

PDE in image processing

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Outline

- *Motivations*
- *Linear Denoising*
- *Non linear PDEs*
- *Variational Methods*
- *Axiomatic Approach*
- *Morphological Operators*
- *Geometrical Schemes*

Motivations

An **image** is a function $u : \Omega \subset \mathbb{R}^2 \longrightarrow \mathbb{R}^d$.

Problem: Restoration and/or denoising of an image before «high-level », operations e.g. **contour extraction** , **segmentation**

Idea: The observed image u_0 depends on the “real” u :

$$u_0 = Au + n ,$$

with A a linear (e.g. **convolution**) or non linear operator and n additive noise;

If the noise is purely additive ($A = Id$) one might smooth the image as proposed in classical **signal processing** by using low-pass filters.

Application



noisy image



denoised image

Application (cont.)



original image



denoised image

Linear denoising

Classical example: the **Gaussian Filter**,

$$G_\sigma(x) = \frac{1}{2\pi\sigma^2} e^{-\frac{|x|^2}{2\sigma^2}}, \quad \text{with } x = (x_1, x_2) \in \mathbb{R}^2,$$

then, by convolution with $u_0 = u + n$,

$$(G_\sigma \star u_0)(x) = \int_{\mathbb{R}^2} G_\sigma(x - y)u_0(y) dy.$$

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- The parameter $\sigma > 0$ determines the spatial size of the details which are “eliminated” by this filter: the bigger σ , the smoother the result, the lesser details are kept.
- Convolution is efficiently computed using the FFT.

Linear denoising (cont.)

Now convolution with the Gaussian amounts to solve the heat equation:

$$\begin{cases} u_t(x, t) = \Delta u(x, t) \\ u(x, 0) = u_0(x). \end{cases}$$

- Thus regularization through convolution is replaced by **isotropic diffusion** with $t = \sigma^2/2$.

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- Example of a **linear scale space** operator $T_t u_0 = u(\cdot, t)$.

Linear denoising (cont.)

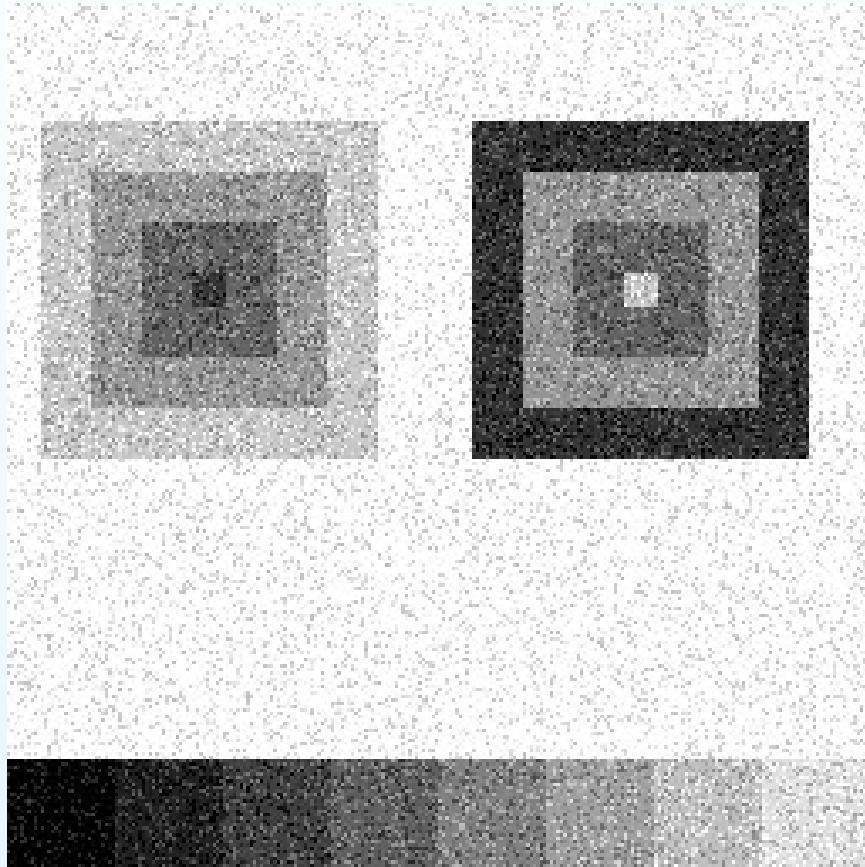
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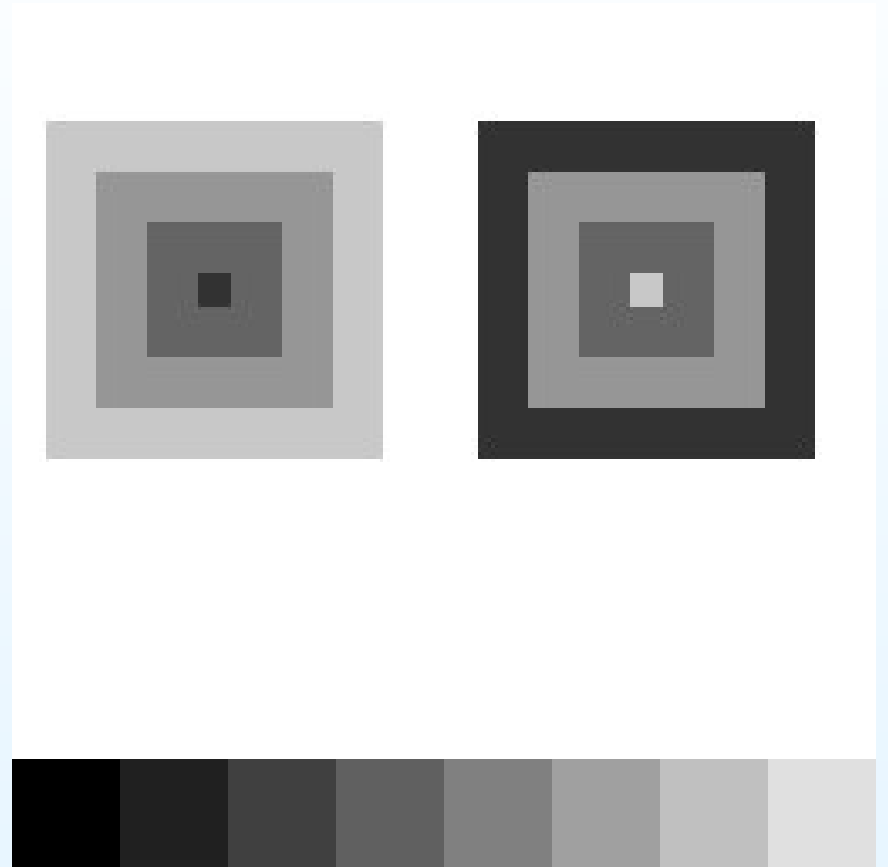
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Conclusion: Isotropic diffusion operates like a weighted mean filter, eliminating noise but blurring contours.

