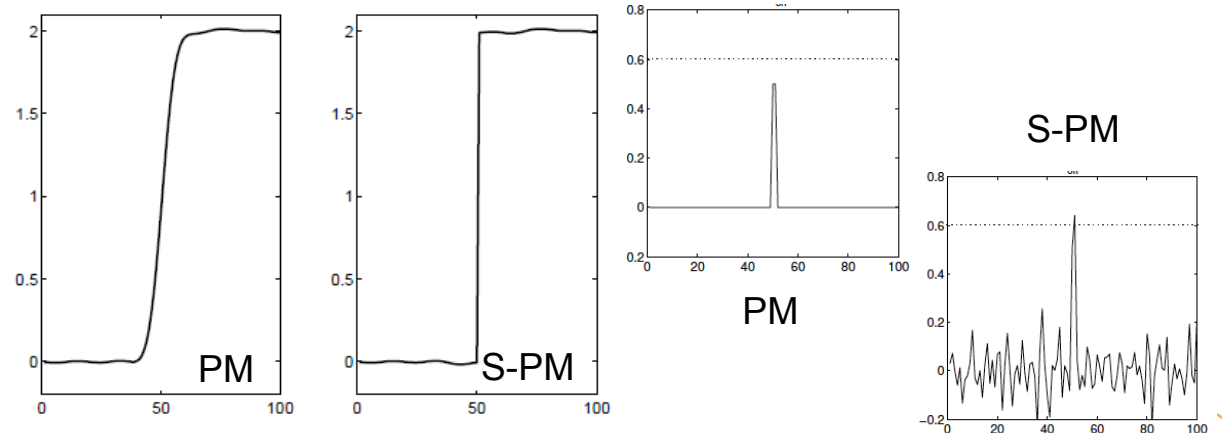


(left) Original noisy contour

(right) Restored one using PM approach with  $k=0.6$

## Result

Purposely injection of  $\eta$  noise in  $g$  function can randomly retune the function





# Useful Noise Effect

## Experiment 2

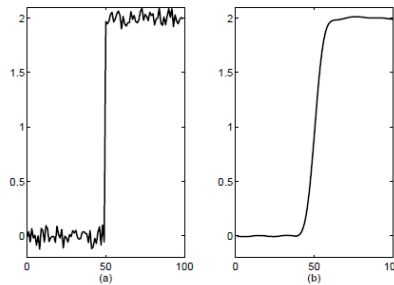
$$g_{\eta}(u) = g(u + \eta(x))$$

with

$$g(s) = \begin{cases} 1 & \text{if } s \geq k \\ 0 & \text{if } s < k \end{cases}$$

Hard-threshold

We consider a case where  $k$  parameter is badly tuned regarding PM approach :



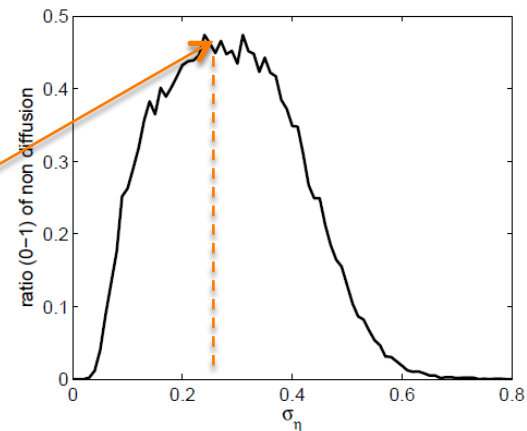
(left) Original noisy contour

(right) Restored one using PM approach with  $k=0.6$

### Result (Quantification)

Variation of the ratio of well restored function of the noise rms amplitude (1000 attempts).

**The non-diffusion ratio is maximum for a non zero amount of noise**



# Useful Noise Effect

## Extension to image restoration

$$\begin{cases} I(x, y, 0) = I_0 \\ \frac{\partial I}{\partial t} = \text{div} \left( g_\eta (\|\nabla I\|) \nabla I \right) \end{cases}$$

with  $g_\eta(u) = g(u + \eta(x, y))$   
 and  $g(u) = e^{-\frac{\|u\|^2}{k^2}}$

Gaussian Noise (PM, S-PM)



Multiplicative Noise (PM, S-PM)



Impulsive Noise (PM, S-PM)

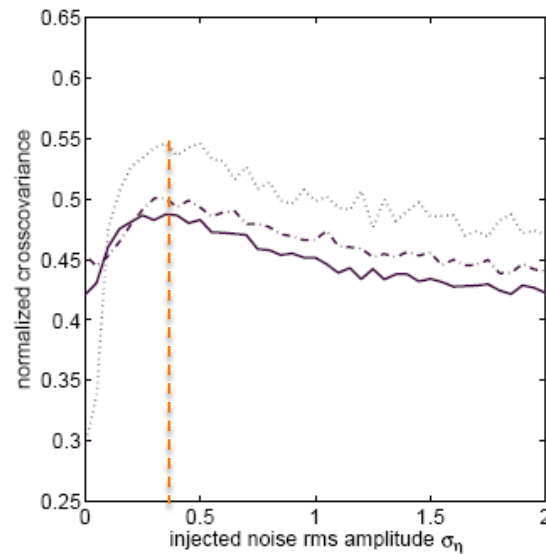




# Useful Noise Effect

## Result (quantification)

Normalized Cross Covariance wrt  
the amount of injected noise  
(1000 attempts)



— Gaussian  
- - - Multiplicative  
..... Impulsive

## Question 1: Answer

**In each case the similarity measure is maximum for a non-zero amount of injected noise**

*Elec. Letters 2006, PSIP 2007, IEEE SocPar 2010, Int Journal of Comp .Infor. Systems and Industrial Management 2012*

# CAD: Main Contributions

## Stochastic Resonance Non-Linear PDE

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



$$g_\eta(u) = g(u + \eta(x, y)) \rightarrow \text{Gaussian Noise}$$

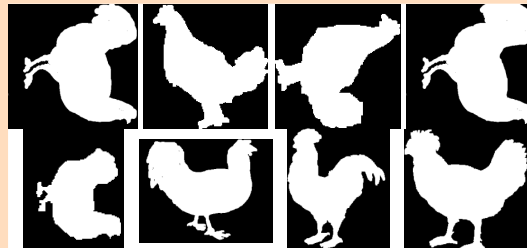
Coll. CREATIS  
David Rousseau

## Active Contour With Shape Prior

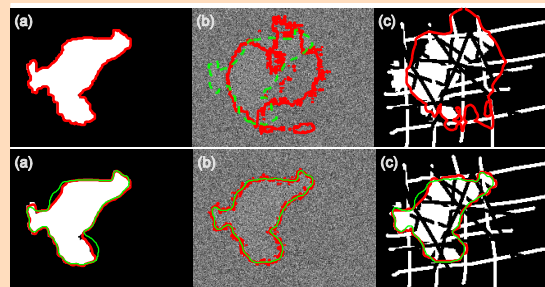
$$E = E_{\text{prior}} + E_{\text{image}} \rightarrow \text{ChanVese}$$



Shape learning



Shape descriptor (Legendre)

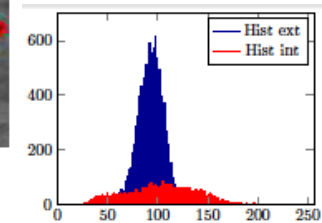
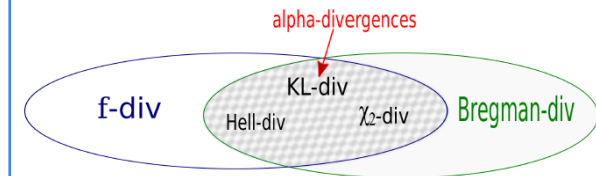


Up : Foulonneau, Down : Our Approach

Coll. UCLan  
B. Matuszewski

## Alpha-Divergence Based Active Contour

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



### Joint Optimization:

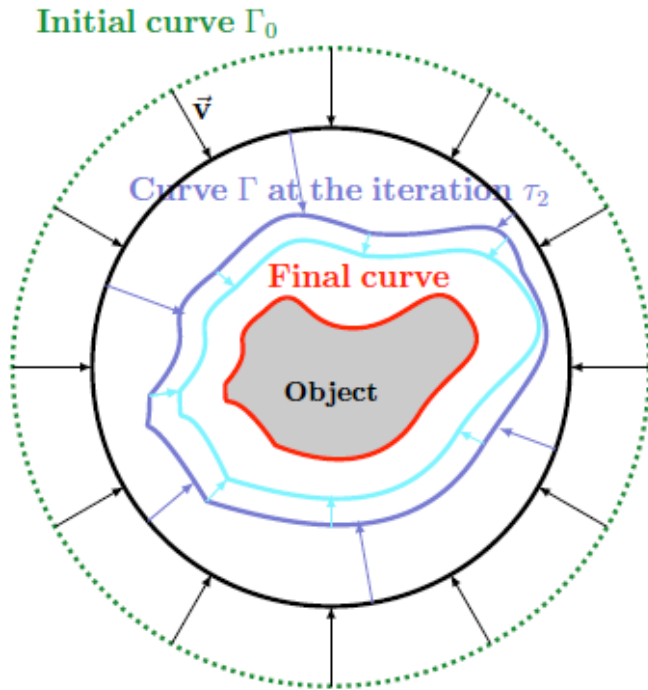
- Segmentation Process
- Metric of the divergence

Coll. I3S  
PhD Leila Meziou



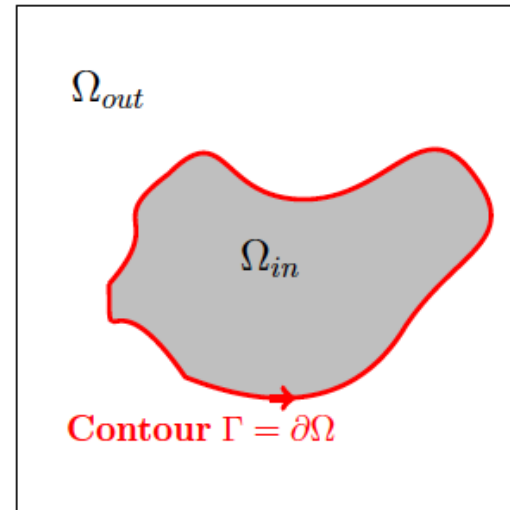
# Active Contours

## Principle



$$\min (E_{image} + E_{regularisation} + \dots)$$

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



### Gradient-based approach:

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

### Region-based approach:

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

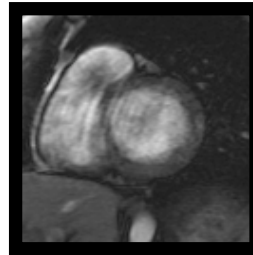


# Shape Prior

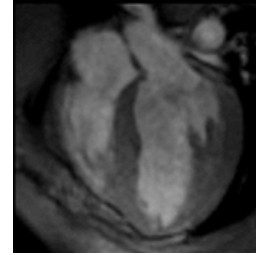
## Main Idea

- 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 ?

