

SECOND-ORDER VARIATIONAL MODELS FOR IMAGE DENOISING AND TEXTURE EXTRACTION

MATINE BERGOUNIOUX & LOIC PIFFET

Colloque JBMU 2010

JBMU R! gMeNALD!A
du 25 au 27 octobre 2010 à l'UT de BAYONNE



OUTLINE

1. Functional framework
2. Variational model for denoising and texture extraction
3. Numerical methods (discretization and algorithms)
4. Examples
5. Anisotropic strategy

1. FUNCTIONAL FRAMEWORK

1.1 Functions of bounded variation

Ω open subset of $\mathbb{R}^2$.

$$|f|_{BV(\Omega)} := \sup \left\{ \int_{\Omega} f \operatorname{div}(\phi) \mid \phi \in \mathcal{C}_c^1(\Omega, \mathbb{R}^2), \|\phi\|_{\infty} \leq 1 \right\}$$

$$BV(\Omega) = \left\{ f \in L^1(\Omega) \mid |f|_{BV(\Omega)} < +\infty \right\}$$

1.2. Functions of second order bounded variation

$$BV^2(\Omega) = \{ f \in W^{1,1}(\Omega) \mid |f|_{BV^2(\Omega)} < +\infty \}$$

$$|f|_{BV^2(\Omega)} := \sup \left\{ \int_{\Omega} \langle \nabla f, \operatorname{div}(\phi) \rangle_{\mathbb{R}^2} \mid \phi \in \mathcal{C}_c^2(\Omega, \mathbb{R}^{2 \times 2}), \|\phi\|_{\infty} \leq 1 \right\}$$

$$\operatorname{div}(\phi) = (\operatorname{div}(\phi_1), \operatorname{div}(\phi_2)), \quad \text{with } \forall i, \phi_i = (\phi_i^1, \phi_i^2) : \Omega \rightarrow \mathbb{R}^2$$

$$W^{1,1}(\Omega) \subset BV(\Omega)$$

$$H^1(\Omega) \subset BV^2(\Omega)$$

$f \in BV^2(\Omega)$ if and only if

$$f \in W^{1,1}(\Omega) \text{ and } \left(\frac{\partial f}{\partial x_1}, \frac{\partial f}{\partial x_2} \right) \in (BV(\Omega))^2.$$

$$|f|_{BV^2(\Omega)} \leq \sum_{i=1}^n \left| \frac{\partial f}{\partial x_i} \right|_{BV(\Omega)} \leq n |f|_{BV^2(\Omega)}$$

2. VARIATIONAL MODELS

2.1 Rudin–Osher–Fatemi (ROF) model for denoising

$$\mathcal{P}_{ROF} : \min_{u \in BV(\Omega)} \mathcal{F}_R(u) := \lambda |u|_{BV(\Omega)} + \frac{1}{2} \|u_d - u\|_{L^2(\Omega)}^2$$

Problem $\mathcal{P}_{ROF}$ has a unique solution

2.1 Second order model (for denoising and texture extraction)

$$\min_{v \in BV^2(\Omega)} \mathcal{F}_{R2}(v) := \lambda |v|_{BV^2(\Omega)} + \frac{1}{2} \|u_d - v\|_{L^2(\Omega)}^2 + \delta \|v\|_{W^{1,1}(\Omega)}$$

Problem $\mathcal{P}_2$ has a unique solution

3. NUMERICAL METHODS

3.1 ROF finite difference discretization

$$(\nabla u)_{i,j} = \left((\nabla u)_{i,j}^1, (\nabla u)_{i,j}^2 \right),$$

$$(\nabla u)_{i,j}^1 = \begin{cases} u_{i+1,j} - u_{i,j} & \text{if } i < N \\ 0 & \text{if } i = N, \end{cases}$$

$$(\nabla u)_{i,j}^2 = \begin{cases} u_{i,j+1} - u_{i,j} & \text{if } j < N \\ 0 & \text{if } j = N. \end{cases}$$

$$(\operatorname{div} p)_{i,j} = \begin{cases} p_{i,j}^1 - p_{i-1,j}^1 & \text{if } 1 < i < N \\ p_{i,j}^1 & \text{if } i = 1 \\ -p_{i-1,j}^1 & \text{if } i = N \end{cases}$$

$$+ \begin{cases} p_{i,j}^1 - p_{i,j-1}^2 & \text{if } 1 < j < N \\ p_{i,j}^2 & \text{if } j = 1 \\ -p_{i,j-1}^2 & \text{if } j = N. \end{cases}$$

3.1 ROF finite difference discretization

$$\inf_{u \in X} \left(J_1(u) + \frac{1}{2\lambda} \|u_d - u\|_X^2 \right)$$

$$J_1(u) := \sum_{1 \leq i, j \leq N} \|(\nabla u)_{i,j}\|_{\mathbb{R}^2},$$

$$X = \mathbb{R}^{N \times N} \text{ and } Y = X \times X$$

Chambolle projection algorithm

The solution to the discretized problem is given by

$$u = u_d - P_{\lambda K_1}(u_d)$$

$$K_1 = \{\operatorname{div} g \mid g \in Y, \|g_{i,j}\|_{\mathbb{R}^2} \leq 1 \ \forall i,j\}$$

$$\min\{\|\lambda \operatorname{div} p - f\|_X^2 \mid \|p_{i,j}\|_{\mathbb{R}^2} \leq 1 \ \forall i, j = 1, \dots, N\}$$

$$p^0 = 0$$

$$p_{i,j}^{n+1} = \frac{p_{i,j}^n + \tau (\nabla (\operatorname{div} p^n - f/\lambda))_{i,j}}{1 + \tau \|(\nabla (\operatorname{div} p^n - f/\lambda))_{i,j}\|_{\mathbb{R}^2}}$$

$$\tau \leq 1/8 \implies \lambda \operatorname{div} p^n \rightarrow P_{\lambda K_1}(f)$$

3.2 ROF2 discretization

$$\begin{aligned}
 (Hv)_{i,j}^{11} &= \begin{cases} v_{i+1,j} - 2v_{i,j} + v_{i-1,j} & \text{for } 1 < i < N, \\ v_{i+1,j} - v_{i,j} & \text{for } i = 1, \\ v_{i-1,j} - v_{i,j} & \text{for } i = N, \end{cases} \\
 (Hv)_{i,j}^{12} &= \begin{cases} v_{i,j+1} - v_{i,j} - v_{i-1,j+1} + v_{i-1,j} & \text{for } 1 < i \leq N, \ 1 \leq j < N, \\ 0 & \text{for } i = 1, \\ 0 & \text{for } i = N, \end{cases} \\
 (Hv)_{i,j}^{21} &= \begin{cases} v_{i+1,j} - v_{i,j} - v_{i+1,j-1} + v_{i,j-1} & \text{for } 1 \leq i < N, \ 1 < j \leq N, \\ 0 & \text{for } i = 1, \\ 0 & \text{for } i = N, \end{cases} \\
 (Hv)_{i,j}^{22} &= \begin{cases} v_{i,j+1} - 2v_{i,j} + v_{i,j-1} & \text{for } 1 < j < N, \\ v_{i,j+1} - v_{i,j} & \text{for } j = 1, \\ v_{i,j-1} - v_{i,j} & \text{for } j = N. \end{cases}
 \end{aligned}$$

$$\min_{v \in X} \left(J_2(v) + \frac{\|u_d - v\|_X^2}{2\lambda} \right).$$

$$J_2(v) := \sum_{1 \leq i, j \leq N} \|(Hv)_{i,j}\|_{\mathbb{R}^4}$$

$$v = u_d - P_{\lambda K_2}(u_d)$$

$$K_2 := \{H^*p \mid \|p_{i,j}\|_{\mathbb{R}^4} \leq 1, \forall i, j = 1, \dots, N\}$$

$$p^0 = 0$$

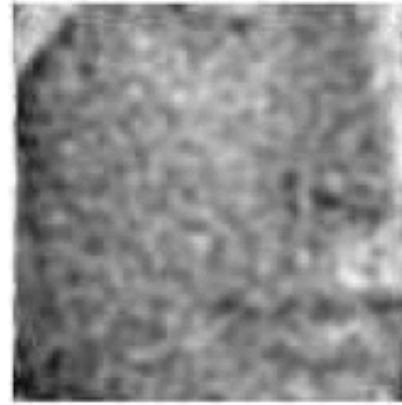
$$p_{i,j}^{n+1} = \frac{p_{i,j}^n - \tau (H [H^* p^n - u_d / \lambda])_{i,j}}{1 + \tau \| (H [H^* p^n - u_d / \lambda])_{i,j} \|_{\mathbb{R}^4}}$$

$$\tau \leq 1/64 \implies \lambda H^* p^n \rightarrow P_{\lambda K_2}(f)$$

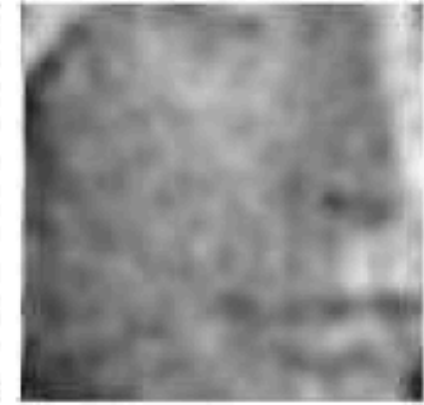
Number of iterations



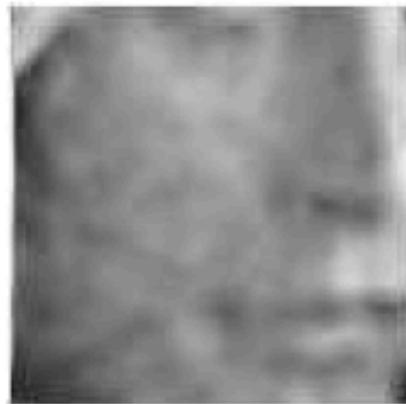
(a) 0 itératon



(b) 10 itérations



(c) 30 itérations



(d) 50 itérations



(e) 100 itérations



(f) 300 itérations



(g) 500 itérations



(h) 1000 itérations



(i) 3000 itérations

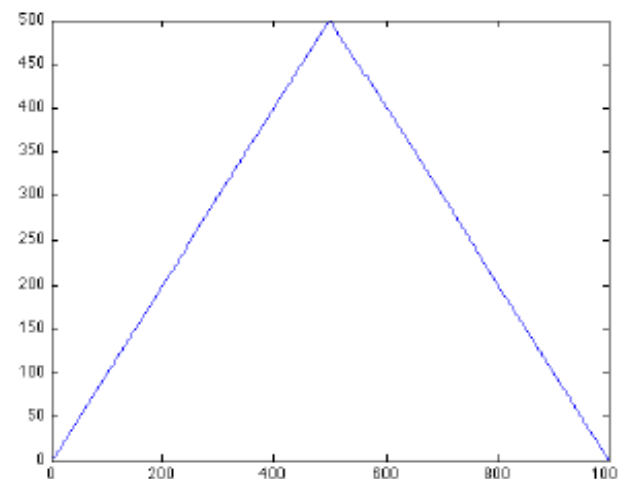
Influence of λ



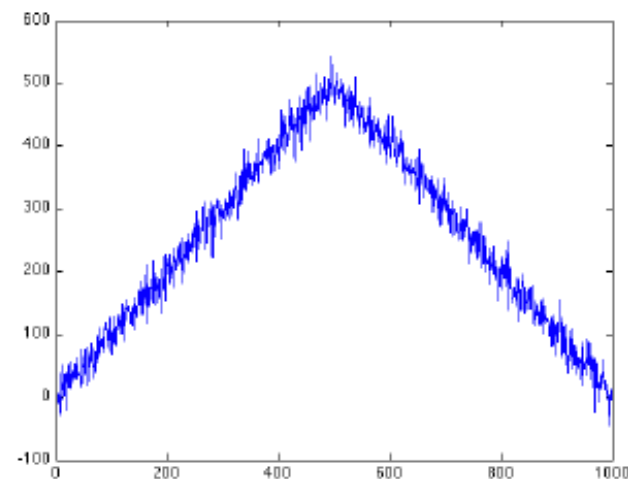
4. NUMERICAL EXAMPLES

4.1 Denoising and staircasing effect

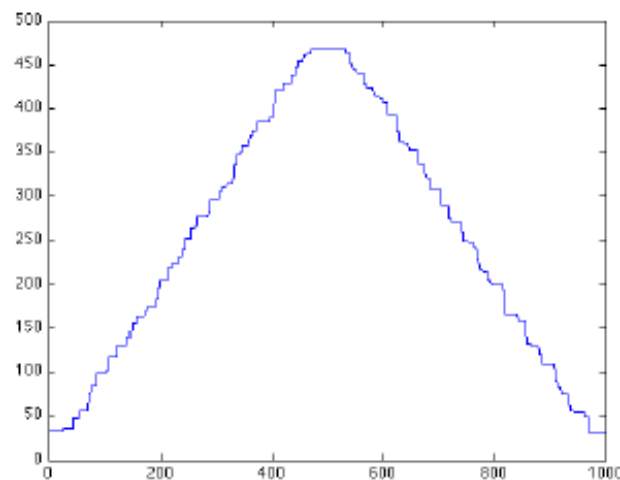
ROF



(a)

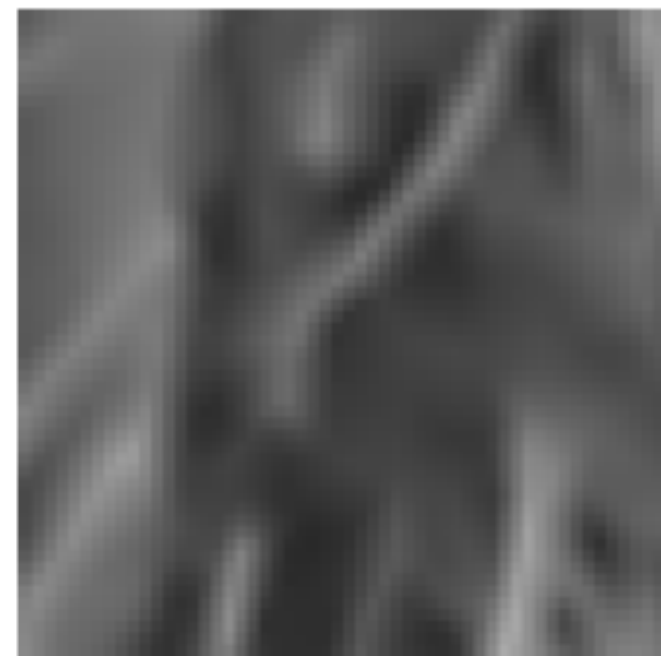
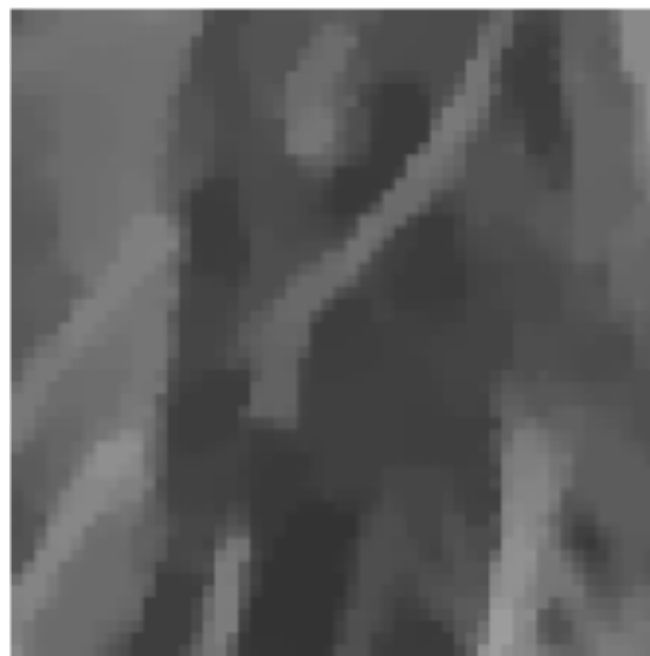


(b)



(c)