Example

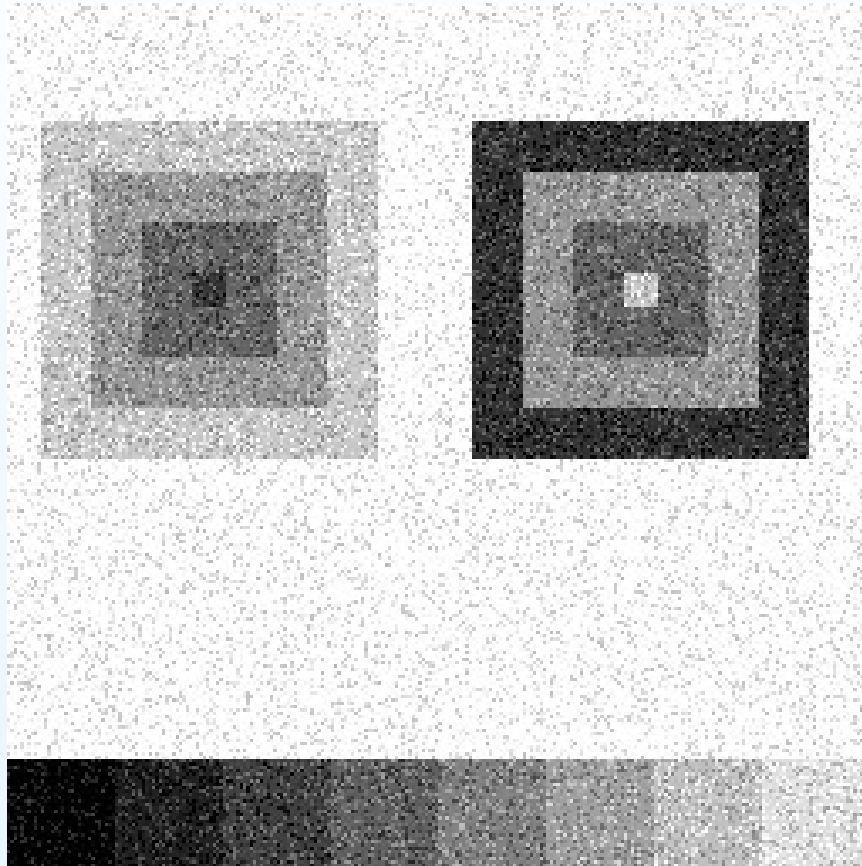


$$u_0 = u + n = u(., 0)$$

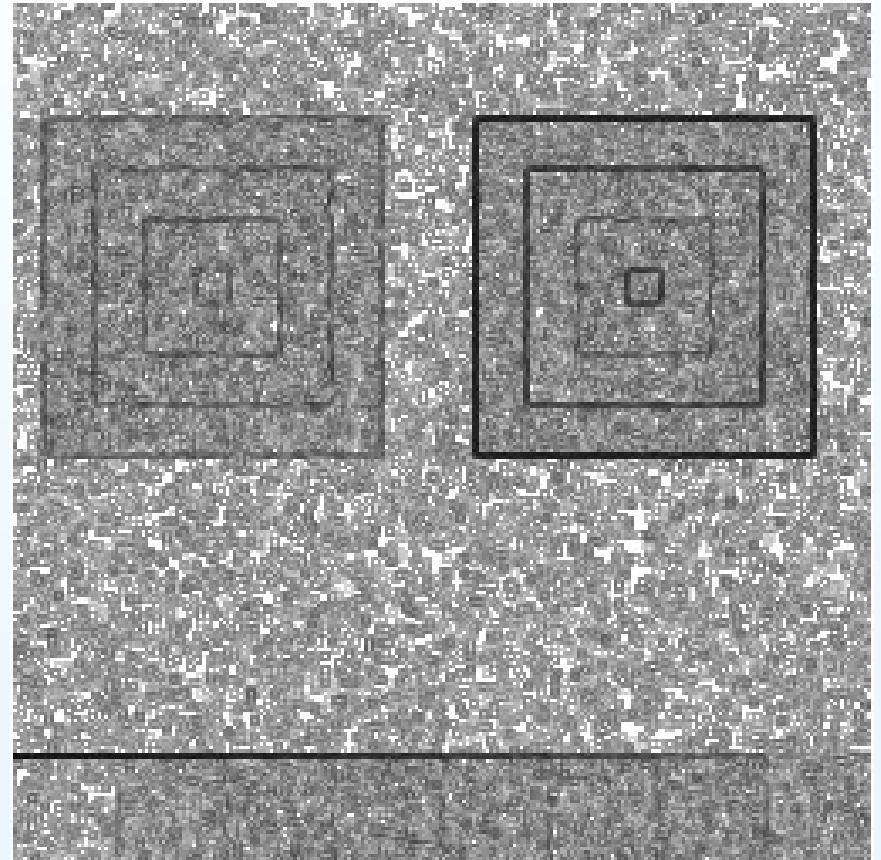


u

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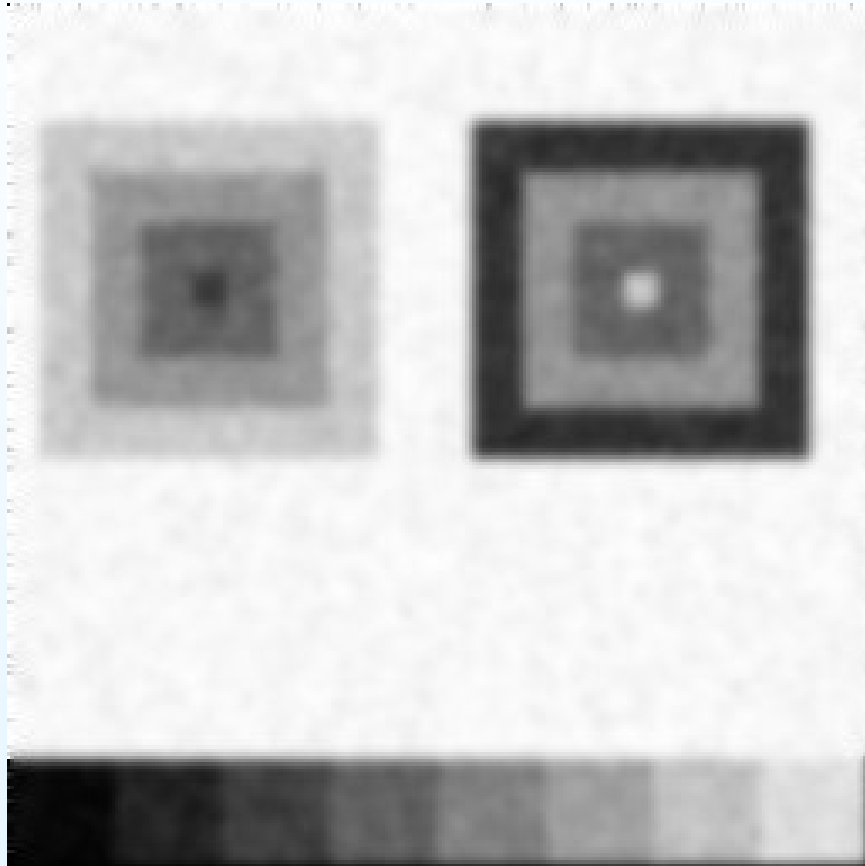


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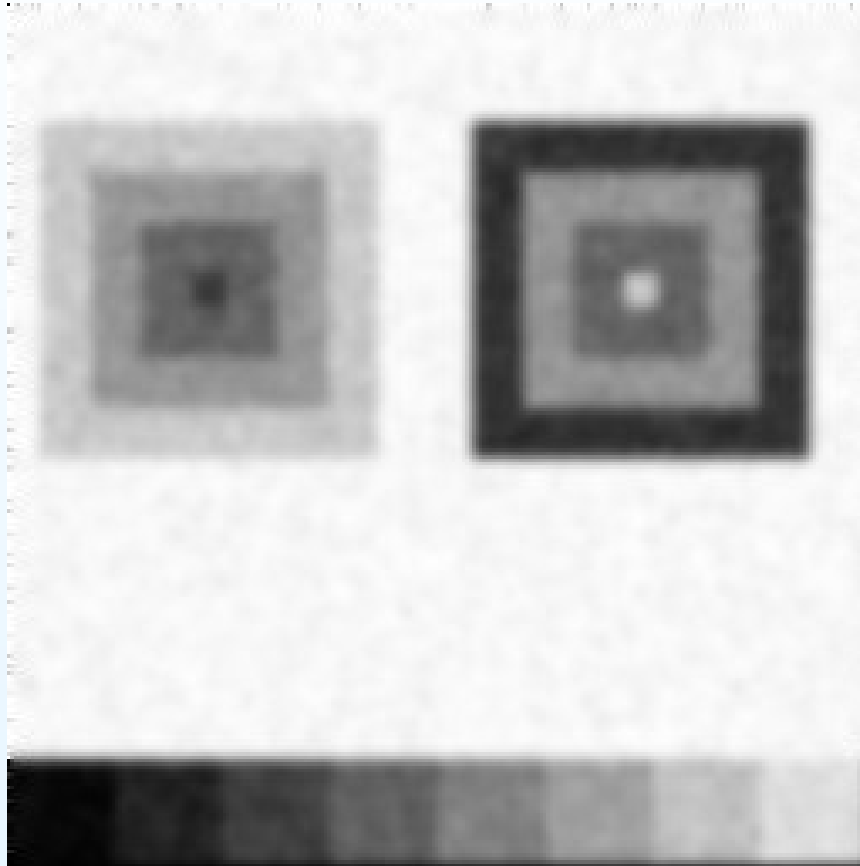
$$\|\nabla u_0\|$$

Example (cont.)

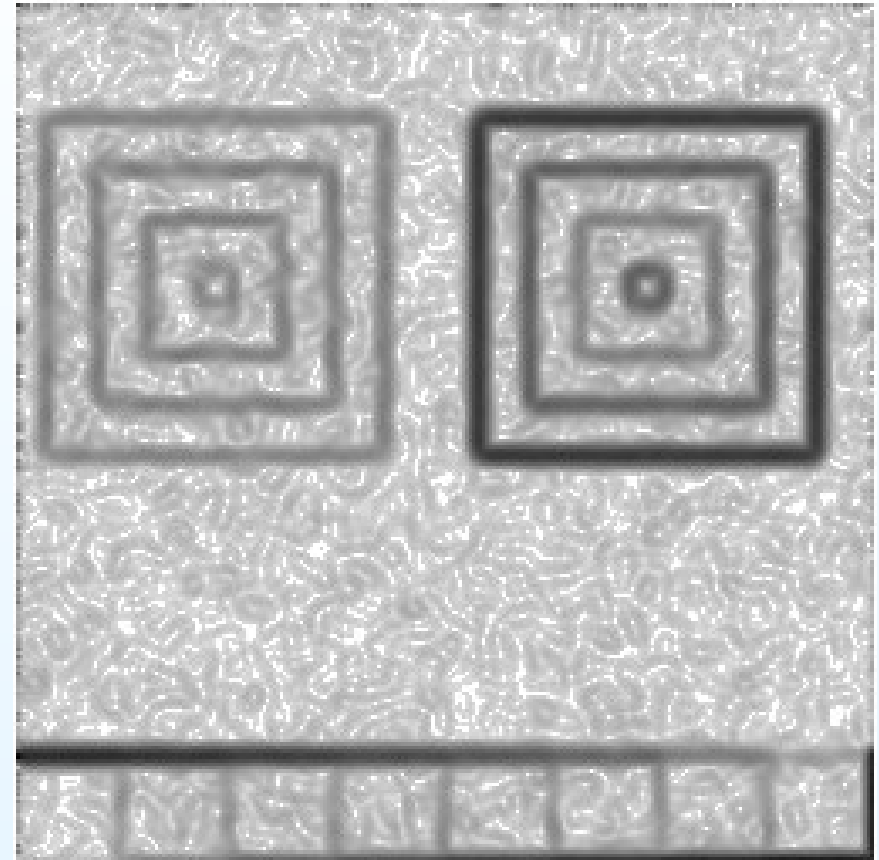


$$G_\sigma \star u_0 = u(\cdot, \sigma^2/2)$$

Example (cont.)

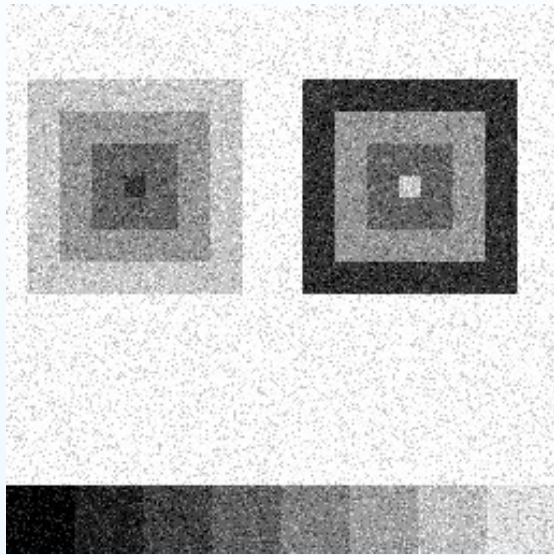


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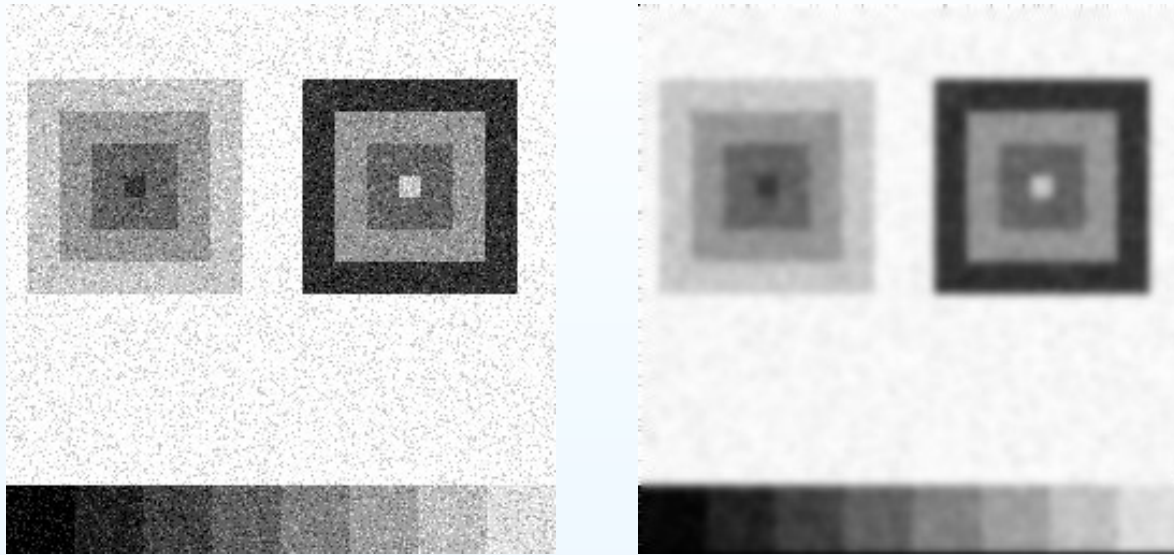


