

MathVisionTools

A high level Mathematica library for image processing

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http://www.tue.nl/

Medical imaging is big business:

- One third of hospital's equipment is for medical imaging
- 80% of all diagnoses are done on images
- Typical 800 bed hospital produces 10 Terabyte/year
- Sector grows steadily by 10% per year

• GE, Philips, Siemens: billions of dollars markets

Medical images are big:

- CT and MRI scan: typically 512 x 512, 800 to 2000 slices, 16 bit (400 MB – 1 GB)
- Digital X-Ray, mammogram: 3000 x 2500 pixels, 16 bit (15 MB)
- Ultrasound: 256 x 256, 20 frames per second, 8 bit (80 MB/min)





Computer Tomography





Multi-slice CT: 4-64 slices per rotation (0.5 sec). Full body trauma scan: 21 sec



Applications







S. 11- 4

emfyseme

peripheral bronchial carcinoma = long tumour



multi-phase study of the liver

Magnetic Resonance Imaging

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Medical workstations quickly become the super-assistants of radiologists and surgeons

- 3D visualization
- Computer aided diagnosis
- Surgery planning
- Virtual endoscopy
- Tissue classification
- Interactive analysis
- etc.

The lightbox has disappeared, now hundreds of workstations



Maximum Intensity Projection

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De overwhelming amount of data calls for condensed presentation and analysis: Strong demands on front-end visualizations







Advanced volume visualization

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Virtual endoscopy



Enhancement by Gaussian curvature

Diffusion Tensor Imaging - visualization



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Brownian motion of water: *diffusion* (sphere - ellipsoid)



Eigenvectors





Tensor components







Color indicates orientation

Visual ToolKit

www.vtk.org



Computer Aided Diagnosis

Mammography:





In a prospective study based on screening exams performed on almost 13,000 consecutive women over a one-year period, Ulissey and colleagues found that CAD increased breast cancer detection by 20% (*Radiology*, September 2001, Vol. 220:3, pp. 781-786).

CT lung pathology



Companies:

R2 Technologies **Deus Technologies CADVision** iCAD CadX Philips GE Siemens

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CADx

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Multi-Scale Image Analysis

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Biologically inspired computer vision → <u>bio-mimicking</u>



Gaussian derivative profiles up to 4th order



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Observation, sampling
= convolution by aperture

$$\frac{\partial L}{\partial x} (L \otimes G) = L \otimes \frac{\partial}{\partial x} G$$

Differentiation of discrete data is done by convolution with Gaussian derivative kernels



Many cells in the visual cortex function as derivative operators









Model: several orders Gaussian derivatives



Receptive fields measure spatio-temporal structure

differential geometry

MathVisionTools

List of currently available functions:

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 - 2D Hankel Transform

Soon available:

- MIP (perspective and orthogonal)
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Geometry-driven diffusion: edge preserving smoothing

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Original







scale = 9

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

$$\frac{\partial L}{\partial s} = \overrightarrow{\nabla} . c \, \overrightarrow{\nabla} L \qquad \qquad c = c \left(L, \ \frac{\partial L}{\partial x}, \ \frac{\partial^2 L}{\partial x^2}, \ \ldots \right)$$

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

The Perona & Malik equation (1991):

$$c_{1} = e^{-\frac{|\vec{\nabla}L|^{2}}{k^{2}}} \qquad \frac{\partial L}{\partial s} = \vec{\nabla} \cdot c(|\vec{\nabla}L|)\vec{\nabla}L$$

$$\frac{e^{-\frac{L_{x}^{2}+L_{y}^{2}}{k^{2}}}(k^{2}-2L_{x}^{2})L_{xx} - 4L_{x}L_{xy}L_{y} + (k^{2}-2L_{y}^{2})L_{yy})}{k^{2}}$$

The solution is knot known analytically, so we have to rely on numerical methods, such as the forward Euler method.

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$$\delta L = \delta s \left(\nabla . c \, \nabla L \right)$$

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Test on a noisy test image:

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



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$$\begin{aligned} \frac{\partial L}{\partial t} &= \vec{\nabla} \cdot e^{\frac{\|\vec{\nabla}t\|^2}{k^2}} \vec{\nabla}L = \\ \frac{1}{k^2} e^{\frac{I_x^2 + I_y^2 + I_z^2}{k^2}} (k^2 (L_{xx} + L_{yy} + L_{zz}) - 2(L_x^2 L_{xx} + L_y^2 L_{yy} + L_z^2 L_{zz}) \\ -4(L_x L_y L_{xy} + L_x L_z L_{xz} + L_y L_z L_{yz})) \end{aligned}$$





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If conductivity is dependent on the second order structure tensor:

Coherence enhancing diffusion



J. Weickert, 2001

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• toppoints



Edge focusing



Structures exist at their own scale:





Example:

Lysosome segmentation in noisy 2-photon microscopy 3D images of macrophages.