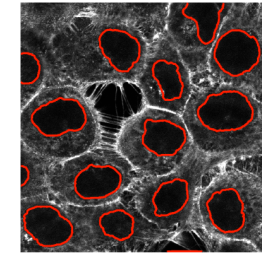
Cardiac MRI



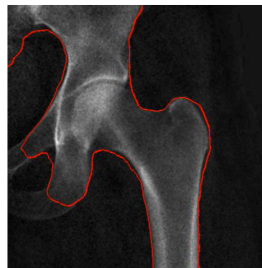
SA



LA



Microconfocal images



X-Ray Radiography (hip bone)

## Proposal


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

with  $\lambda_r$  a reduced shape descriptor (statistical learning)

# Shape Prior

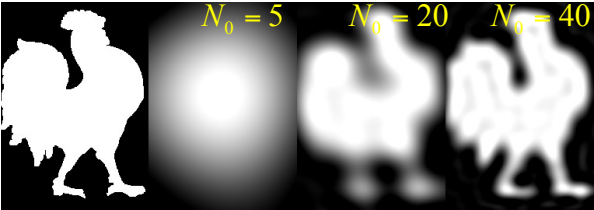
## Shape Space Representation

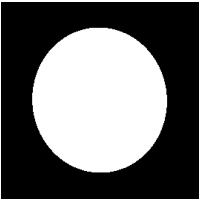
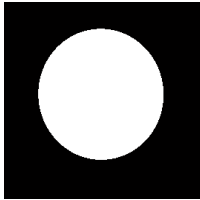
**Shape descriptor**

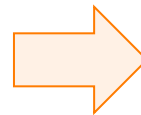
Shape  $\Omega$  

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


$N_0 = 5$   $N_0 = 20$   $N_0 = 40$



Zernike moments  Legendre moments 



**Statistical Learning (PCA)**



Test image

The chicken image set used to build the statistical shape model

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

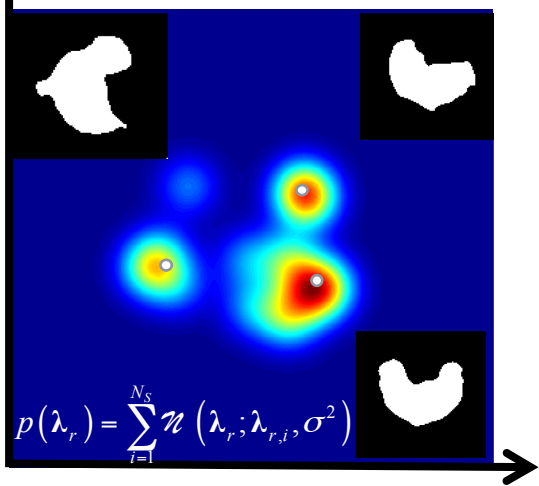
$$\lambda_{r,i} = \mathbf{P}^T (\lambda_i - \bar{\lambda})$$



# Shape Prior

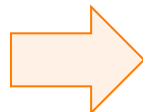
## Shape Space of Moments

### Eigen Shapes



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

$$E_{prior}(\lambda_r) = -\ln \left( \sum_{i=1}^{N_s} \mathcal{N}(\lambda_r; \lambda_{r,i}, \sigma^2) \right)$$

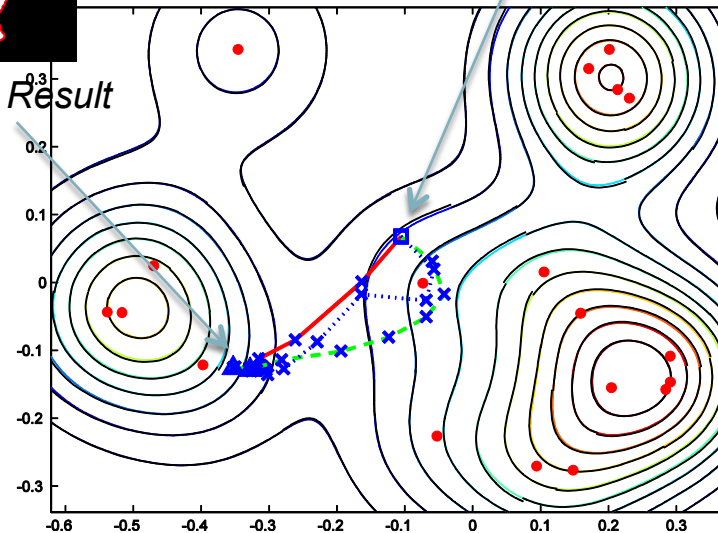


### How it works

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



Final Result



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

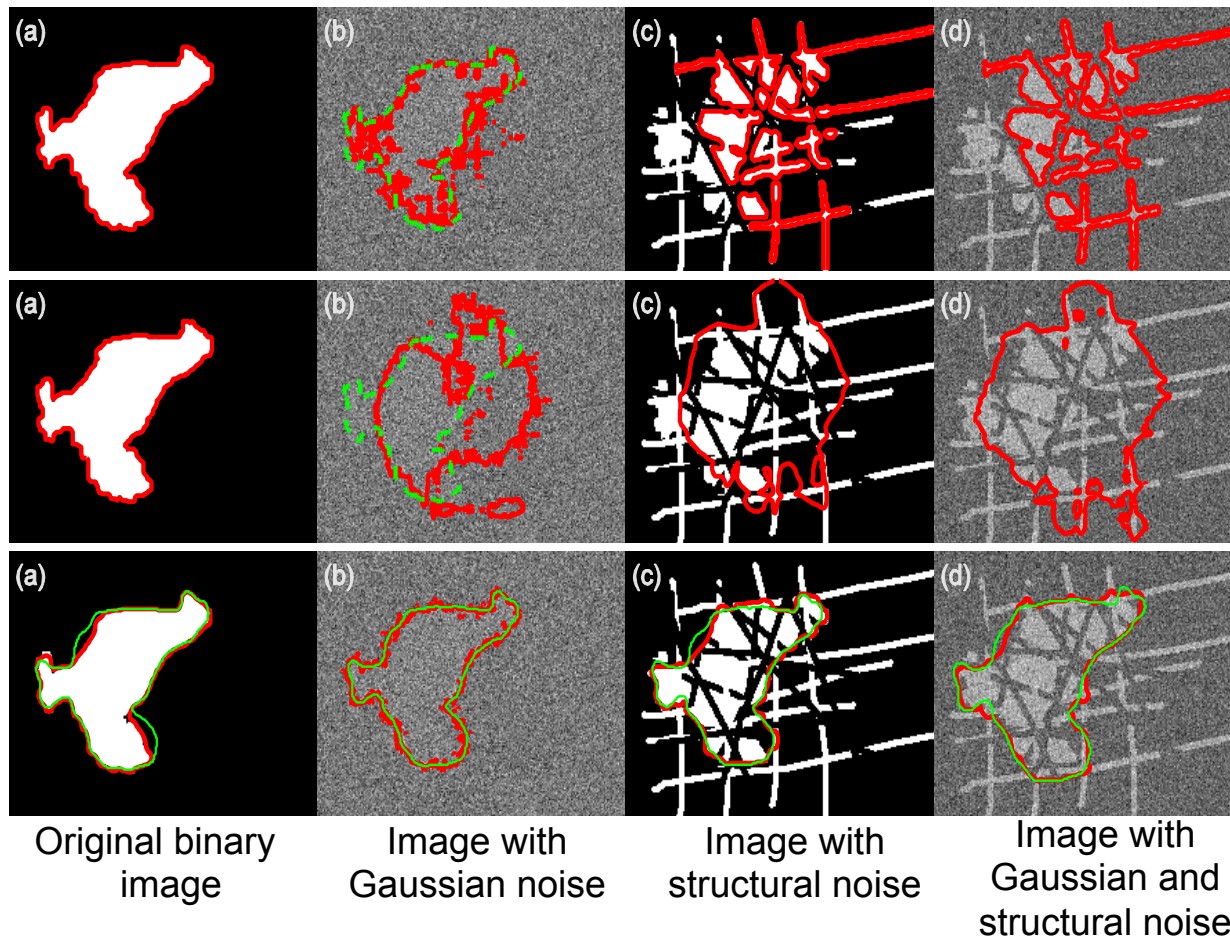
Different from Template Matching





# Shape Prior

## Results 1 (Legendre Moments)



Chan-Vese method

Multi-reference shape prior method (Foulonneau 09)

The proposed method

Original binary image

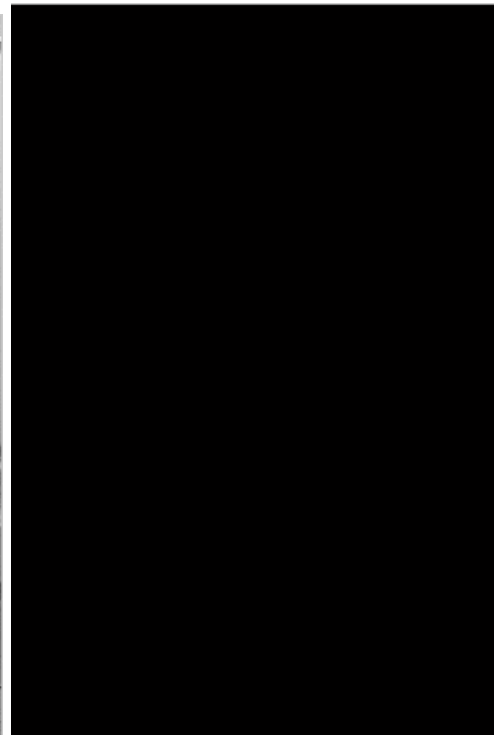
Image with Gaussian noise

Image with structural noise

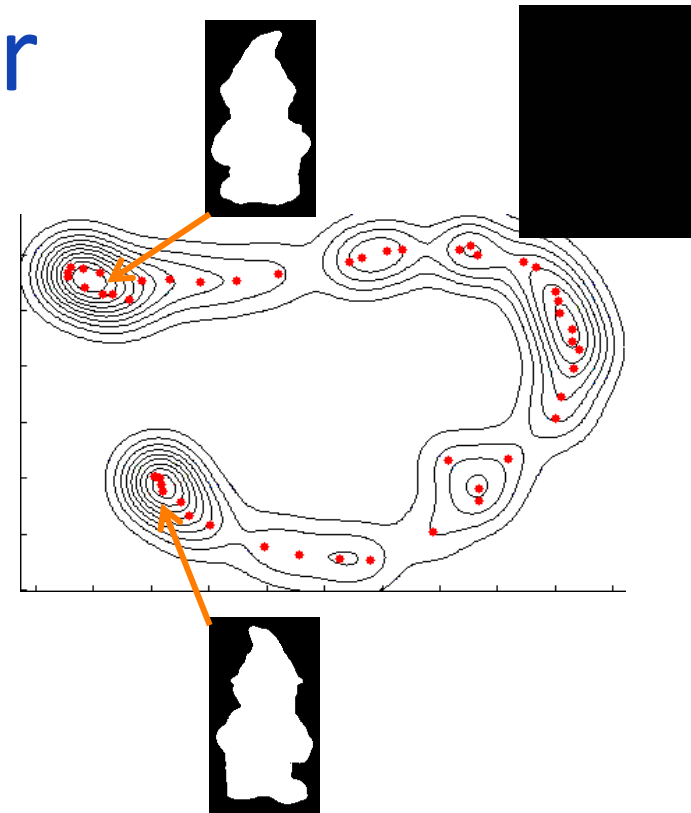
Image with Gaussian and structural noise

# 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

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



$$g_\eta(u) = g(u + \eta(x, y)) \rightarrow \text{Gaussian Noise}$$

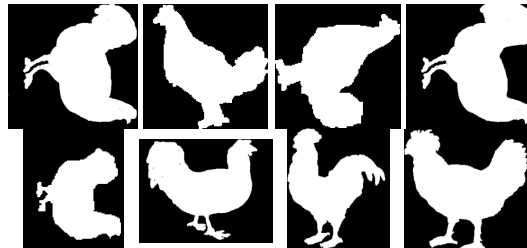
Coll. CREATIS  
David Rousseau

## Active Contour With Shape Prior

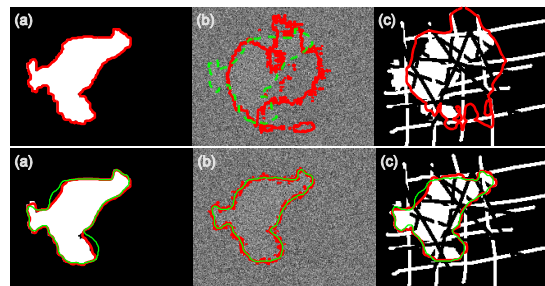
$$E = E_{\text{prior}} + E_{\text{image}} \rightarrow \text{ChanVese}$$



Shape learning



Shape descriptor (Legendre)

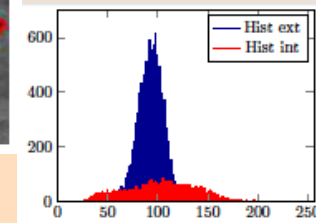
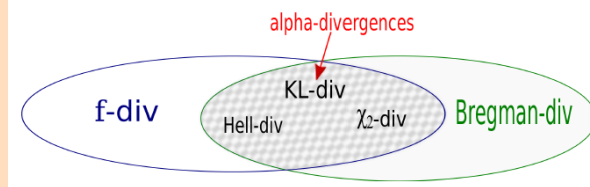


Up : Foulonneau, Down : Our Approach

Coll. UCLan  
B. Matuszewski

## Alpha-Divergence Based Active Contour

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



### Joint Optimization:

- Segmentation Process
- Metric of the divergence

Coll. I3S  
PhD Leila Meziou



# Alpha-divergence

## Histogram-Based Active Contour

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

Divergence

$$D(p_1 \parallel p_2, \Omega) = \int_{\mathfrak{R}^m} \varphi(p_1, p_2, \lambda) d\lambda \quad \text{with}$$

Probability density function

- $\varphi$  a similarity function
- $p_i$  the pdf of  $\Omega_i$
- $\lambda$  the quantization level

### Questions:

- How to model the pdf  $p_i$  (derivation constraints)?
- Which  $\varphi$  function?





