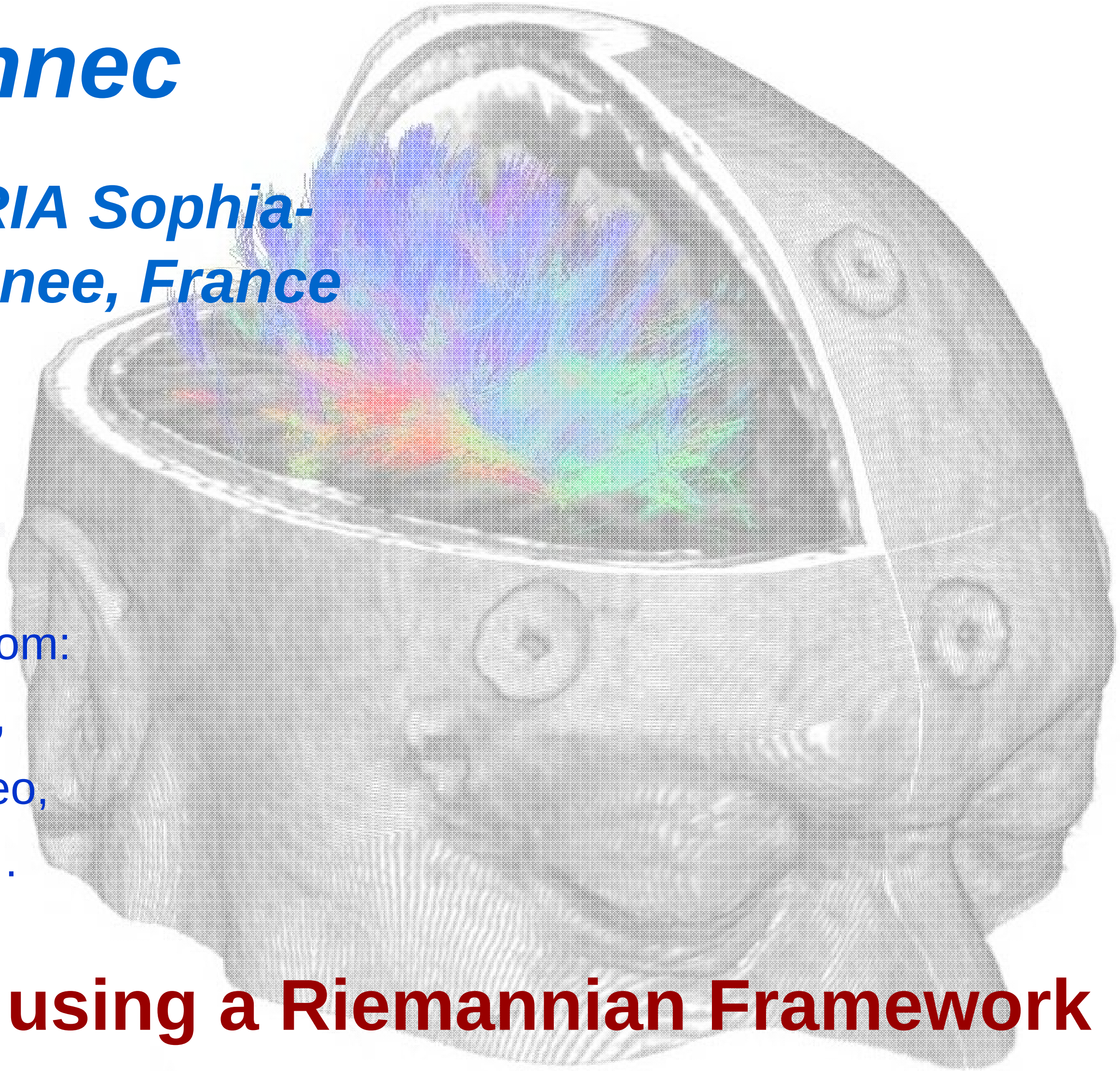
Xavier Pennec

Asclepios team, INRIA Sophia-Antipolis – Mediterranee, France



With indebting contributions from:
Pierre Fillard, Vincent Arsigny,
Jean-Marc Peyrat, Thomas Yeo,
Tom Vercauteren and others…

Diffusion analysis using a Riemannian Framework

MICCAI Diffusion MRI Tutorial

New York, Sept. 6th 2008

Diffusion Tensor Imaging

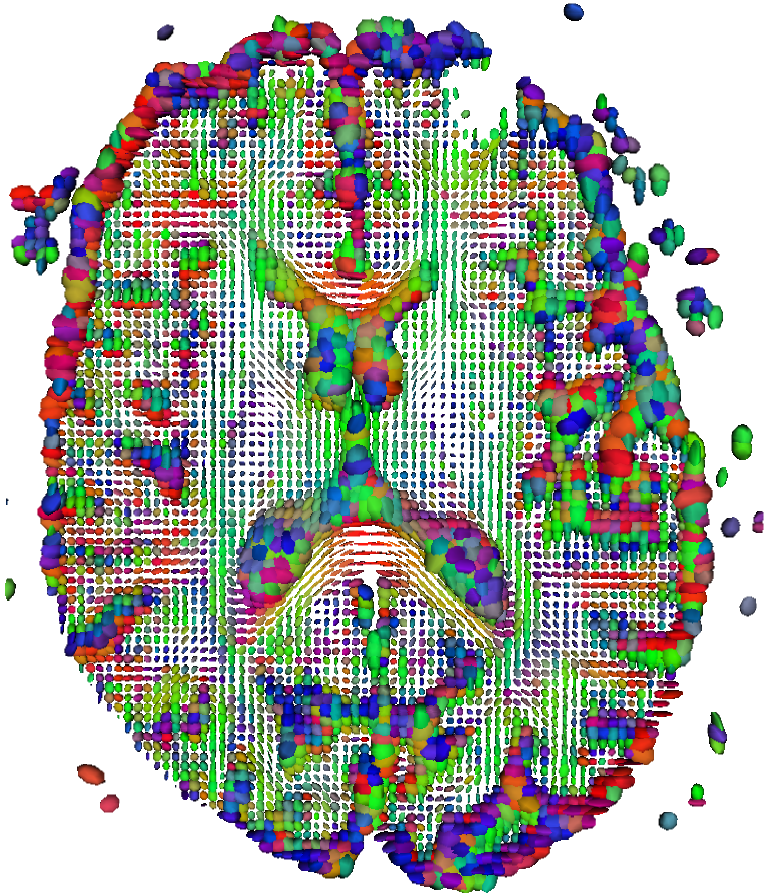
Covariance of the Brownian motion of water
-> Architecture of axonal fibers

Very noisy data

- Tensor image processing
  - Robust estimation
  - Filtering, regularization
  - Interpolation / extrapolation
- Information extraction (fibers)

Symmetric positive definite matrices

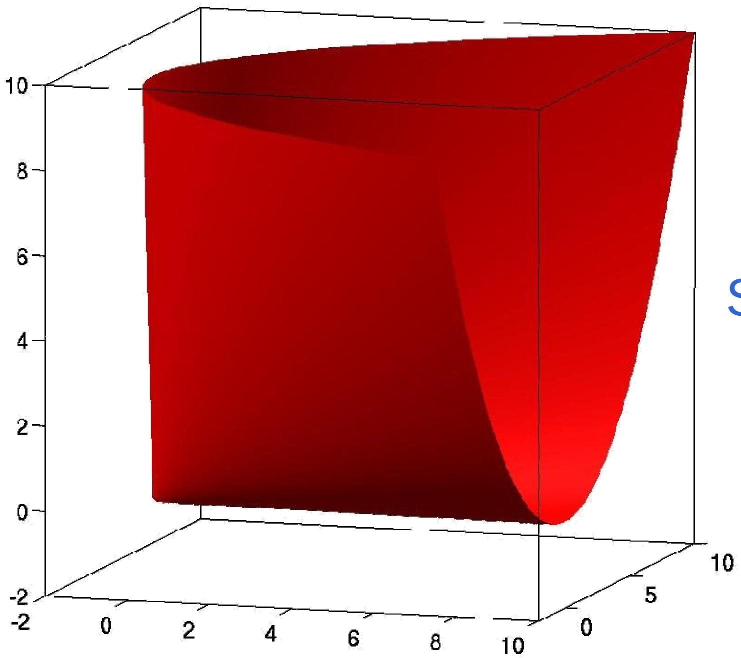
- Convex operations are stable
  - mean, interpolation
- More complex operations are not
  - PDEs, gradient descent…



Diffusion Tensor Filed
(slice of a 3D volume)

The Tensor Space is not a Vector Space

Tensors = Space of positive definite matrices:



Space of 2D tensors in R^3.

Matrices with null eigenvalues are reachable in a finite time

- Null and negatives eigenvalues are not physical

Intrinsic computing on Manifold-valued images?