First the 3D maxima are detected at scale σ = 3 pixels



We interpolate with cubic splines 35 radial tracks in 35 orientations for 12 maxima



The profiles are extremely noisy:



Observation: visually we can reasonably point the steepest edgepoints

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Edge focusing over all profiles.

Choose a start level based on the *task*, i.e. find a single edge.







Detected 3D points per maximum.

We need a 3D shape fit function.



The 3D points are least square fit with 3D spherical harmonics:

$$\begin{cases} \frac{1}{2 \ \pi}, \ \frac{1}{2} \ e^{-i\phi} \sqrt{\frac{3}{2\pi}} \sin(\theta), \ \frac{1}{2} \sqrt{\frac{3}{\pi}} \cos(\theta), \\ -\frac{1}{2} \ e^{i\phi} \sqrt{\frac{3}{2\pi}} \sin(\theta), \ \frac{1}{4} \ e^{-2i\phi} \sqrt{\frac{15}{2\pi}} \sin^2(\theta), \\ \frac{1}{2} \ e^{-i\phi} \sqrt{\frac{15}{2\pi}} \cos(\theta) \sin(\theta), \ \frac{1}{4} \sqrt{\frac{5}{\pi}} \ (3 \cos^2(\theta) - 1), \\ -\frac{1}{2} \ e^{i\phi} \sqrt{\frac{15}{2\pi}} \cos(\theta) \sin(\theta), \ \frac{1}{4} \ e^{2i\phi} \sqrt{\frac{15}{2\pi}} \sin^2(\theta) \end{cases}$$



Resulting detection:



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Multi-scale optic flow



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

Many approaches are taken:

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

The Lie derivative (denoted with the symbol $\mathcal{L}_{\vec{v}}$) of a function F(g) with respect to a vectorfield \vec{v} is defined as $\mathcal{L}_{\vec{v}} F(g)$. The optic flow constraint equation (OFCE) states that the luminance does not change when we take the derivative along the vectorfield of the motion:

$$\mathcal{L}_{\vec{v}} F(g) \equiv 0$$

Multi-scale optic flow constraint equation:

For scalar images:

$$\mathcal{L}_{\vec{v}} F(g) = \overrightarrow{\nabla} F.\vec{v}$$

For density images:

$$\mathcal{L}_{\vec{v}} \rho = \rho \operatorname{Div} \vec{v} + \vec{v} \cdot \overrightarrow{\nabla} \rho = 0$$

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.