ROF



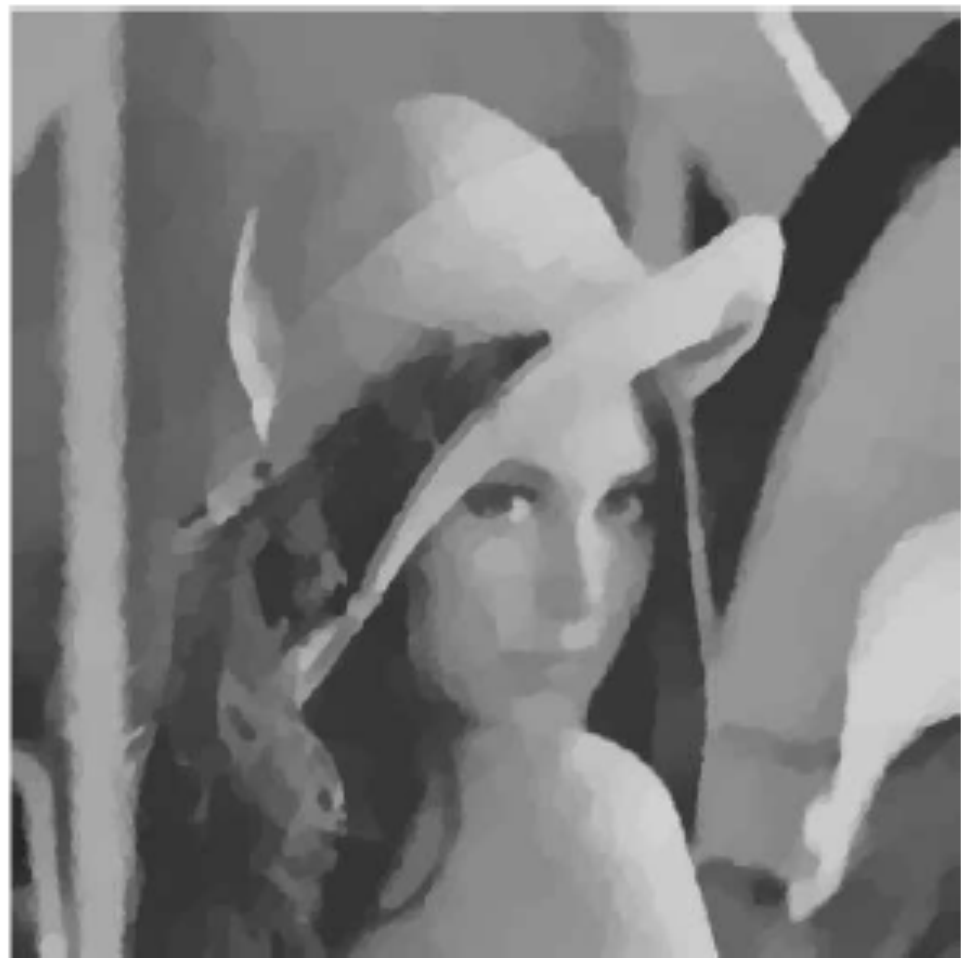
ROF2





ROF

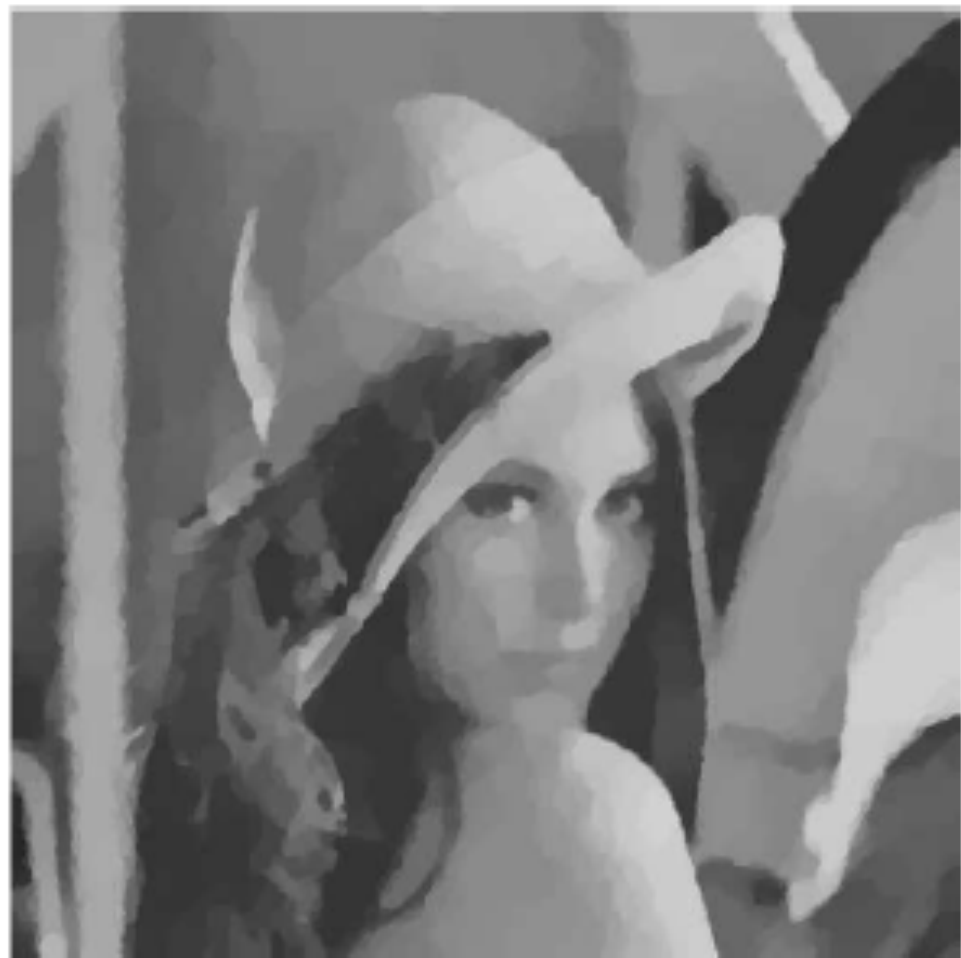
ROF2



ROF



ROF2

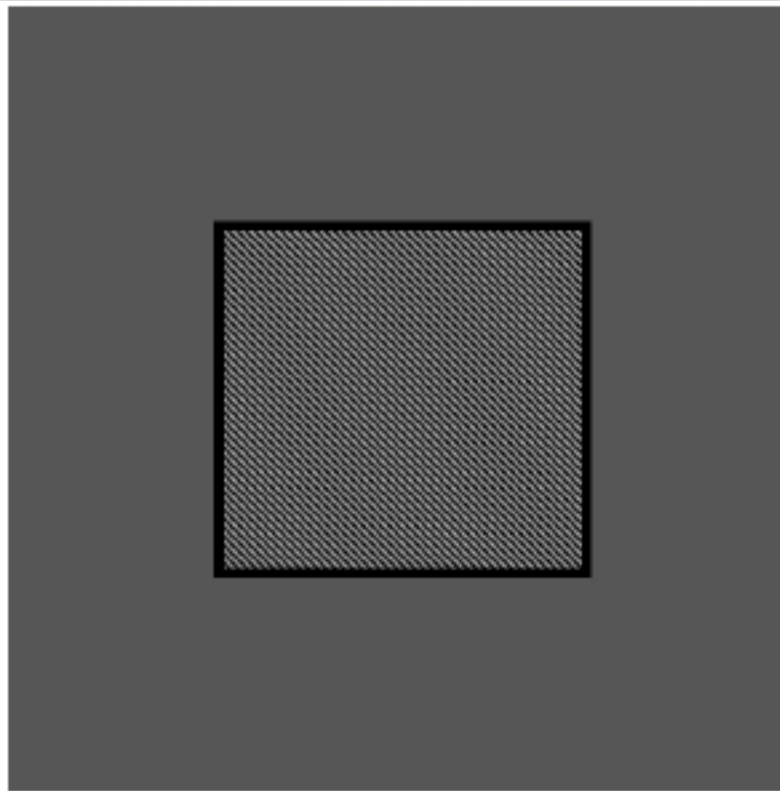


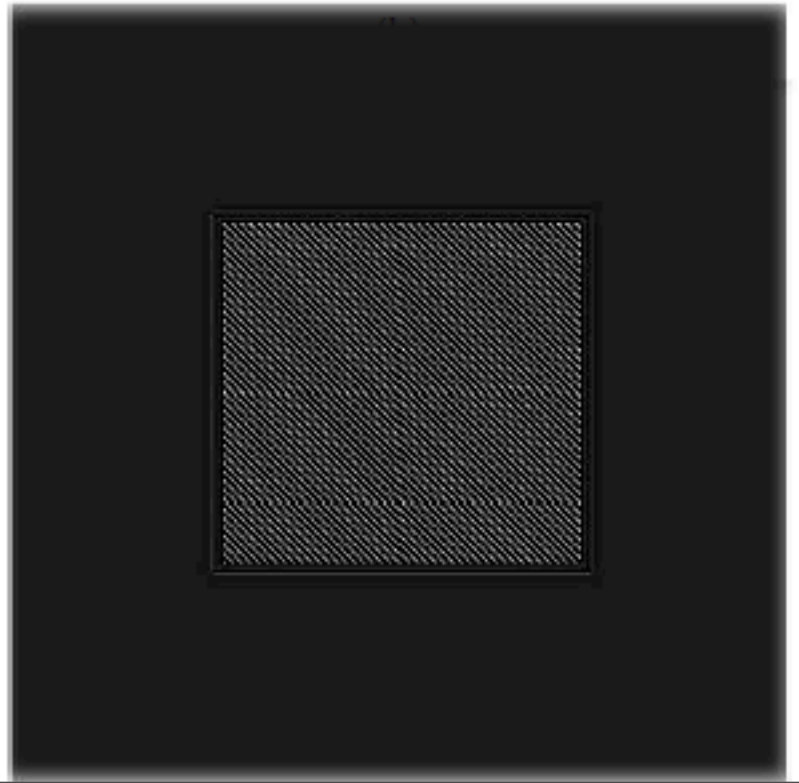
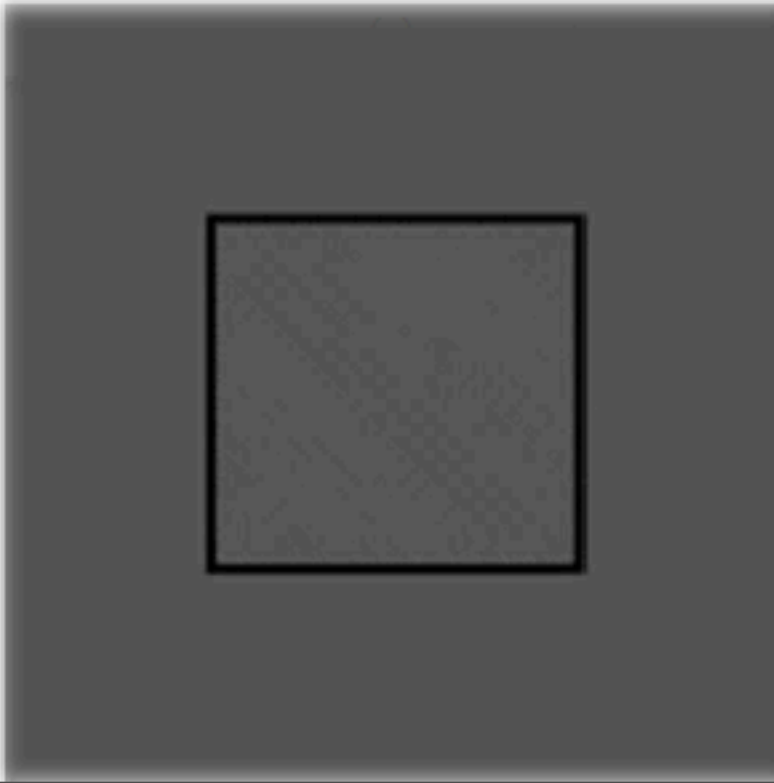
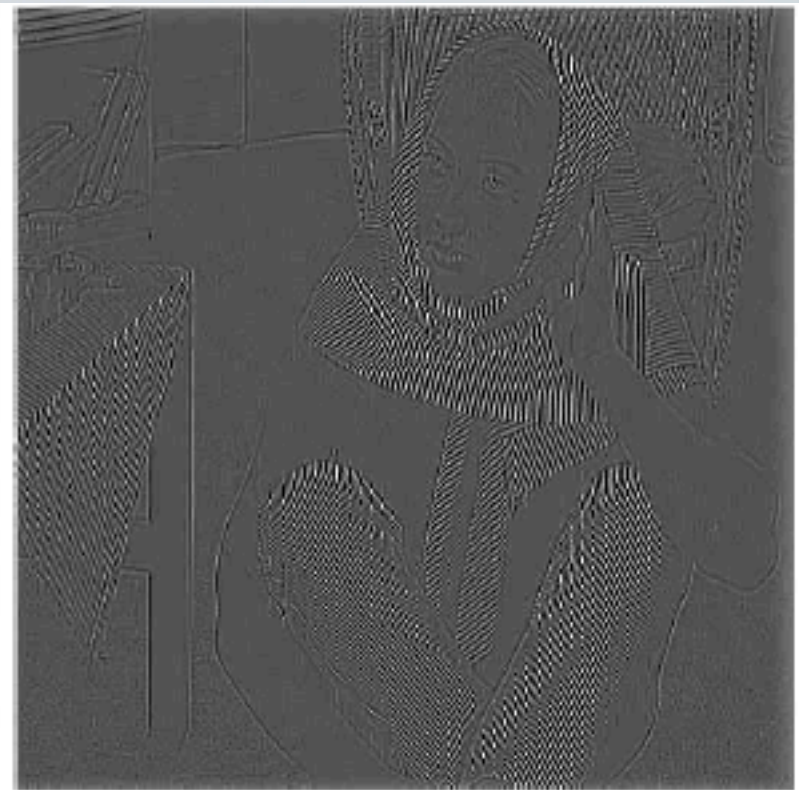
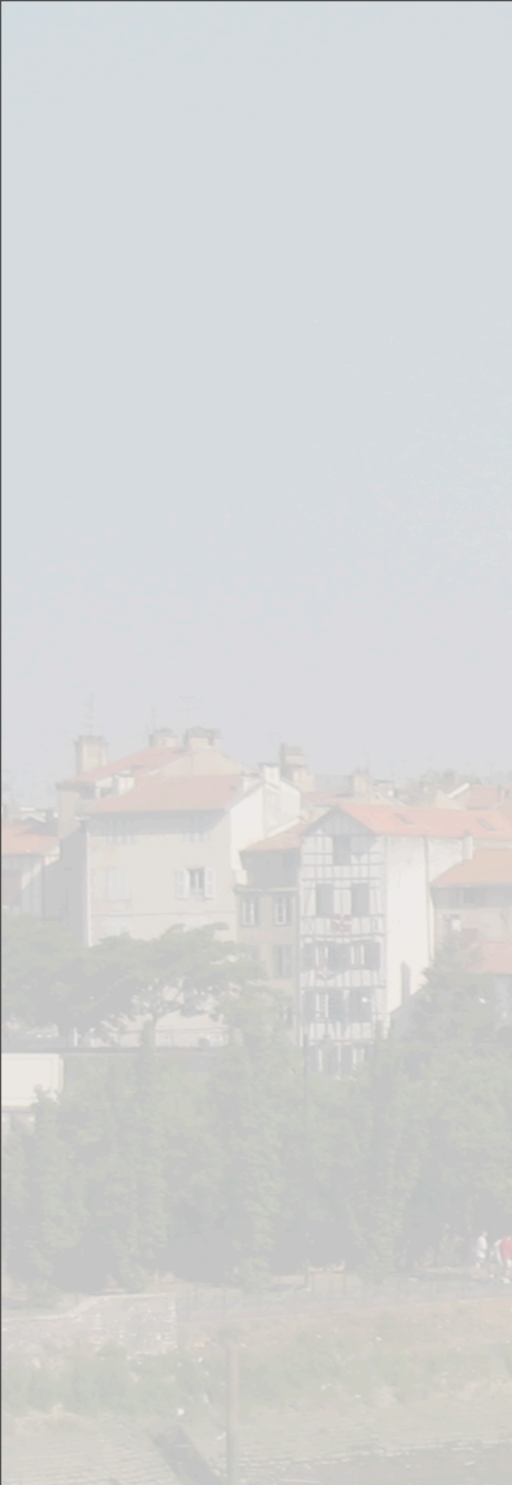
ROF



ROF2

4.2 Texture extraction





5. ANISOTROPIC STRATEGY

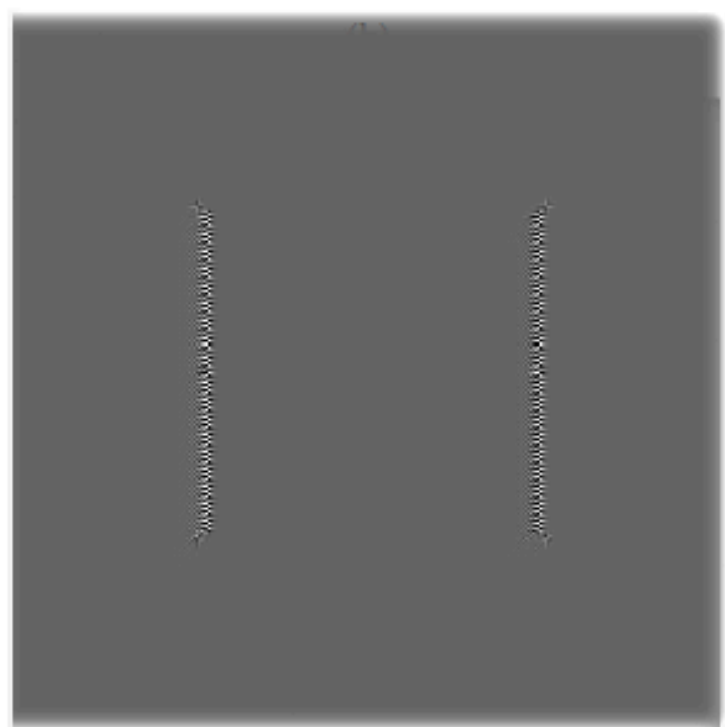
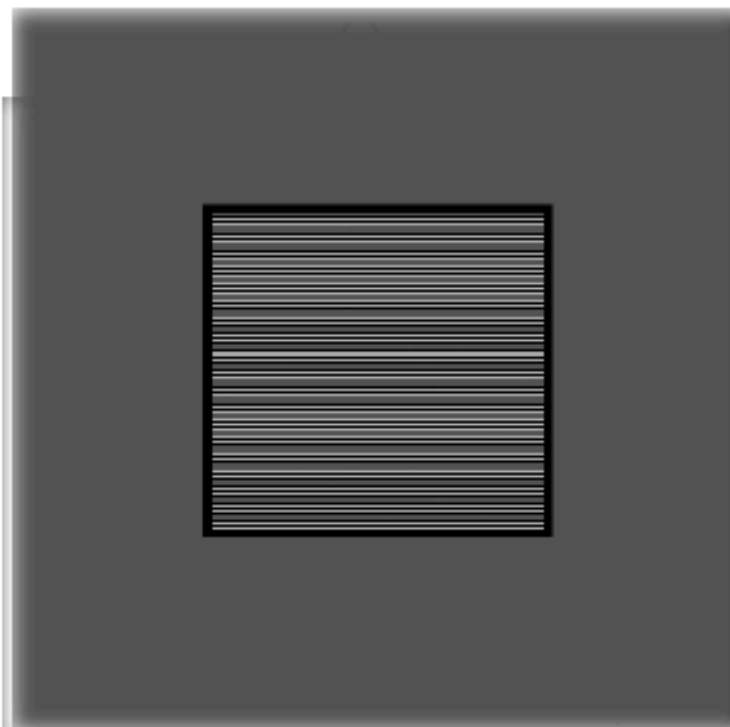
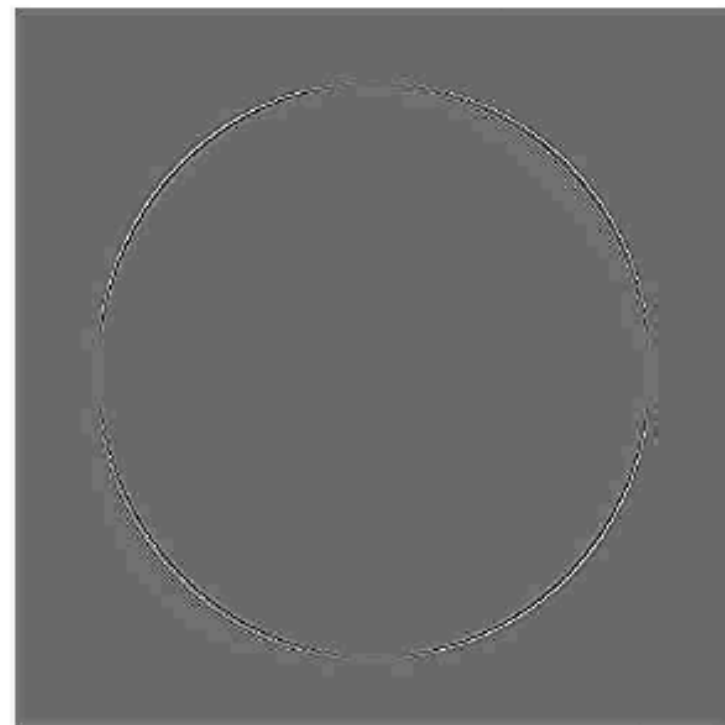
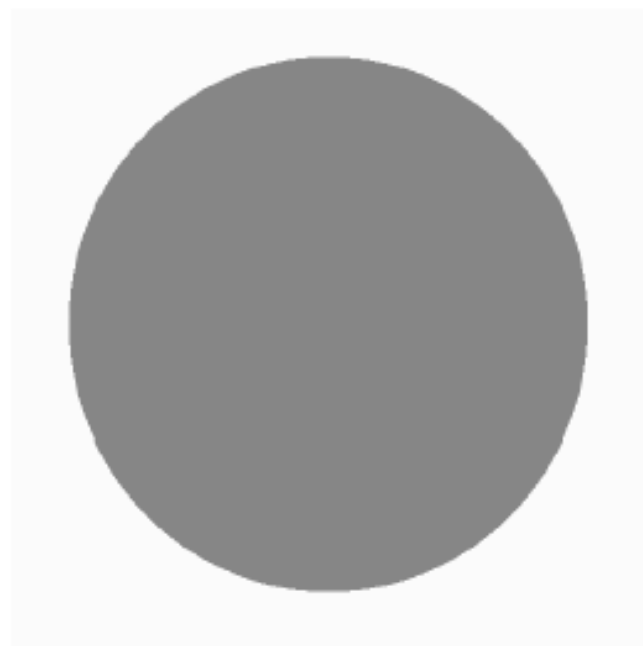
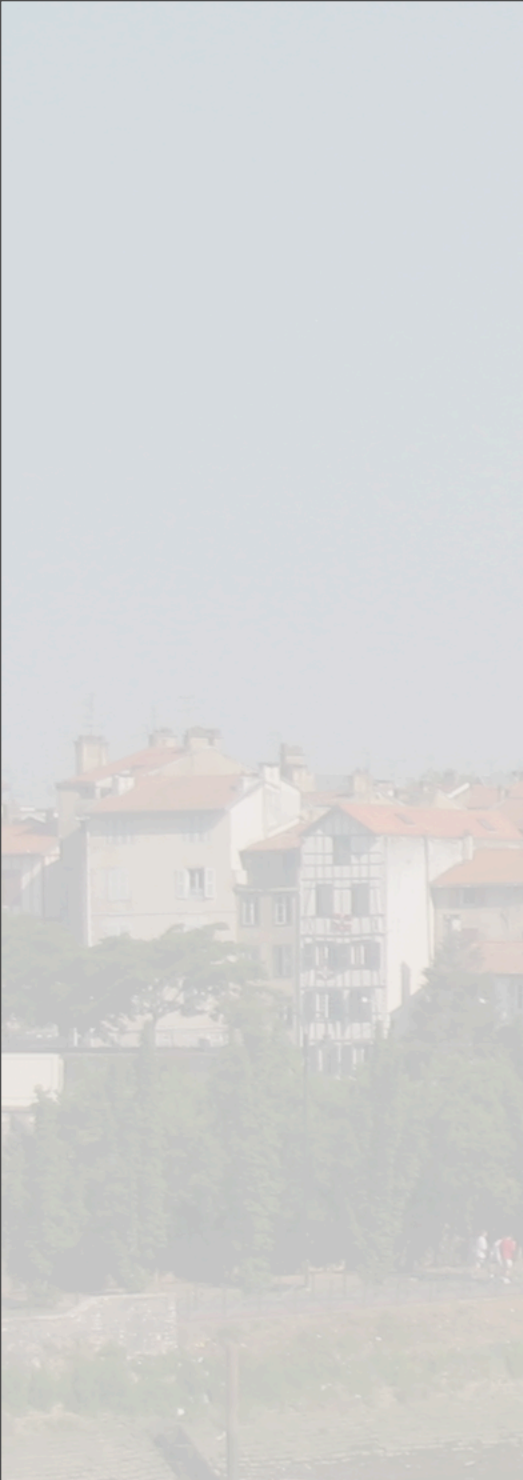
5.1 Global strategy