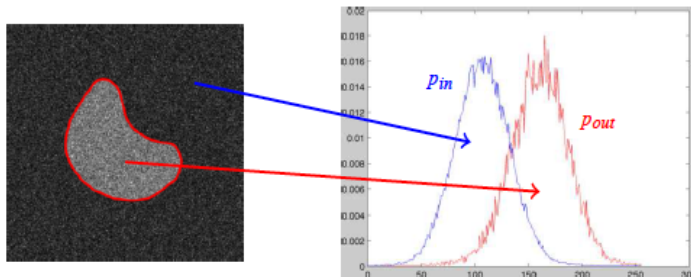
# Alpha-divergence

## Histogram-Based Active Contour

### pdf modeling (Parzen Window)

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

with  $g_\sigma$  a Gaussian kernel of variance  $\sigma$



### Divergence

#### Usually

- Kullback-Leibler
- Hellinger
- $Kl^2$

#### Our proposal

- Alpha-divergence

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

Generalization



# Alpha-divergence

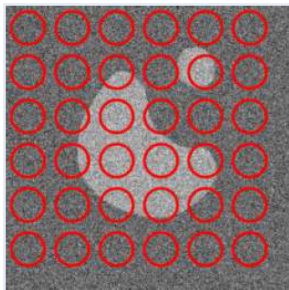
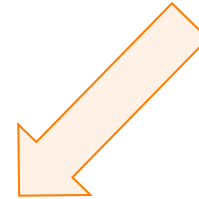
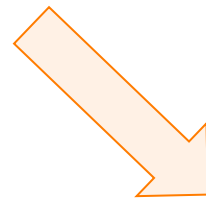
## Joint Optimization

**Maximization of  
the divergence**

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

**Optimization of  
alpha-parameter**

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



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

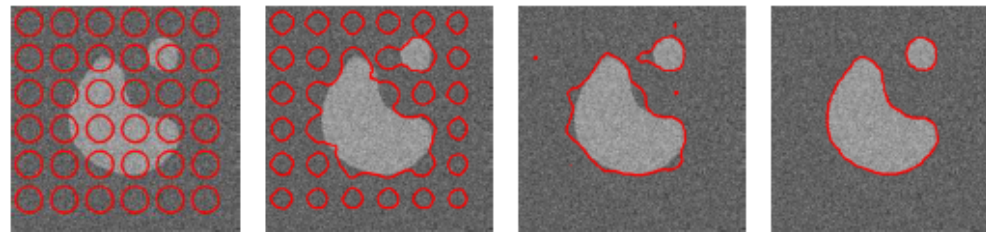
### Algorithm

1.  $\alpha_{t+1}$  ( $\alpha_{init} = 1$ )
2.  $\Gamma_{t+1}$



# Alpha-divergence

## Result 1 (Synthetic images)

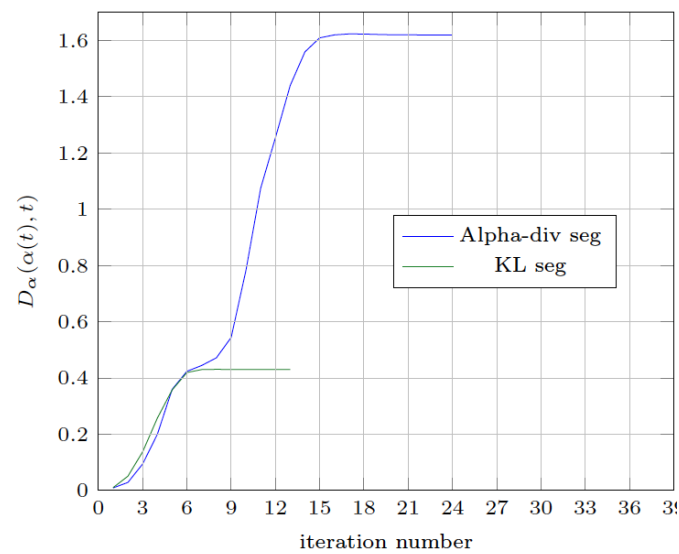
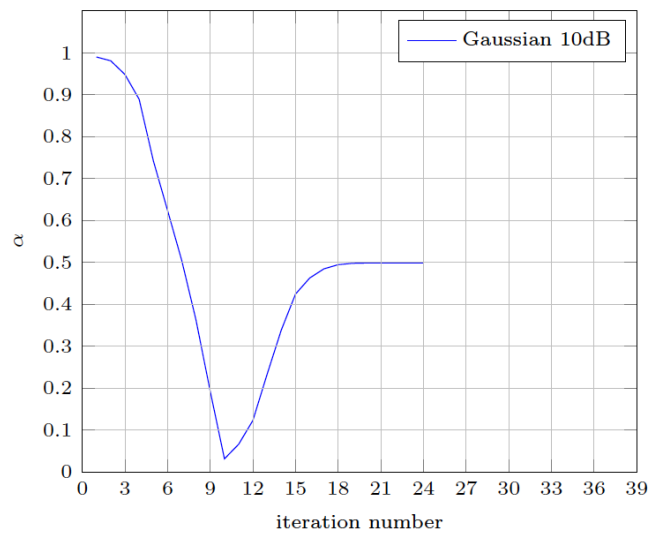


(a)  $t = 0$

(b)  $t = 5$

(c)  $t = 10$

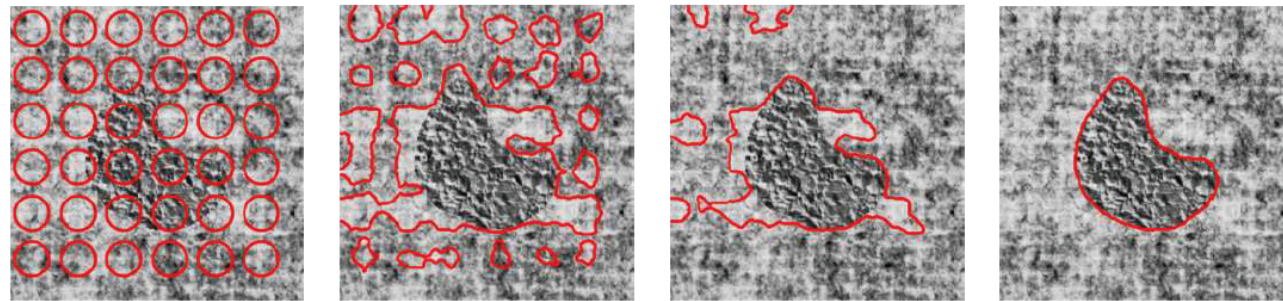
(d)  $t = 24$



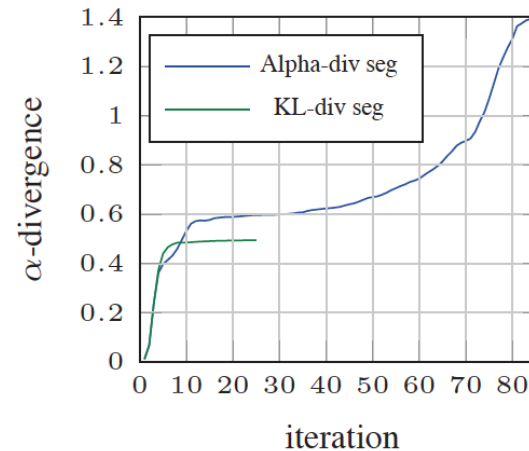
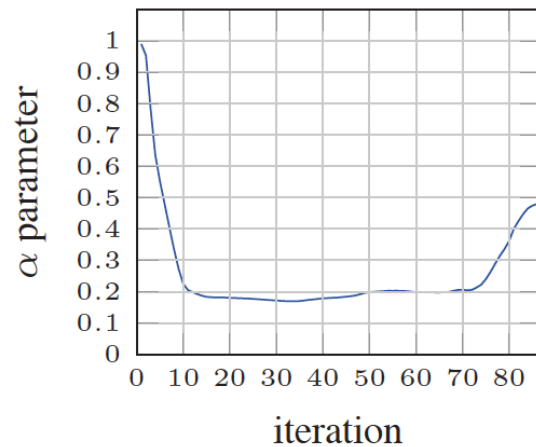


# Alpha-divergence

## Result 2 (Synthetic images)



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

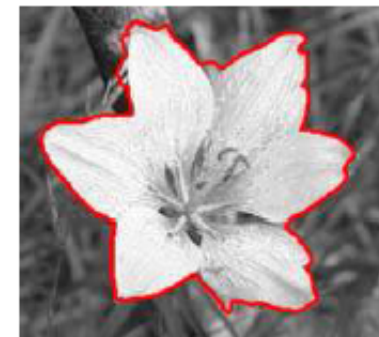
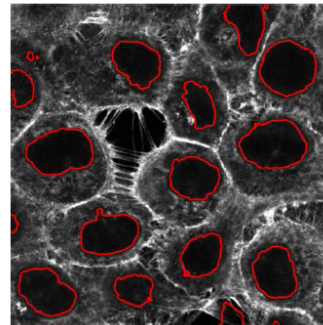




# Alpha-divergence

## Result 3 (Natural Images)

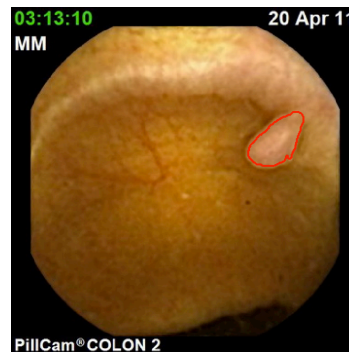
Microconfocal  
images  
of cells



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)

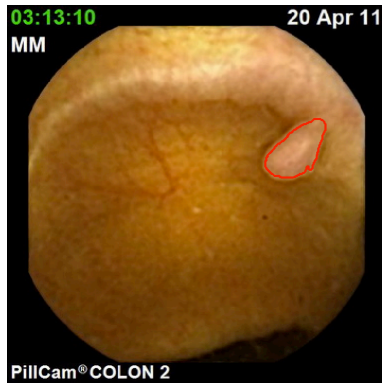


X-Ray images

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



# CAD to *in situ* Diagnosis



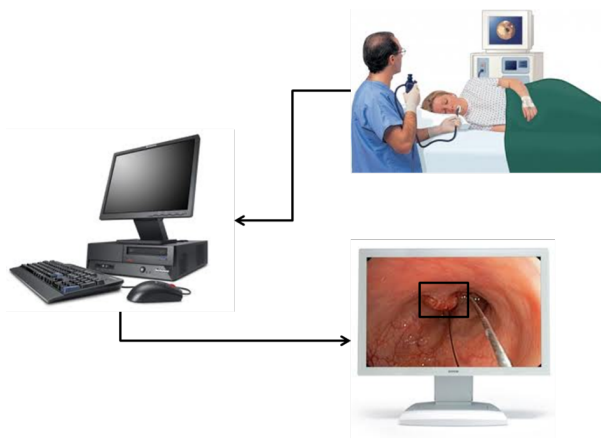
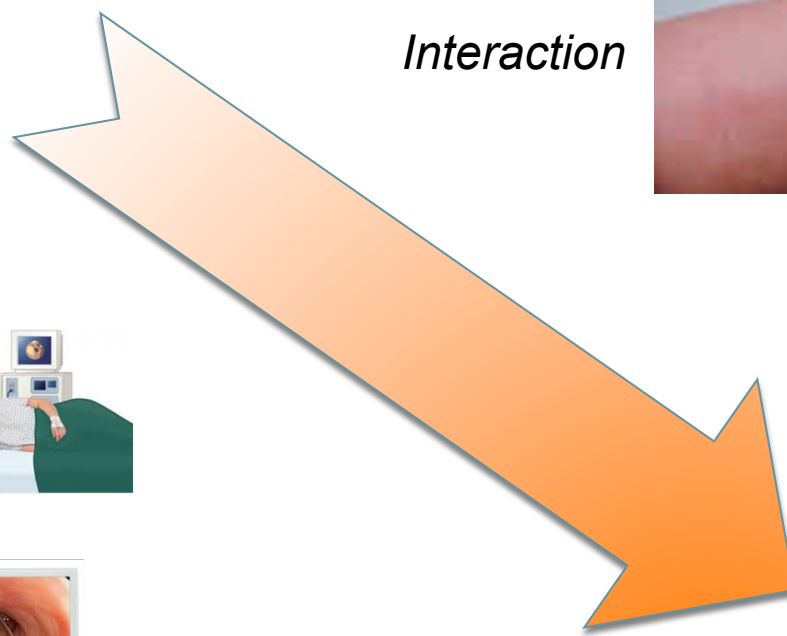
*Energy*

