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Biologically Inspired Multi-Scale Image Analysis

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TU/e, Department of Biomedical Engineering

ter Haar Romeny, Neuroinformatics 2004

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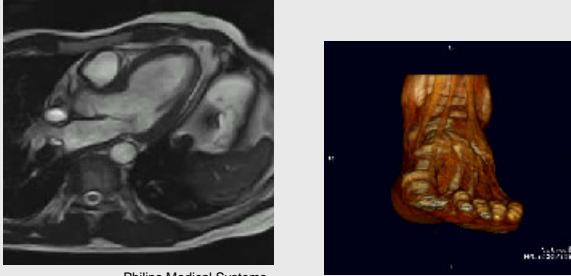
Medical imaging is big business:

- 1/3 of hospital's equipment is for medical imaging
- 80% of all diagnoses are done on images
- 800 bed hospital: 10 Terabyte/year, stored 10 yrs
- Sector grows steadily by 10% per year
- GE, Philips, Siemens: billions of dollars markets
- Philips Medical Systems: 22% of company turnover

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Trend: Higher resolution (space & time), more slices



Philips Medical Systems

Vital Images
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Radiological Society of North America: 65.000 participants
European Congress of Radiology: 13.000 participants



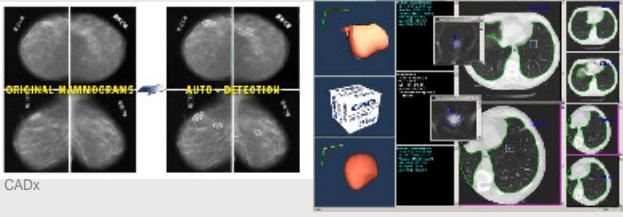
"Imagine" exhibit

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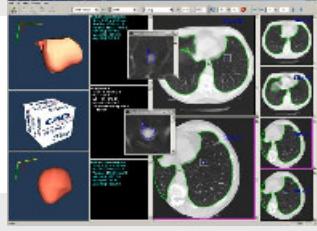
Computer-aided diagnosis

Mammography:



CADx

X-Thorax:



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Computer-Aided Diagnosis

The challenge



How do we do it?

*If I live Mackay
Bey Doolin, The forest has eyes*

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Multi-Scale Image Analysis




Biologically inspired computer vision
→ **bio-mimicking**

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"Scale-Space Theory in Computer Vision" Conference Series



Utrecht, 1997
Corfu, 1999
Vancouver, 2001
Isle of Skye, 2003

Hofgeismar, 6-10 April 2005
www.scalespace.org

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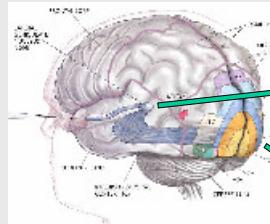
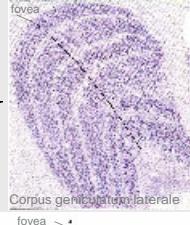
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The first stages of our visual system

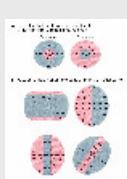

fovea
Corpus geniculatum laterale
fovea
Visual cortex : Accurate map

David Huel
Torsten Wiesel

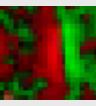
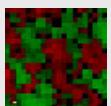
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Bio-mimicking visual perception


In the visual cortex the first analysis takes place

Receptive fields measure spatio-temporal structure

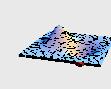
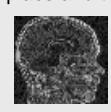
differential geometry

Model:
several orders
Gaussian derivatives

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The visual system measures changes in place and time: derivatives

1st order





2nd order





3rd order

$$\frac{1}{6\sqrt{2}+12\sqrt{3}} (-L_{xx}L_{yy} + L_x^2 + L_{yy} - L_xL_{xy} - 2L_{xx}L_{yy} + L_xL_{yy}) + \\ \frac{1}{4} (L_x^2L_{yy} - L_xL_{yy} + L_{yy}L_{yy}) + \frac{1}{4} (L_x^2L_{yy} - 2L_{yy} + L_x(L_{xx} + L_{yy})) = 0.1L_{xx}L_{yy} + 0.1L_{yy}^2 + \\ 0.1L_x^2L_{yy} - 0.1L_xL_{yy} + 0.1L_{yy}L_{yy} + 0.1L_xL_{yy} - 0.1L_{yy}L_{yy}$$

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Singular Value Decomposition:
Eigen-patches

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The formal mathematical method to solve the problems of ill-posed differentiation was given by Laurent Schwartz:

A regular tempered distribution associated with an image is defined by the action of a smooth test function on the image.

$$T_L = \int_{-\infty}^{\infty} L(x) \phi(x) dx$$

The derivative is:

$$\partial_{i_1 \dots i_n} T_L = (-1)^n \int_{-\infty}^{\infty} L(x) \partial_{i_1 \dots i_n} \phi(x) dx$$

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Fields Medal 1950 for his work on the theory of distributions.
Schwartz has received a long list of prizes, medals and honours in addition to the Fields Medal. He received prizes from the Paris Academy of Sciences in 1955, 1964 and 1972. In 1972 he was elected a member of the Academy. He has been awarded honorary doctorates from many universities including Humboldt (1960), Brussels (1962), Lund (1981), Tel-Aviv (1981), Montreal (1985) and Athens (1993).