Riemannian geometric approaches

Shape spaces & directional statistics

- [Kendall StatSci 89, Small 96, Dryden & Mardia 98]

Numerical integration of dynamical systems

- [Helmke & Moore 1994, Hairer et al 2002]
- Matrix Lie groups [Owren BIT 2000, Mahony JGO 2002]

Information Geometry (statistical manifolds)

- [Amari 1990 & 2000, Kass & Vos 1997]
- [Oller Annals Stat. 1995, Battacharya Annals Stat. 2003 & 2005]

Statistics for Computer vision

- Rigid body transformations [Pennec PhD96]
- General Riemannian manifolds [Pennec JMIV98, NSIP99, JMIV06]
- PGA for M-Reps [Fletcher IPMI03, TMI04]
- Planar curves [Klassen & Srivastava PAMI 2003]

Content

Introduction

An affine invariant Riemannian metric on tensors

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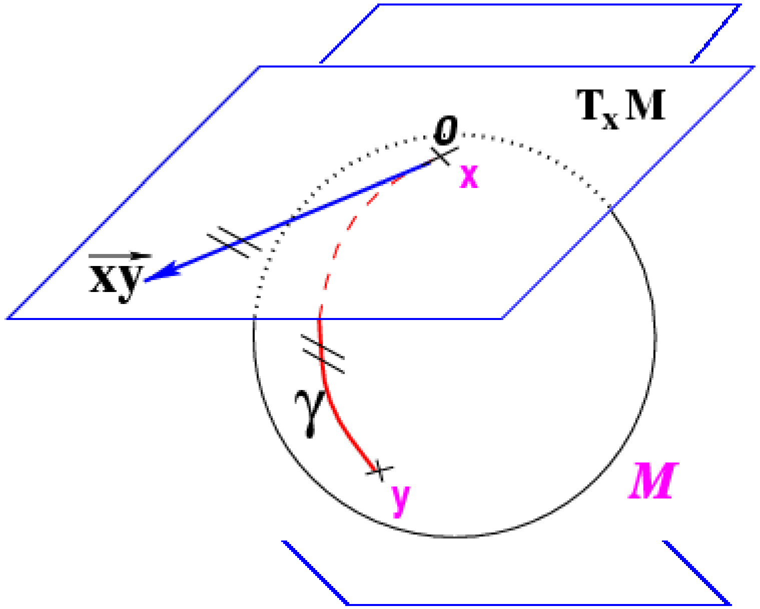
Conclusion

The geometric framework: Riemannian Manifolds

Riemannian metric :

- Dot product on tangent space
- Speed, length of a curve
- Distance and geodesics
  - Closed form for simple metrics/manifolds
  - Optimization for more complex



Exponential map (Normal coord. syst.) :

- Geodesic shooting: $Exp_x(v) = \gamma_{(x,v)}(1)$
- Log: find vector to shoot right

Unfolding (Log_x), folding (Exp_x)

Operator	Euclidean space	Riemannian manifold
Subtraction	$\overrightarrow{xy} = y - x$	$\overrightarrow{xy} = Log_x(y)$
Addition	$y = x + \overrightarrow{xy}$	$y = Exp_x(\overrightarrow{xy})$
Distance	$\mathrm{dist}(x, y) = \lVert y - x \rVert$	$\mathrm{dist}(x, y) = \lVert \overrightarrow{xy} \rVert_x$
Gradient descent	$x_{t+\varepsilon} = x_t - \varepsilon \nabla C(x_t)$	$x_{t+\varepsilon} = Exp_{x_t}(-\varepsilon \nabla C(x_t))$

Affine Invariant Metrics on Tensors

Action of the Linear Group GL_n $$A * \Sigma = A.\Sigma.A^T$$

Invariant distance $$dist(A*\Sigma_1, A*\Sigma_2) = dist(\Sigma_1, \Sigma_2)$$

Invariant metric $$\langle W_1 \mid W_2 \rangle_\Sigma \stackrel{def}{=} \left\langle \Sigma^{-1/2} * W_1, \Sigma^{-1/2} * W_2 \right\rangle_{Id}$$

- All rotationally invariant scalar products at identity:

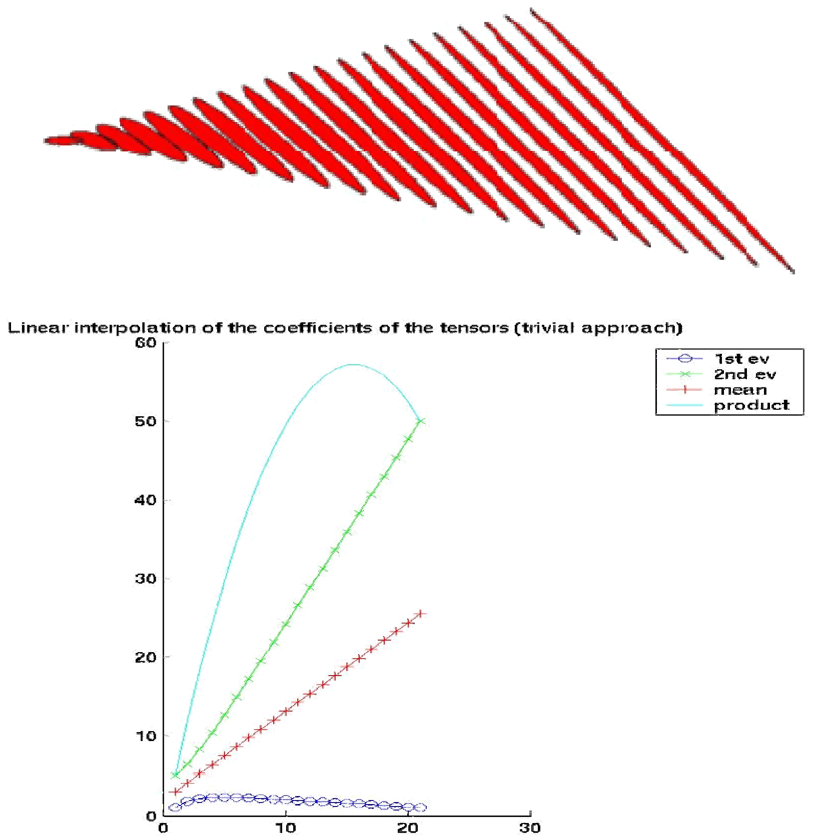
$$\langle W_1 \mid W_2 \rangle_{Id} \stackrel{def}{=} \mathrm{Tr}\left(W_1^T W_2\right) + \beta\, \mathrm{Tr}(W_1).\mathrm{Tr}(W_2) \quad (\beta > \text{-}1/\mathrm{n})$$

- Geodesics $$\exp_\Sigma(\overrightarrow{\Sigma\Psi}) = \Sigma^{1/2} \exp(\Sigma^{-1/2}.\overrightarrow{\Sigma\Psi}.\Sigma^{-1/2})\Sigma^{1/2}$$

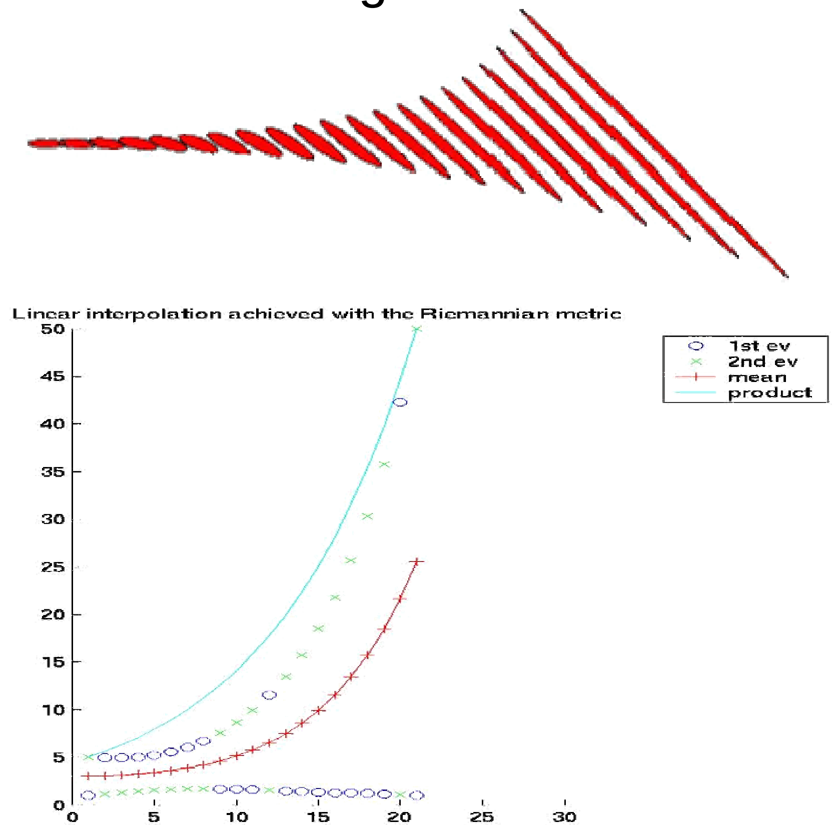
- Distance $$\boxed{dist(\Sigma, \Psi)^2 = \left\langle \overrightarrow{\Sigma\Psi} \mid \overrightarrow{\Sigma\Psi} \right\rangle_\Sigma = \left\| \log(\Sigma^{-1/2}.\Psi.\Sigma^{-1/2}) \right\|_{L_2}^2}$$