*Interaction*



*Computation*

*Size*



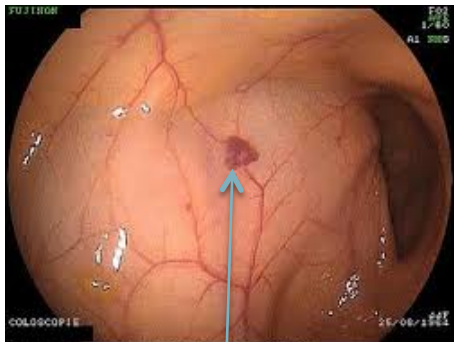


# Cyclope Project

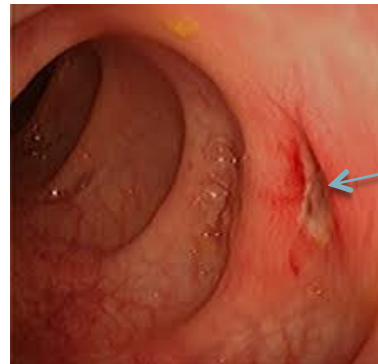
*Main idea (induced by Question 3)*

To develop a smart autonomous videocapsule with embedded image processing capabilities

*In situ detection of intestinal pathologies*

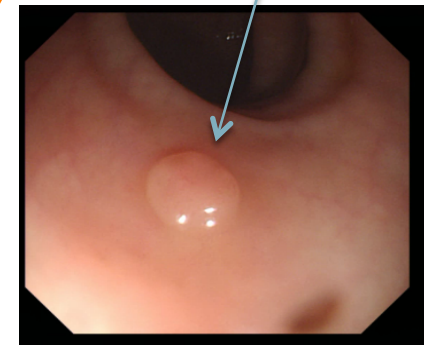


Angioma



Ulcer

Chrone disease



Polyp  
Colorectal Cancer



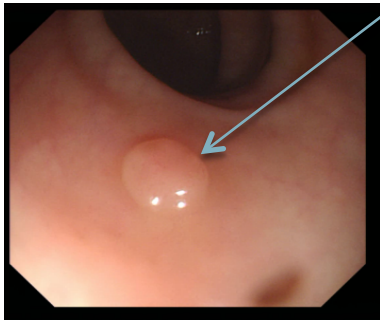
# Cyclope Project

Main idea (induced by Question 3)

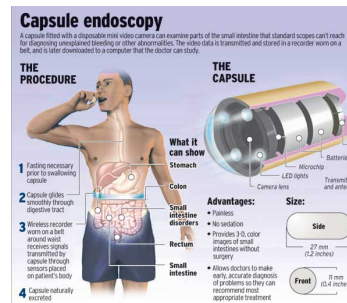
To develop a smart autonomous videocapsule with embedded image processing capabilities

Context

polyp



Colorectal Cancer



### Advantages

- Total control
- Possibility of biopsy's
- Real-time analysis

### Drawbacks

- Anaesthesia
- Hospitalization

### Advantages

- Painless
- No sedation
- No hospitalization
- Just swallow it!

### Drawbacks

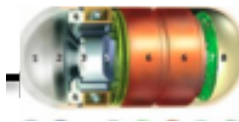
- **Battery life**
- Low resolution
- No control
- ~150k images



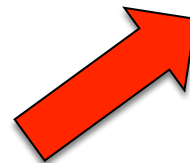
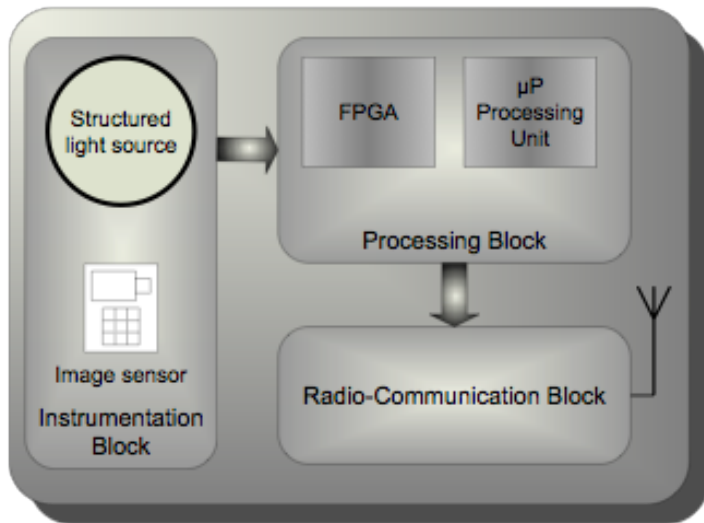
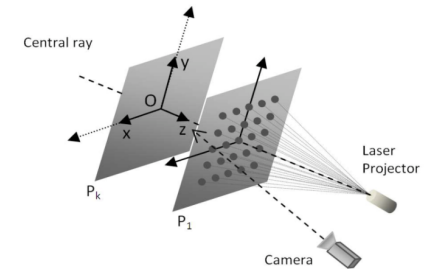


# The Cyclope Pill

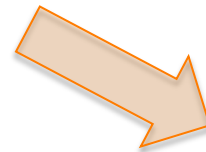
## A Multispectral WCE



Infrared  
(Active Stereo Vision)

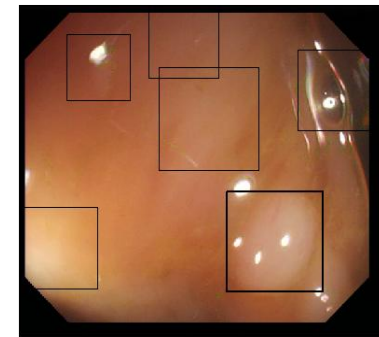


3D feature-based detection



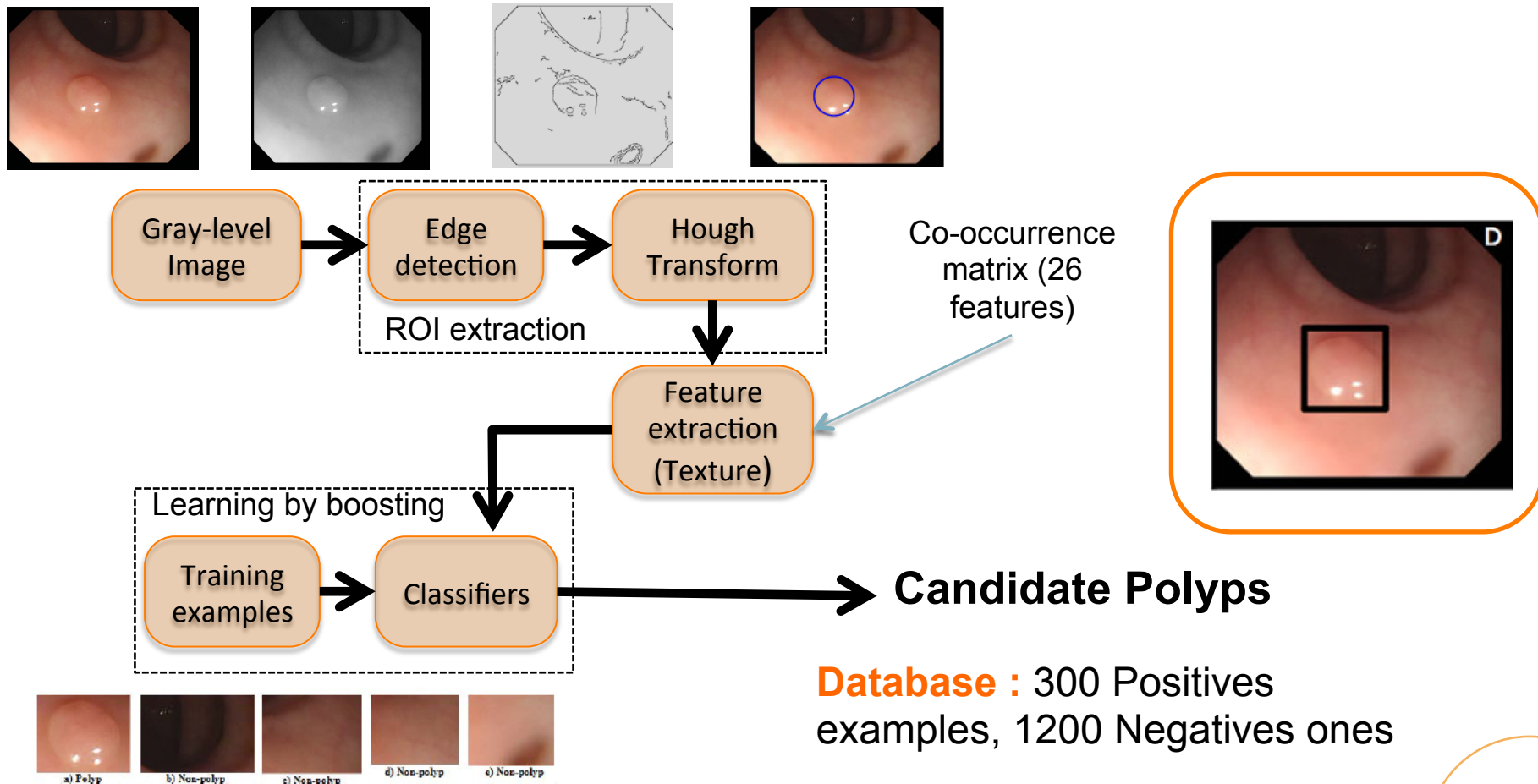
Visible

2D feature based detection





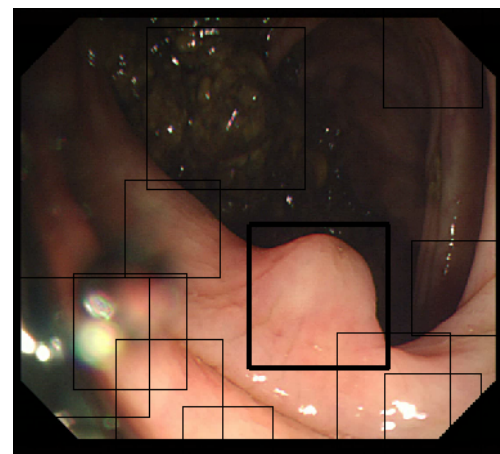
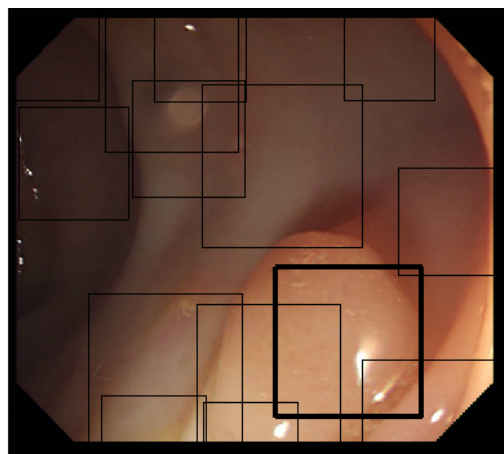
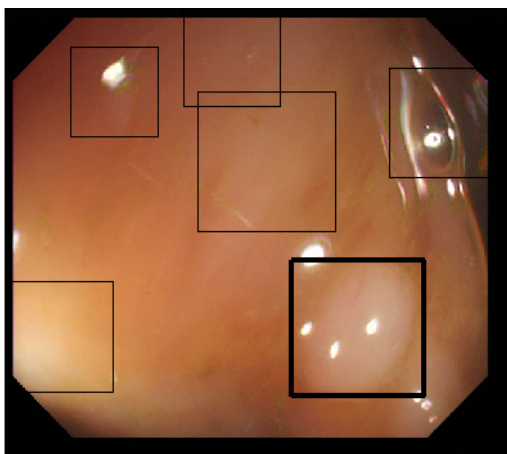
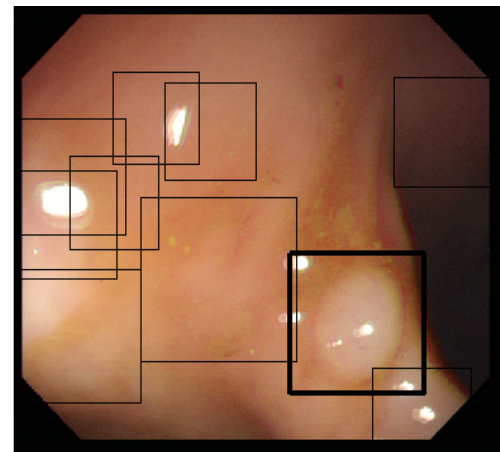
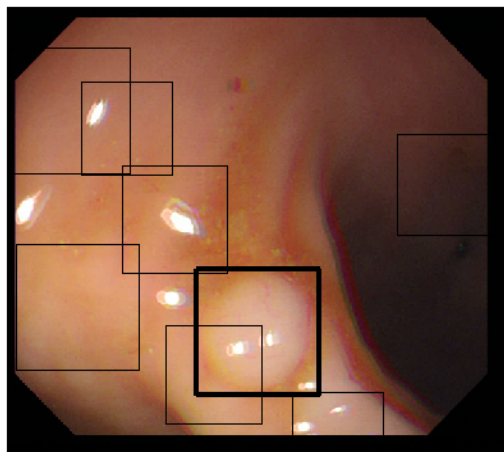
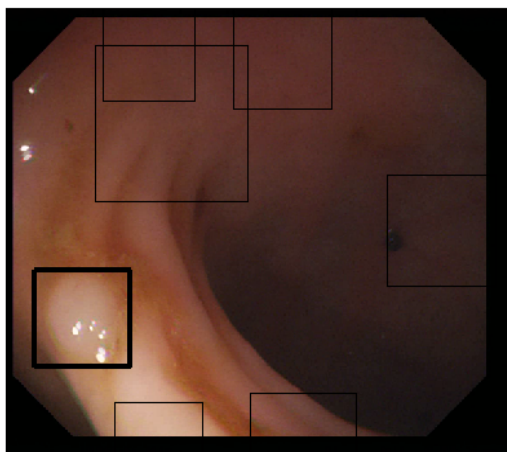
# 2D Detection (Compatible With Embedding Constraints)