$$\|\nabla u(\cdot, \sigma^2/2)\|$$

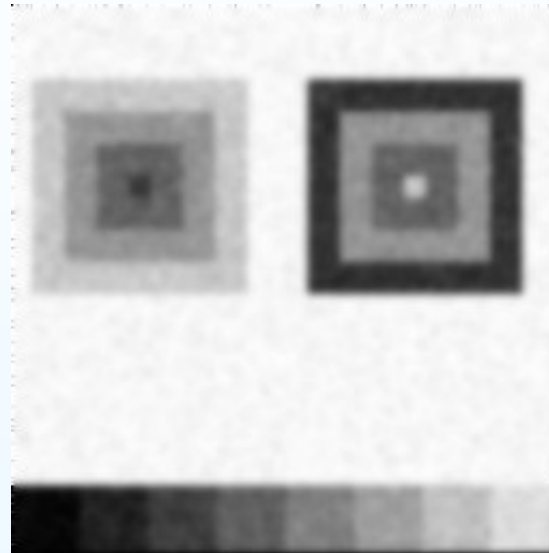
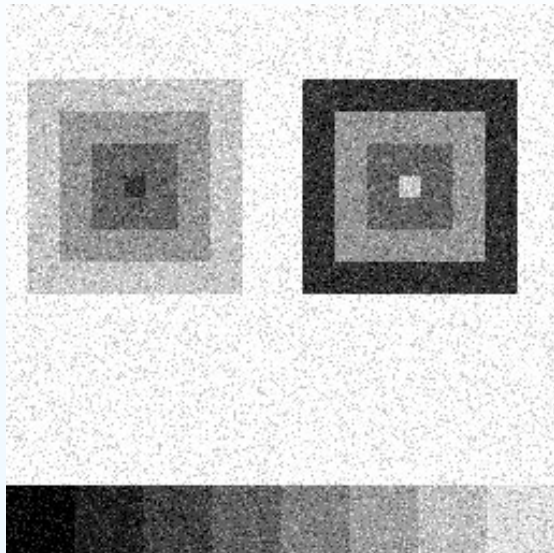
Linear scale space, for $t = 0$



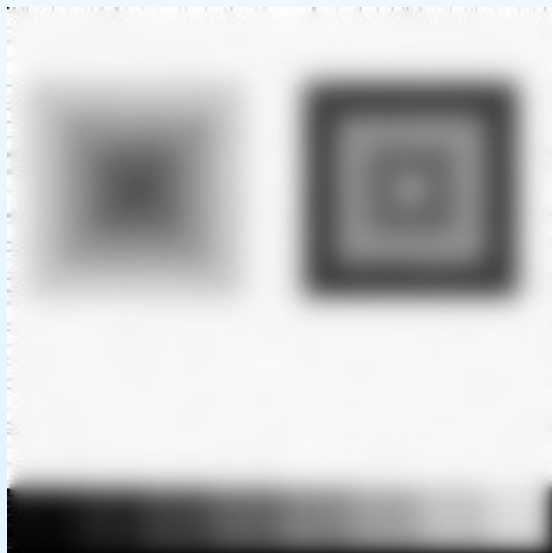
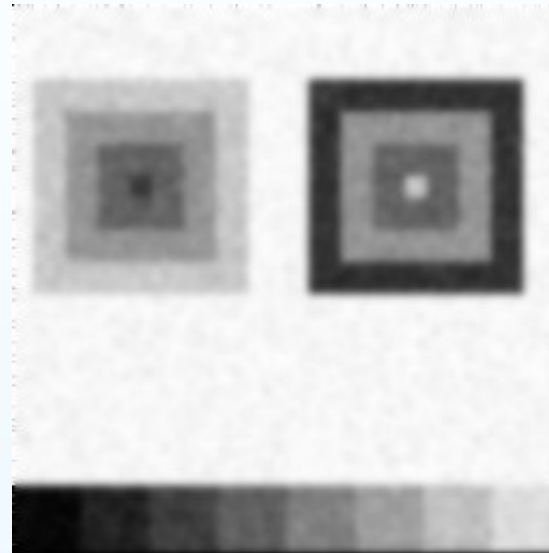
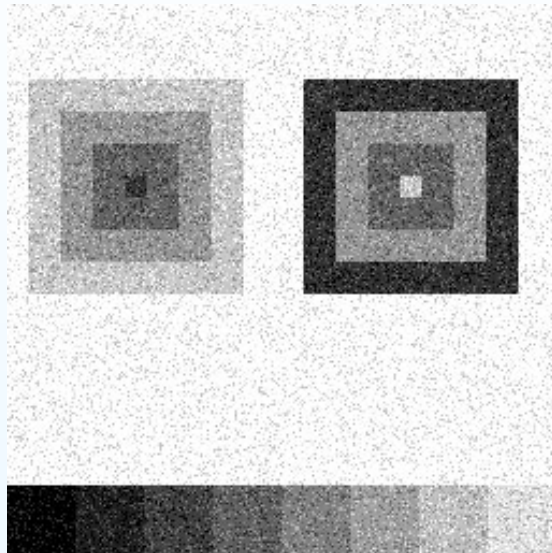
Linear scale space, for $t = 0, 20$



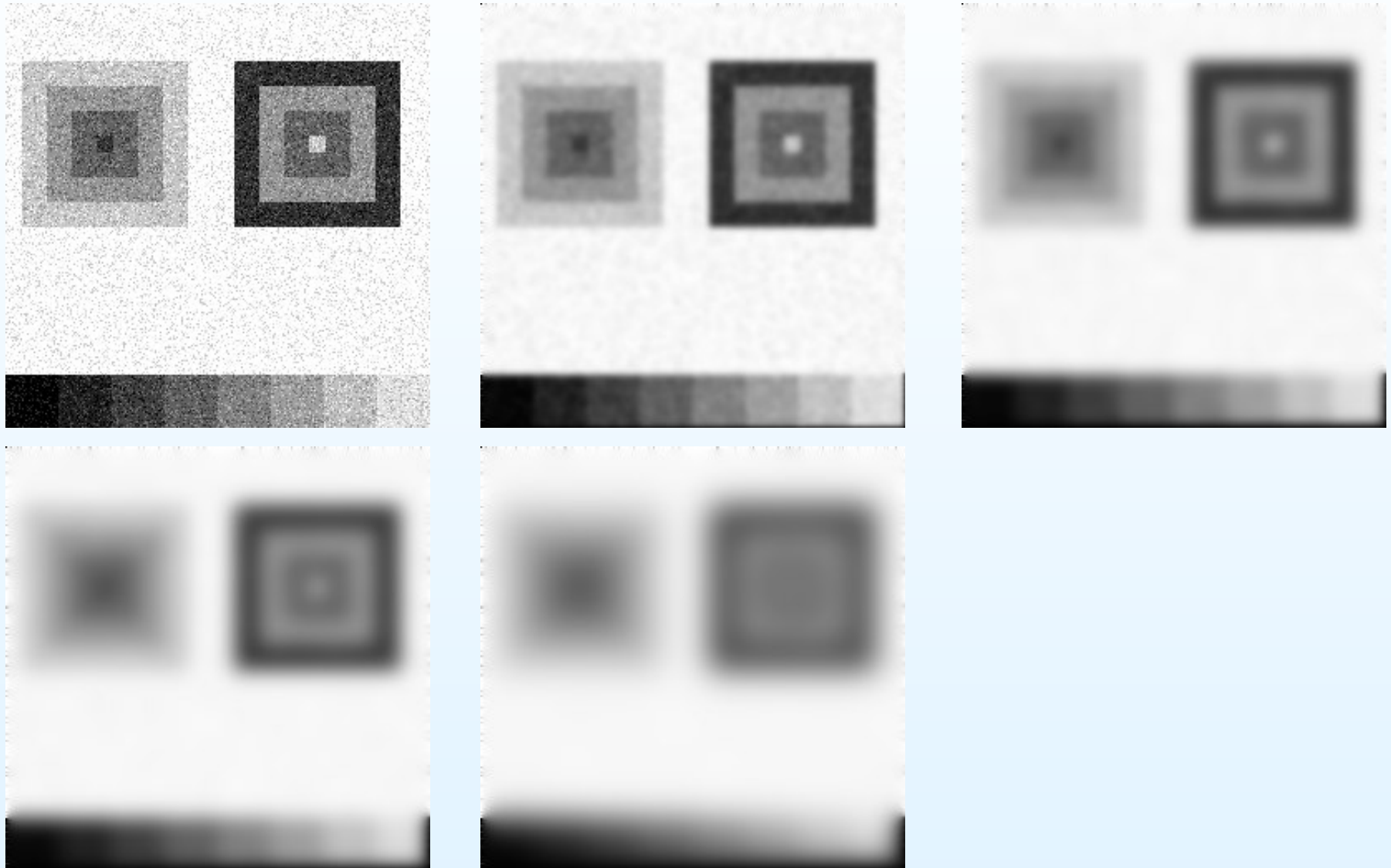
Linear scale space, for $t = 0, 20, 100$



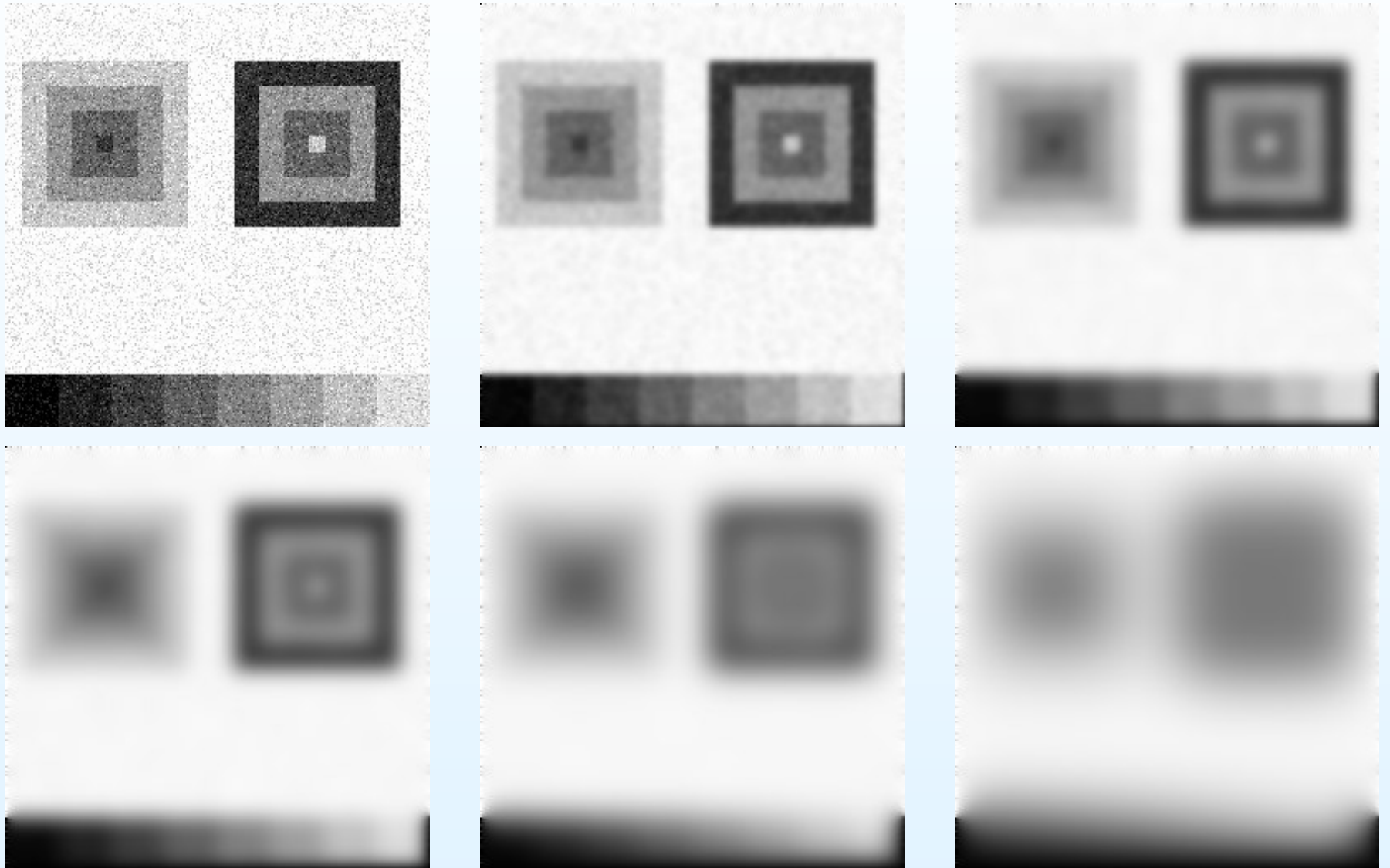
Linear scale space, for $t = 0, 20, 100, 200$