Linear vs. Riemannian Interpolation: walking along geodesics

Interpolation of the coefficients:



Interpolation along the Riemannian geodesic:



Affine Invariant Metrics on Tensors

$$\|W\|_{\Sigma}^{2} = \mathrm{Tr}\left(W.\Sigma^{-1}W\Sigma^{-1}\right) + \beta\,\mathrm{Tr}\left(W\Sigma^{-1}\right)^{2} \quad (\beta > -1/\mathrm{n})$$

Statistics on Riemannian spaces

- [Pennec, Fillard, Ayache, IJCV 66(1), Jan 2006 / INRIA RR-5255, 2004]
- PGA on tensors [Fletcher & Joshi CVMIA04, SigPro 87(2) 2007]

Space of Gaussian distributions

- Fisher information metric [Burbea & Rao J. Multivar Anal 12 1982, Skovgaard Scand J. Stat 11 1984, Calvo & Oller Stat & Dec. 9 1991]
- DTI segmentation [Lenglet RR04 & JMIV 25(3) 2006]

Geometric means

- Covariance matrices in computer vision [Forstner TechReport 1999]
- Math. properties [Moakher SIAM J. Matrix Anal App 26(3) 2004]
- Geodesic Anisotropy [Batchelor MRM 53 2005]

Homogeneous Embedding

- $\beta=-1/(n+1)$ [Lovric & Min-Oo, J. Multivar Anal 74(1), 2000]

First statistical tools: moments

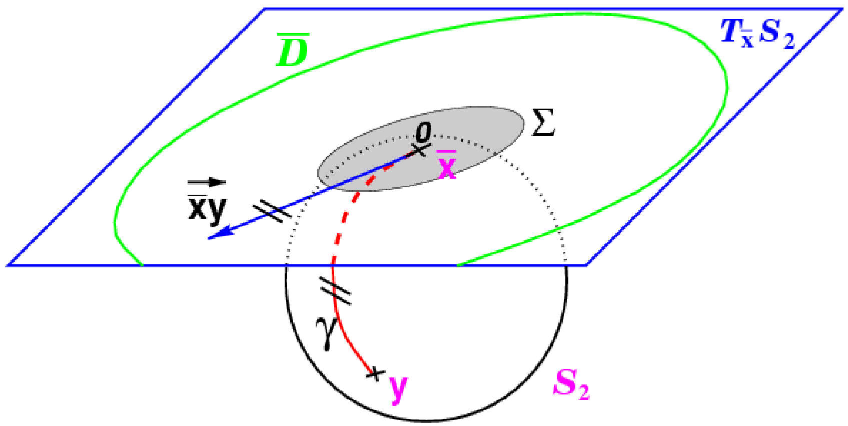
Fréchet / Karcher mean:

- Minimize the variance $$\sigma^2(y) = \mathrm{E}\left[\mathrm{dist}(y,\mathbf{x})^2\right] = \frac{1}{\mathrm{n}}\sum_{\mathrm{i}} \mathrm{dist}(y,x_i)^2$$
- Optimum: $$\mathrm{E}\left[\overrightarrow{\bar{\mathrm{x}}\mathbf{x}}\right] = \frac{1}{n}\sum_i \overrightarrow{\bar{\mathrm{x}}x_{\mathrm{i}}} = 0 \qquad \left[P(C)=0\right]$$
- Algorithm: Geodesic marching

$$\bar{\mathrm{x}}_{t+1} = \exp_{\bar{\mathrm{x}}_t}(v) \quad \text{avec} \quad v = \mathrm{E}\left[\overrightarrow{\mathrm{y}\mathbf{x}}\right] = \frac{1}{n}\sum_i \overrightarrow{\bar{\mathrm{x}}x_{\mathrm{i}}}$$

Covariance and higher orders

$$\Sigma_{\mathbf{xx}} = \mathrm{E}\left[\left(\overrightarrow{\bar{\mathrm{x}}\mathbf{x}}\right).\left(\overrightarrow{\bar{\mathrm{x}}\mathbf{x}}\right)^{\mathrm{T}}\right] = \frac{1}{n}\sum_i \overrightarrow{\bar{\mathrm{x}}z}.\overrightarrow{\bar{\mathrm{x}}x_{\mathrm{i}}}^{\mathrm{T}}$$



[Pennec, NSIP'99, JMIV06]

[Oller et Corcuera, Annls Stat 1995]

A Statistical Atlas of the Cardiac Fiber Structure

[J.M. Peyrat, et al., MICCAI'06, TMI 26(11), 2007]

Database

- 7 canine hearts from JHU
- Anatomical MRI and DTI

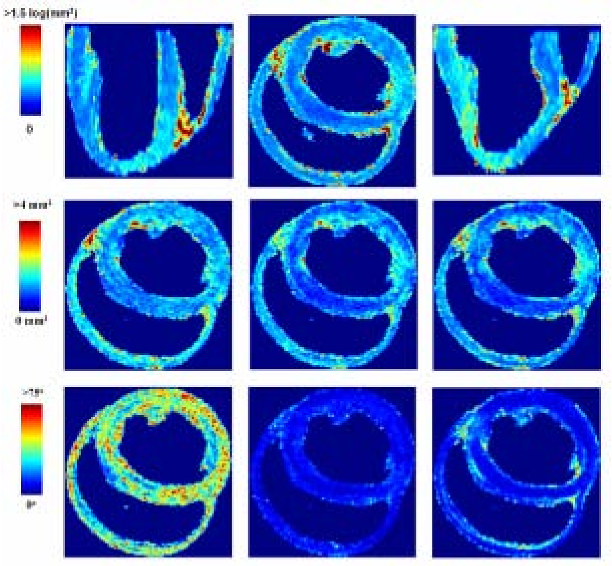
Method

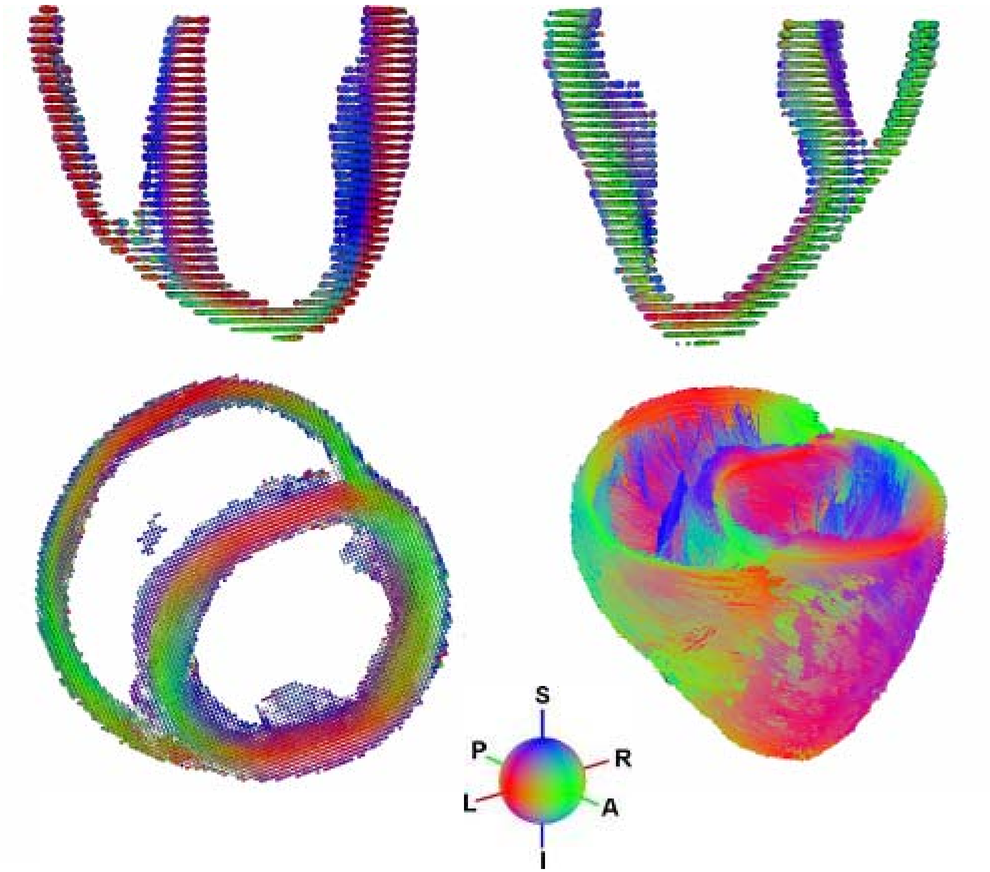
- Normalization based on aMRIs
- Log-Euclidean statistics of Tensors

Norm covariance

Eigenvalues covariance (1^{st}, 2^{nd}, 3^{rd})

Eigenvectors orientation covariance (around 1st, 2nd, 3rd)