# 2D Detection

## Results and Performance

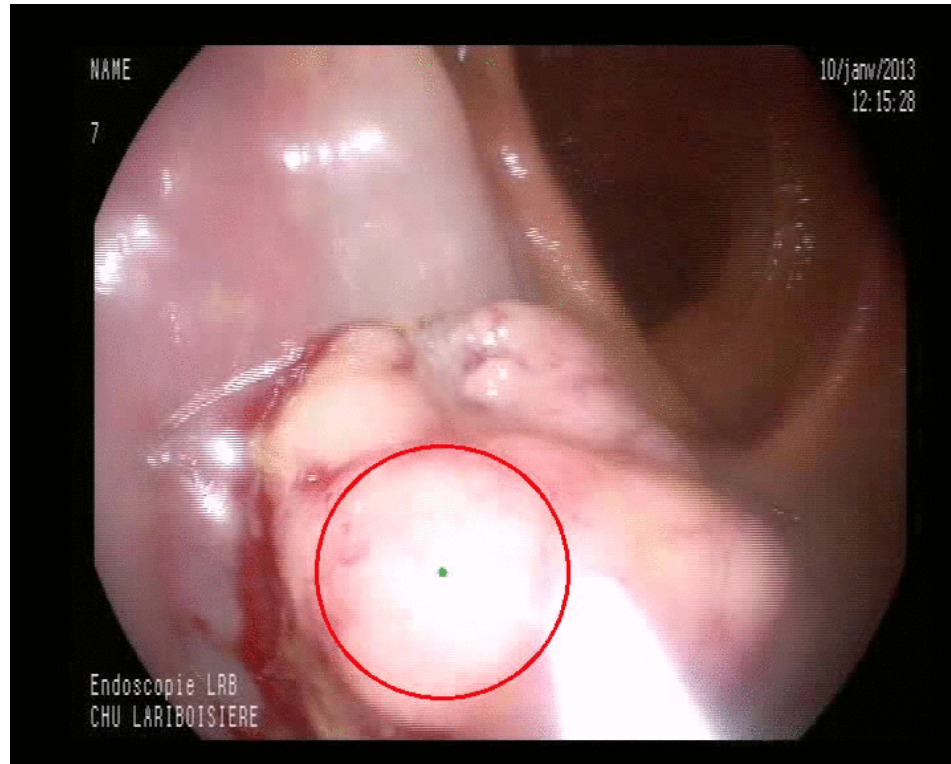


28/11/14

Aymeric Histace - HDR  
Defense

# 2D Detection

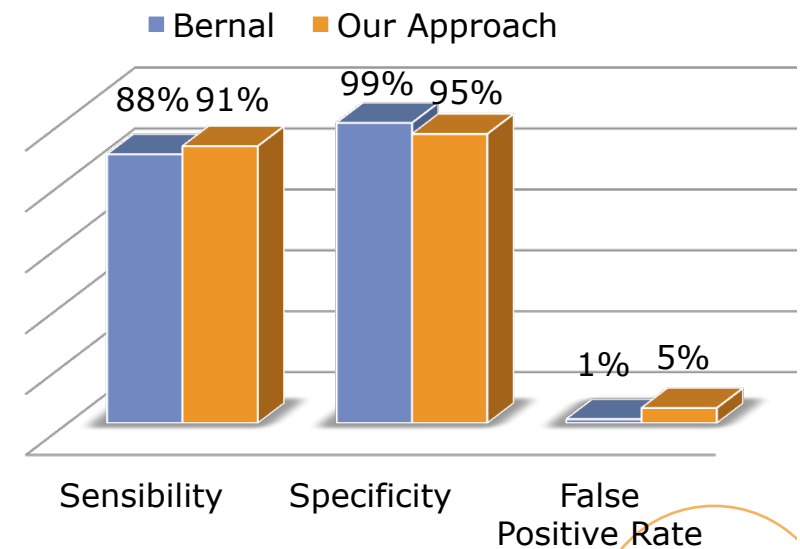
## Results and Performance (Real Time Tracking)



DCIS 2012, IEEE EMBC 2013, GRETSI 13, International Journal of Computer Assisted Radiology and Surgery, 2014

### Question 3: Answer

It is possible to design low complexity detection/recognition algorithms in accordance with:  
 (i) embedding constraints, and  
 (ii) expected performance





# Synthesis of contributions



## Question 1

- Stochastic Resonance
- Non-linear PDE-based image restoration process
- *Double Well potential*

## Question 2

Active contour with:

- Shape Space moments
- Alpha-divergence
- *Fractional entropy*

## Question 3

- Early Detection of Colorectal Cancer
- Real-Time tracking of colonic polyps
- In Situ Diagnosis



What are my contributions?

# Related Publications (2006-2014)



## 9 Journals, 1 Patent:

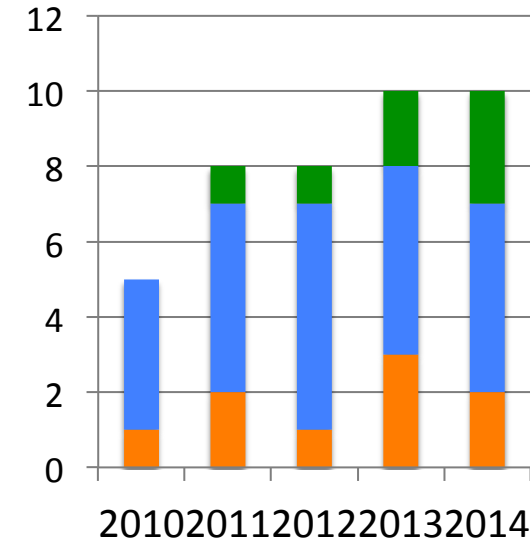
*PRL\**, *JMIV\**, *EL\**, *IJCARS\*+*,  
*IJBI+*, *Annals of BMVA*,...

## 28 Int. Conferences:

*ICIP*, *ICASSP*, *CAIP*, *EMBC*,  
*MIUA*, *CARS*,...

## Others:

*3 Book Chapters*, *1 Book Editing*, *1 Proceeding Editing*, *6 National Conferences (GRETSI)*



■ Journals, Patents  
 ■ Inter. Conf.  
 ■ Others

\* Indexed by JCR  
 + Indexed by PubMed





# Research Activities-Evolution

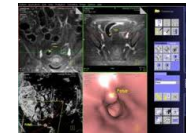
ECSON, TERAFS,  
SIMBAD

Cyclope



In Situ Diagnosis

CAD



Embedded Systems

Signal and Image  
Processing

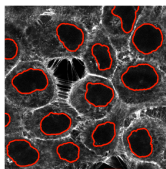
Smart-Aided  
Diagnosis

Medecine - Biology

Electronic, Data-Base

Understanding  
of Living  
mechanisms

e-diagnosis



FibroSES  
iFib

SmartEEG  
PAPILLON







...and The Story Does Not End

# Research Project

(Short and Mid Terms)

**Image Processing / Pattern recognition**

**Electronics, Embedded Systems**

**Alpha-Divergence in Pattern Detection**

- Collaboration with *D. Rousseau* (CREATIS Lyon)

**Smart-Videoendoscopy**

- PhD of Quentin Angermann
- SATT
- Evolucare Medical Imaging

**Cell shape characterization**

- Collaboration with UCLan and UB

**Electrical Characterization of Fibrosis Induced by Implants**

- IMS, INL, LIP6, ERRMECe

**Smart EEG**

- LIP6, INL, SME

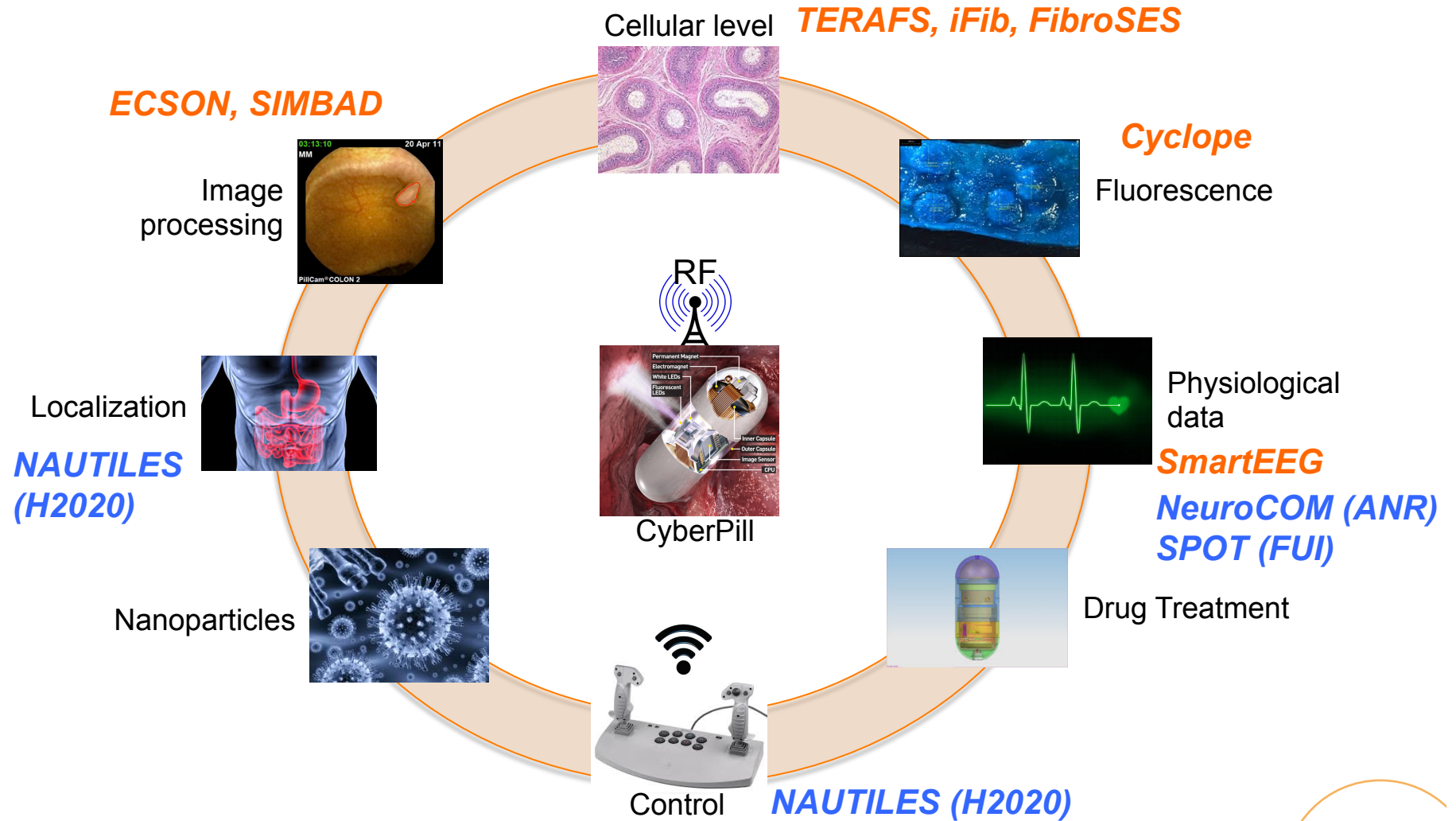
**Cyclope**

- H2020 Project (Greece, Switzerland, UK, Spain, France, Belgium)



Long term

# Research Project



28/11/14

Aymeric Histace - HDR  
Defense



# THANKS TO THEM

Q. Angermann (2014-...), C. Azib (2013), E. Bonnefoye (2012), M. Breuilly (2009), N. Cazin (2014), M. Degaudez (2007), M.-C. Desseroit (2013), H. Diouane (2014), C. Fouquet (2011-2014), M. Garnier (2009, 2011), C. Georgel (2013), M. Ibouchichene (2014), A. Izard (2013), L.-A. Latchimy (2013), T. Longret (2013), L. Meziou (2010-2013), S. Mouzai (2014), C. Nzuzi (2013), M. Rémignon (2014), A. Riaz (2013), H. Saidi (2014), J. Silva-Quintero (2012), A. Sittadannam (2014), Y. Zhang (2009-2010).