Linear scale space, for $t = 0, 20, 100, 200, 500$



Linear scale space, for $t = 0, 20, 100, 200, 500, 2000$



Model of MALIK and PERONA (1987)

Idea: No diffusion across the boundaries, *i.e.* diffuse only in the direction of the gradient ∇u when $\|\nabla u\|$ is large.

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The proposed PDE writes:

$$\frac{\partial u}{\partial t} = \operatorname{div} \left(g(|\nabla u|) \nabla u \right) \quad \text{with } u(x, 0) = u_0(x),$$

with $g(r)$, $r \geq 0$, a non increasing function and $g(0) = 1$.
An often used diffusion coefficient is

$$g(r) = \frac{1}{1 + (r/\lambda)^2}, \quad \lambda \in \mathbb{R}_+^*.$$

Interpretation

Suppose u is a smooth function and let (e_1, e_2) be the canonical basis of \mathbb{R}^2 , then

$$H_u(x, y) = \begin{pmatrix} u_{xx}(x, y) & u_{xy}(x, y) \\ u_{xy}(x, y) & u_{yy}(x, y) \end{pmatrix} \text{ is the } \textit{Hessian matrix}$$

and $\Delta u(x, y) = \text{Tr}(H_u(x, y))$, $\nabla u(x, y) = \begin{pmatrix} u_x(x, y) \\ u_y(x, y) \end{pmatrix}$.

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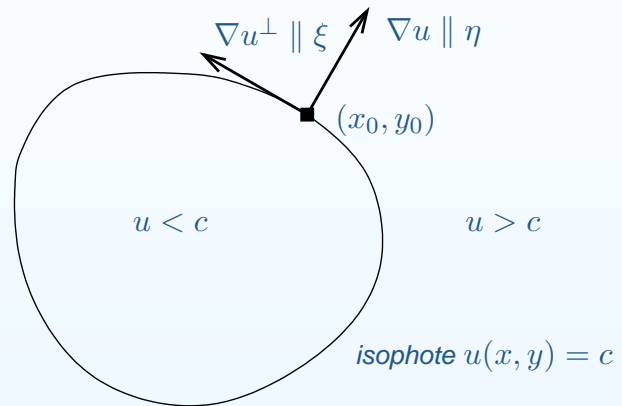
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For η, ξ in \mathbb{R}^2 we write

$$u_\eta \triangleq \frac{du}{d\eta} = \nabla u^t \eta \quad \text{and} \quad u_{\eta\xi} \triangleq d^2u(\eta, \xi) = \eta^t H_u \xi.$$

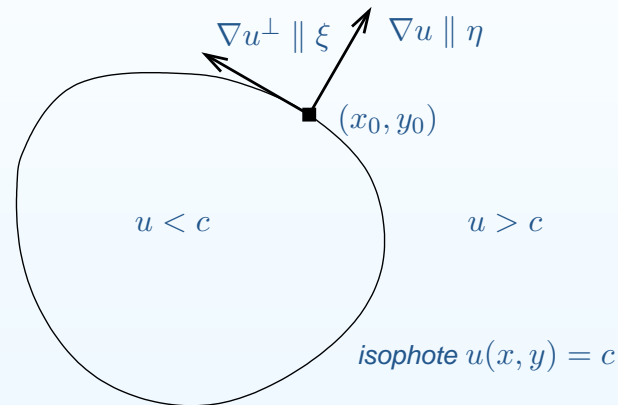
Interpretation (cont.)

The set $I_c = \{(x, y) / u(x, y) = c\}$ is an *isophote* :



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In $(x_0, y_0) \in I_c$ define the local frame

$$(\eta, \xi)|_{(x_0, y_0)} = \left(\frac{\nabla u}{|\nabla u|}, \frac{\nabla u^\perp}{|\nabla u|} \right)|_{(x_0, y_0)}$$

Then $u_\xi = \nabla u^t \xi = 0$ and $u_\eta = \nabla u^t \eta = |\nabla u|$.

Interpretation (cont.)

In each $(x, y) \in I_c$:

$$\operatorname{div} \left(\frac{\nabla u}{|\nabla u|} \right) = \frac{1}{|\nabla u|} (\Delta u - d^2 u(\eta, \eta)) = \frac{1}{|\nabla u|} d^2 u(\xi, \xi) .$$

and $\Delta u = d^2 u(\eta, \eta) + d^2 u(\xi, \xi) = u_{\eta\eta} + u_{\xi\xi} .$

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The MALIK-PERONA model writes

$$u_t = (g(u_\eta) + u_\eta g'(u_\eta)) u_{\eta\eta} + g(u_\eta) u_{\xi\xi} .$$

Interpretation of the MALIK-PERONA model

$$u_t = G'(u_\eta)u_{\eta\eta} + g(u_\eta)u_{\xi\xi},$$

where $G(r) = rg(r)$ and $G'(r) = g(r) + rg'(r)$.

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- $G'(u_\eta) < 0$ inverse, unstable, diffusion in the direction of ∇u ;

A limiting case is the **total variation minimization** pde :

$$\frac{\partial u}{\partial t} = \operatorname{div} \left(\frac{\nabla u}{|\nabla u|} \right),$$

here $g(r) = 1/r$, we recall that for u regular $TV(u) = \int_{\Omega} \|\nabla u\|$.

Variational approach

Idea: For $u_0 = Au + n$ characterize u to be the minimum of

$$E(u) = \frac{1}{2} \|u_0 - Au\|^2 + \lambda \int_{\Omega} \Phi(|\nabla u|) dx .$$

i.e. data fidelity term + regularization

Here λ is a “**scale**” parameter.

Most common examples:

- $\Phi(|\nabla u|) = |\nabla u|^2/2;$
- $\Phi(|\nabla u|) = |\nabla u|.$

Variational approach (cont.)

Compute the first variation δE of E and write a *gradient descent*.

$$u_t = A^*(u_0 - Au) + \lambda \operatorname{div} \left(\Phi'(|\nabla u|) \frac{\nabla u}{|\nabla u|} \right)$$

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If $\Phi(|\nabla u|) = |\nabla u|^2/2$, L^2 regularization

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If $\Phi(|\nabla u|) = |\nabla u|$, Total Variation regularization

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diffusion perpendicular to the gradient

Axiomatic approach

Idea: Formalize the properties of multiscale filters T_t .

- **[Causality]** $T_0 = Id$ and $\forall s < t, \exists T_{s,t} : T_t = T_{s,t} \circ T_s ;$
 \implies no creation of information

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- **[Local Maximum]** If $u(x) > v(x)$ in $B(x_0, r) \setminus \{x_0\}$, then, for all t and for h small enough: $(T_{t,t+h}u)(x_0) \geq (T_{t,t+h}v)(x_0)$;
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- **[Regularity]** For $Q(x) = \frac{1}{2}(x - x_0)^t A(x - x_0) + p^t(x - x_0) + c$, with $A^t = A$, $p \in \mathbb{R}^2$ and $c \in \mathbb{R}$ then there exists F :
$$\frac{\partial(T_{t,t+h}Q)}{\partial h}(x_0) = F(A, p, c, x_0, t),$$

with F continuous everywhere, except $p = 0$.
 \implies locally second order characteristics rule over T_t

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We call these the **[Natural]** properties of a filter.

Axiomatic approach (cont.)

Other desirable invariance properties of the filters T_t :

- **[Translation Invariance]** For $(\tau_\alpha u)(x) = u(x + \alpha)$:
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where λ is increasing in t (zooms influence the filter scale).

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- **[Contrast invariance]** For H continuous, nondecreasing:
$$T_t(H(u)) = H(T_t(u)) ;$$

Axiomatic approach: results

Definition: A family of operators $(T_t)_t$ is called **morphological** if **[Translation Invariance]** and **[Contrast invariance]** hold.