Laurent Schwartz (1915 -)

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Mathematics	\Leftrightarrow	Smooth test function
Computer vision	\Leftrightarrow	Kernel, filter
Biological vision	\Leftrightarrow	Receptive field

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Very extensive feedback from primary visual cortex to LGN: RF tuning

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A conductivity coefficient (c) is introduced in the diffusion equation:

$$\frac{\partial L}{\partial s} = \vec{\nabla} \cdot c \vec{\nabla} L \quad c = c(L, \frac{\partial L}{\partial x}, \frac{\partial^2 L}{\partial x^2}, \dots)$$

It is a divergence of a flow. We also call $c \vec{\nabla} L$ the flux function. With $c = 1$ we have normal linear, isotropic diffusion: the divergence of the gradient flow is the Laplacian.

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Test on a small test image:

Note the preserved steepness of the edges with the strongly reduced noise.

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Geometry-driven diffusion: nonlinear scale-space

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In 3D:

$$\frac{\partial L}{\partial t} = \vec{\nabla} \cdot e^{-t/\tau} \vec{\nabla} L = \frac{1}{k^2} e^{-t/\tau} (\vec{\nabla}^2 (L_{xx} + L_{yy} + L_{zz}) - 2(L_x^2 L_{xx} + L_y^2 L_{yy} + L_z^2 L_{zz})) - 4(L_x L_z L_{yz} - L_y L_z L_{xz} + L_x L_y L_{xy})$$

E. Meijering, ISI
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Coherence enhancing diffusion

J. Weickert, 2001
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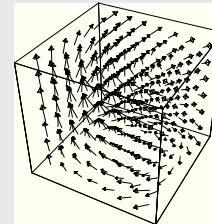
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Multi-scale optic flow



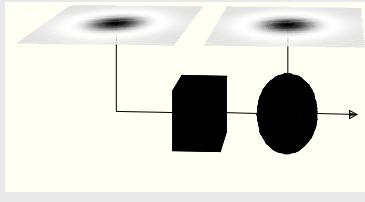
How can we find a dense optic flow field from a motion sequence in 2D and 3D?

Many approaches are taken:

- gradient based (differential);
- phase-based (frequency domain);
- correlation-based (area);
- feature-point (sparse data) tracking.

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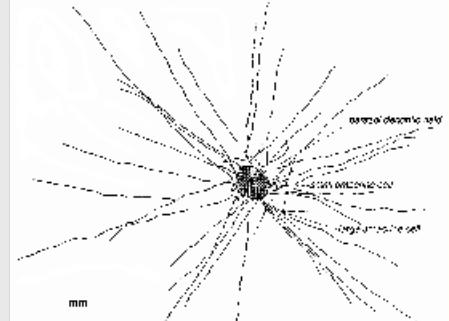


Neurons act as temporal coincidence detectors

This leads to a redundant representation, all velocities and directions are measured at all scales.

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Amacrine cells are found next to ganglion cell bodies

Similar RF pairs are present in both eyes for disparity detection

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Multi-scale optic flow constraint equation:

For scalar images: $\mathcal{L}_{\vec{v}} F(g) = \vec{\nabla} F \cdot \vec{v}$

For density images: $\mathcal{L}_{\vec{v}} \rho = \rho \operatorname{Div} \vec{v} + \vec{v} \cdot \vec{\nabla} \rho = 0$

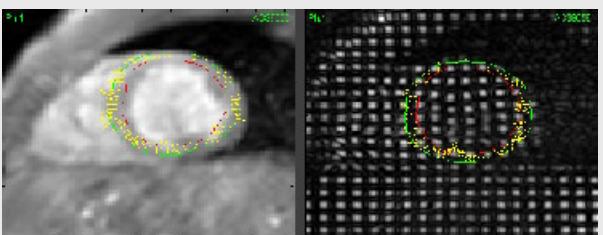
The velocity field is unknown, and this is what we want to recover from the data. We like to retrieve the velocity and its derivatives with respect to x, y, z and t.

We insert this unknown velocity field as a truncated Taylor series, truncated at first order.