# ***THANK YOU FOR YOUR ATTENTION***

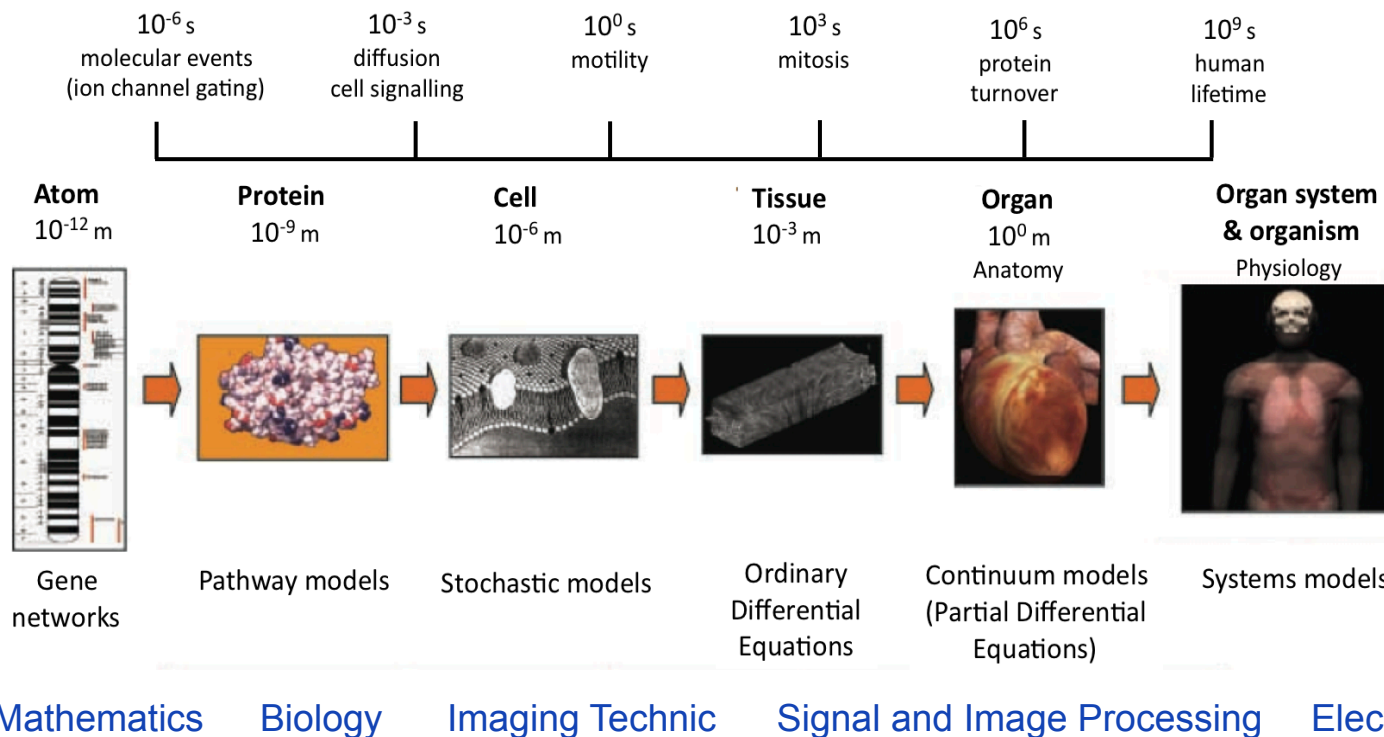






# Research Project

## From Nano to Macro



**To understand manifestations of a same pathologic phenomenon from cell to organ scales (even nano) and draw some possible connections**

# Synthesis

- Elected member of the Research Council of ETIS
- Co-head of MSc MADOCS
- Different types of experiences (IUT, UCP)

Administrative  
Tasks

- In charge of the SES axis of ASTRE team
- 8 research projects
- Active inter. and Nat. Collaborations
- 8 Journal papers, 28 Int. Conf.
- 2 defended PhD, 2 on-going

Research

2006-2014

Teaching

- L1, L2, L3, MSc, ENSEA
- Interaction Teaching/ Research
- In charge of the industrial relationship (2008-2014)



*And what about the future now ?*



# Today-Teaching

- **Neuville Intitute of Technology, UCP, ENSEA**

Students	Classes	Lecture and Tuto (h)	Labs (h)
1 <sup>st</sup> year (L1)	Electrical Engineering and Energy	32	
2 <sup>nd</sup> year (L2)	Electrical Engineering and Energy		48
2 <sup>nd</sup> year (L2)	Control Theory	28	
2 <sup>nd</sup> year App. (L2)	Control Theory	54	32
Prof. Licence (L3)	Electrical Engineering and Energy	30	
MSc SIC	Image Processing	15	
MSc MADOCS	Statistical Learning	6	
ENSEA 3rd year (EIB)	Signal Processing for ECG	6	
<b>Total</b>		<b>171</b>	<b>80</b>



# Today-Supervising



## 3 PhD students: 120%+50%

- 2 *Defended* (11/2013, 06/2014)
- 1 *just started* (50%)

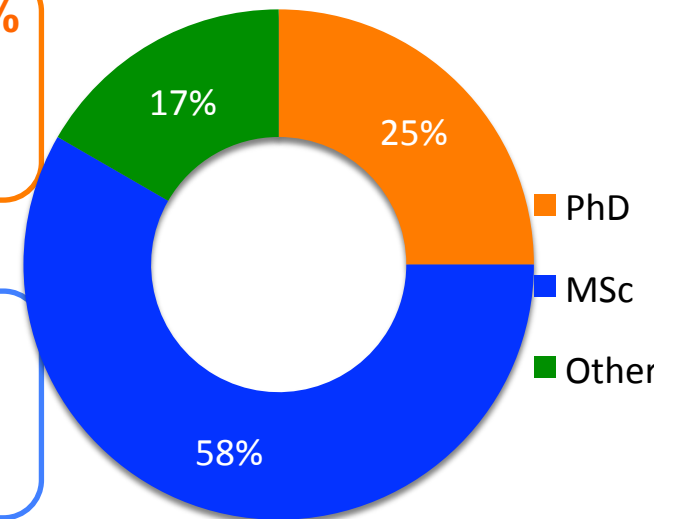
## 7 MSc students: 330%

- *MSc SIC, ESA*

## Others:

- 1 *Post-doc* (50%-1 year)
- 1 *Research Engineer* (50%)
- *Several Initiation-to-Research projects*

## Synthesis





# Useful Noise Effect

## Theory (particular case)

$$g_\eta(u) = g(u + \eta(x))$$

with

$$g(s) = \begin{cases} 1 & \text{if } s \geq k \\ 0 & \text{if } s < k \end{cases}$$

Hard-threshold

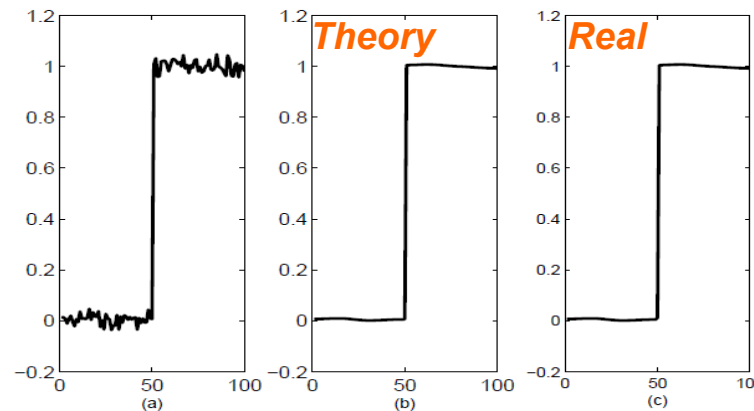
- $g_\eta$ : a static or memory less non-linear function
- Shaping by noise of the input-output characteristic:

$$g_{eff}(s) = E[g(s + \eta(x, y))] = \int_{-\infty}^{+\infty} g(u) f_\eta(u - s) du$$

$f_\eta(u)$ : pdf of purposely injected noise (uniform)

## Experiment 1

Comparison between real stochastic diffusion process and theoretical one.





# Useful Noise Effect

## Theory (particular case)

$$g_\eta(u) = g(u + \eta(x))$$

with

$$g(s) = \begin{cases} 1 & \text{if } s \geq k \\ 0 & \text{if } s < k \end{cases}$$

Hard-threshold

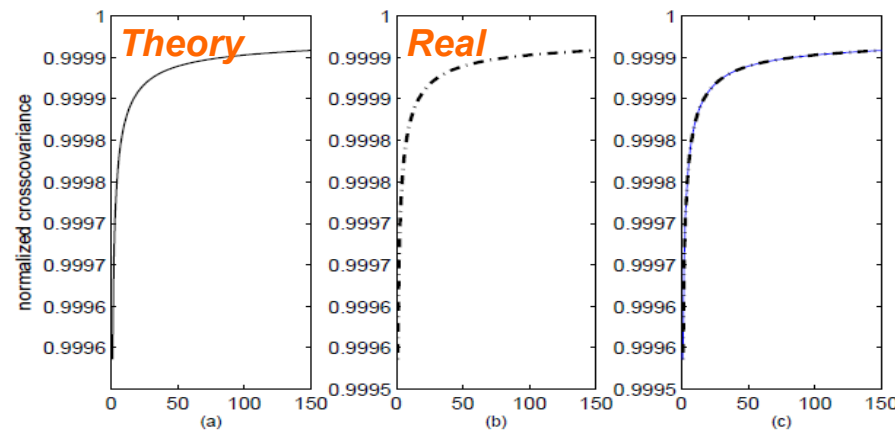
- $g_\eta$ : a static or memory less non-linear function

- Shaping by noise of the input-output characteristic:

$$g_{\text{eff}}(s) = E[g(s + \eta(x, y))] = \int_{-\infty}^{+\infty} g(u) f_\eta(u - s) du$$

## Experiment 2

Comparison of the evolution of normalized cross-covariance (1000 attempts)