Pixel (i,j)

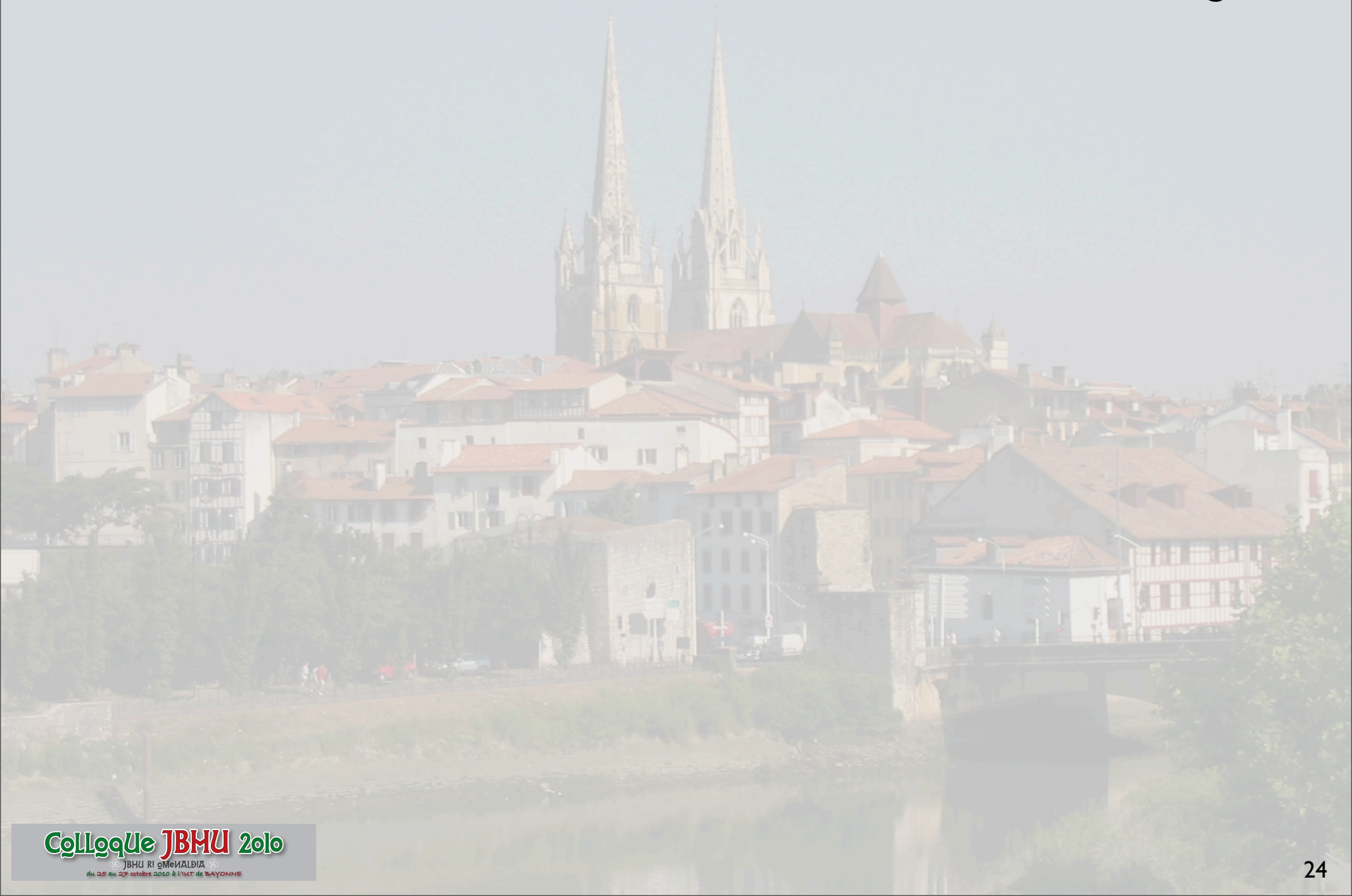
$$H(i, j) = \begin{bmatrix} H^{11} & H^{12} \\ H^{21} & H^{22} \end{bmatrix}$$

$$\Rightarrow \tilde{H}(i, j) = \begin{bmatrix} 0 & H^{12} \\ H^{21} & H^{22} \end{bmatrix}$$

$\Rightarrow$ No vertical contour any longer



5.2 Local strategy

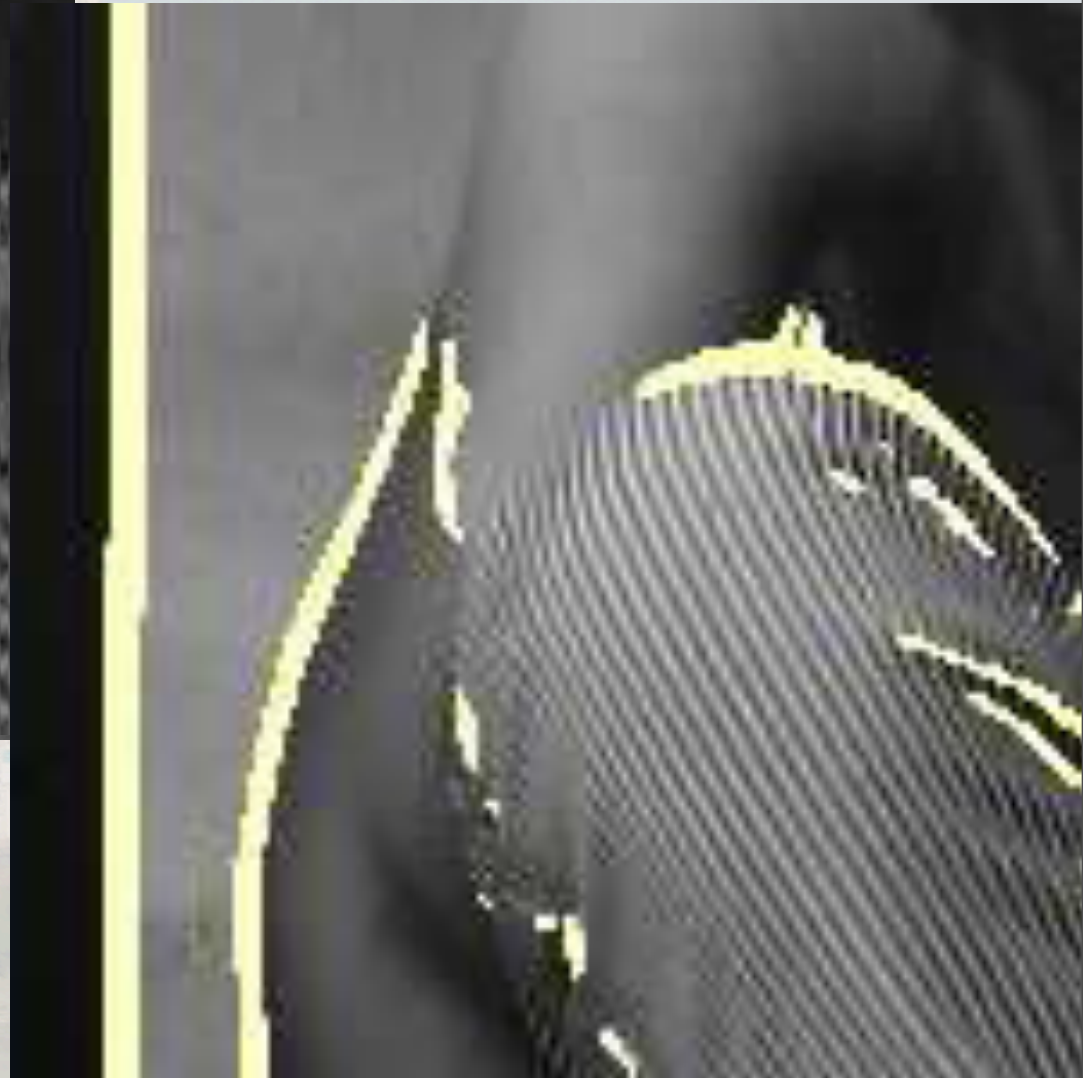


5.2 Local strategy



5.2 Local strategy

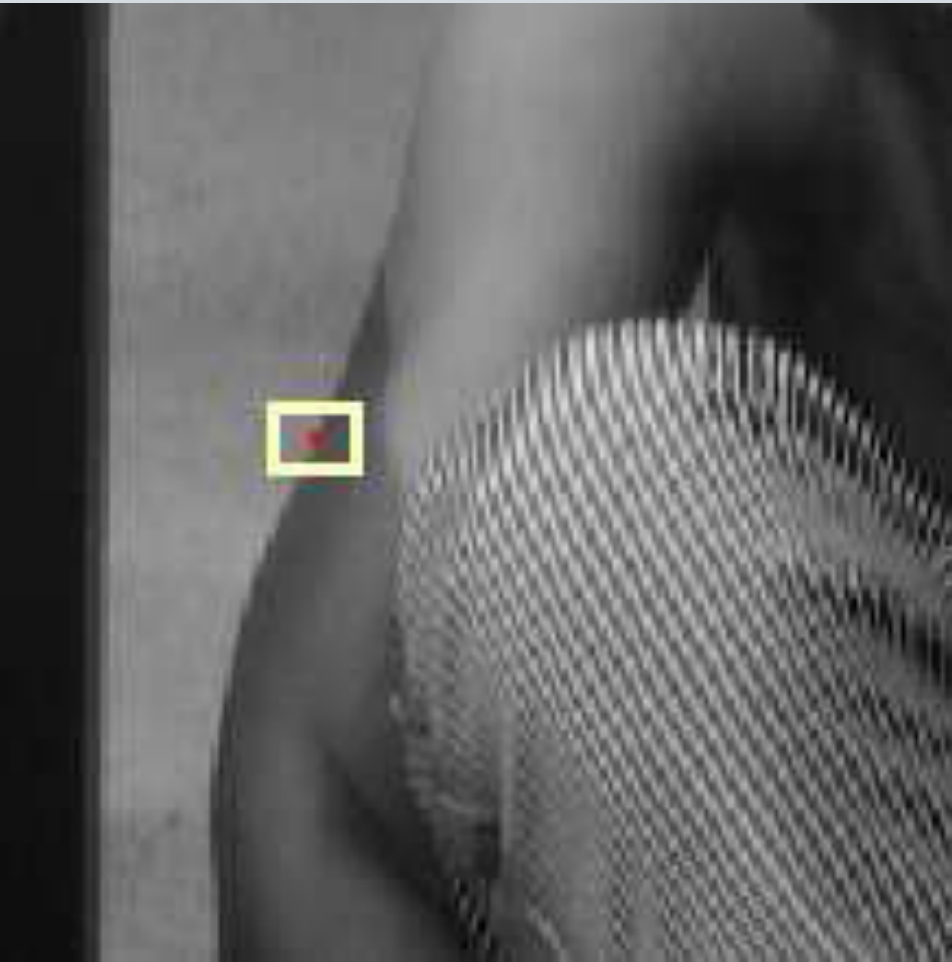
5.2 Local strategy



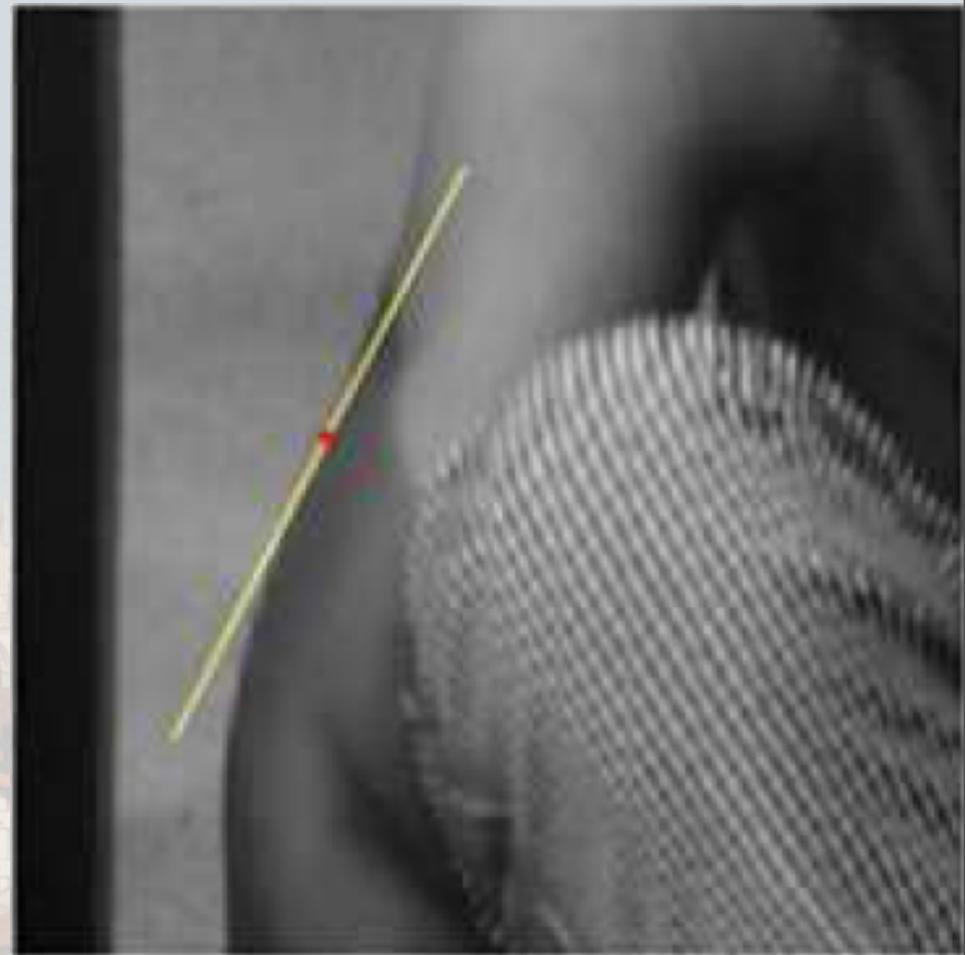
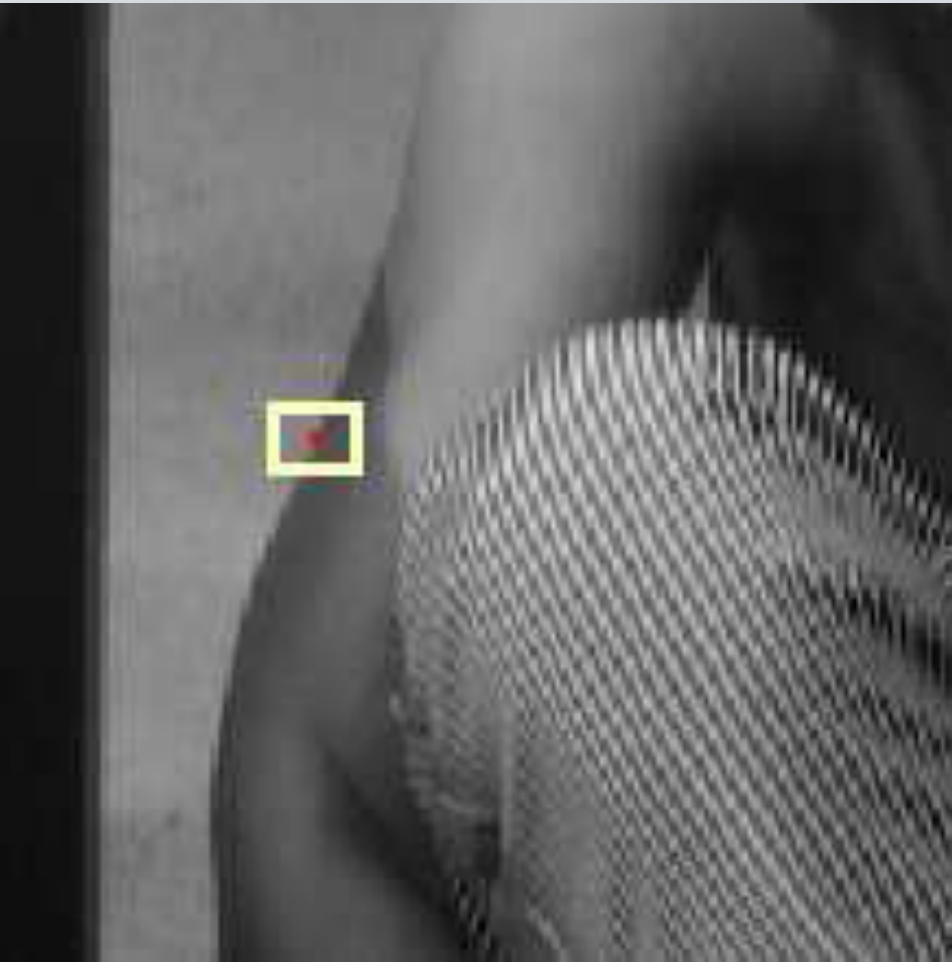
5.2 Local strategy