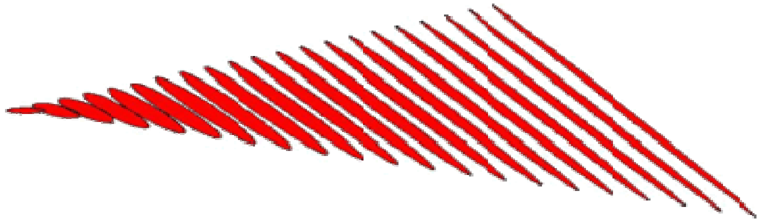


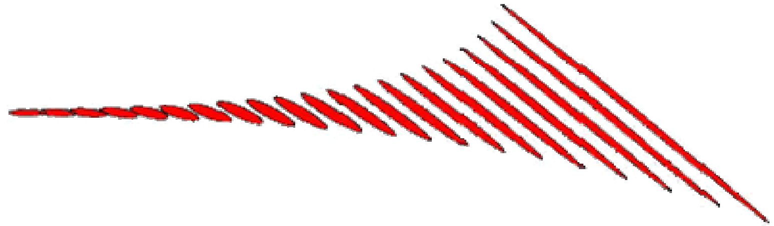
Content

Tensor interpolation

Geodesic walking in 1D

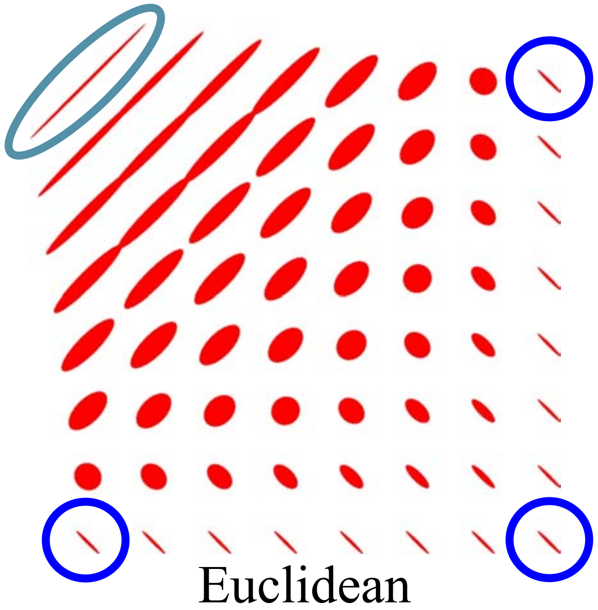
$$\Sigma(t) = \exp_{\Sigma_1}(t\overrightarrow{\Sigma_1\Sigma_2})$$

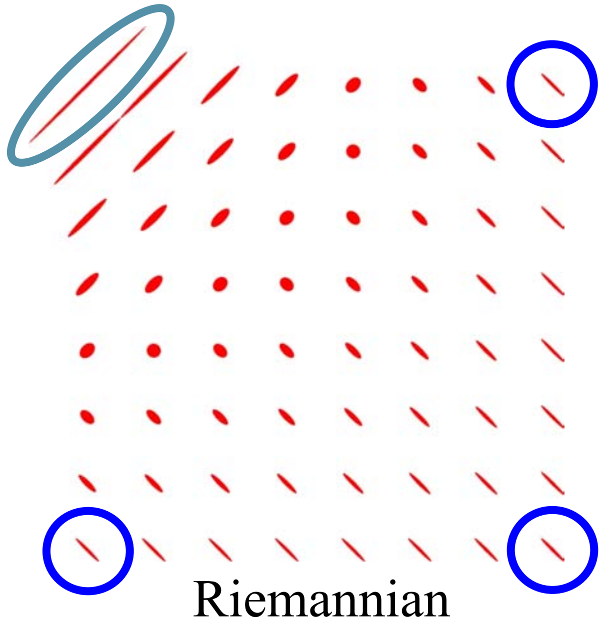




Weighted mean in general

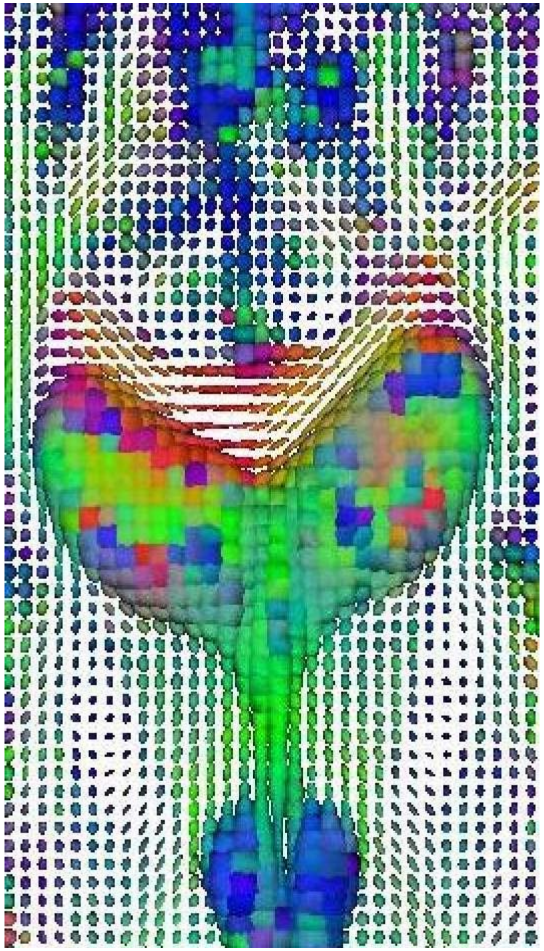
$$\Sigma(x) = \min_{\Sigma} \sum w_i(x)\ \ dist(\Sigma, \Sigma_i)^2$$



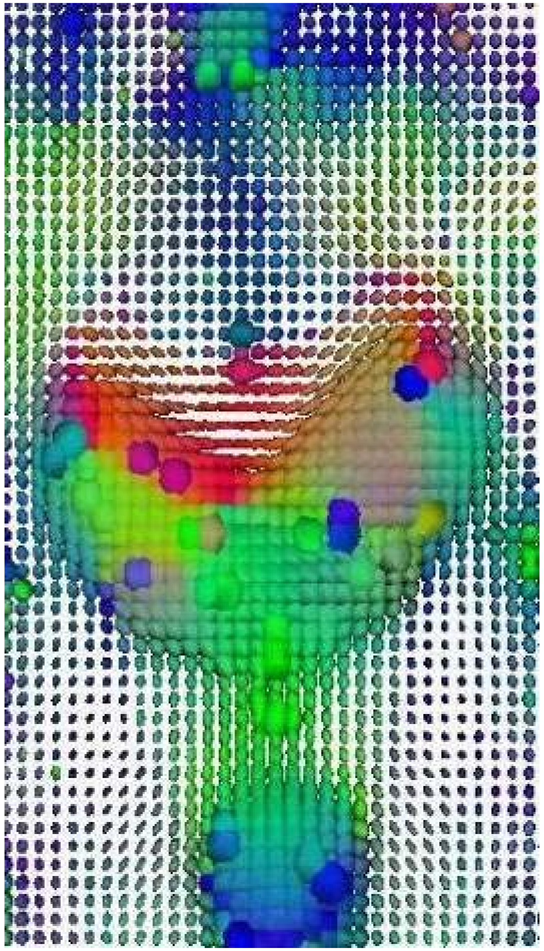


Gaussian filtering: Gaussian weighted mean

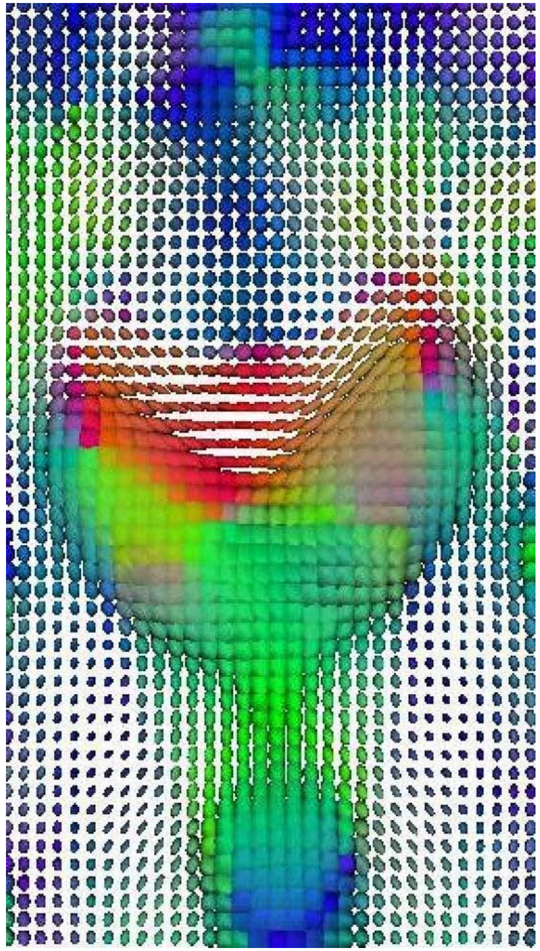
$$\Sigma(x) = \arg\min_{\Sigma} \sum_{i=1}^{n} G_{\sigma}(x - x_i) \; dist(\Sigma, \Sigma_i)^2$$