# Useful Noise Effect

## Result (quantification)

Normalized Cross Covariance wrt the iteration number of the diffusive process

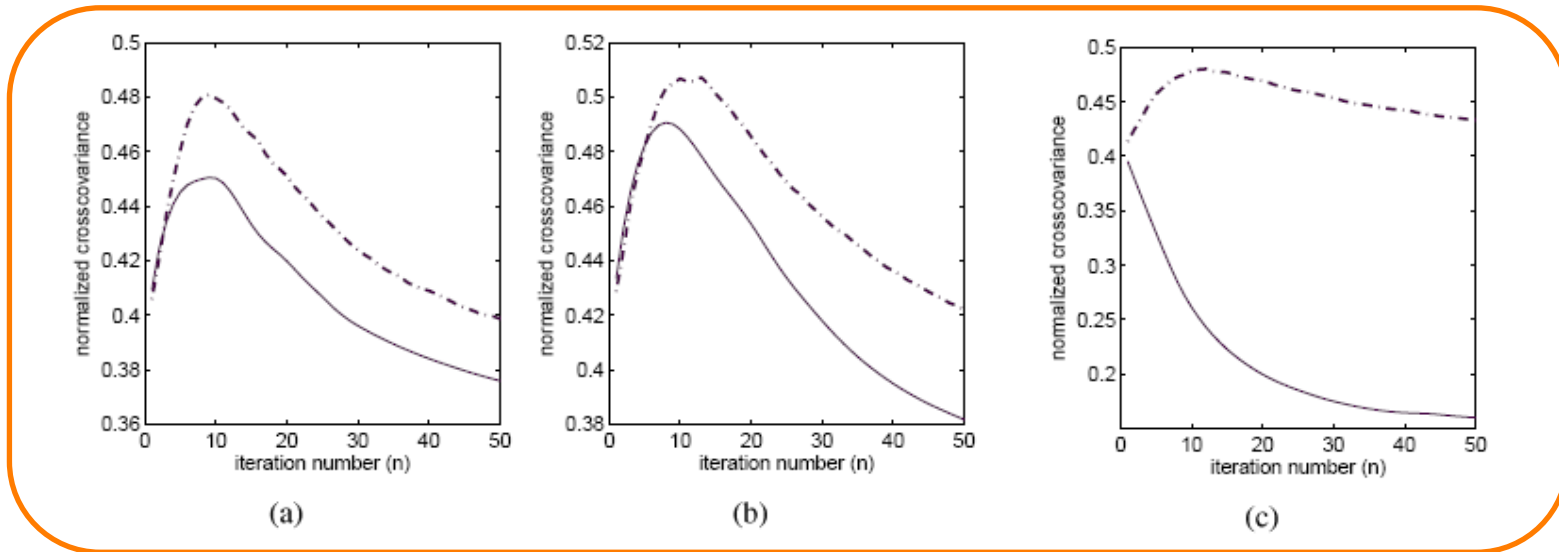


Gaussian

Multiplicative

Impulsive

— PM  
- - - S-PM



# Useful Noise Effect

## Extension to Image Restoration

$$\begin{cases} I(x, y, 0) = I_0 \\ \frac{\partial I}{\partial t} = \text{div} \left( g_\eta \left( \|\nabla I\| \right) \nabla I \right) \end{cases}$$

with  $g_\eta(u) = g(u + \eta(x, y))$

and  $g(u) = e^{-\frac{\|u\|^2}{k^2}}$

- (a) Additive zero-mean Gaussian noise with  $\psi_0 = \psi_{ori} + \xi$
- (b) Multiplicative Gaussian noise of mean unity with  $\psi_0 = \psi_{ori} + \xi \cdot \psi_{ori}$
- (c) Impulsive noise
- (d) Original image



(a)



(b)



(c)




(d)

# Shape Prior

## Shape Space of Legendre Moments

### Legendre Moments

Shape  $\Omega$

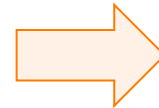



$$\lambda_{qp} = \frac{1}{|\Omega|} \int_{\Omega} L_{pq}(x, y, \Omega) dx dy$$

with

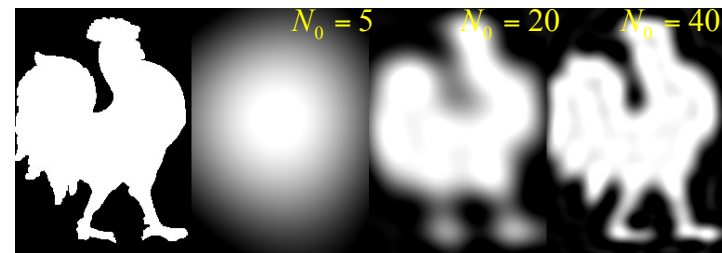
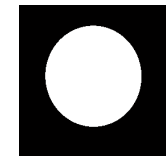
$$L_{pq}(x, y, \Omega) = L_p\left(\frac{x - \bar{x}}{|\Omega|^{1/2}}\right) L_q\left(\frac{y - \bar{y}}{|\Omega|^{1/2}}\right)$$

$$L_n(x) = \sqrt{\frac{2n+1}{2}} \frac{1}{2^n n!} \frac{d^n}{dx^n} \left[ (x^2 - 1)^n \right]$$



### Reconstruction

$$\sum_{p,q}^{p+q \leq N_0} \lambda_{pq} L_{pq}(x, y)$$



Images reconstructed from the Legendre moments for different moments' order  $N_0$



# Shape Prior

## Shape Space of Legendre Moments

### Greedy algorithm

•  $\Omega^{(k)} \rightarrow \Omega^{(k)}$

$$\frac{\partial \varphi}{\partial t} = \left( (I - \mu_{\Omega})^2 + (I - \mu_{\Omega^c})^2 \right) |\nabla \varphi| + \gamma \nabla \left( \frac{\nabla \varphi}{|\nabla \varphi|} \right) |\nabla \varphi|$$

•  $\Omega^{(k)} \rightarrow \lambda_r^{(k)}$

$$\lambda_r^{(k)} = \mathbf{P}^T (\lambda_r - \bar{\lambda}) \quad E_{image} \text{ (Chan Vese)}$$

•  $\lambda_r^{(k)} \rightarrow \lambda_r^{(k)}$

$$\lambda_r^{(k)} = \lambda_r^{(k)} - \beta \frac{\partial E_{prior}}{\partial \lambda_r} \Big|_{\lambda_r = \lambda_r^{(k)}}$$

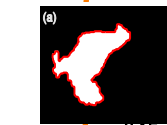
•  $\lambda_r^{(k)} \rightarrow \Omega^{(k+1)}$

$$\Omega^{(k+1)} = \left\{ (x, y) : \left( \sum_{p,q}^{p+q \leq N_0} \lambda'_{pq} L_{pq}(x, y, \Omega^{(k)}) \right) > 0.5 \right\}$$

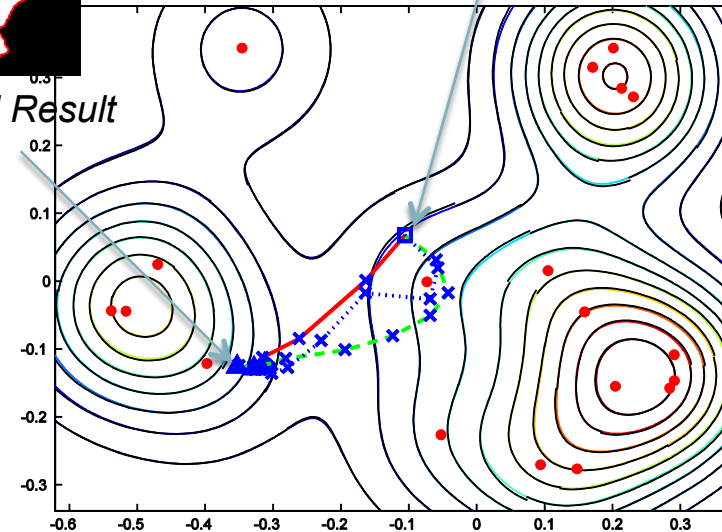
### How it works



Starting shape



Final Result



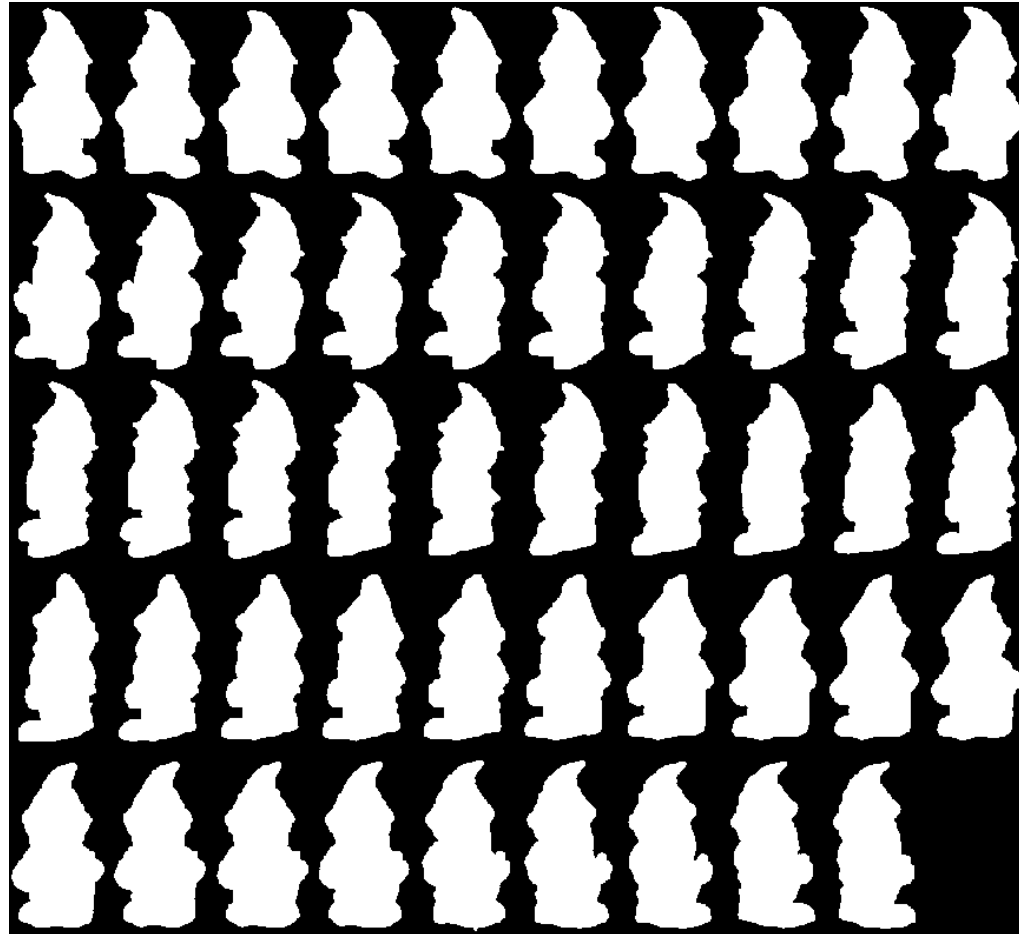
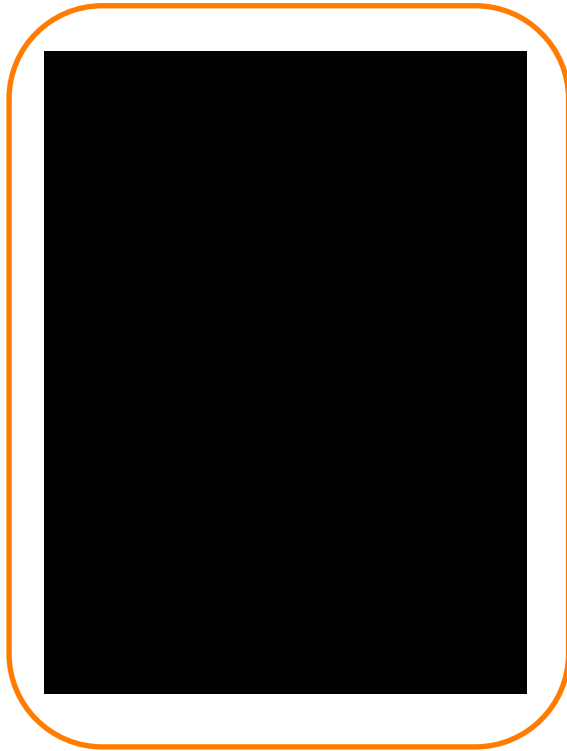
Iterations shown in the feature space spanned by the first two principal axes

Different from Template Matching



# Shape Prior

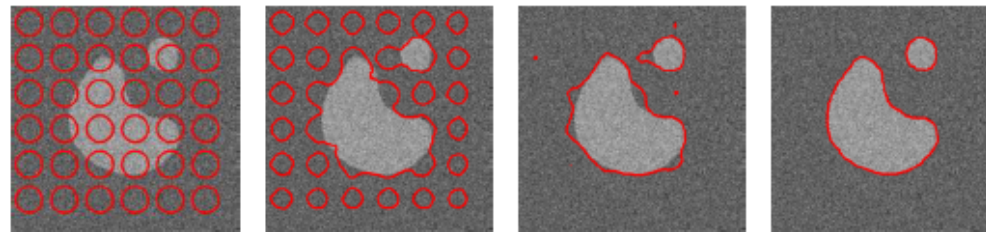
## Results 2





# Alpha-divergence

## Result 1 (Synthetic images)

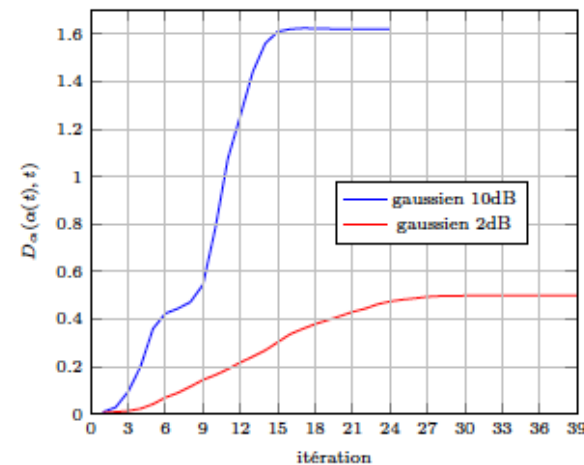
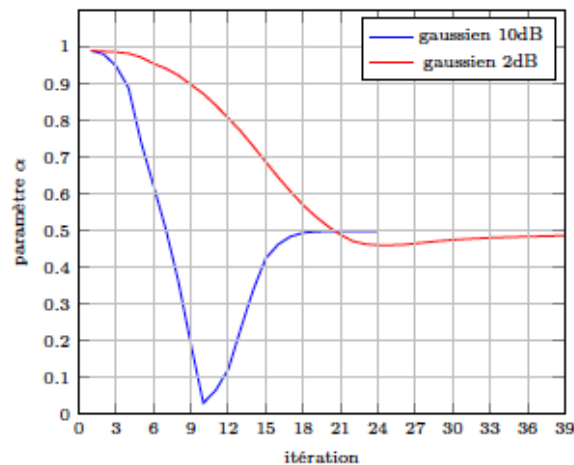