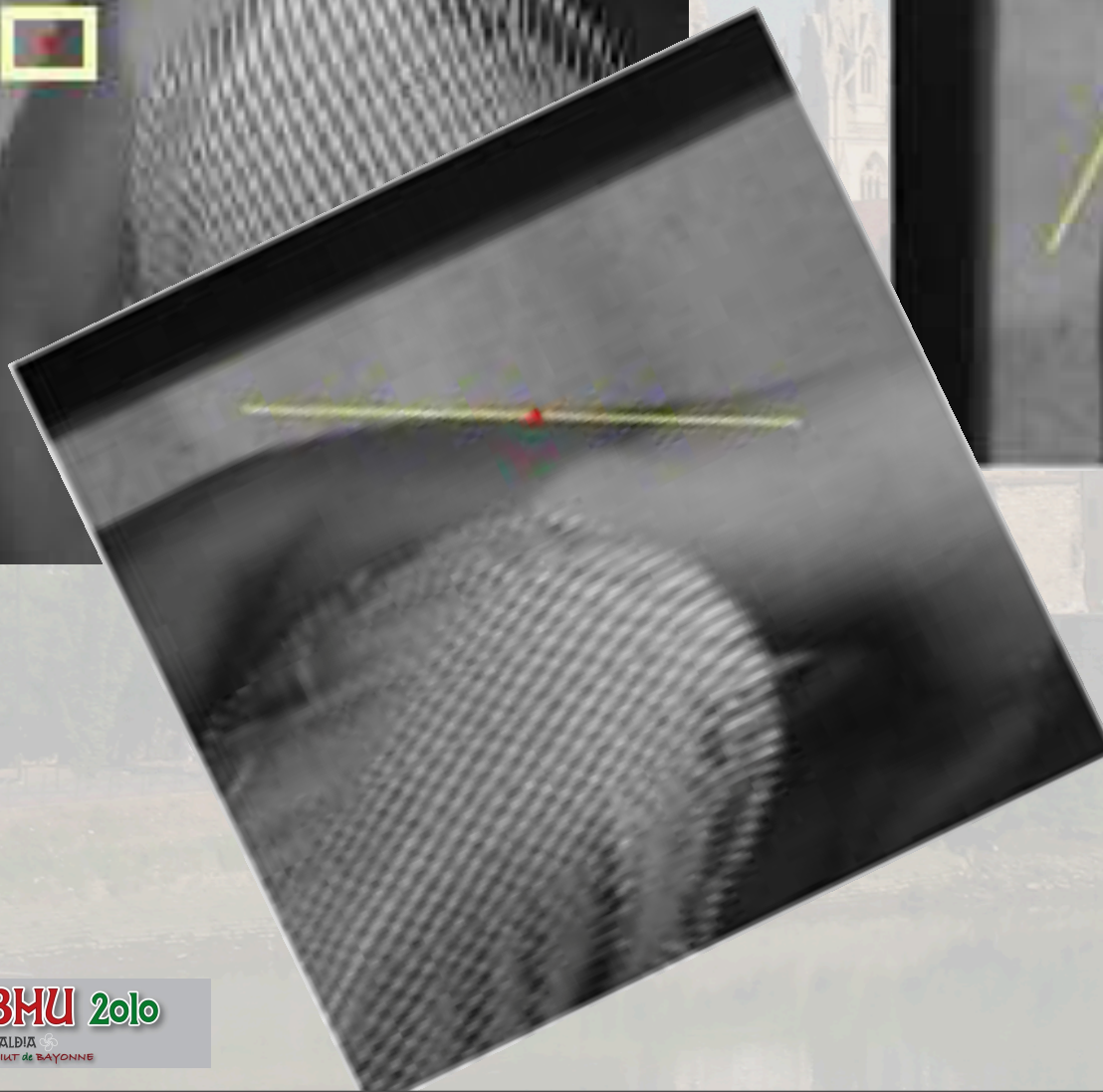
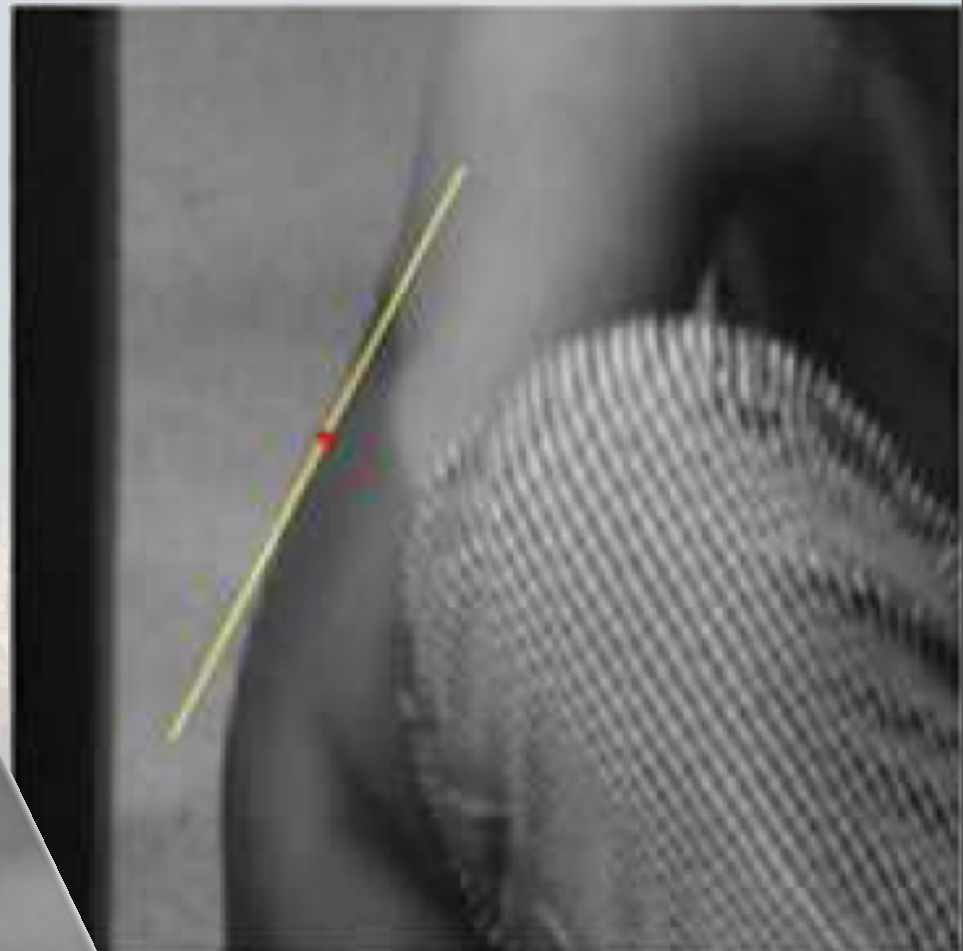
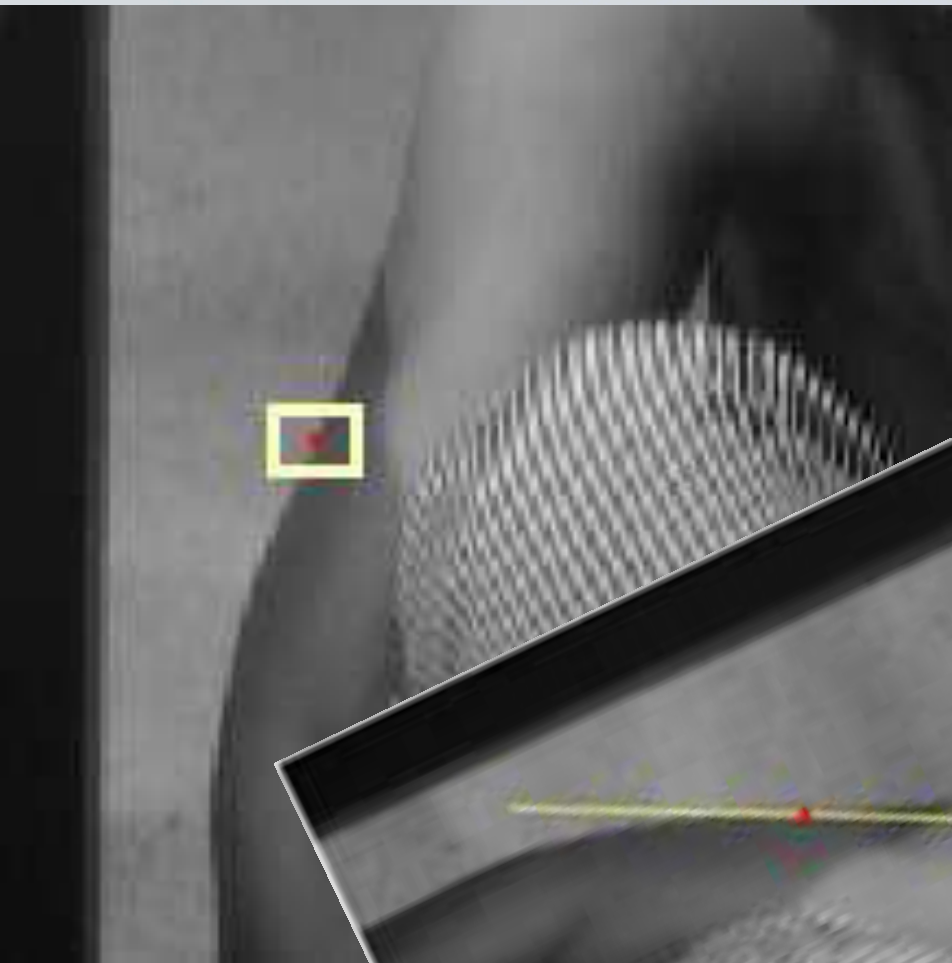
5.2 Local strategy



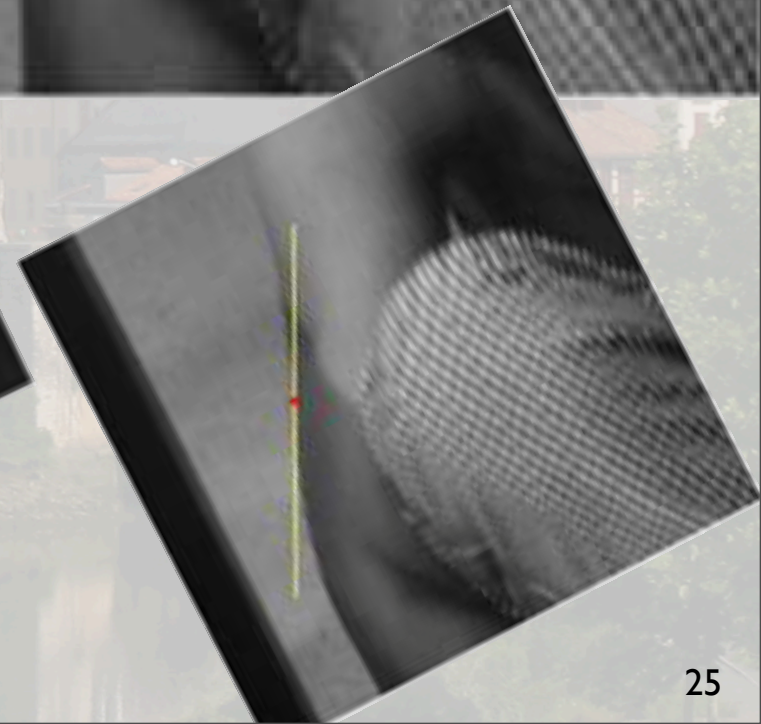
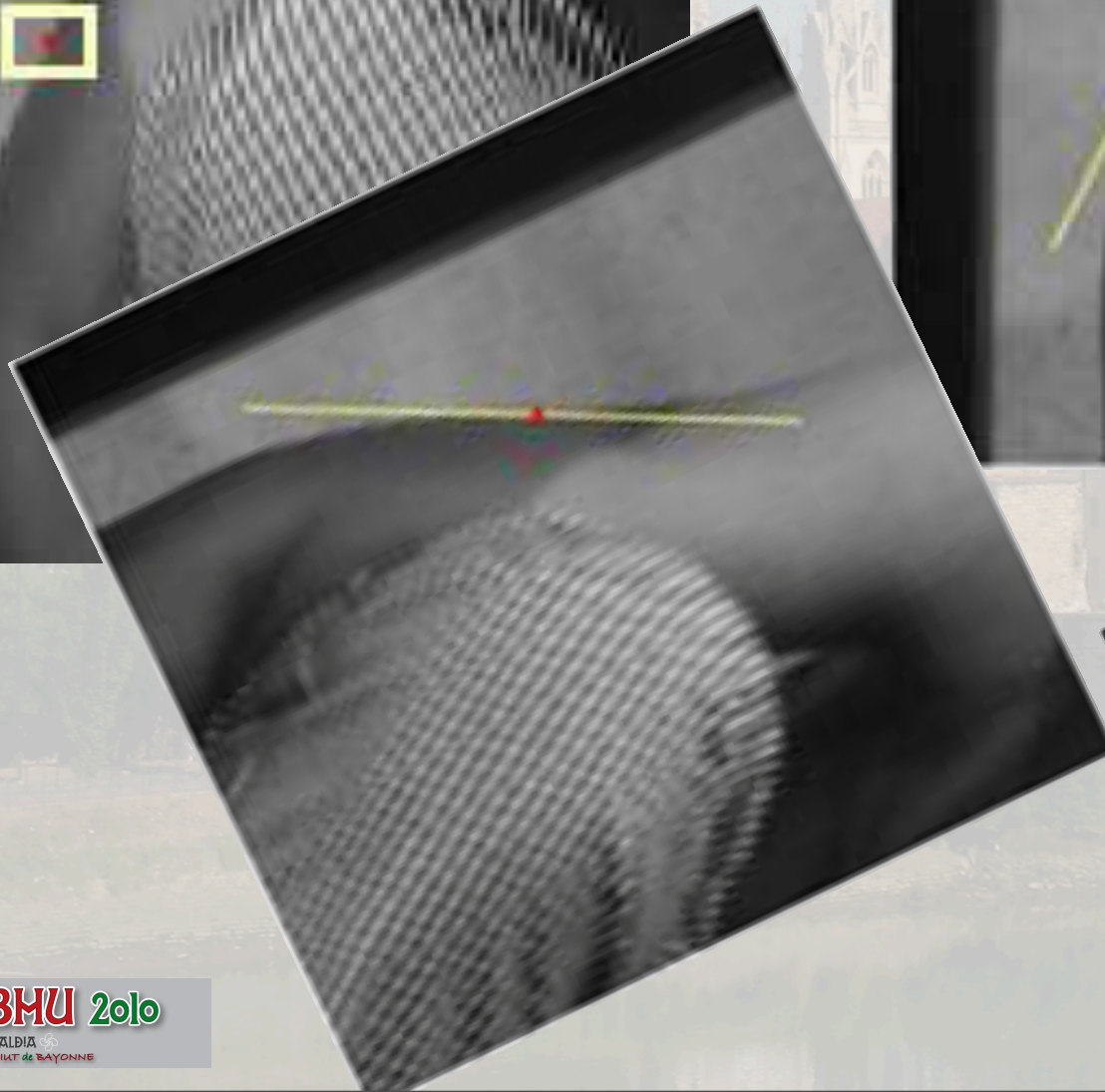
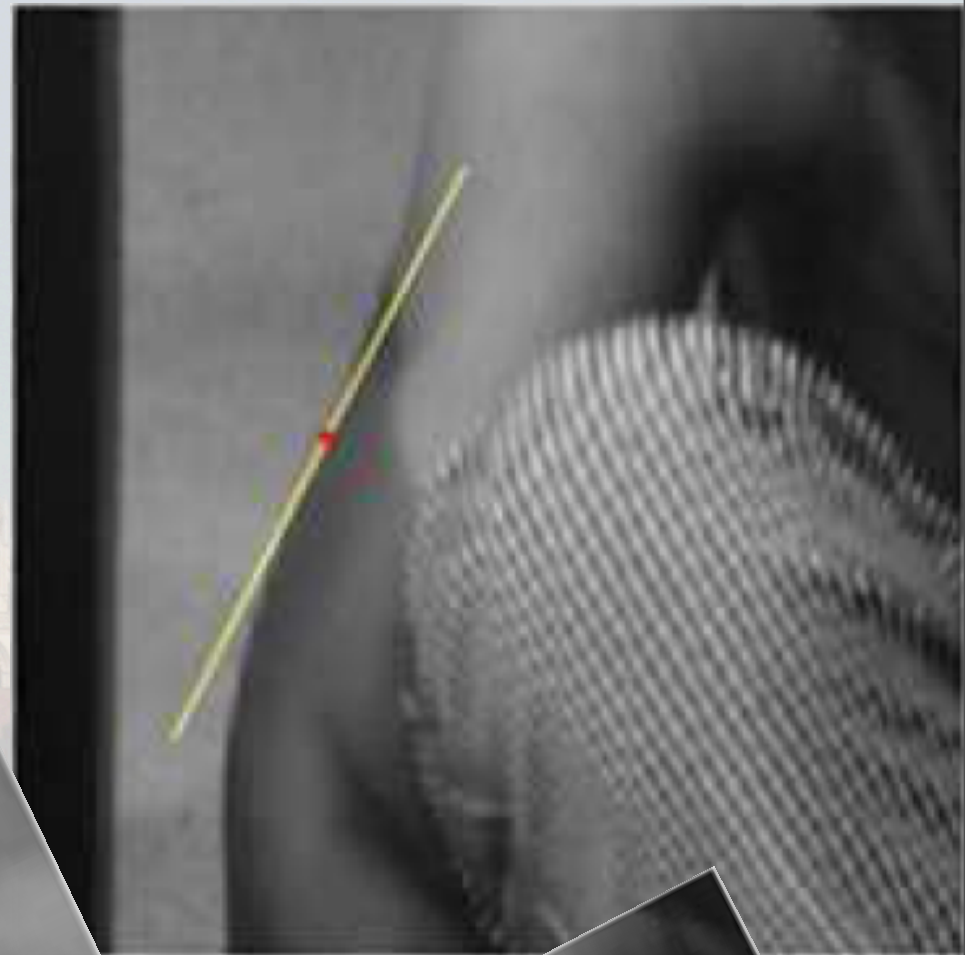
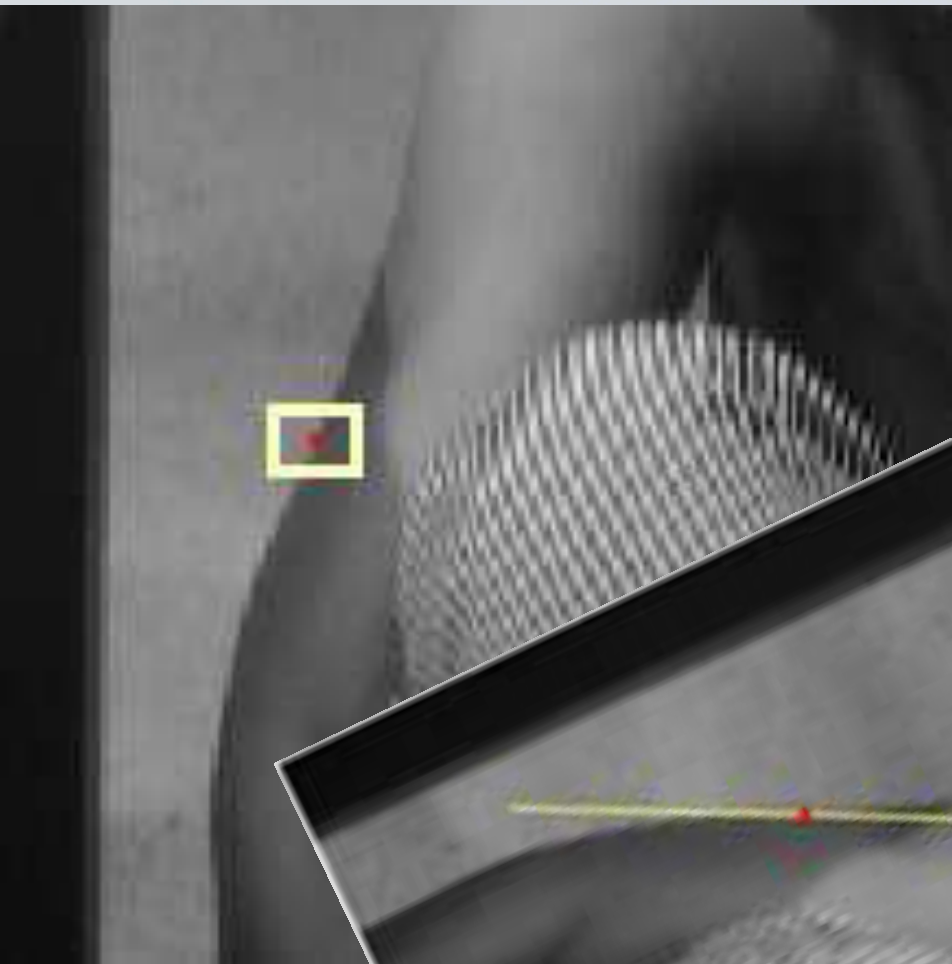
5.2 Local strategy