Raw



Coefficients σ=2



Riemann σ=2

PDE for filtering and diffusion

Harmonic regularization

$$C(\Sigma) = \int_{\Omega} \left\| \nabla \Sigma(x) \right\|^2_{\Sigma(x)} dx$$

- Gradient: manifold Laplacian $\Delta\Sigma(x) = \sum_i \partial_i^2 \Sigma - \sum_i \left(\partial_i \Sigma\right) \Sigma^{(-1)} \left(\partial_i \Sigma\right)$
- Intrinsic numerical scheme thanks to exponential chart $\Delta\Sigma(x) = \sum_u \frac{\overrightarrow{\Sigma(x)\Sigma(x+u)}}{\|u\|^2} + O\left(\|u\|^2\right)$
- Integration with geodesic marching $\Sigma_{t+1}(x) = \exp_{\Sigma_t(x)}\left(-\varepsilon \nabla C(\Sigma)(x)\right)$

Anisotropic regularization

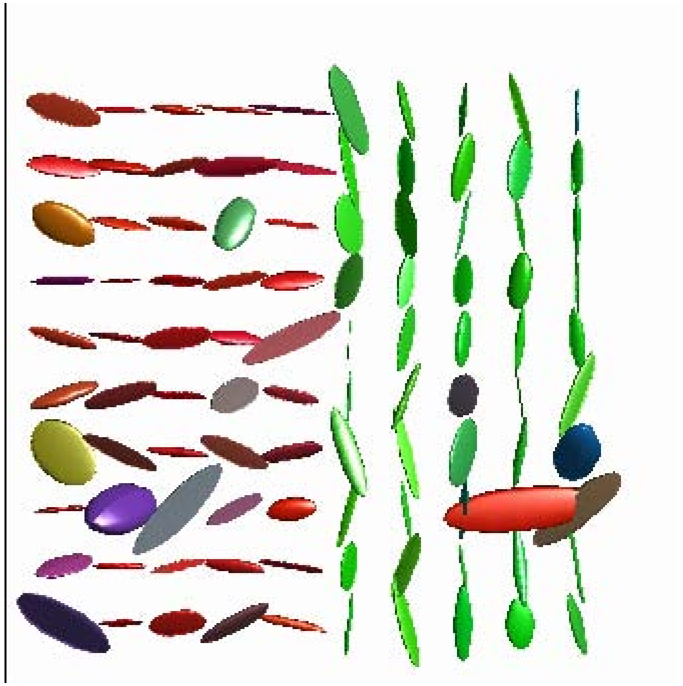
- [Perona-Malik 90 / Gerig 92]
- Phi functions formalism [Deriche / Faugeras 1996]

Isotropic vs. Anisotropic Diffusion

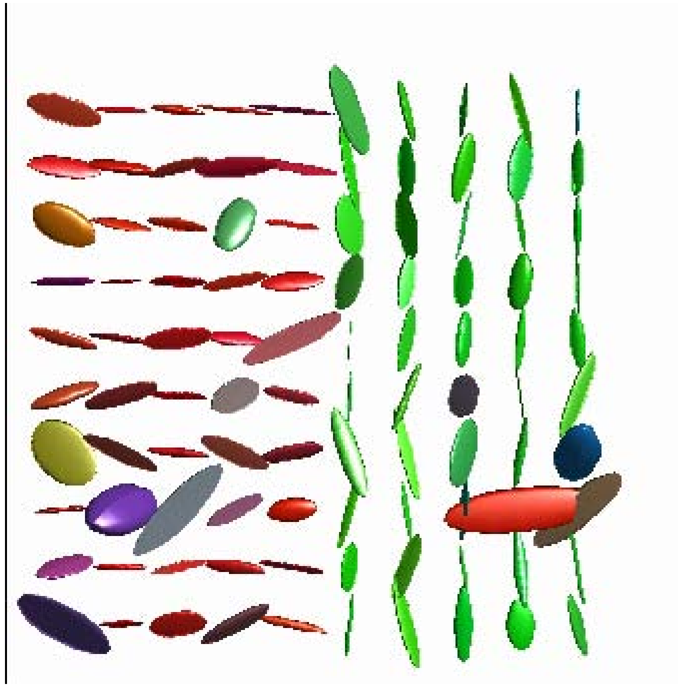
$$C(\Sigma) = \int \left\| \nabla \Sigma(x) \right\|_{\Sigma}^{2} dx$$

$$C(\Sigma) = \int \phi\left(\left\| \nabla \Sigma(x) \right\|_{\Sigma} \right) dx$$

$$\phi(x) = \exp(-x^2 / \kappa^2)$$

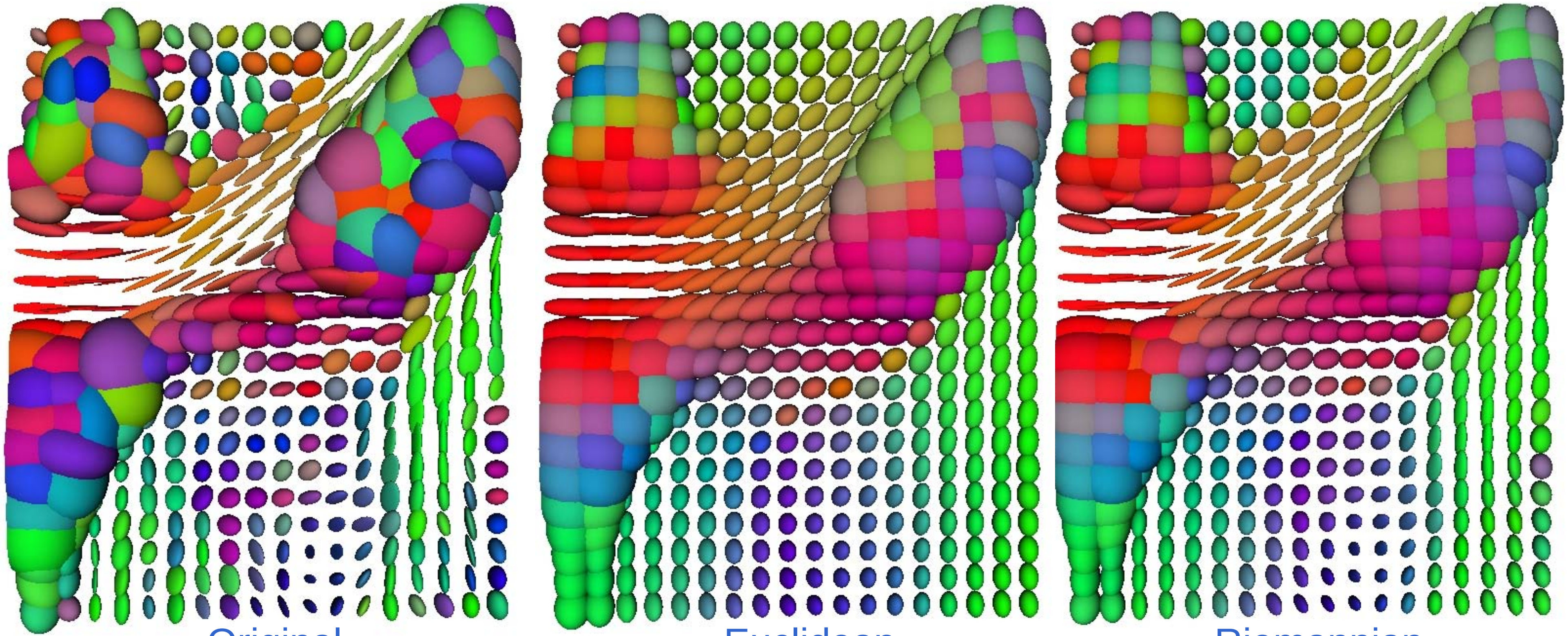


Isotropic



Anisotropic

Anisotropic Diffusion Euclidean vs Riemannian

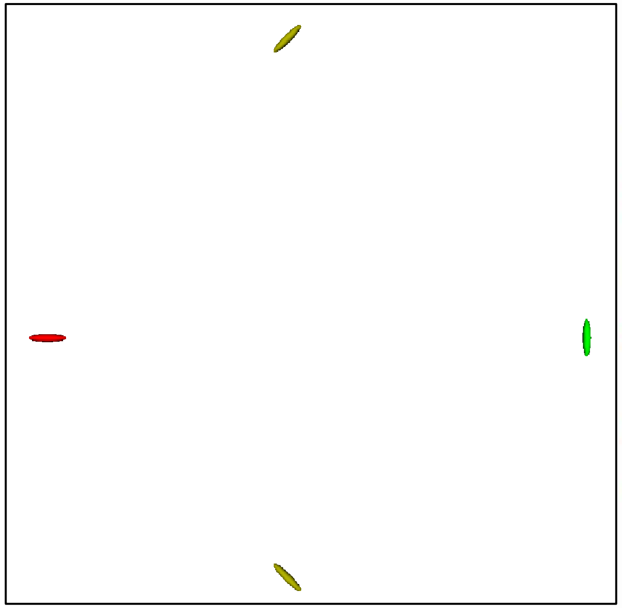


Original Euclidean Riemannian

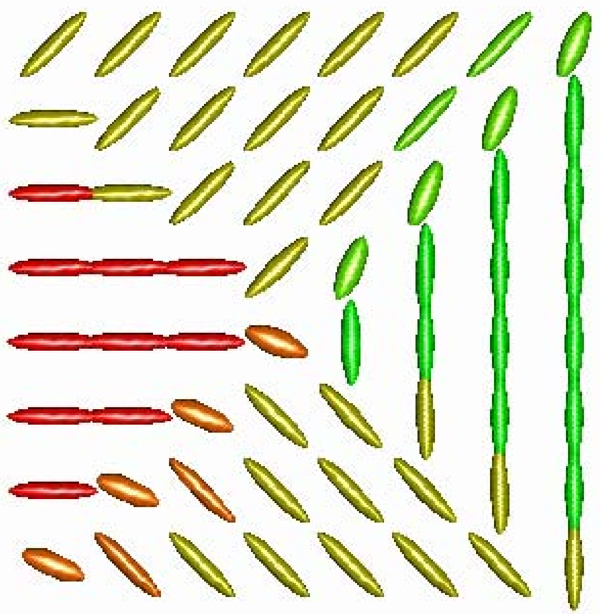
Extrapolation by Diffusion (Restoration)