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Exact quantitative analysis.
Optic flow: detailed motion analysis of the ventricular wall

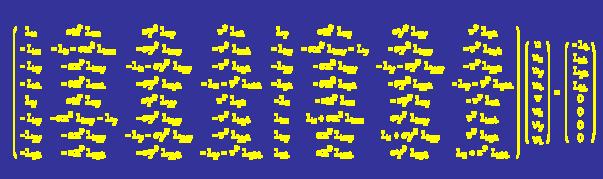


A. Suinesiaputra, UMCL / TUE, MICCAI 2002

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Multi-scale density flow: in each pixel 8 equations of third order and 8 unknowns:



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Collaboration
Prof. David
Fitzpatrick

Neurobiology,
Duke University

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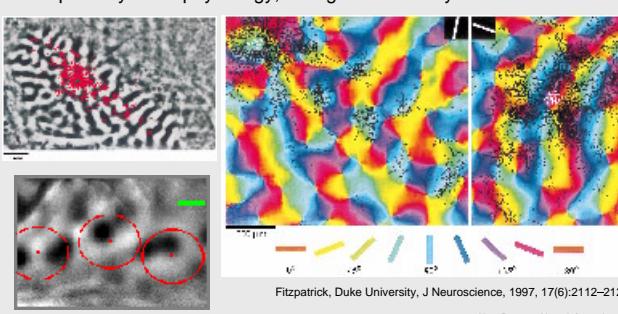
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Math: New wavelet class of orientation adaptive context filters inspired by neurophysiology, voltage sensitive dyes

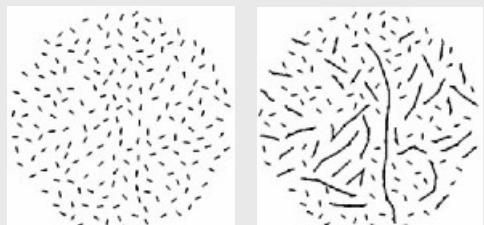


Fitzpatrick, Duke University, J Neuroscience, 1997, 17(6):2112-2127

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Perceptual grouping (Gestalt)
from orientations: robust detection



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$\mathcal{F}[\phi_{\alpha,\beta}](\omega) = \alpha \omega^2 \cdot p(\omega - \frac{\beta}{\alpha \omega^2}) e^{-\frac{\beta}{\alpha \omega^2}} e^{-\frac{1}{2} \ln^2(\alpha \omega^2) \left(1 - \frac{1}{\alpha \omega^2}\right)}, \beta \in [0, \frac{1}{2}]$

RemcoDuits:
Invertible Orientation Wavelet Transform [Siam2004]
Best paper award at PRIA 2004

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Gaussian Orientation Bundle

$\Phi_n(z, \sigma) = a_n(-\sigma \partial)^n e^{\frac{-z\bar{z}}{\sigma^2}},$
 $\Phi_{-n}(z, \sigma) = \overline{a_n}(-\sigma \bar{\partial})^n e^{\frac{-z\bar{z}}{\sigma^2}}; n \geq 0$

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Context orientation bundle with tensor voting
Ultra-low dose catheter detection

Erik Franken, TUE & PMS, 2004
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Steerable tensor voting

$$\nabla_b^L(x) = \begin{pmatrix} 0 & 0 & e^{i\pi\theta} & e^{2i\pi\theta} & 0 & 4e^{-2i\pi\theta} & e^{-4i\pi\theta} & 0 & 0 \\ e^{i\pi\theta} & 4e^{4i\theta} & 3e^{2i\theta} & 4 & e^{-2i\theta} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & e^{i\pi\theta} & 4 & 0 & 4e^{2i\theta} & 4e^{4i\theta} \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix} \begin{pmatrix} u & v \\ u & v \\ \vdots \\ u & v \\ 0 & 0 \end{pmatrix}$$

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Strong non-linear filtering in orientation space

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Vessel detection for Computer Aided Diagnosis in Mammography

E. Franken, M. van Almsick
ter Haar Romeny, Neuroinformatics 2004

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Examples of student projects with Mathematica:

Finding the Adamkiewicz vessel

New wavelet for invertible orientation transform

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Tensor voting

(a) (b) (c)
(d) (e) (f)

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The retina measures on many resolutions simultaneously

scale-space

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• topoints
slice hartcoronair
↑ scale

• graph theory
• EC project

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Critical Paths in Scale Space

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The nesting of the iso-intensity manifolds

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Image guided database retrieval

Frans Kanters, TUE BMT BioMIM

Florack: VICI proposal 2004 (1.2 M€)

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Graph Theory

A new paradigm in multi-scale computer vision

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Outlook

- Scale-space: robust mathematical basis
- Regularized differential operators
- Deep structure hierarchical structure
 - graph extraction & reasoning
- Perceptual grouping – Gestalt
 - context operators
- Inspiration from the visual front-end
 - Cortical connections
 - Feedback connections
 - Need to go to higher levels

Mathematics Biology
generic analysis algorithms

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