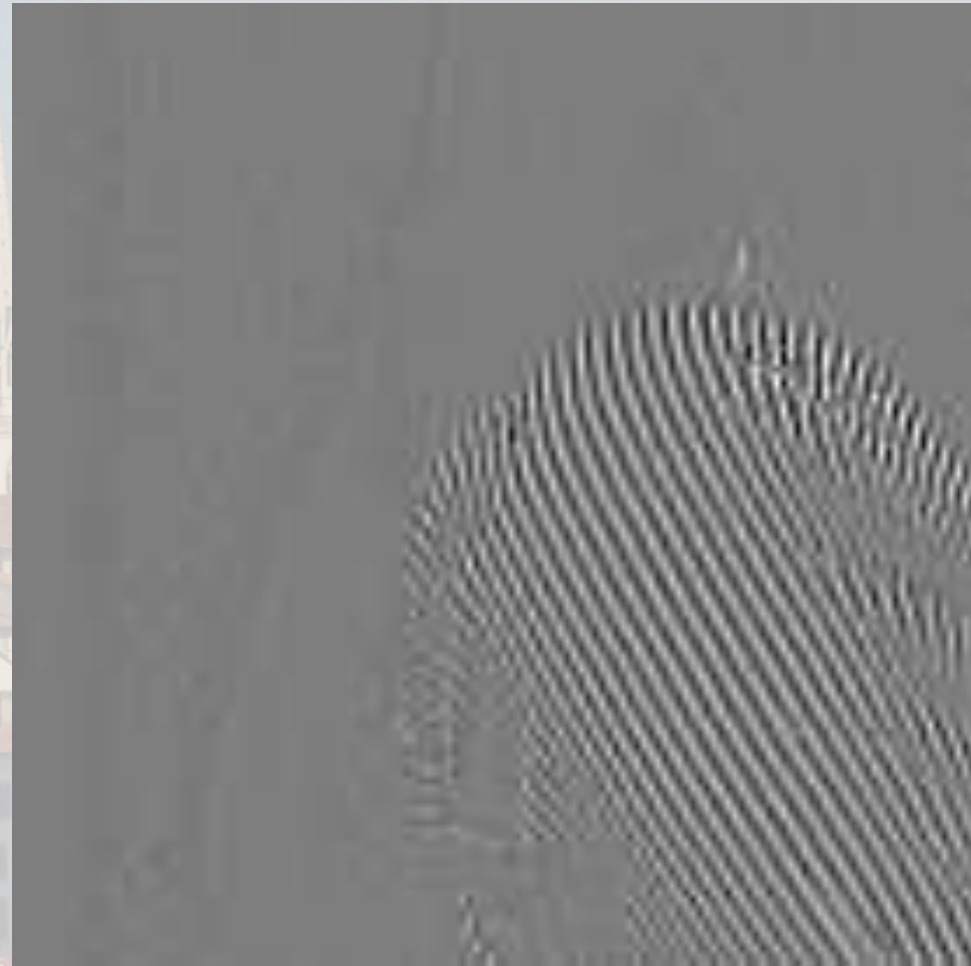
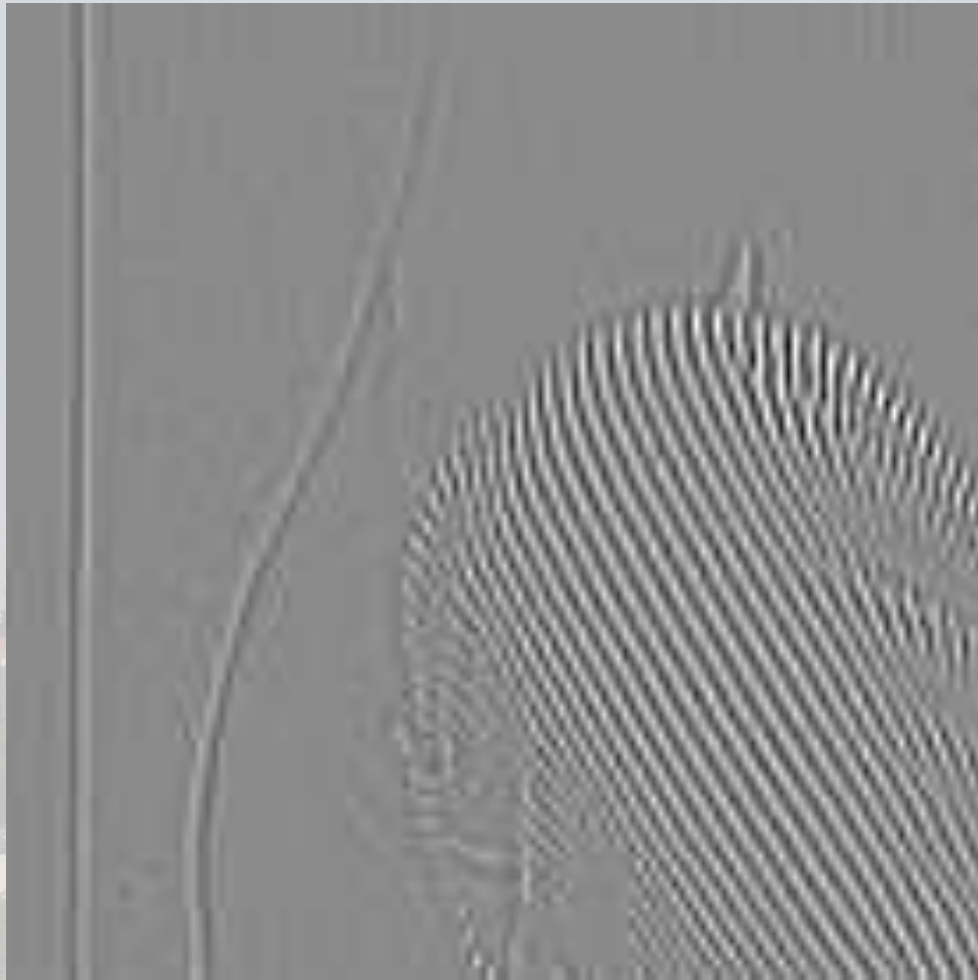