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

$ \begin{array}{c} \mathbf{L}_{\mathbf{x}} \\ -\mathbf{L}_{\mathbf{x}\mathbf{x}} \\ -\mathbf{L}_{\mathbf{x}\mathbf{y}} \\ -\mathbf{L}_{\mathbf{x}\mathbf{t}} \\ \mathbf{L}_{\mathbf{y}} \\ -\mathbf{L}_{\mathbf{x}\mathbf{y}} \\ -\mathbf{L}_{\mathbf{y}\mathbf{y}} \\ -\mathbf{L}_{\mathbf{y}\mathbf{t}} \end{array} $	$\sigma x^2 L_{xx}$ $-L_x - \sigma x^2 L_{yex}$ $-\sigma x^2 L_{yex}$ $-\sigma x^2 L_{xy}$ $-\sigma x^2 L_{xy}$ $-\sigma x^2 L_{xy}$ $-\sigma x^2 L_{yy}$ $-\sigma x^2 L_{yy}$	$\sigma y^2 \mathbf{L}_{xy}$ $-\sigma y^2 \mathbf{L}_{xxy}$ $-\mathbf{L}_x - \sigma y^2 \mathbf{L}_{xyy}$ $-\sigma y^2 \mathbf{L}_{xyt}$ $\sigma y^2 \mathbf{L}_{yy}$ $-\sigma y^2 \mathbf{L}_{yy}$ $-\sigma y^2 \mathbf{L}_{yyy}$ $-\mathbf{L}_y - \sigma y^2 \mathbf{L}_{yyy}$ $-\sigma y^2 \mathbf{L}_{yyt}$	$\begin{aligned} \tau^2 \ \mathbf{L}_{st} \\ -\tau^2 \ \mathbf{L}_{sxt} \\ -\tau^2 \ \mathbf{L}_{syt} \\ -\tau^2 \ \mathbf{L}_{syt} \\ -\mathbf{L}_{s} - \tau^2 \ \mathbf{L}_{syt} \\ \tau^2 \ \mathbf{L}_{yz} \\ -\tau^2 \ \mathbf{L}_{syt} \\ -\tau^2 \ \mathbf{L}_{syt} \\ -\tau^2 \ \mathbf{L}_{syt} \\ -\tau^2 \ \mathbf{L}_{syz} \end{aligned}$	$\begin{array}{c} \mathbf{L}_{\mathbf{y}} \\ - \mathbf{L}_{\mathbf{x}\mathbf{y}} \\ - \mathbf{L}_{\mathbf{y}\mathbf{y}} \\ - \mathbf{L}_{\mathbf{y}\mathbf{t}} \\ - \mathbf{L}_{\mathbf{x}} \\ \mathbf{L}_{\mathbf{z}\mathbf{x}} \\ \mathbf{L}_{\mathbf{z}\mathbf{y}} \\ \mathbf{L}_{\mathbf{x}\mathbf{t}} \end{array}$	$\sigma x^2 L_{xy}$ $-\sigma x^2 L_{xyy} - L_y$ $-\sigma x^2 L_{xyy}$ $-\sigma x^2 L_{xyt}$ $-\sigma x^2 L_{xyt}$ $L_x + \sigma x^2 L_{xox}$ $\sigma x^2 L_{xyy}$ $\sigma x^2 L_{xyt}$	$\sigma \mathbf{y}^2 \mathbf{L}_{\mathbf{y}\mathbf{y}}$ $-\sigma \mathbf{y}^2 \mathbf{L}_{\mathbf{x}\mathbf{y}\mathbf{y}}$ $-\mathbf{L}_{\mathbf{y}} - \sigma \mathbf{y}^2 \mathbf{L}_{\mathbf{y}\mathbf{y}\mathbf{y}}$ $-\sigma \mathbf{y}^2 \mathbf{L}_{\mathbf{y}\mathbf{y}\mathbf{t}}$ $-\sigma \mathbf{y}^2 \mathbf{L}_{\mathbf{x}\mathbf{y}}$ $\sigma \mathbf{y}^2 \mathbf{L}_{\mathbf{x}\mathbf{y}}$ $\mathbf{u}_{\mathbf{x}} + \sigma \mathbf{y}^2 \mathbf{L}_{\mathbf{y}\mathbf{y}\mathbf{t}}$ $-\sigma \mathbf{y}^2 \mathbf{L}_{\mathbf{x}\mathbf{y}\mathbf{y}}$	$ \begin{array}{c} \boldsymbol{\tau}^2 \ \mathbf{L}_{yt} \\ -\boldsymbol{\tau}^2 \ \mathbf{L}_{yyt} \\ -\boldsymbol{\tau}^2 \ \mathbf{L}_{yyt} \\ -\boldsymbol{\tau}^2 \ \mathbf{L}_{yyt} \\ -\mathbf{L}_{y} - \boldsymbol{\tau}^2 \ \mathbf{L}_{yzt} \\ -\boldsymbol{\tau}^2 \ \mathbf{L}_{yzt} \\ \boldsymbol{\tau}^2 \ \mathbf{L}_{zot} \end{array} $	$ \begin{pmatrix} \mathbf{u} \\ \mathbf{u}_{\mathbf{x}} \\ \mathbf{u}_{\mathbf{y}} \\ \mathbf{u}_{\mathbf{y}} \\ \mathbf{u}_{\mathbf{y}} \\ \mathbf{v}_{\mathbf{y}} \\ \mathbf{v}_{\mathbf{y}} \\ \mathbf{v}_{\mathbf{y}} \\ \mathbf{v}_{\mathbf{y}} \end{pmatrix} $	=	- L _t L _{st} L _{yt} 0 0 0 0 0	
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A. Suinesiaputra, UMCL / TUE, MICCAI 2002



For *hierarchical image reasoning* we consider images on many resolutions simultaneously (like the eye)



scale-space



Critical Points, Paths and Top Points









• toppoints





A new paradigm in multi-scale computer vision:

Hierarchical reasoning by graphs







Image guided database retrieval



Point cloud matching (earth mover distance), very efficient

We can now reconstruct from the toppoints the image again (with Mathematica)

Frans Kanters, TUE BMT BioMIM

Catheter & electrode detection



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Perceptual grouping (Gestalt) from orientations: robust detection







Context filters

Gaussian Orientation Bundle



$$\Phi_n(z,\sigma) = a_n(-\sigma\partial)^n e^{-\frac{zz}{\sigma^2}},$$

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



Strong non-linear filtering in orientation space



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Context orientation bundle with tensor voting





Erik Franken, TUE & PMS, 2004



Vessel detection for Computer Aided Diagnosis in Mammography



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The numerical and symbolic power of Mathematica is used

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You are invited for a mutual collaboration to develop the library (on exchange basis)

Contact: prof. Bart M. ter Haar Romeny, PhD dipl.ing. Markus van Almsick



Multi-scale watershed segmentation

Watershed are the boundaries of merging water basins, when the image landscape is immersed by punching the minima.

At larger scale the boundaries get blurred, rounded and dislocated.







Regions of different scales can be linked by calculating the largest overlap with the region in the scales just above.







The method is often combined with nonlinear diffusion schemes



E. Dam, ITU



Nabla Vision is an interactive 3D watershed segmentation tool developed by the University of Copenhagen.



Sculpture the 3D shape by successively clicking precalculated finer scale watershed details.







The challenge



How do we do it?