(a)  $t = 0$

(b)  $t = 5$

(c)  $t = 10$

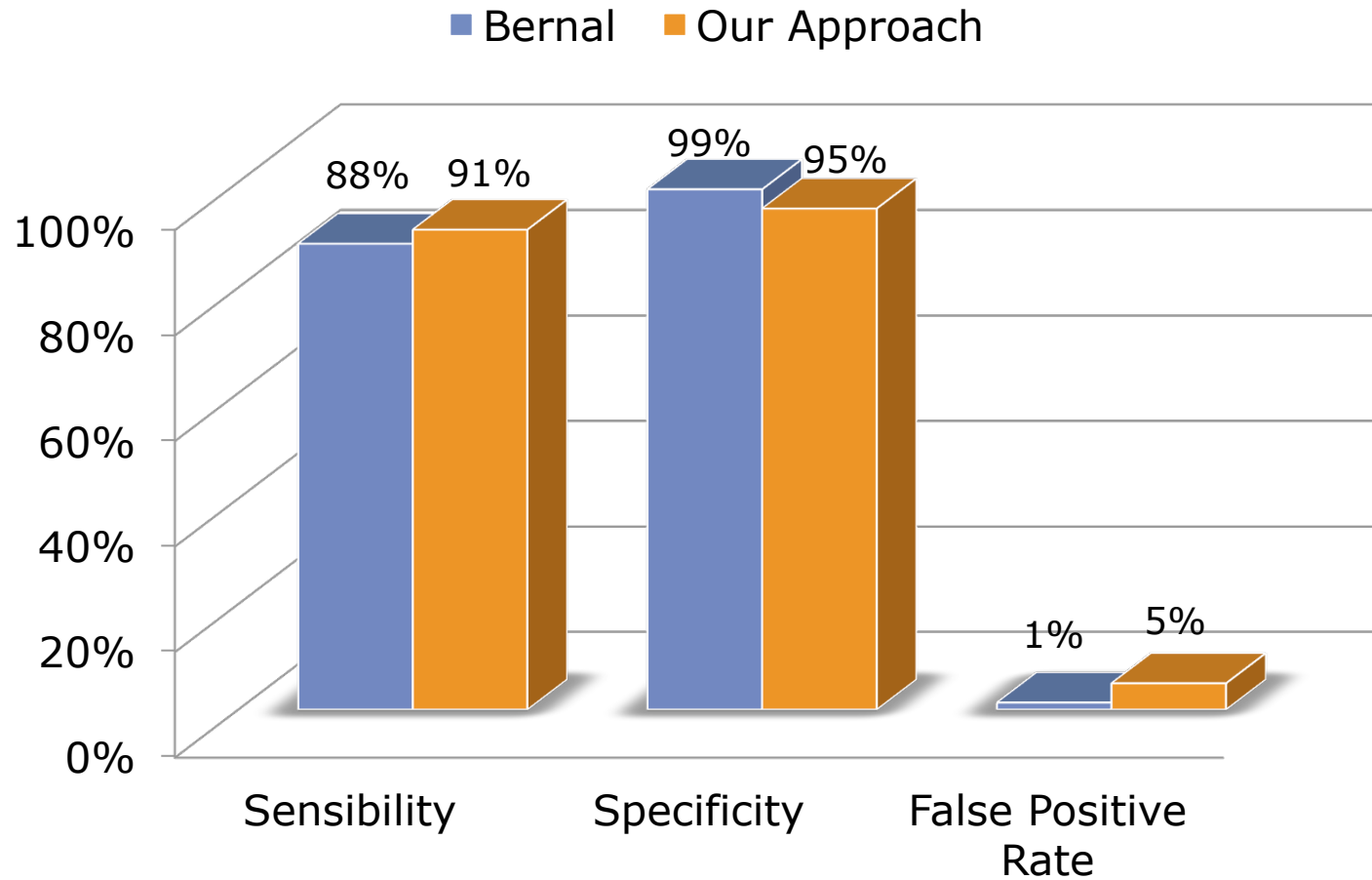
(d)  $t = 24$





# 2D Detection

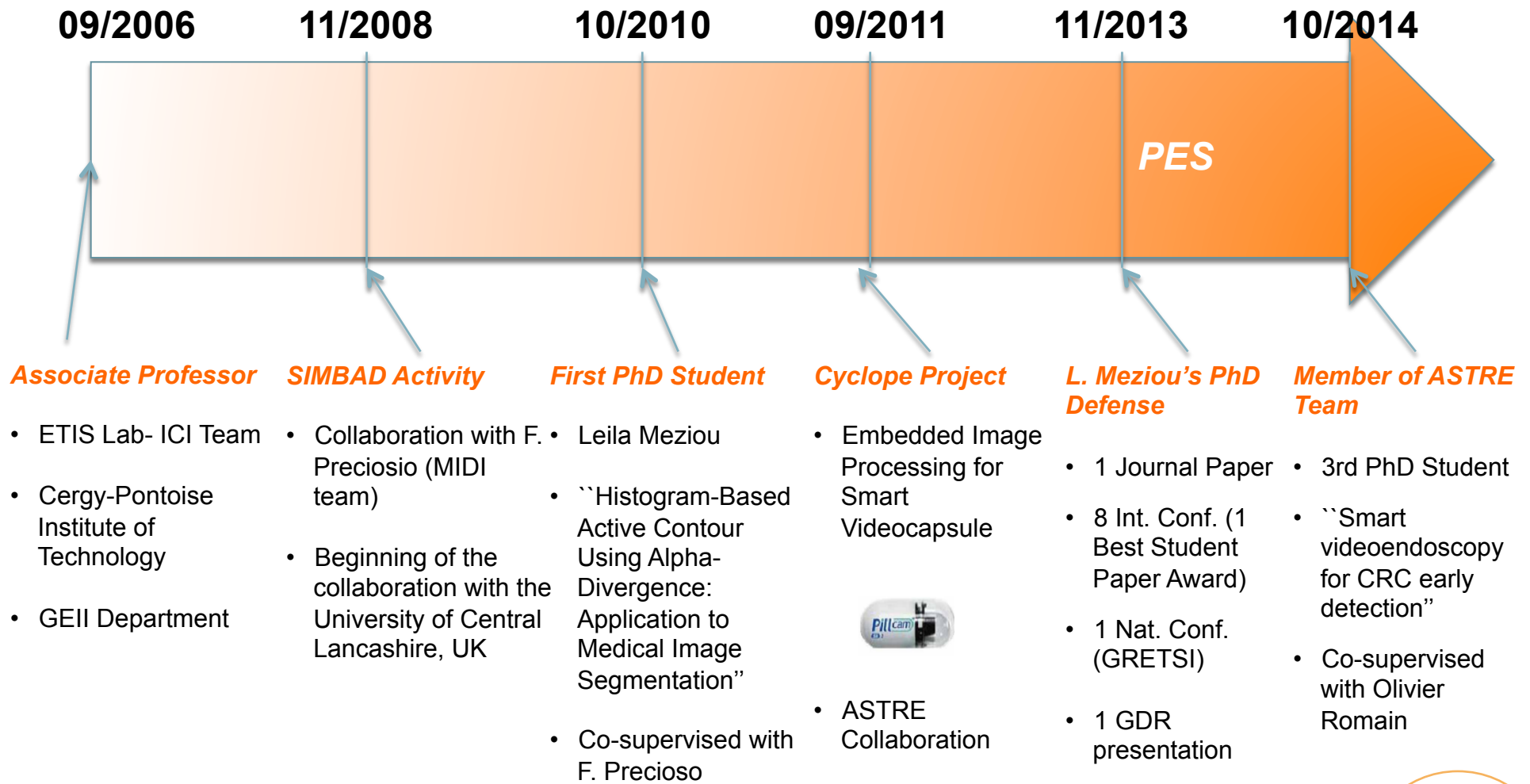
## Results and Performance





# Important Dates

## From 2006 to 2014



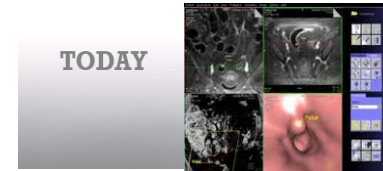


Who am I?

# Research/Teaching



**Computer-Aided  
Diagnosis**



<2001

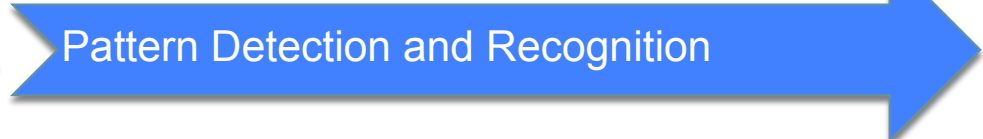
2014



2006

**MSc SIC, MADOCS**

2010



**MSc SIC, MADOCS**

2011



**ENSEA**

2012



**CMI BioSan, IUT**



Who am I?

# 8 Research Projects

(2006-...)

Local  
(UCP, ENSEA, Region)

International

## ECSON (07-09)

Oncology Network of Competences

(partner)

EPSRC

## TERAFS (09-11)

Laser Confocal Imaging of Cells for Study of Radiotherapy Insult

(WP co-Leader)

## PAPILLON (14-...)

On-line Characterization of Dypters using Image Processing

(partner)

AUF

BQR, Scientific Council

## SIMBAD (08-...)

Biomedical Image Segmentation for CAD

(Leader)

National

## FibroSES, iFib (2013-...)

In Vivo and In Vitro Electric Characterization of Fibrosis Induced by Electronic Implant

(WP Leader)

CNRS DEFISENS

## Cyclope (11-...)

Smart Videoendoscopy for CRC early-diagnosis

(Leader)

BQR, Doctoral School, SATT

UCP  
Foundation

LE, SME

## TRAPIL (10-14)

Automatic Detection of Defect in Pipelines Using Ultrasonic Images

(Co-Leader)

CIFRE Trapil

## SmartEEG (13-...)

Smart Mobile System for ExG Signals Acquisition and Analysis

(WP Leader)

FUI

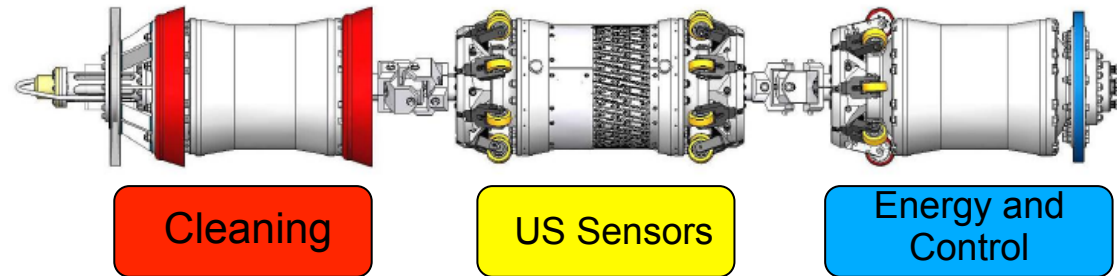
28/11/14

Aymeric Histace - HDR  
Defense

69

# TRAPIL project

Ultrasonic probes for pipeline inspection



**Objectives :**  
 CAD for automated detection of defect signatures in pipelines using Ultrasonics imaging technology

## Ultrasonic Images [NDT2011, ICNDT13]

**1. Weld detection**  
 [NDT in Progress 12]

- Restoration  
 - Rupture detection

**2. Defect detection and segmentation**  
 EM and Active Contours [ICNDT13]

**3. Pattern recognition (RF)** [ECNDT2014]

Enfoncement  
 Corrosion  
 Délaminage  
 Sous-épaisseur