5.2 Local strategy



5.2 Local strategy





4. EXAMPLES



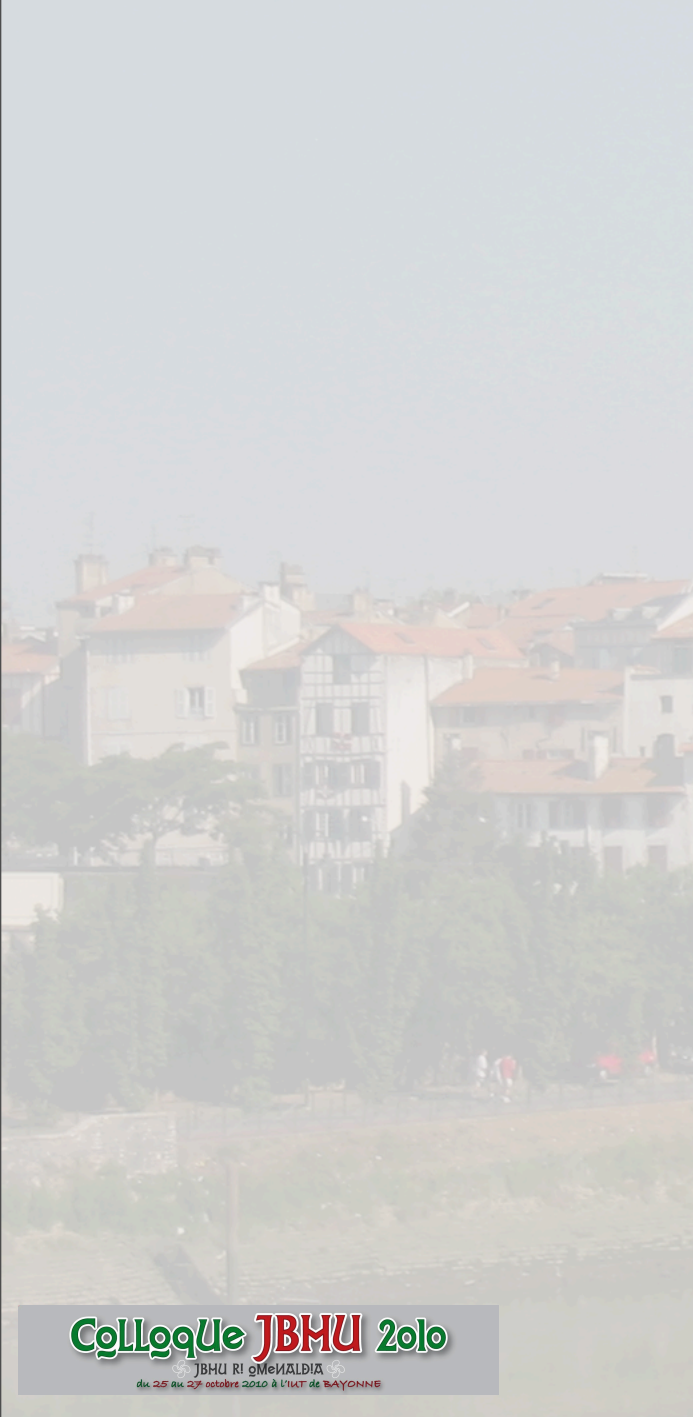
4. EXAMPLES



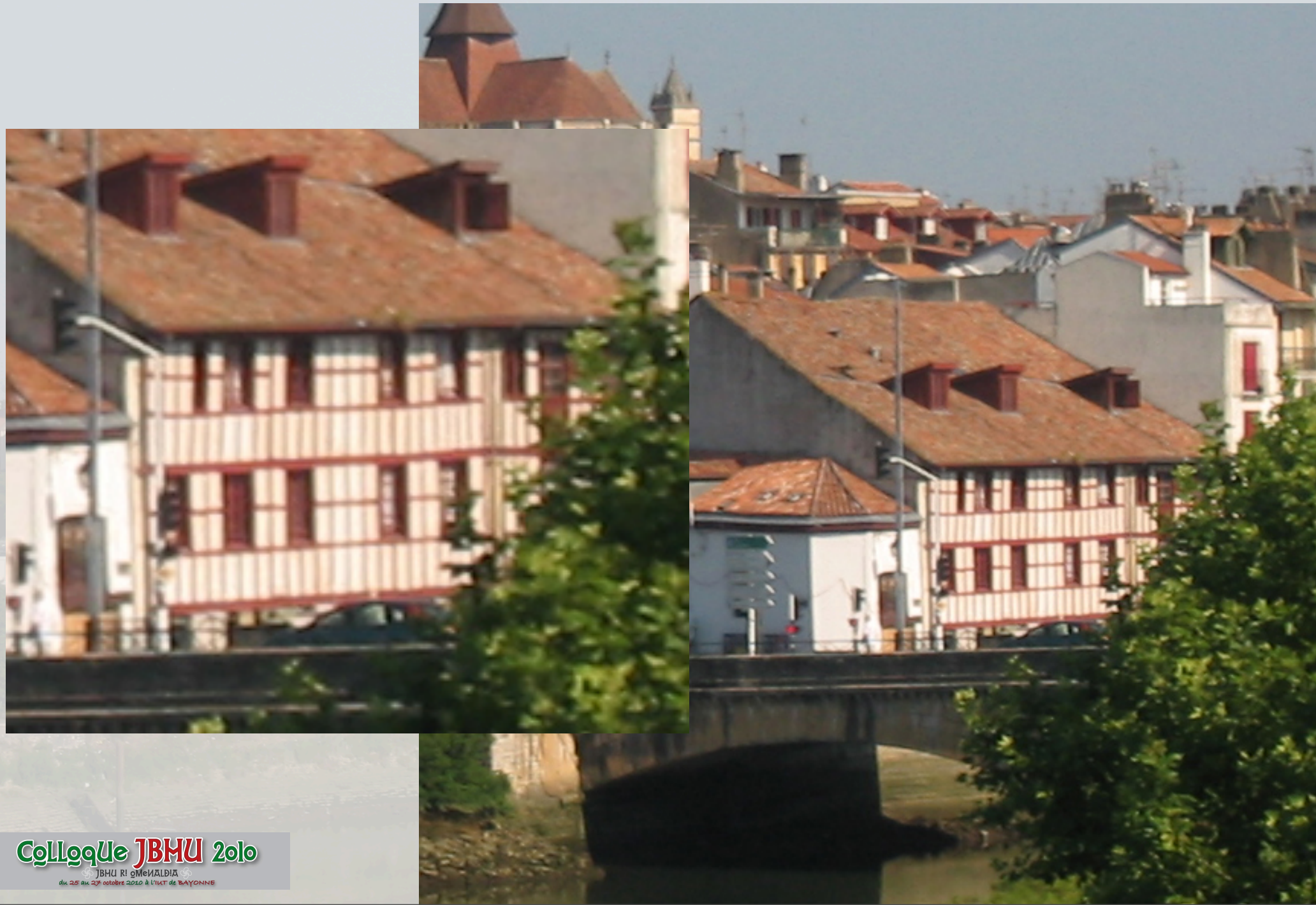
4. EXAMPLES



4. EXAMPLES



4. EXAMPLES



Cartoon

100 iterations

Texture

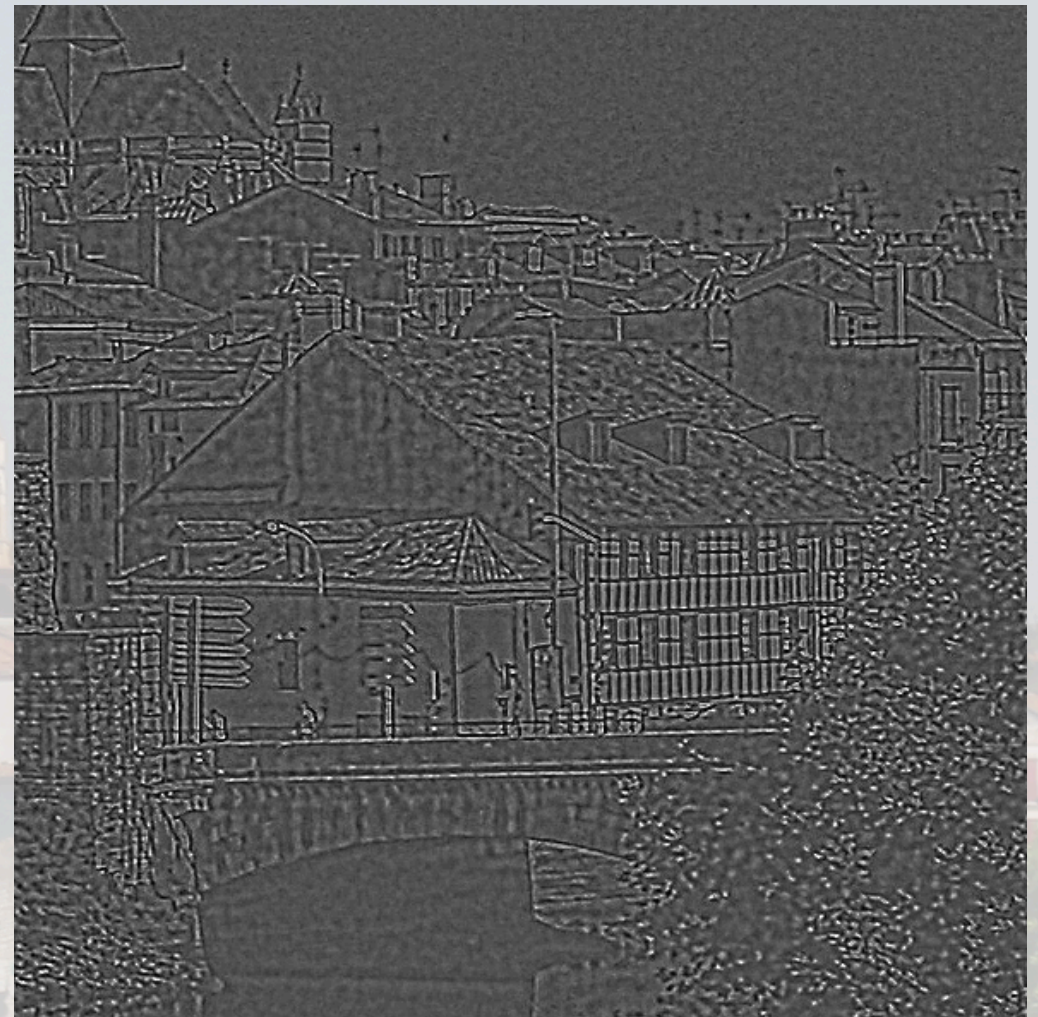
Without anisotropy strategy

$$\lambda = 10$$

Cartoon

100 iterations

Texture



Without anisotropy strategy

$$\lambda = 10$$

Cartoon

100 iterations

Texture

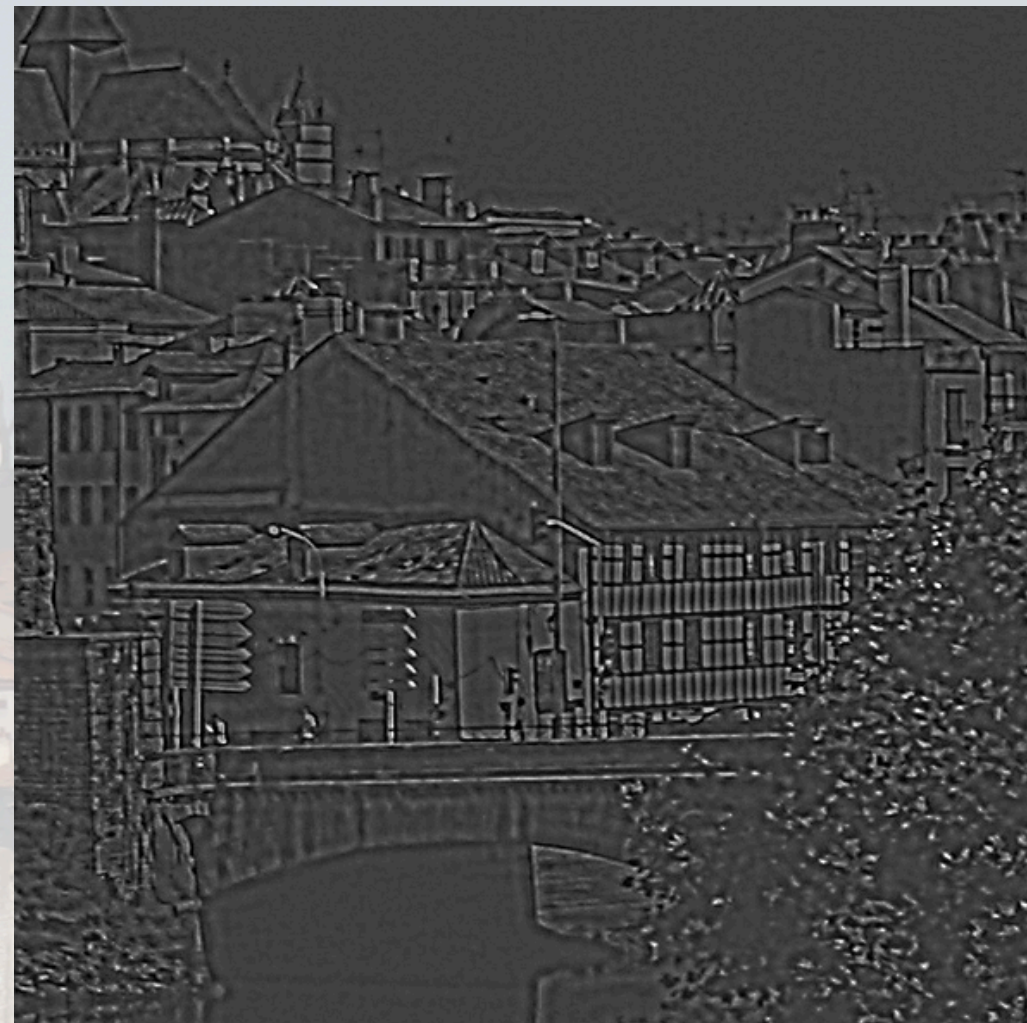
Without anisotropy strategy

$$\lambda = 50$$

Cartoon

100 iterations

Texture



Without anisotropy strategy

$$\lambda = 50$$

Cartoon

100 iterations

Texture

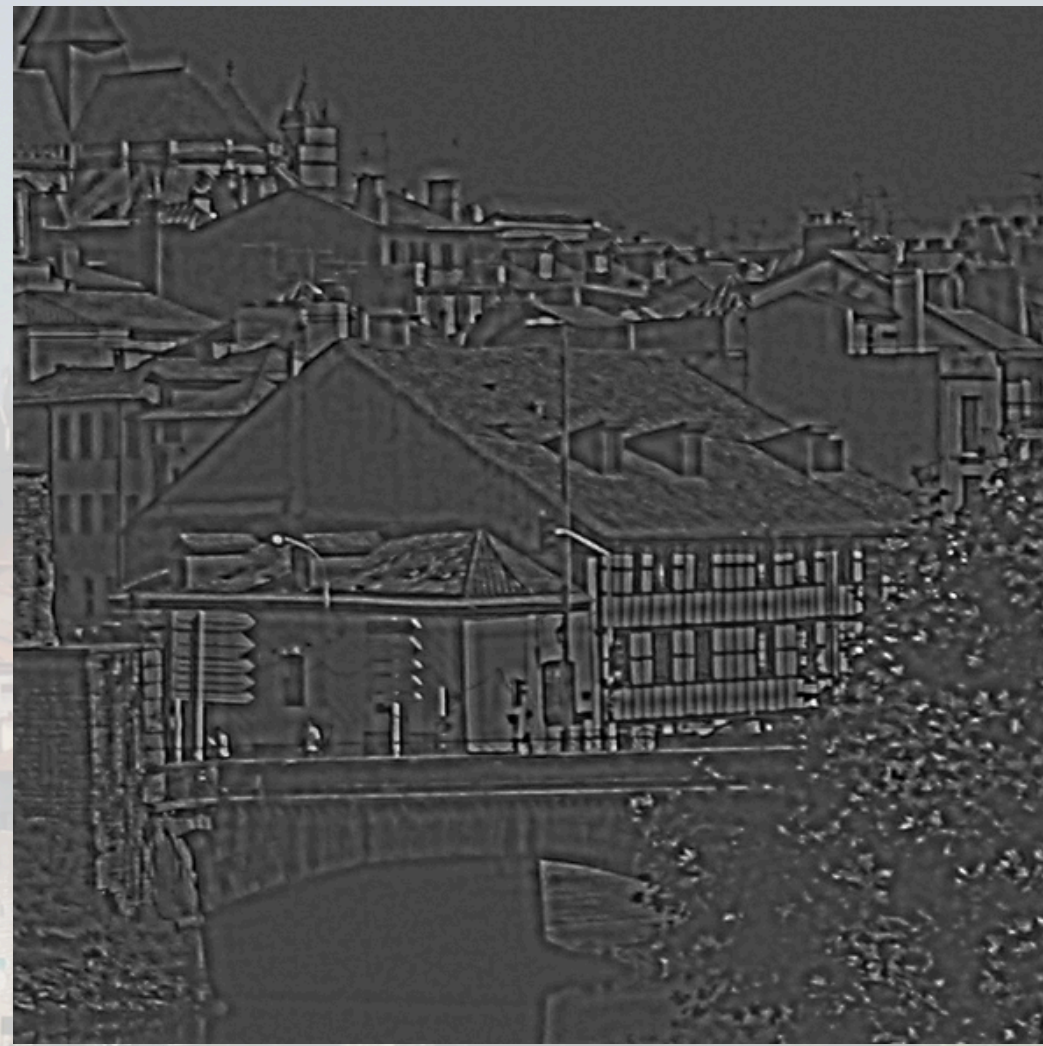
Without anisotropy strategy

$$\lambda = 100$$

Cartoon

100 iterations

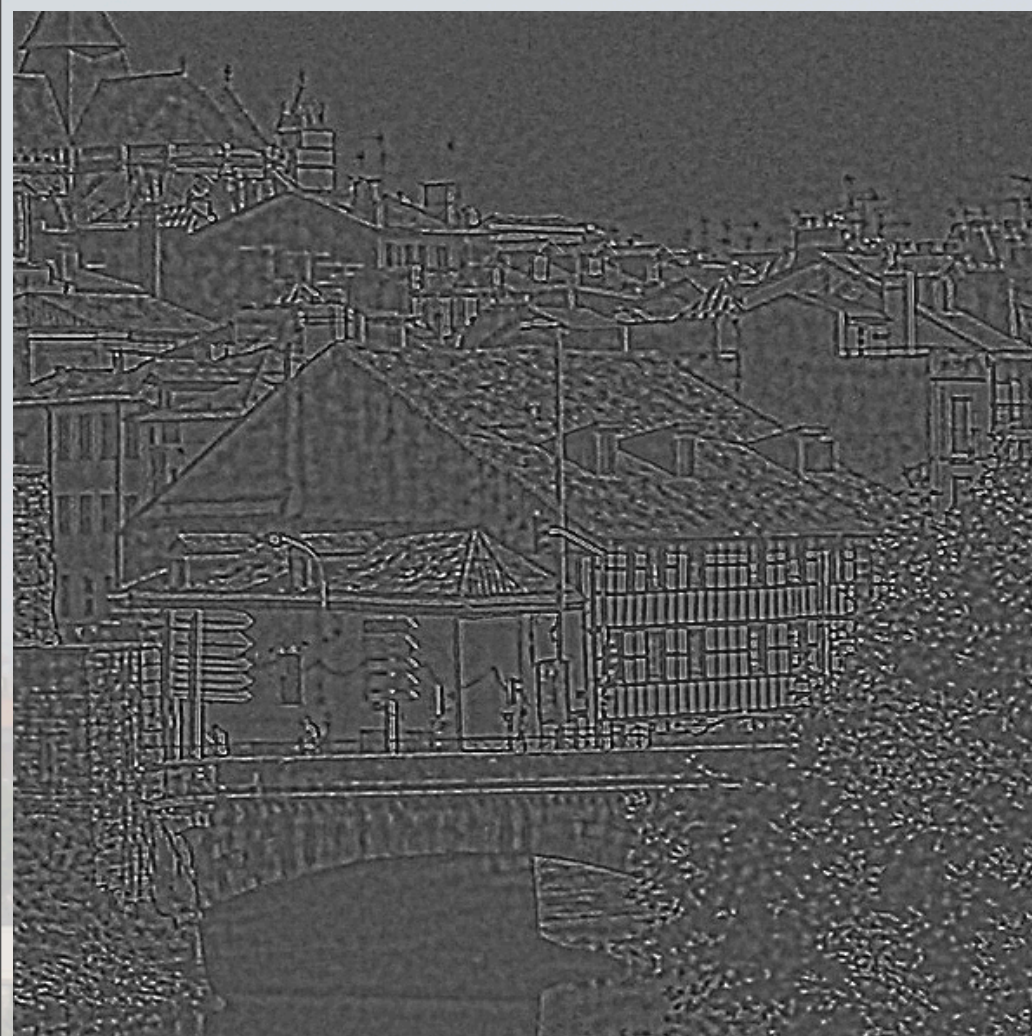
Texture



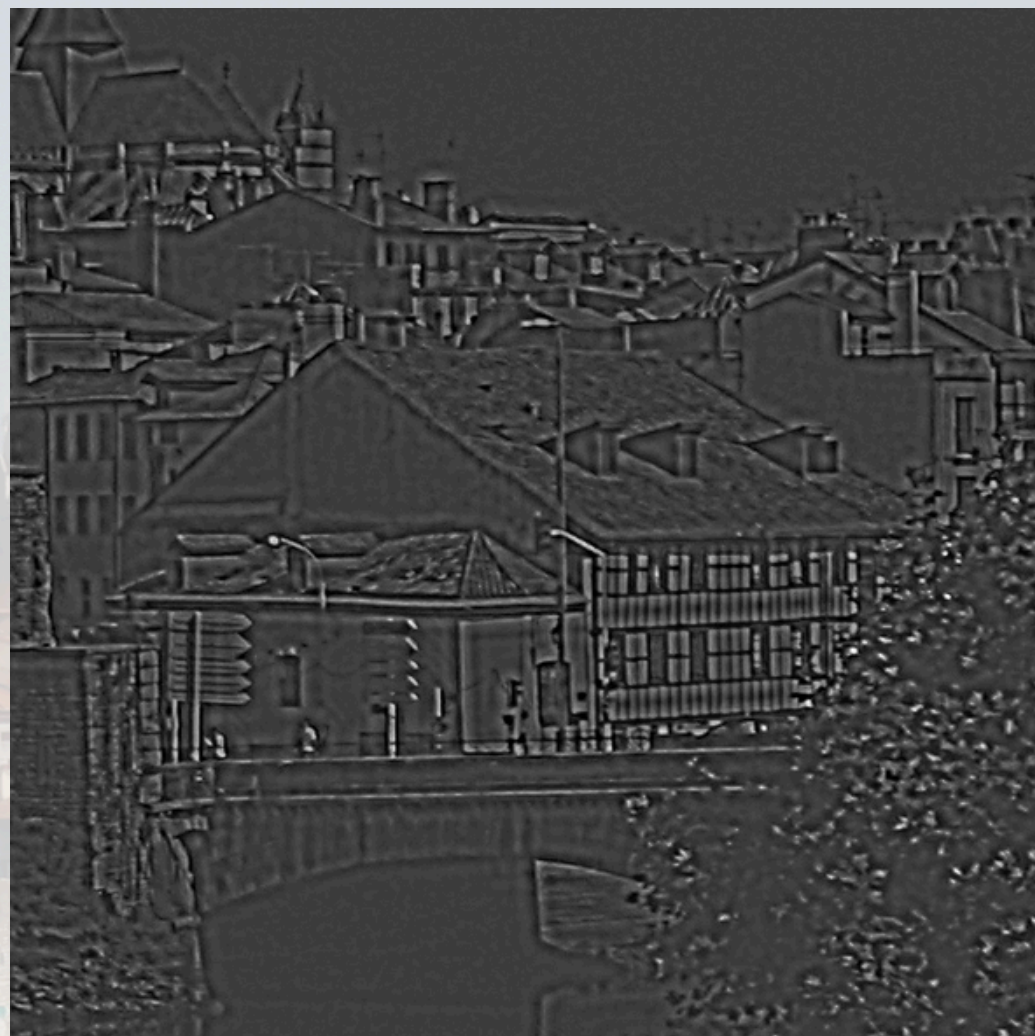
Without anisotropy strategy

$$\lambda = 100$$

Texture



$\lambda = 10$



$\lambda = 100$

Without anisotropy strategy

Cartoon

100 iterations

Texture

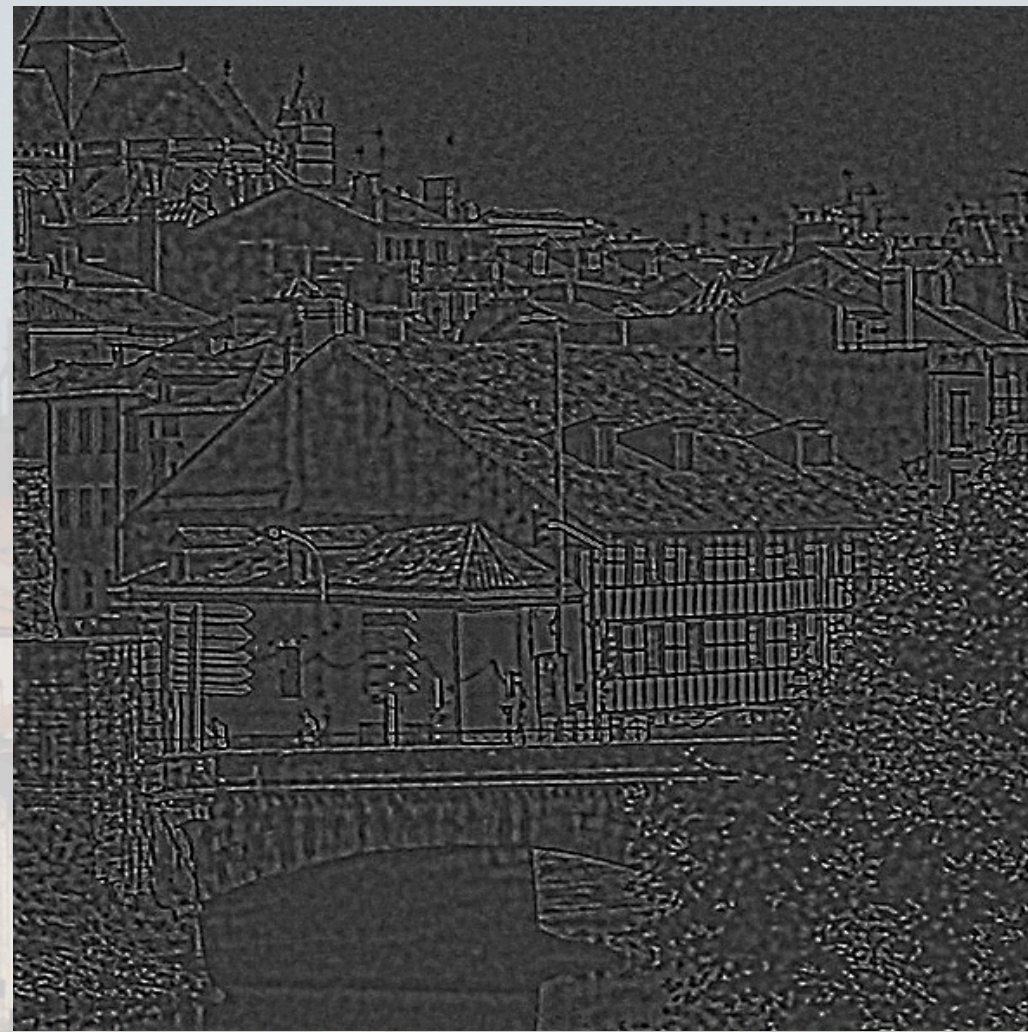