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All the **[Natural]**, **[Isotropic Invariant]** and **morphological** filters verify:

$$u_t = |\nabla u| G(\text{curv}(u), t)$$

with G a continuous, decreasing function w.r. to

$$\begin{aligned} \text{curv}(u) &= \text{div}(\nabla u / |\nabla u|) \\ &= \text{curvature of the isophote } I_c . \end{aligned}$$

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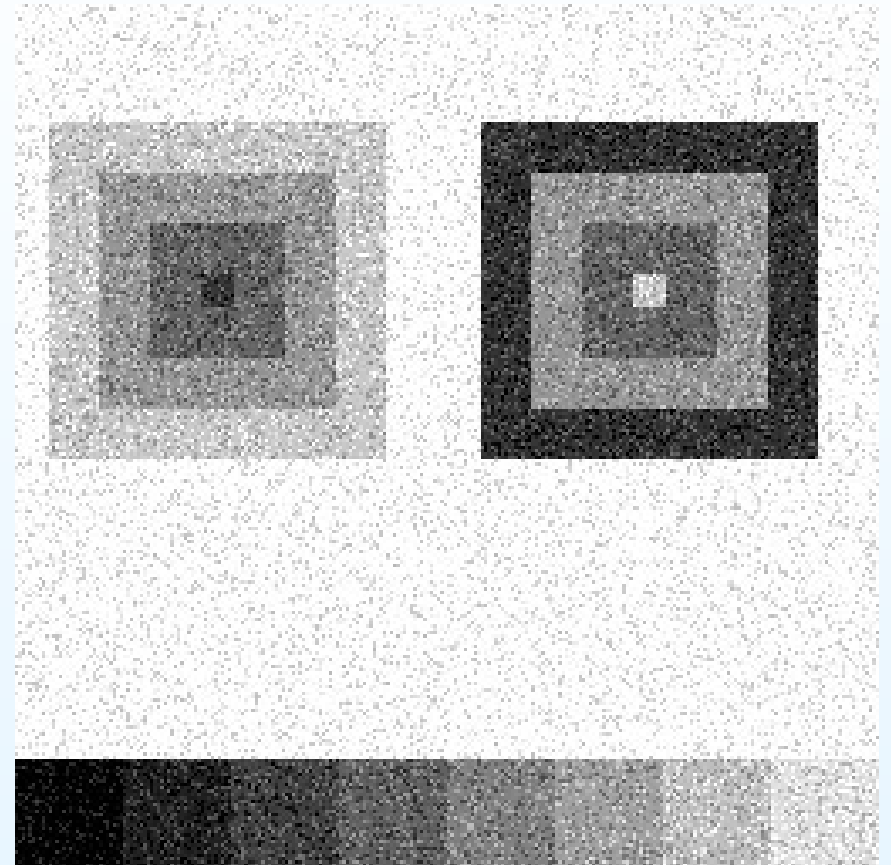
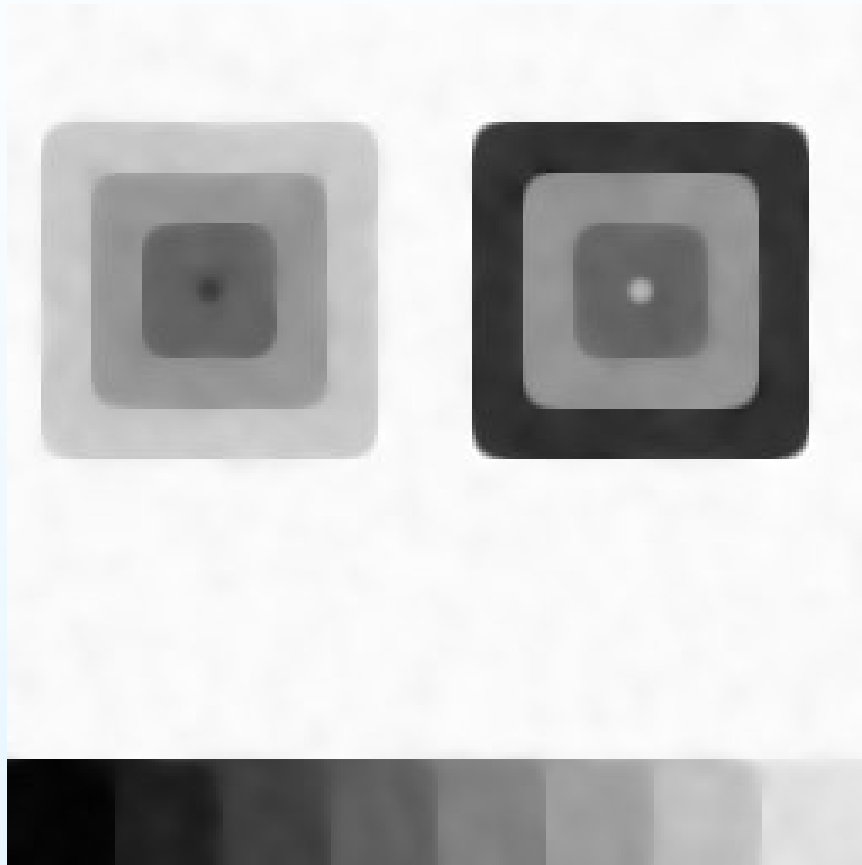
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If $G(\text{curv}(u), t) = \text{curv}(u)$ we obtain the **mean curvature motion** :

$$u_t = |\nabla u| \text{div} \left(\frac{\nabla u}{|\nabla u|} \right) = u_{\xi\xi}$$

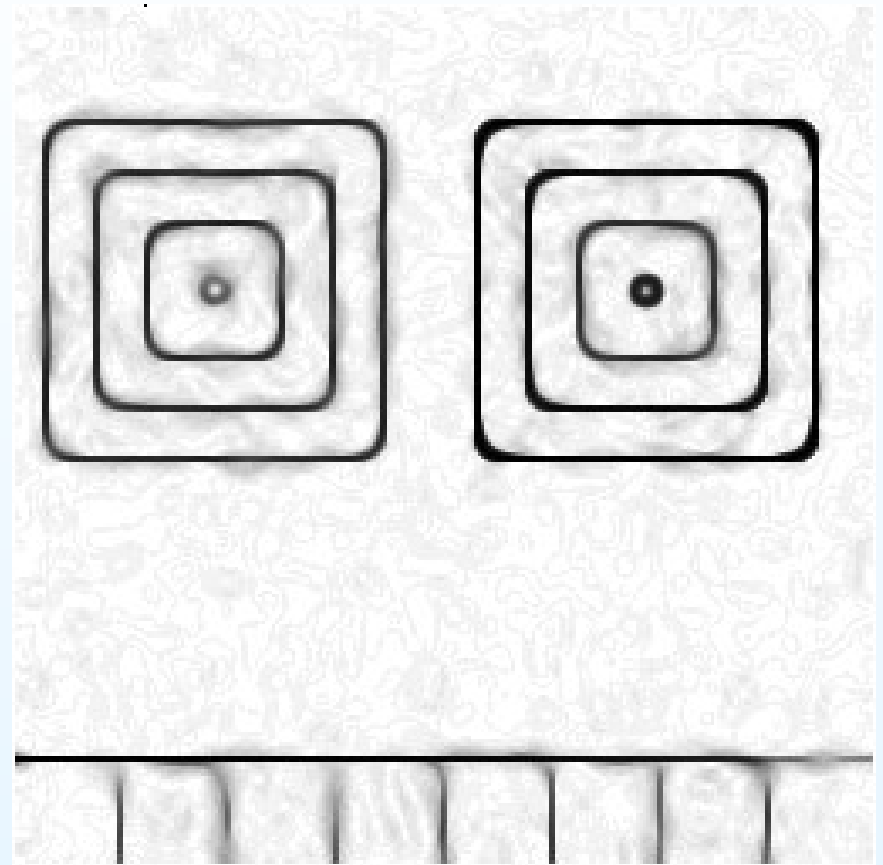
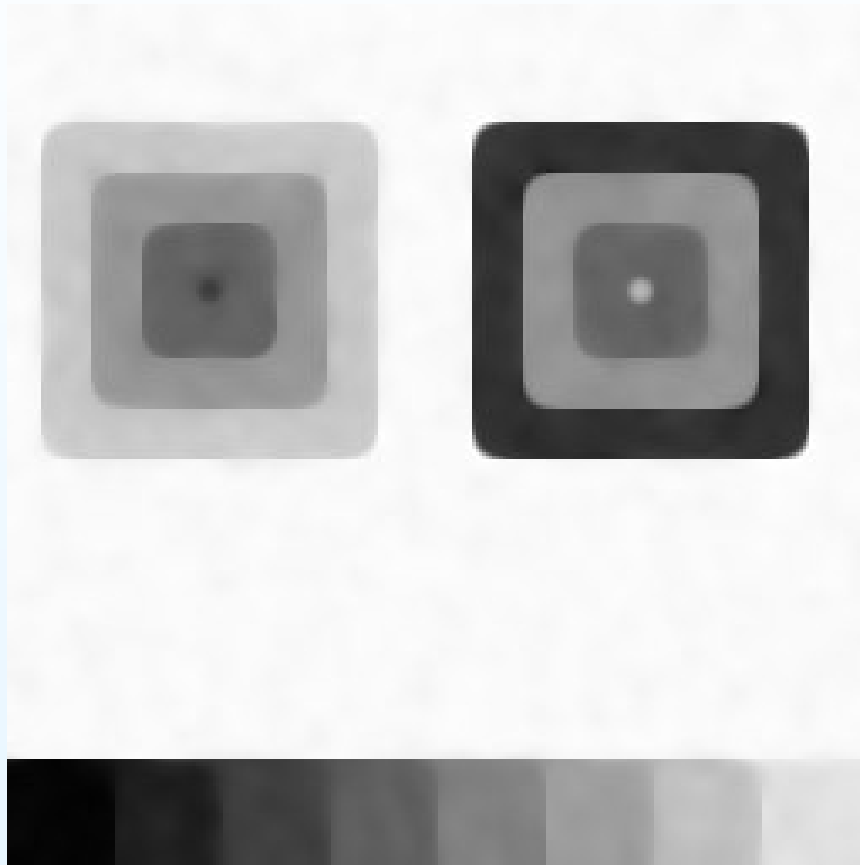
Example of mean curvature motion



$$\frac{\partial u}{\partial t} = |\nabla u| \operatorname{div} \left(\frac{\nabla u}{|\nabla u|} \right) = u_{\xi\xi}$$

original

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$$\|\nabla u\|$$

Axiomatic approach: results (cont.)

If we replace [Isotropic Invariance] by [Affine Invariance]
a unique pde is obtained

$$u_t = |\nabla u| \operatorname{curv}(u)^{1/3} = (u_y^2 u_{xx} + u_x^2 u_{yy} - 2u_x u_y u_{xy})^{1/3}.$$

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Thus there exists a unique **affine morphological scale space**.

- In the preceding u is a weak solution in the sense of *viscosity solutions*.
- It is difficult/impossible to obtain numerical schemes verifying all the desired properties, *e.g.*
 - rotation invariance on a rectangular grid;
 - contrast invariance with finite difference schemes;

Morphological operators

Idea: Mathematical morphology shows that monotone increasing and translation invariant operators acting on continuous functions can be written:

$$(T_t u)(x) = \inf_{B \in \mathcal{B}_t} \sup_{y \in x+B} u(y) \quad (1)$$

or

$$(T_t u)(x) = \sup_{B \in \mathcal{B}_t} \inf_{y \in x+B} u(y) \quad (2)$$

with \mathcal{B}_t , the sets of **structuring elements**, a family of convex subsets of \mathbb{R}^2 .

For $\mathcal{B}_t = B(O, t)$, (1) defines a dilation and (2) an erosion.

Morphological operators (cont.)

Theorem: Consider the morphological operator C_t defined by

$$(C_t u)(x) = \frac{1}{2} \left(\inf_{\theta \in [0, \pi[} \sup_{x + S(\theta, 2t)} u(y) + \sup_{\theta \in [0, \pi[} \inf_{x + S(\theta, 2t)} u(y) \right)$$

with $S(\theta, 2t)$ a segment of center 0, length $4\sqrt{t}$ and direction $\theta \in [0, \pi[$. Then

$$\lim_{m \rightarrow \infty} C_{\frac{t}{m}}^m u = u$$

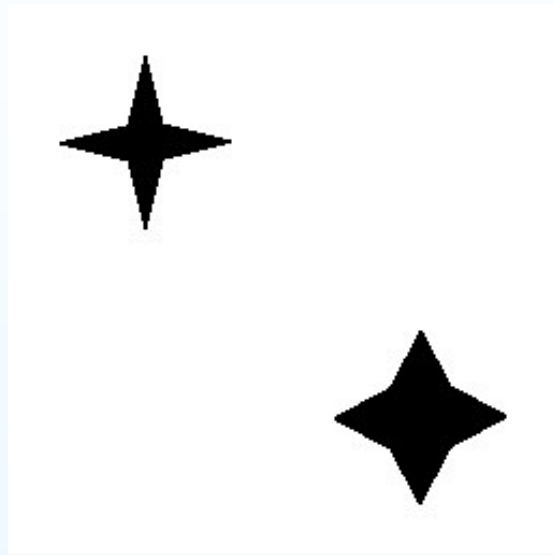
uniformly in t , to the viscosity solution of the *mean curvature motion*

$$u_t = |\nabla u| \operatorname{curv}(u) .$$

Thus by iterating morphological operators we obtain $u(., t)$.