$$C(\Sigma) = \frac{1}{2}\int_{\Omega}\sum_{i=1}^{n} G_{\sigma}(x - x_i)\, dist(\Sigma(x), \Sigma_i)^2\, dx + \frac{\lambda}{2}\int_{\Omega}\left\|\nabla\Sigma(x)\right\|^2_{\Sigma(x)}$$

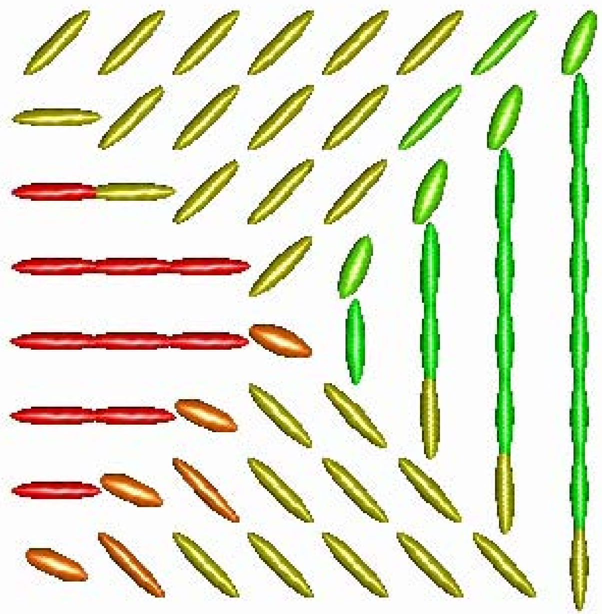
$$\nabla C(\Sigma)(x) = -\sum_{i=1}^{n} G_{\sigma}(x - x_i)\,\overrightarrow{\Sigma(x)\Sigma_i} - \lambda(\Delta\Sigma)(x)$$



Original tensors



Diffusion λ=0.01



Diffusion λ=∞

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Log Euclidean Metric on Tensors

Exp/Log: global diffeomorphism Tensors/sym. matrices

- Vector space structure carried from the tangent space to the manifold
  - Log. product $\Sigma_1 \otimes \Sigma_2 \equiv \exp(\log(\Sigma_1) + \log(\Sigma_2))$
  - Log scalar product $\alpha \bullet \Sigma \equiv \exp(\alpha \log(\Sigma)) = \Sigma^{\alpha}$
  - Bi-invariant metric $\boxed{dist(\Sigma_1, \Sigma_2)^2 \equiv \|\log(\Sigma_1) - \log(\Sigma_2)\|^2}$

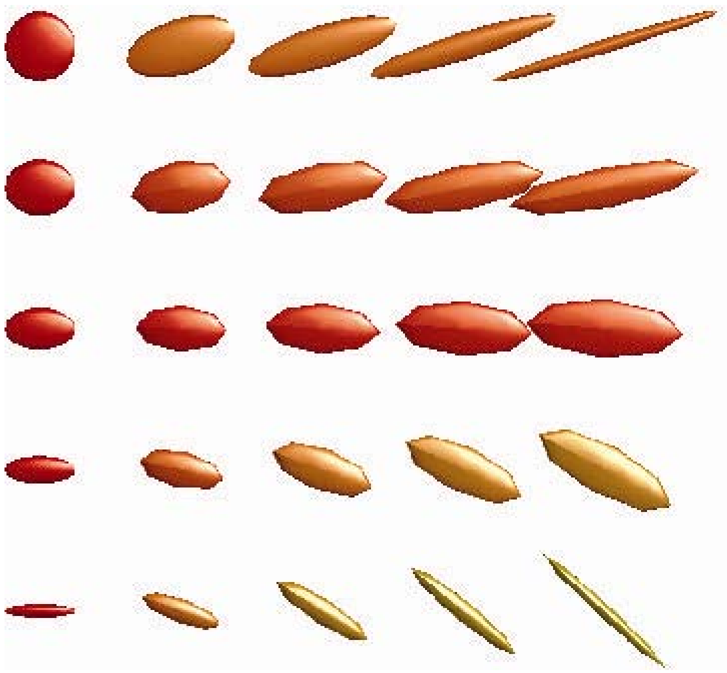
Properties

- Invariance by the action of similarity transformations only
- Very simple algorithmic framework

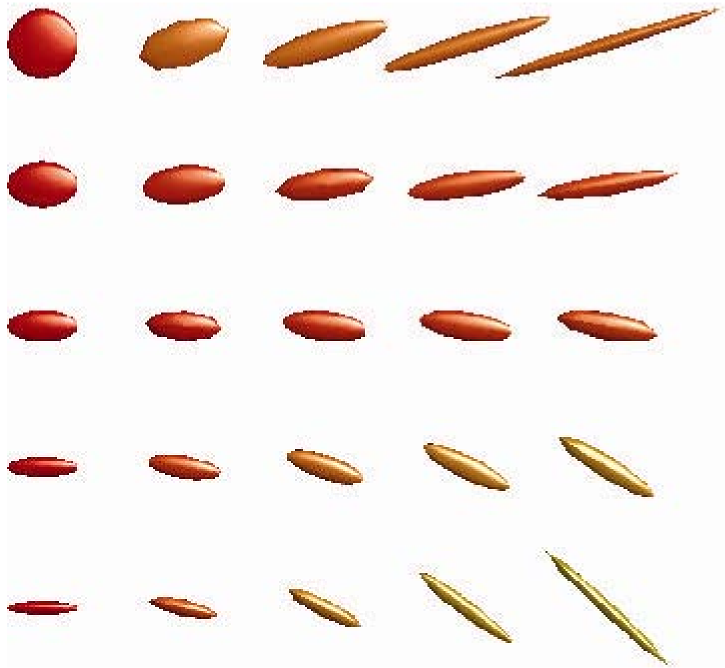
[Arsigny, Fillard, Pennec, Ayache, MICCAI 2005, T1, p.115-122]

Log Euclidean vs Affine invariant

- Both means are geometric (vs arithmetic for Euclidean)
- Log Euclidean slightly more anisotropic
- Speedup ratio: 7 (aniso. filtering) to >50 (interp.)



Euclidean



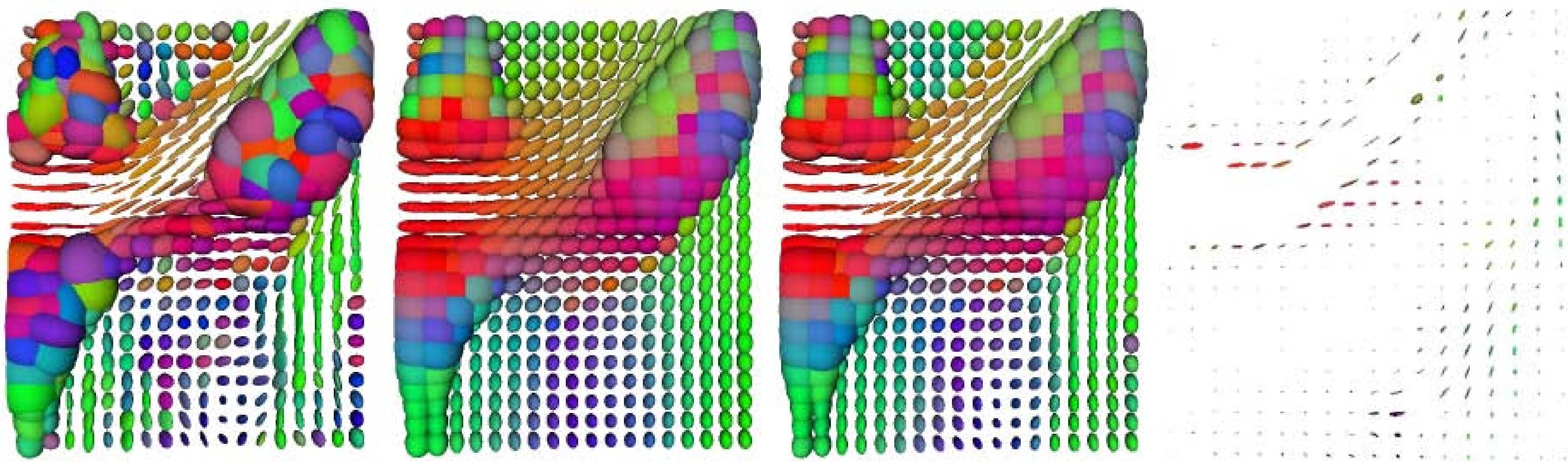
Affine invariant
Log-Euclidean

[Arsigny, Fillard, Pennec, Ayache, MICCAI 2005, MRM'06]

Log Euclidean vs Affine invariant

Real DTI images: anisotropic filtering

- Both means are geometric (vs arithmetic for Euclidean)
- Log Euclidean slightly more anisotropic
  but the difference is not significant
- Speedup ratio: 7 (aniso. filtering) to >50 (interp.)