With anisotropy strategy

$$\lambda = 10$$

Cartoon

100 iterations

Texture



With anisotropy strategy

$$\lambda = 10$$

Cartoon

100 iterations

Texture

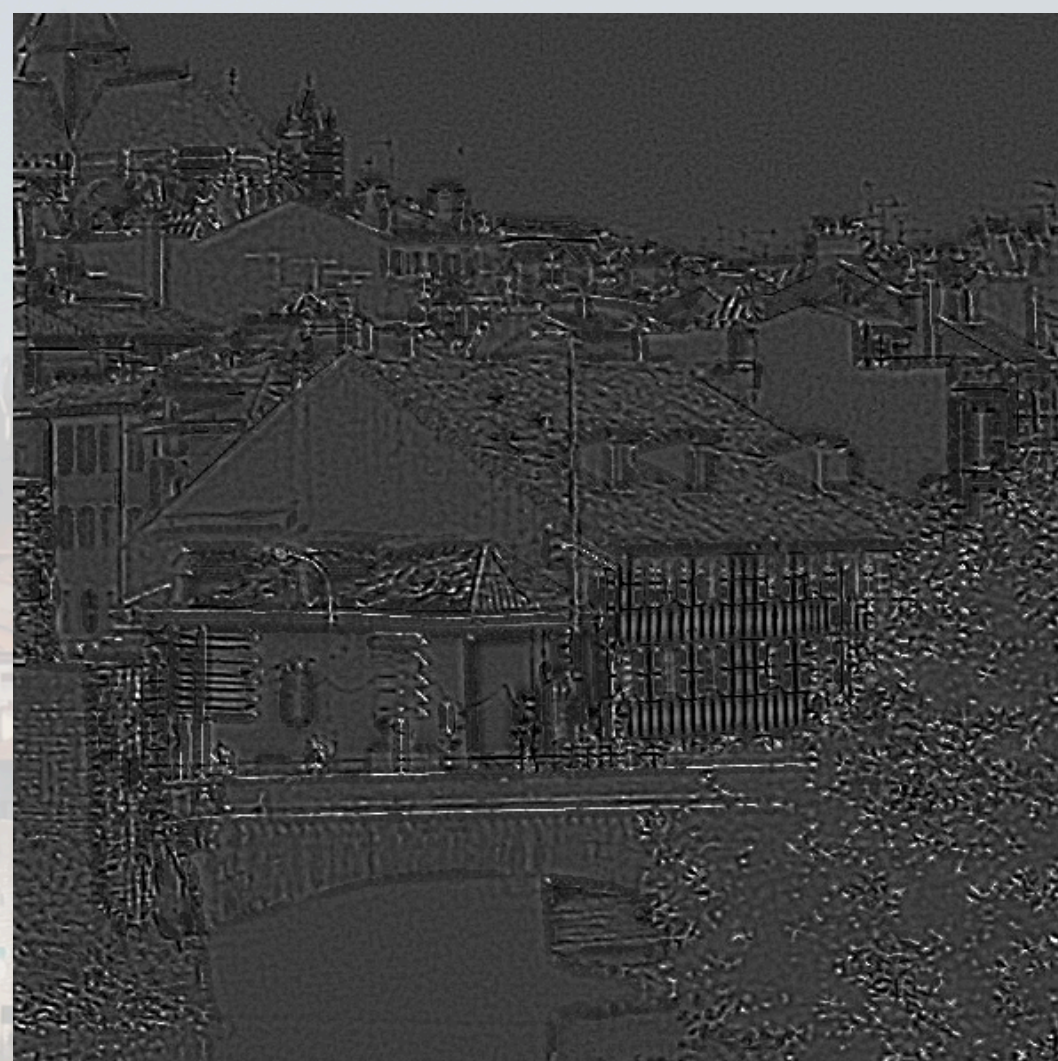
With anisotropy strategy

$$\lambda = 50$$

Cartoon

100 iterations

Texture



With anisotropy strategy

$$\lambda = 50$$

Cartoon

100 iterations

Texture

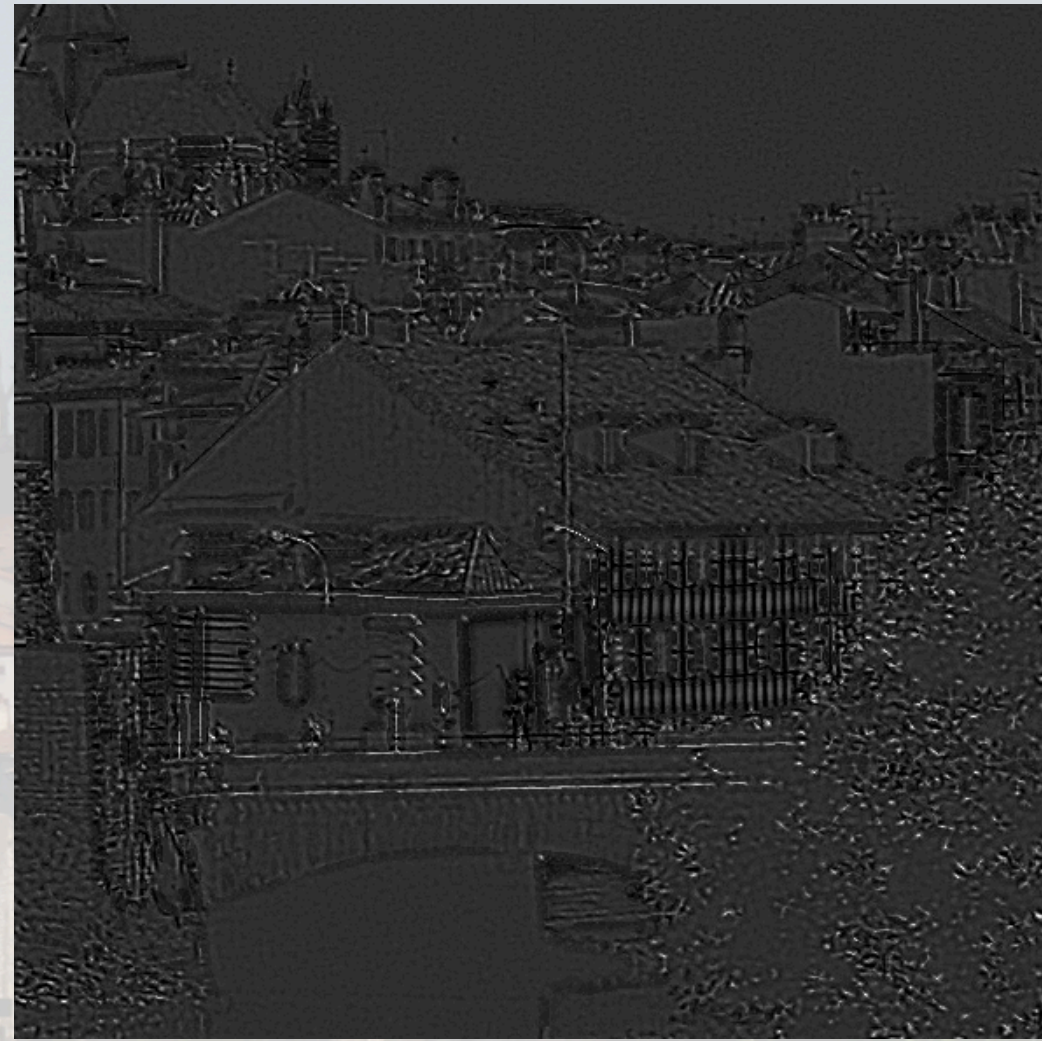
With anisotropy strategy

$$\lambda = 100$$

Cartoon

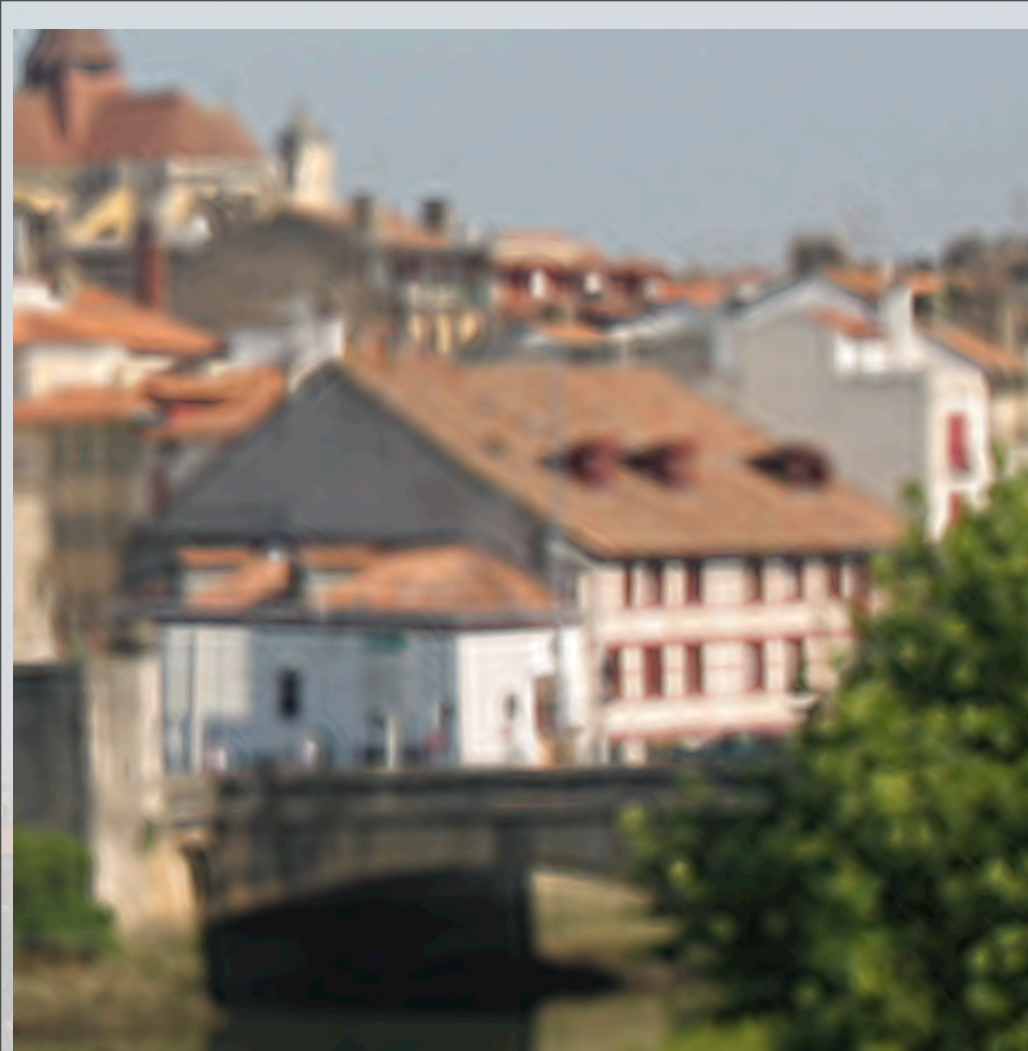
100 iterations

Texture



With anisotropy strategy

$$\lambda = 100$$

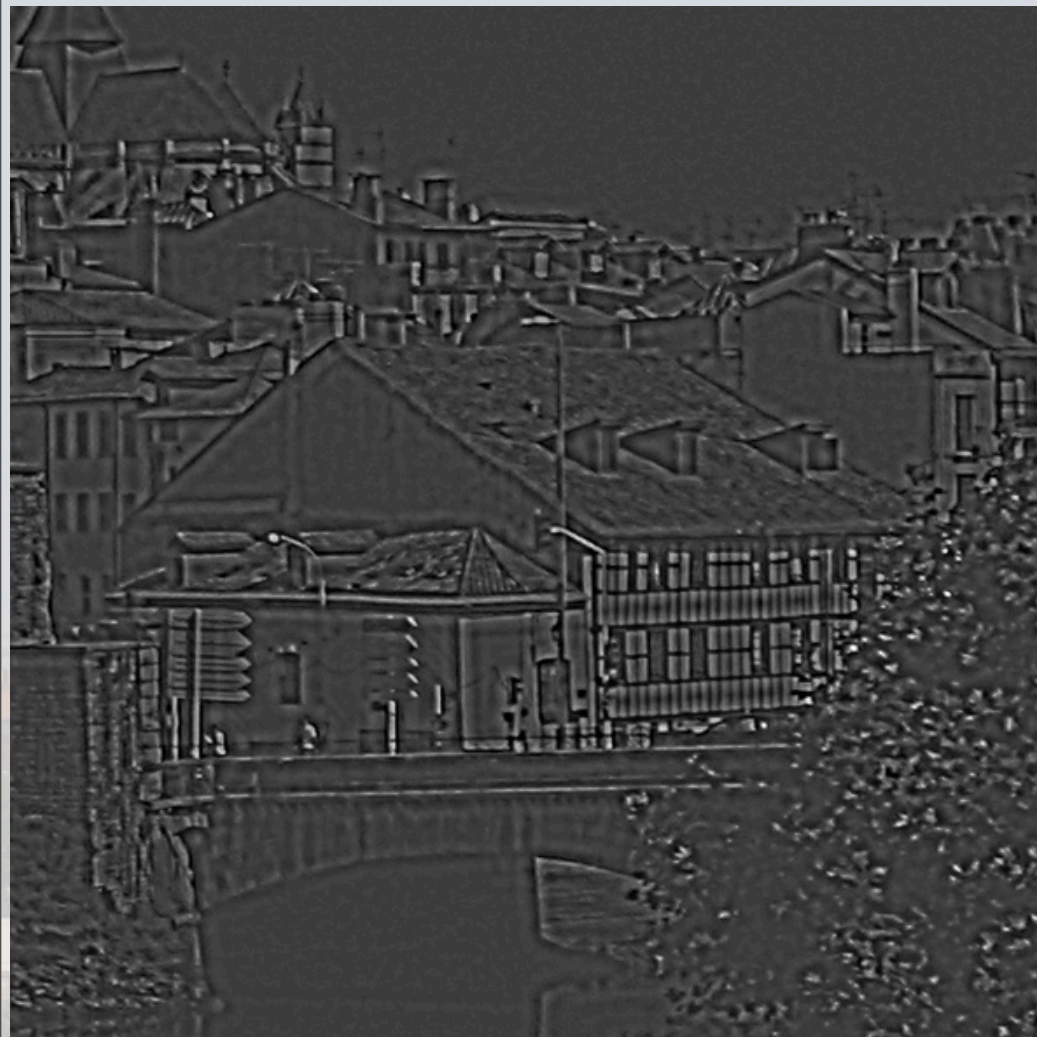


Without

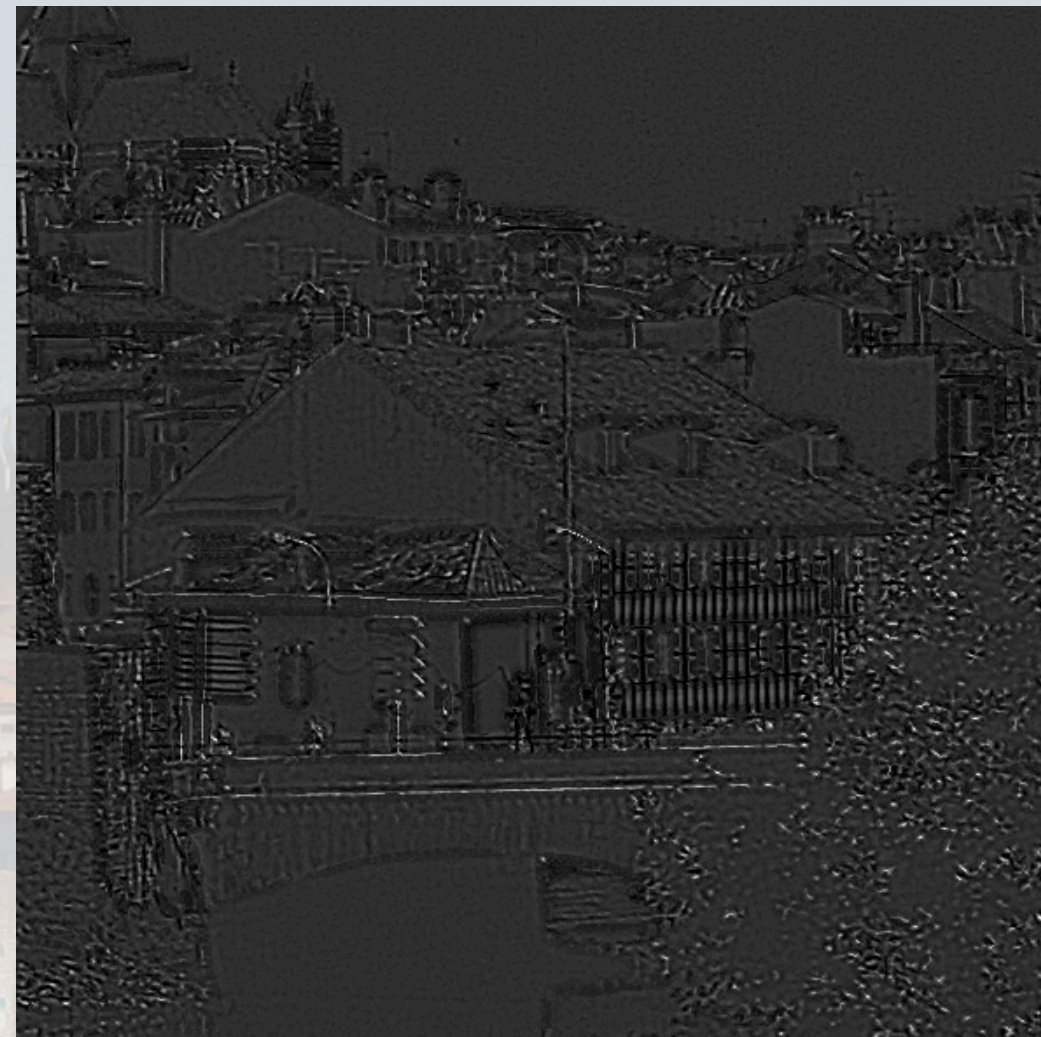


With

$$\lambda = 100$$

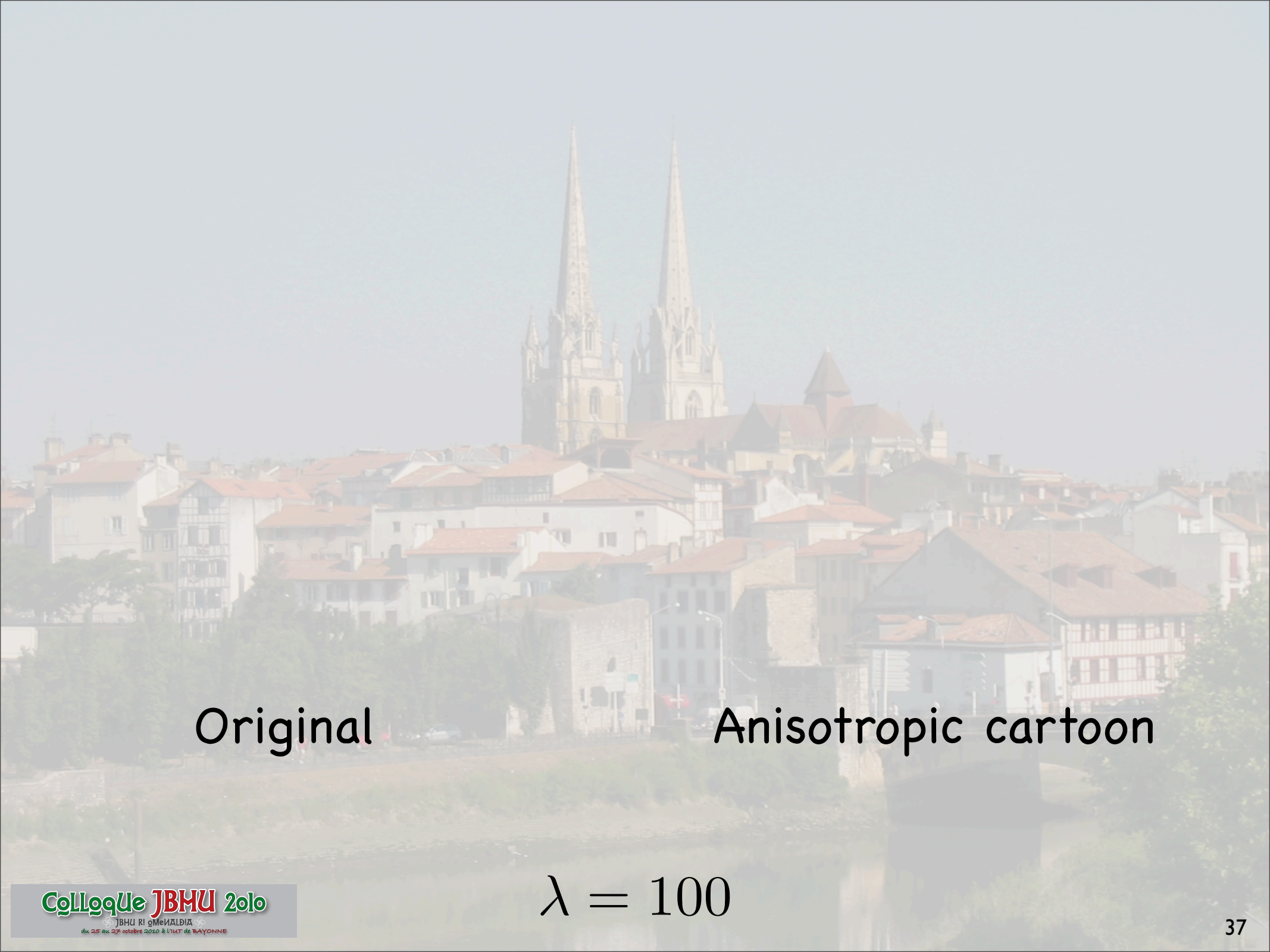


Without



With

$$\lambda = 100$$



Original

Anisotropic cartoon

$$\lambda = 100$$



Original

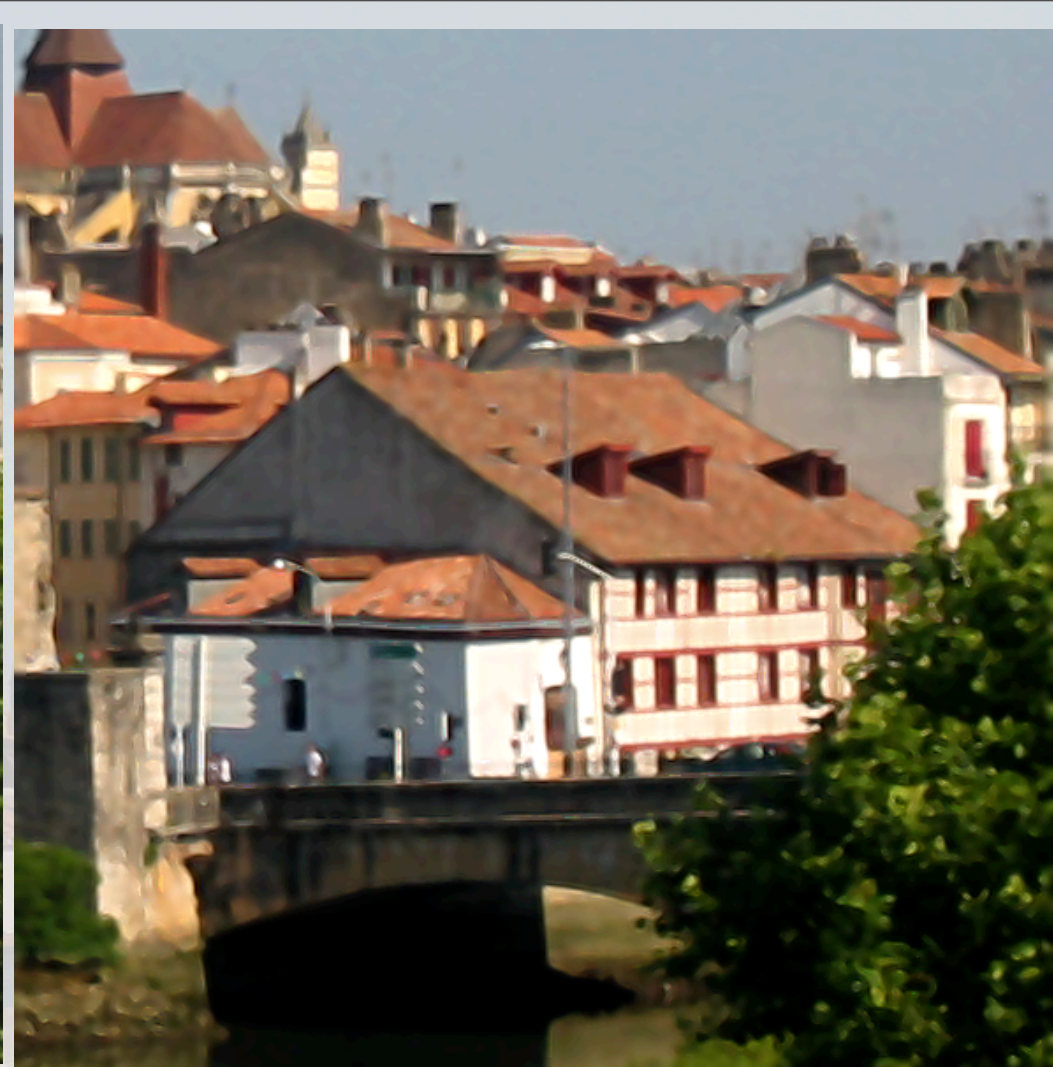


Anisotropic cartoon

$$\lambda = 100$$



Original



Anisotropic cartoon

$$\lambda = 100$$



Original

Anisotropic cartoon

$$\lambda = 100$$



Original

Anisotropic cartoon