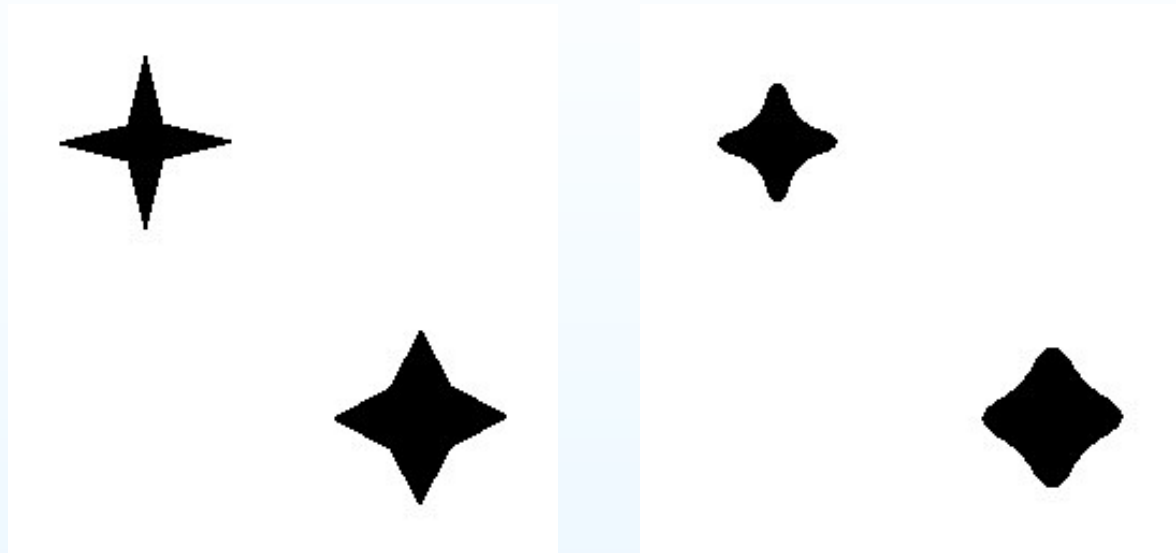
MCM scale space, for 0

iterations



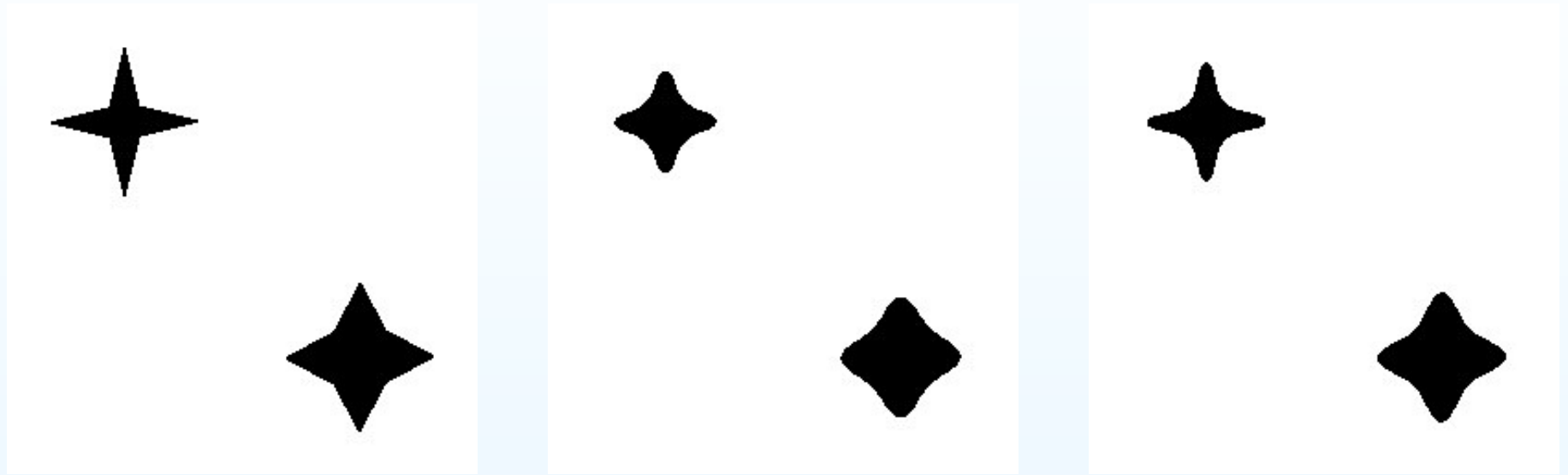
MCM scale space, for 0 , 20

iterations



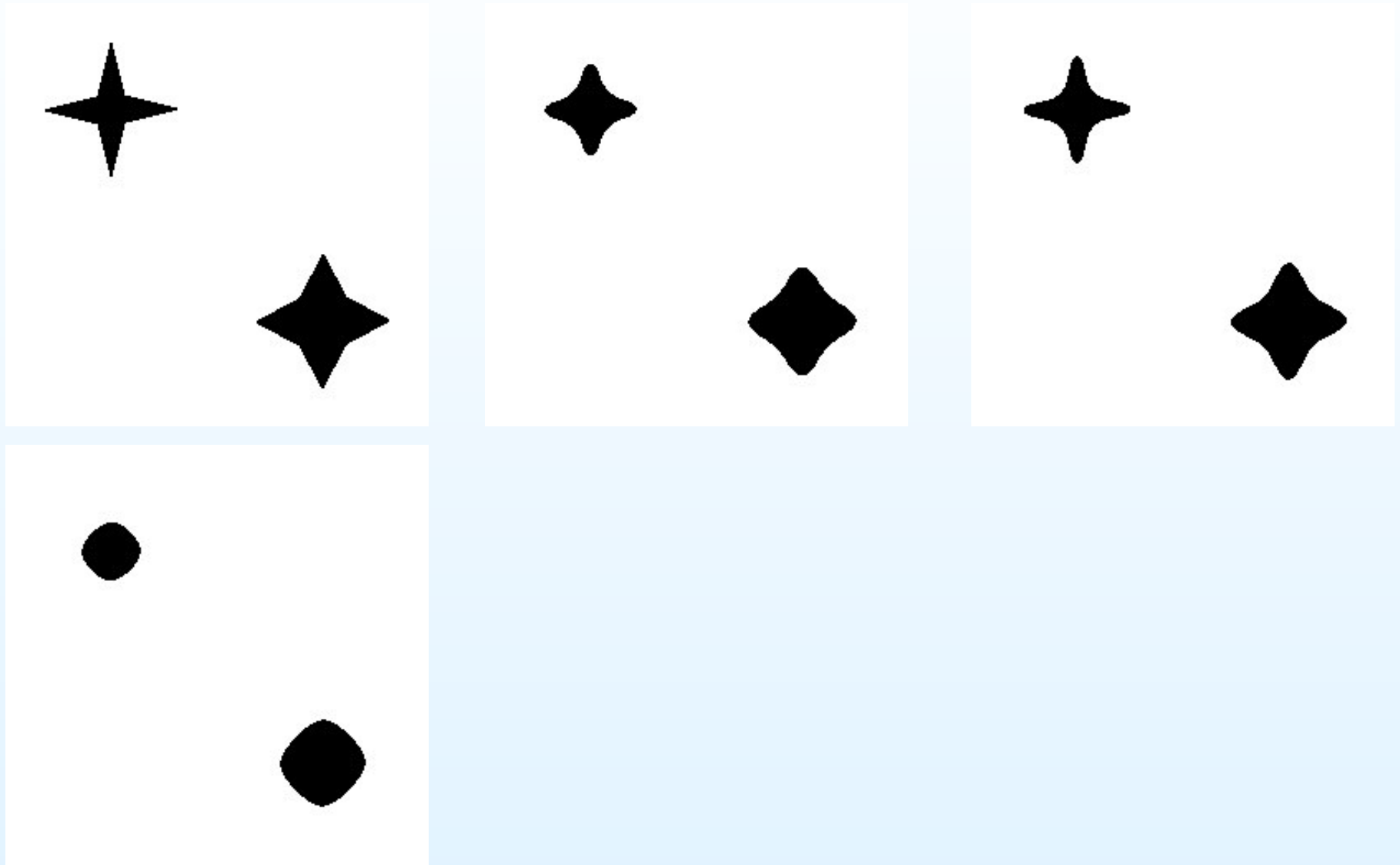
MCM scale space, for 0 , 20 , 40

iterations



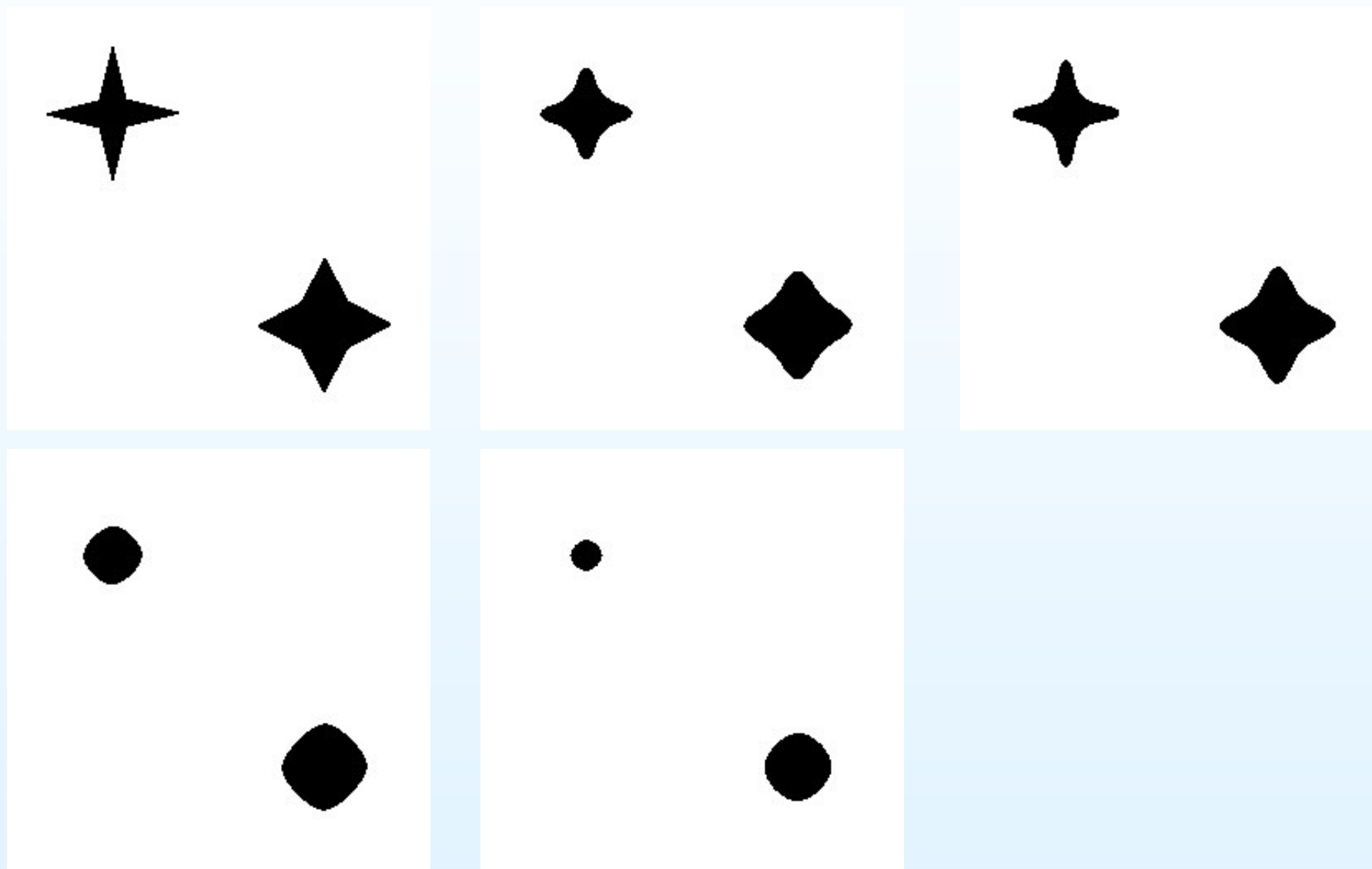
MCM scale space, for 0 , 20 , 40 , 140

iterations

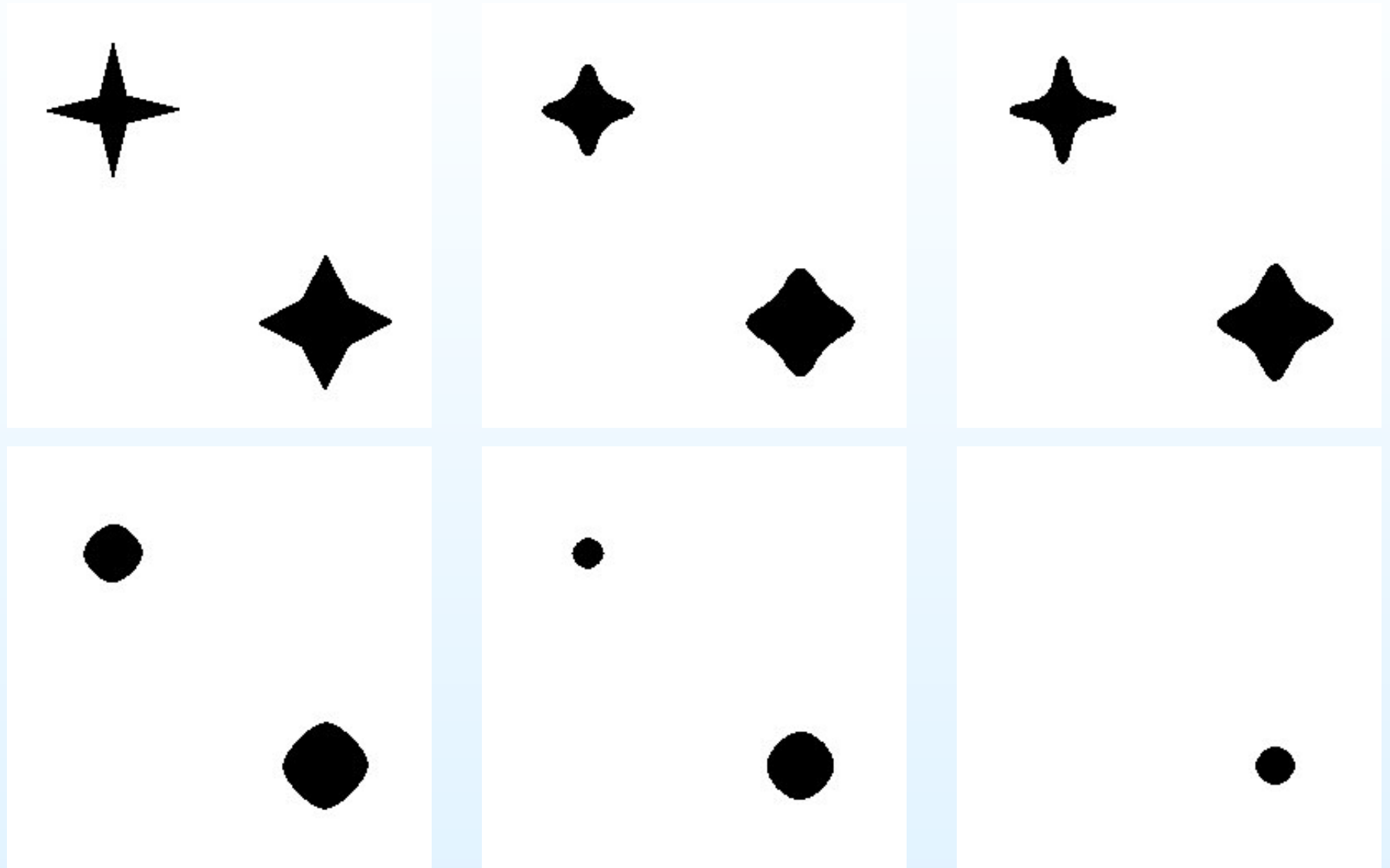


MCM scale space, for 0 , 20 , 40 , 140 , 300

iterations



MCM scale space, for 0 , 20 , 40 , 140 , 300 , 500 iterations



Geometric scheme I

Idea: Decompose an image into **lower level sets**

$$\chi_\lambda(u) = \{x \in \mathbb{R}^2; u(x) \leq \lambda\}$$

or **upper level sets**

$$\chi^\mu(u) = \{x \in \mathbb{R}^2; u(x) \geq \mu\} .$$

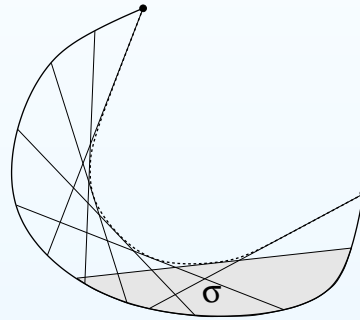
Each collection of planar sets is equivalent to the function u itself since one has the reconstruction formula

$$u(x) = \sup\{\lambda; x \in \chi_\lambda(u)\} = \inf\{\mu; x \in \chi^\mu(u)\}.$$

Then evolve the **level curves** and **reconstruct..**

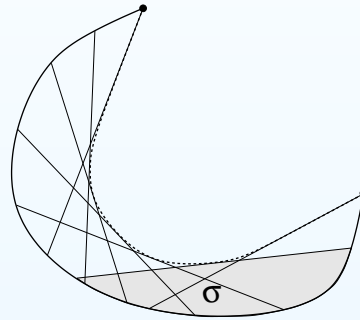
Geometric scheme I (cont.)

We define **affine erosion** of a curve C to be the envelope of cords delimiting a region of area σ :



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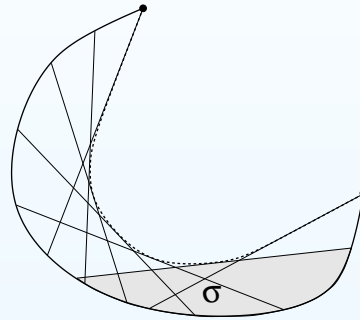


The evolution of C follows
$$\frac{\partial \vec{C}}{\partial t} = \kappa^{1/3} \vec{N}$$