Original Euclidean Log-Euclidean Diff. LE/affine (x100)

[Arsigny, Fillard, Pennec, Ayache, MICCAI 2005, MRM'06]

Comparison of Metrics

	Euclidean	Affine Invariant	Log-Euclidean
Null/Negative eigenvalues	Reachable	Unreachable!	Unreachable!
Invariance	Rotation	Affine transforms	Similarity
Swelling effect	Yes	No	No
Computational burden	Low	Important	Low

A metric for all applications?

Structure tensor (guide for diffusion) $\Sigma_\sigma(x) = G_\sigma * \left(\nabla I \, \nabla I^t\right)$

Original

SNR 10% added

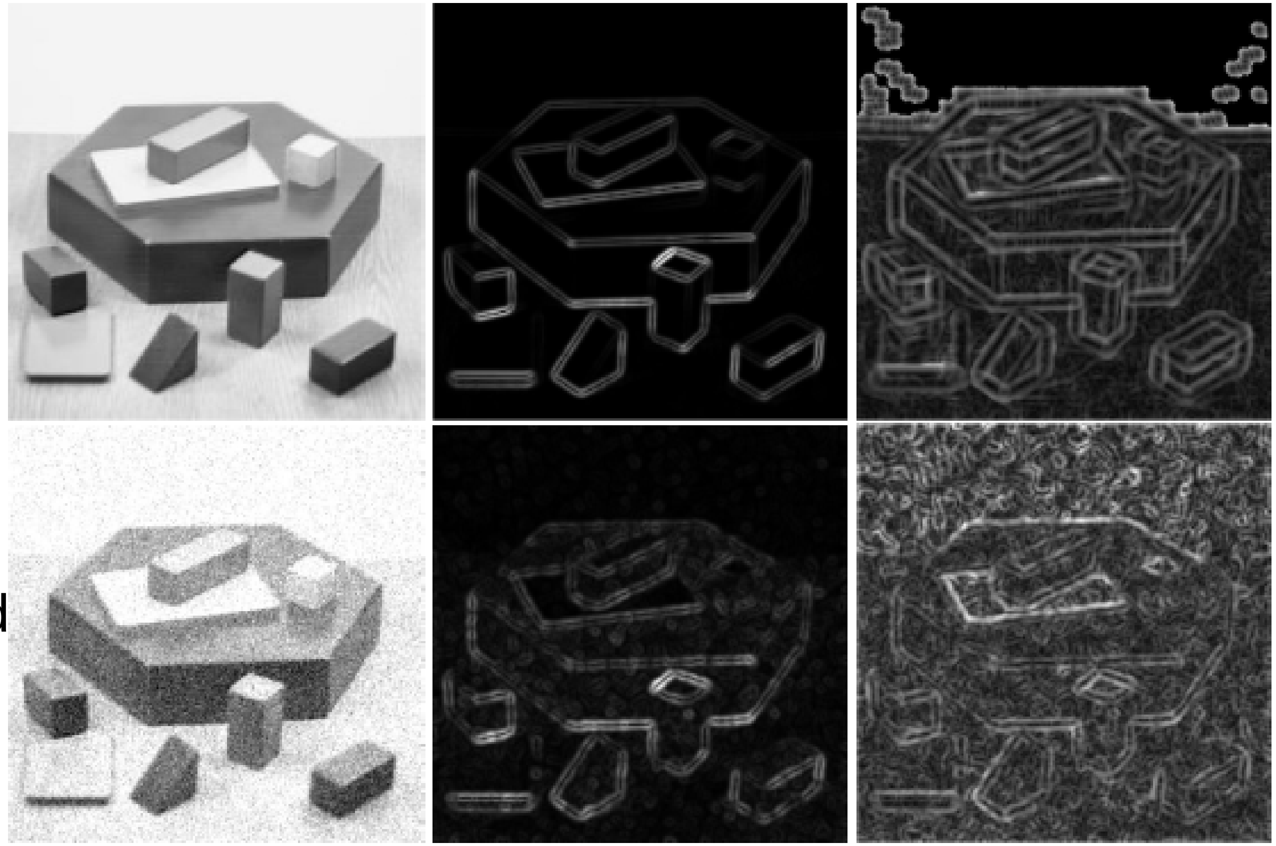


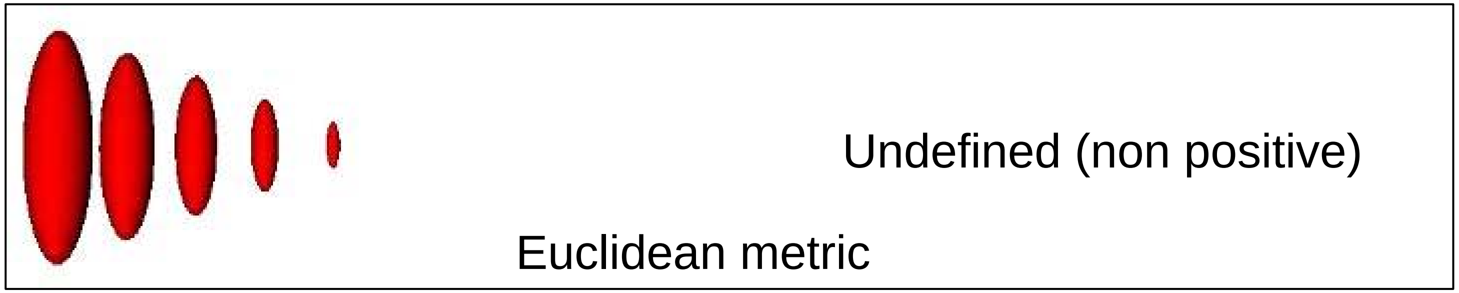
Image Euclidean grad Riemannian grad

A null eigenvalue is physically OK (perfect straight edge)

Need to change the metric?

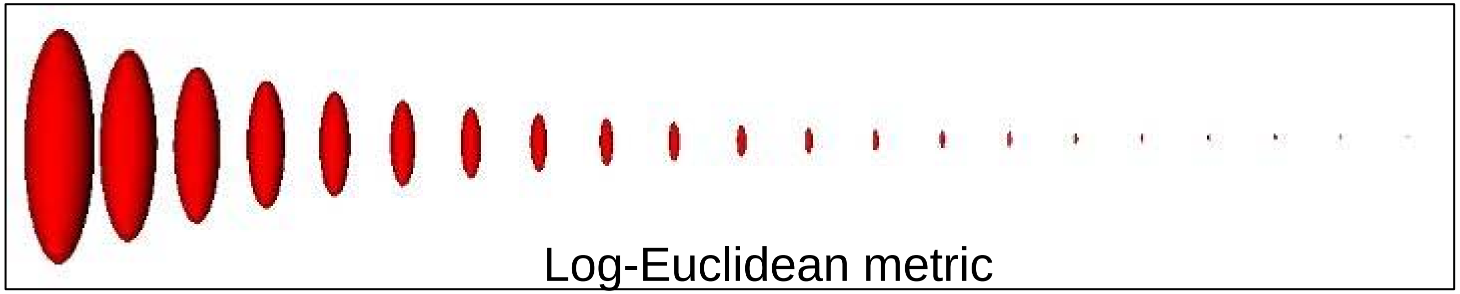
[Fillard, Arsigny, Ayache, Pennec, DSSCV'05]

Geodesic shooting in tensors spaces



Euclidean metric


Choleski metric


Log-Euclidean metric

Some references on other metrics

Log-Euclidean

- [Arsigny, MICCAI 2005 & MRM 56(2), 2006]

Square root metrics

- Cholesky [Wang Vemuri et al, IPMI'03, TMI 23(8) 2004.]
- Size and shape space [Dryden, Koloydenko & Zhou, 2008]

Non Riemannian distances

- J-Divergence [Wang & Vemuri, TMI 24(10), 2005]
- Geodesic Loxodromes [Kindlmann et al. MICCAI 2007]

4th order tensors

- [Gosh, Descoteau & Deriche MICCAI'08]