$$\lambda = 100$$



JBHU (and Fermat) lifting...

$$\lambda = 20$$

50 iterations
without anisotropy



JBHU (and Fermat) lifting...

$$\lambda = 20$$



50 iterations
without anisotropy



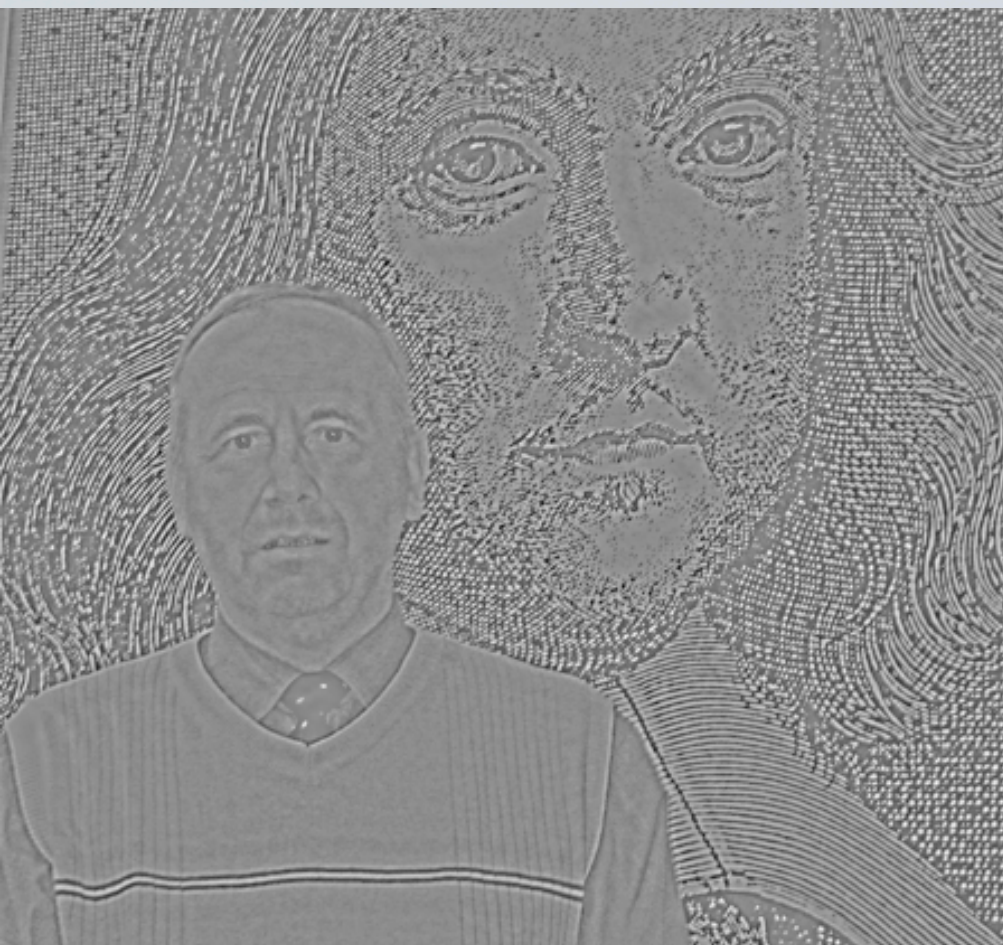
100 iterations
without anisotropy

$$\lambda = 50$$

100 iterations
without anisotropy

$$\lambda = 50$$





100 iterations
without anisotropy

$$\lambda = 50$$





100 iterations
with anisotropy

$$\lambda = 50$$

100 iterations
with anisotropy

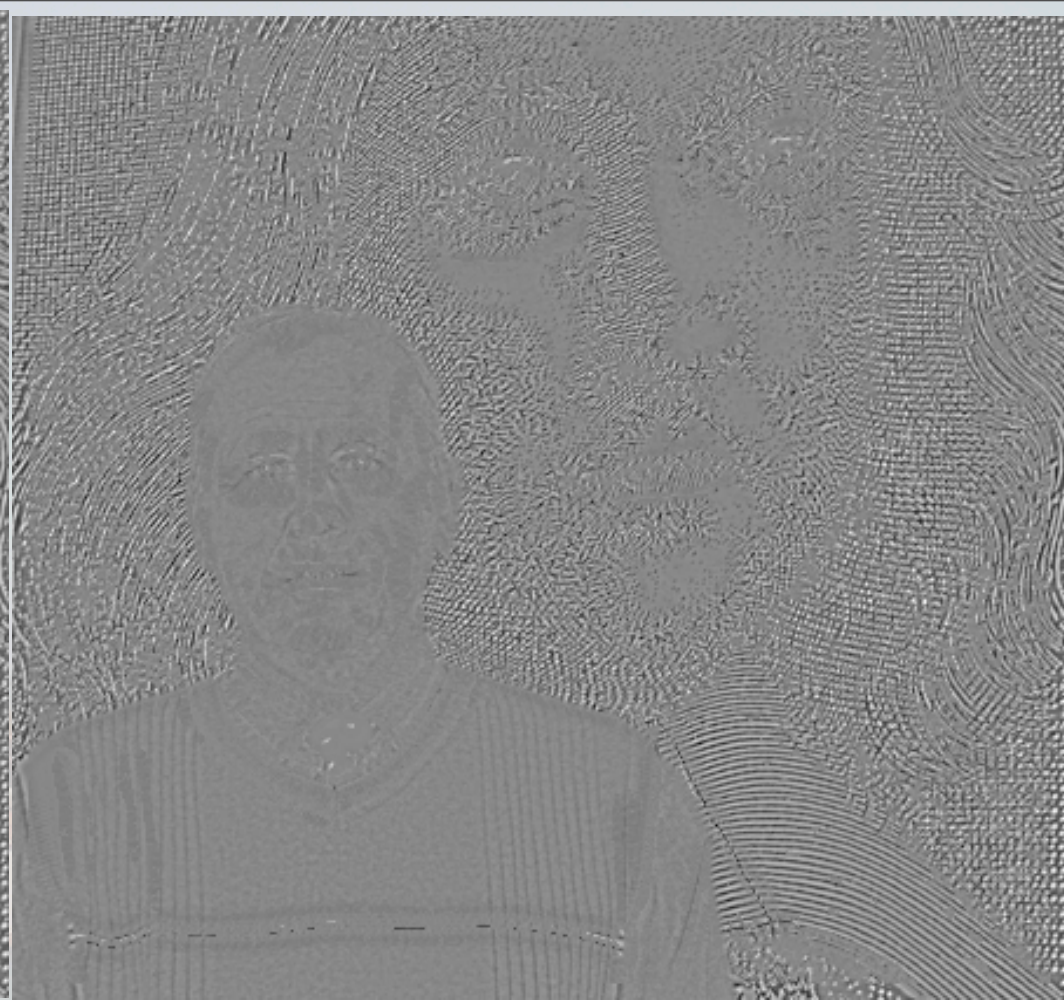
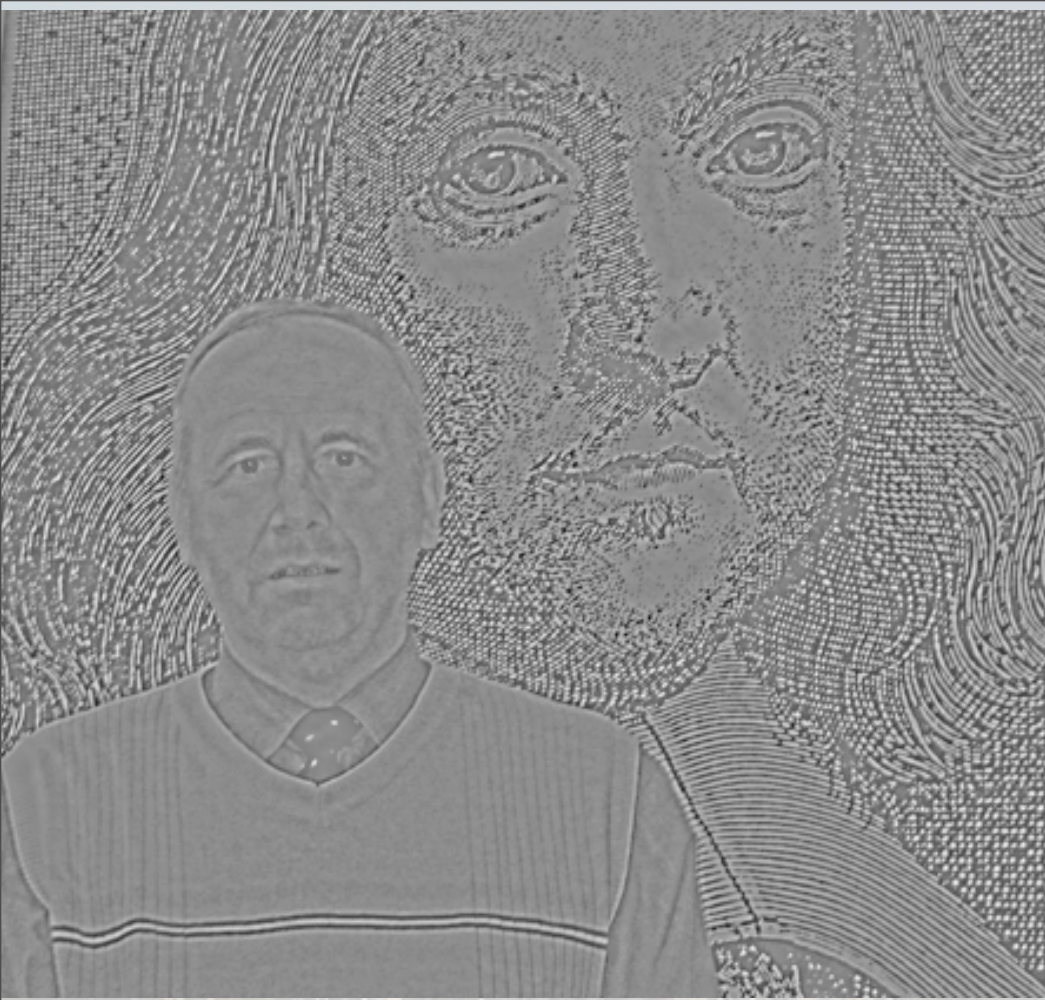
$$\lambda = 50$$





100 iterations
with anisotropy

$$\lambda = 50$$



Without

With

$$\lambda = 50$$

Martel (46)

18- 22 avril 2011



Organisation

Pierre Maréchal et Maitine Bergounioux

Conférenciers

Antonin Chambolle (X), Didier Auroux (Nice), Simon Masnou (Lyon), Cécile Louchet (Orléans), Régis Monneau (ENPC), Pierre Weiss (Toulouse)

[http://web.me.com/maitine.bergounioux/EcoleMartel/
Bienvenue.html](http://web.me.com/maitine.bergounioux/EcoleMartel/Bienvenue.html)