Here κ is the local curvature at a point of C and \vec{N} the normal vector at this point.

Geometric scheme I (cont.)

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The evolution of C follows
$$\frac{\partial \vec{C}}{\partial t} = \kappa^{1/3} \vec{N}$$

Here κ is the local curvature at a point of C and \vec{N} the normal vector at this point.

Now this is the restriction to the level curves of

$$u_t = |\nabla u| \text{curv}(u)^{1/3}$$

the unique morphological, affine invariant multiscale analysis.

Evolution



original



evolve+reconstruct



level lines



level lines

Evolution



original



evolve+reconstruct



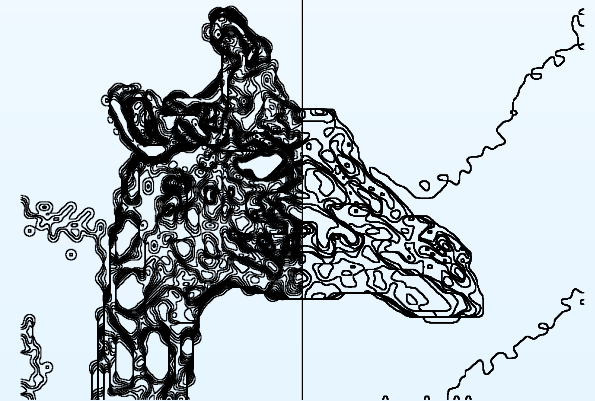
different schemes



level lines



level lines



scalar scheme
vs. geometric

Geometric scheme II

Idea: Integrate the **total variation minimization** pde

$$u_t = \operatorname{div} \left(\frac{\nabla u}{|\nabla u|} \right)$$

over the upper/lower level sets χ and with the **Coarea formula**:

$$\int_{\chi} u_t dx = \int_{\chi} \operatorname{div} \left(\frac{\nabla u}{|\nabla u|} \right) dx = \int_{\partial\chi} \frac{\nabla u}{|\nabla u|} \cdot \vec{N} dl = \mathcal{P}(\chi)$$

where \mathcal{P} = perimeter of χ .

Thus we will only modify the **level** not the **set**
by addition or subtraction of $\Delta t \mathcal{P}(\chi) / |\chi|$.

Geometric scheme II (cont.)

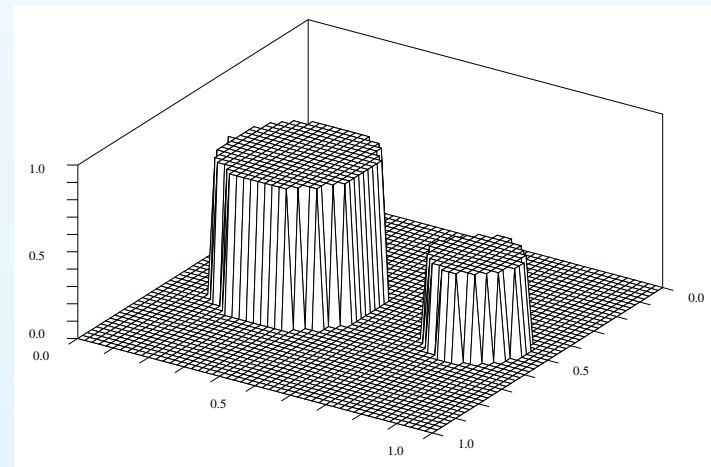
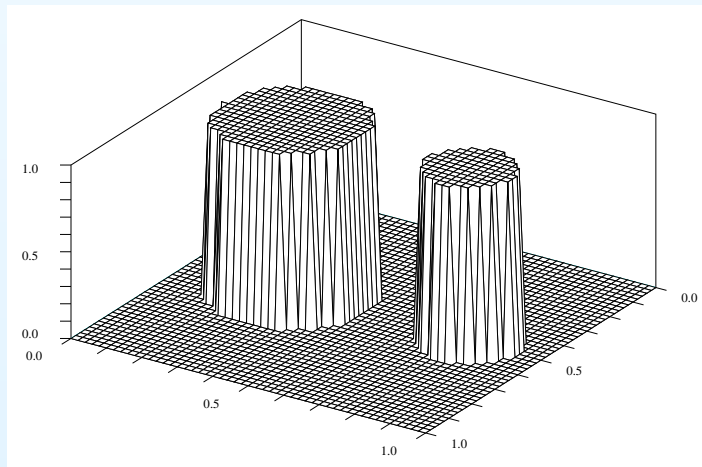
Consider discs $D_1(r_1)$ and $D_2(r_2)$ with $r_1 < r_2$.

Then $\chi^1 = \{x/u(x) \geq 1\} = D_1 \cup D_2$ and for small t :

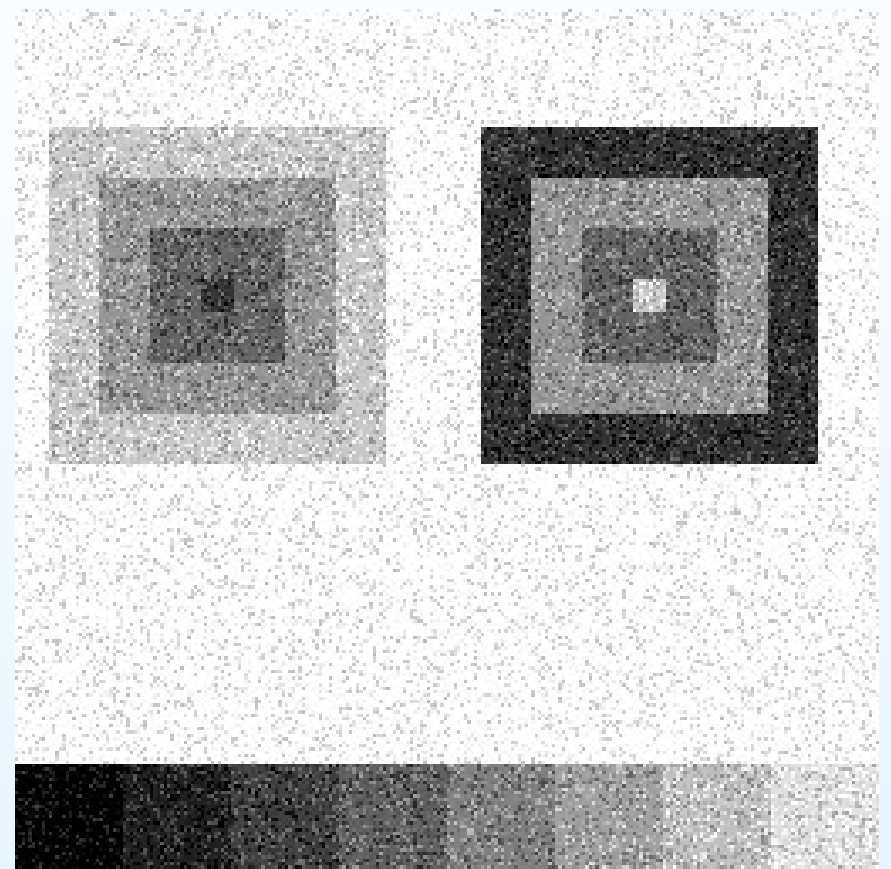
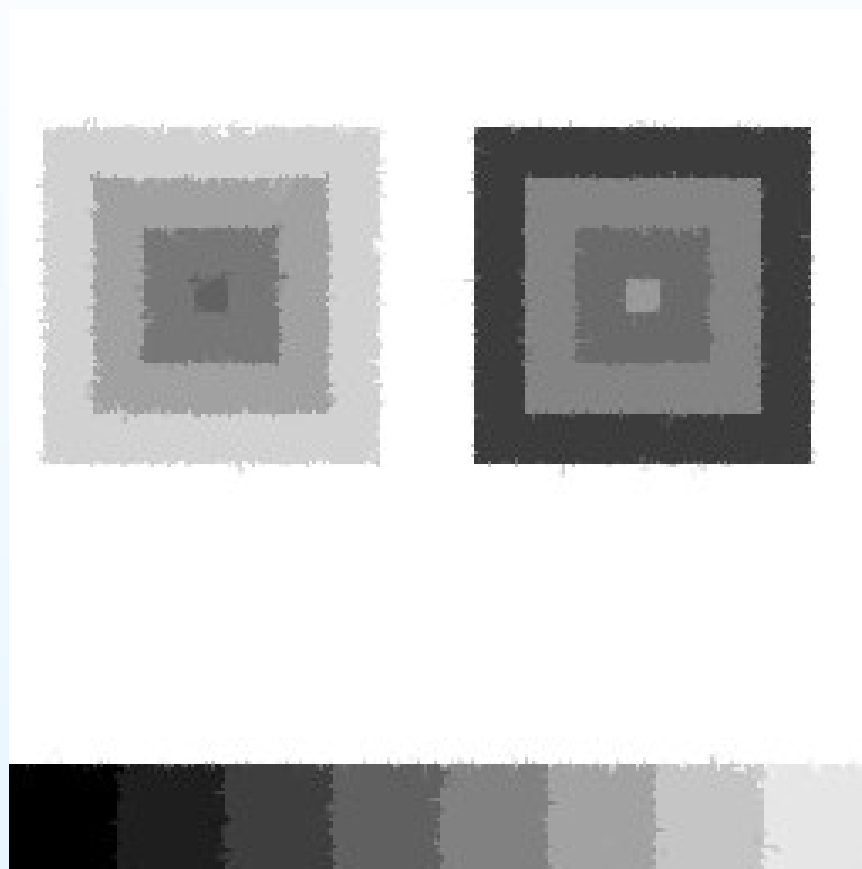
$$\forall x \in D_1 : u(t, x) = u(x) - t \frac{\mathcal{P}(\partial D_1)}{|D_1|} = 1 - \frac{2t}{r_1} < 1 ,$$

$$\forall x \in D_2 : u(t, x) = u(x) - t \frac{\mathcal{P}(\partial D_2)}{|D_2|} = 1 - \frac{2t}{r_2} < 1 ,$$

$$\forall x \in \Omega \setminus (D_1 \cup D_2) : u(t, x) = u(x) = 0 .$$



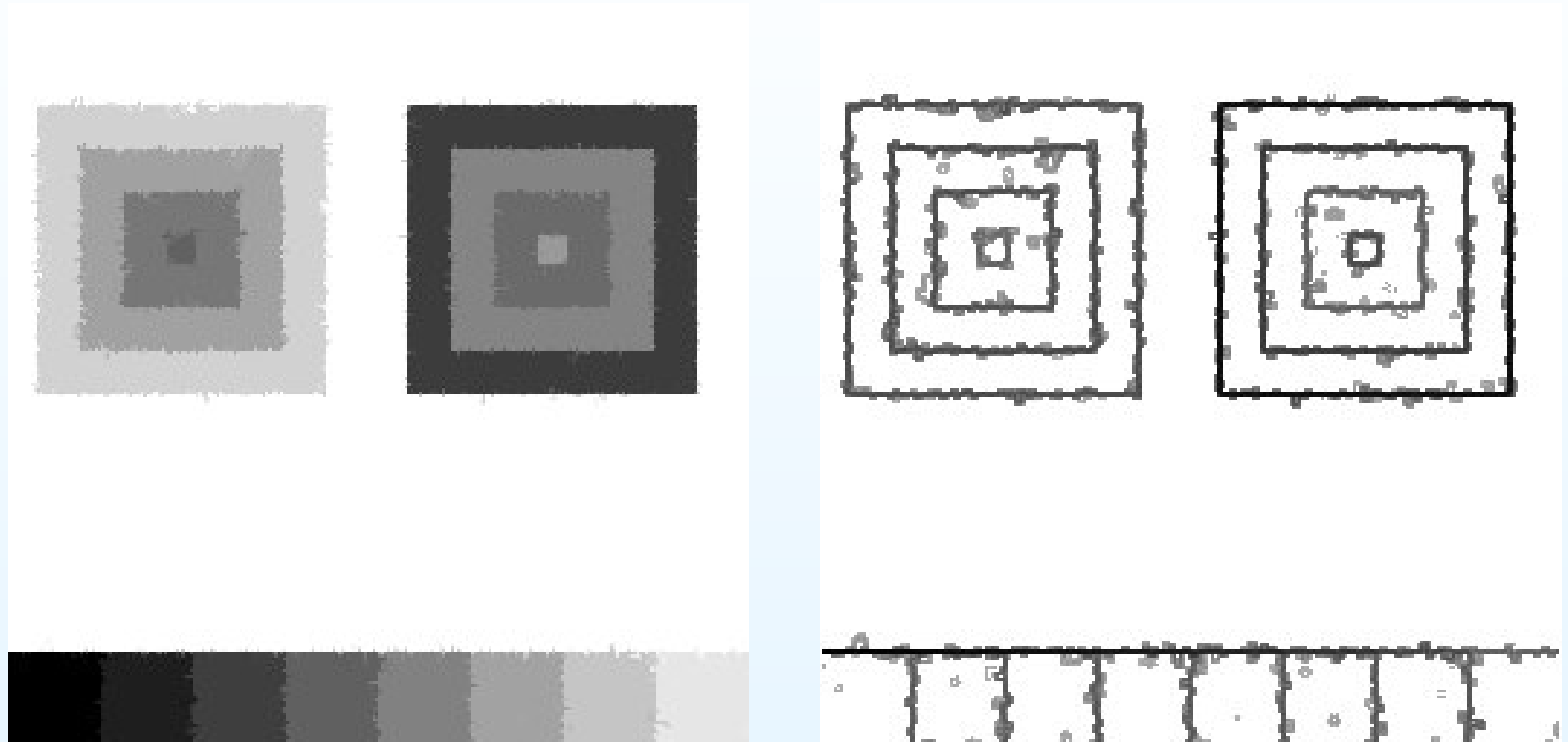
Geometric scheme II (cont.)



$$\frac{\partial u}{\partial t} = \operatorname{div} \left(\frac{\nabla u}{|\nabla u|} \right)$$

original

Geometric scheme II (cont.)



$$\frac{\partial u}{\partial t} = \operatorname{div} \left(\frac{\nabla u}{|\nabla u|} \right)$$

$$\|\nabla u\|$$

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