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DTI Estimation from DWI

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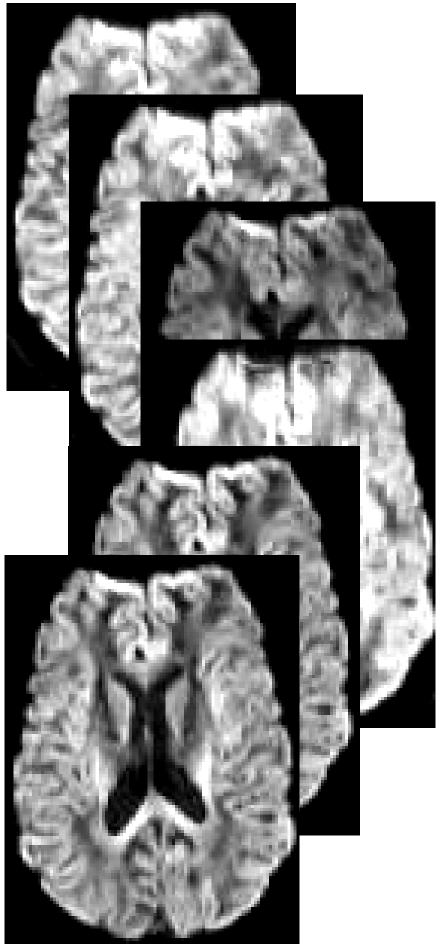
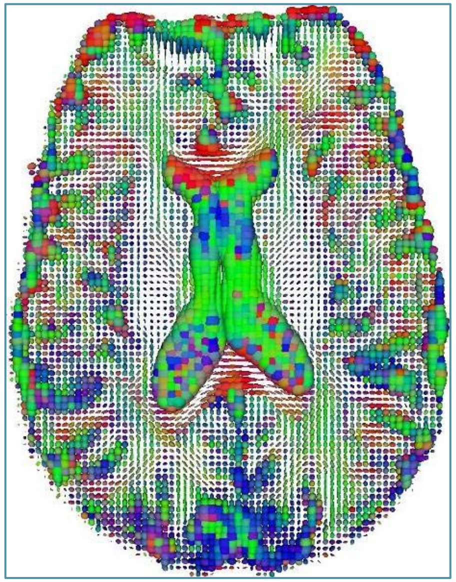


$$S_i = S_0 \exp\left(-b g_i^T D g_i\right)$$

Stejskal & Tanner diffusion equation



Diffusion Tensor Field

Baseline + at least 6 DWI

[Westin, Media 2002]

DTI Estimation from DWI

Maximum Likelihood Estimation

$$S_i = S_0 \exp\left(-b\, \mathbf{g}_i^T \Sigma\, \mathbf{g}_i\right) + Noise$$

- ML with Log-Gaussian noise:
  - linear system on the log-Images

$$\arg\min_D \sum_i \left(\log(S_i / S_0) + b g_i^T D g_i\right)^2$$

- ML with Gaussian noise on the MRIs:
  - non-linear optimization

$$\arg\min_D \sum_i \left(S_i - S_0 \exp(-b g_i^T D g_i)\right)^2$$

Actual MRI Noise

- Gaussian on the complex signal
- Rician on the amplitude

$$\boxed{\hat{S}_i = \sqrt{\left(S_i + N_1(0,\sigma)\right)^2 + N_2(0,\sigma)^2}}$$

- This leads to a bias for low SNRs [Sijbers, TMI 1998]

$$E\left[\hat{S}_i\right] \approx E[S_i] + \frac{\sigma^2}{2S_i}$$

DTI Estimation: A Few References

Standard log-Gaussian estimation:

- [Westin et al., MedIA 2002]

Robust estimation on the log of the signal:

- [Tschumperlé et al., ISBI'04]

Robust estimation on the signal itself:

- [Chang et al., MRM'05]

Joint Estimation / Regularization from the complex DW signal:

- Anisotropic diffusion on Choleski factors [Wang & Vemuri, TMI'04]

Estimation with a Rician noise model:

- Smoothing DWI before estimation [Basu & Fletcher, MICCAI 2006]
- ML (MMSE) [Aja-Fernández, Alberola-López, Westin, TMI 2008]
- MAP with log-Euclidean prior [Fillard et al., ISBI 2006, TMI 2007]

MAP Estimation with a Rician Noise Model

Minimize an energy functional:

$$E(L) = \underbrace{Sim(L)}_{\text{Data fidelity term}} + \lambda\, \underbrace{Reg(L)}_{\text{Smoothing term}}$$

Maximum Likelihood estimator for Rician noise:

$$Sim(L) = -\sum_{i=1}^{N} \log\left(p\left(\hat{S}_i / S_i\right)\right) \qquad p\left(\hat{S}_i / S_i\right) = \frac{\hat{S}_i}{\sigma^2} \exp\left(-\frac{\hat{S}_i^{\,2} + S_i(L)^2}{2\sigma^2}\right) I_0\left(\frac{S_i(L)\hat{S}_i}{\sigma^2}\right)$$

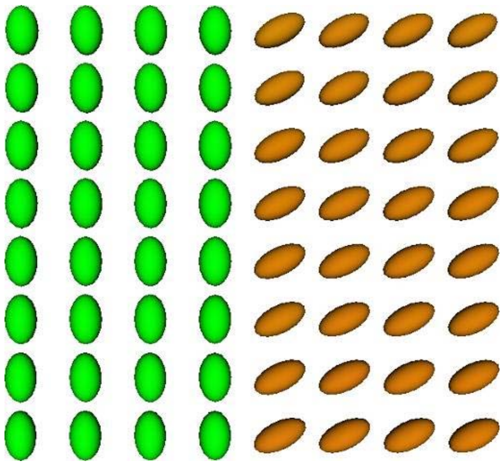
Anisotropic Log-Euclidean spatial prior

$$Reg(L) = \int \Phi\left(\left\| \nabla \Sigma(x) \right\|^2_{\Sigma(x)}\right) dx$$

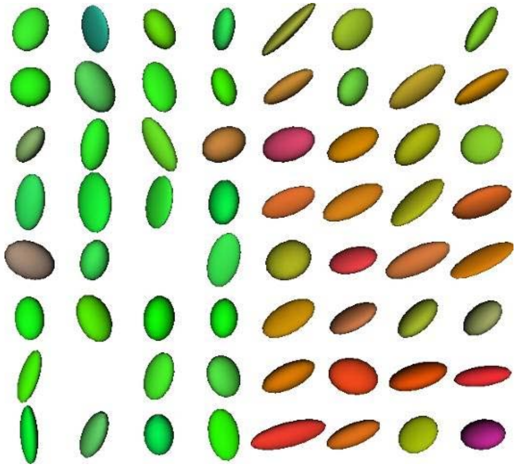
Gradient descent in Log-Euclidean space

[Fillard, Arsigny, Pennec, Ayache ISBI'06, TMI 26(11) 2007]

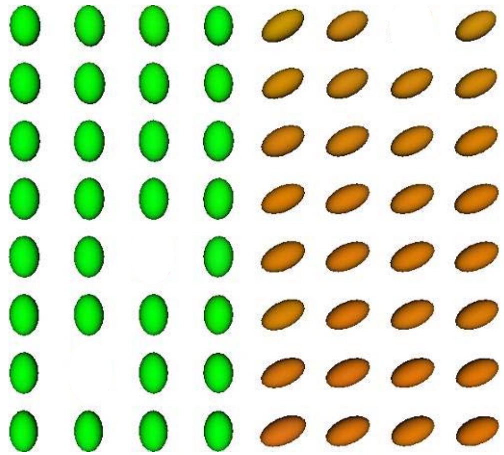
Synthetic Data



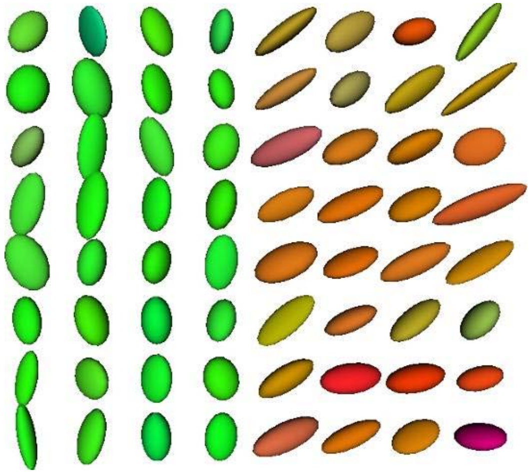
Initial



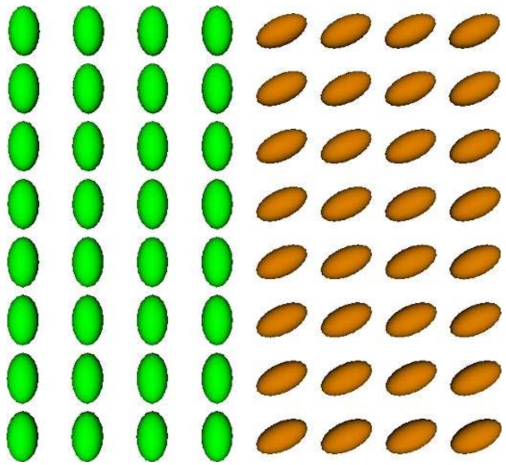
Standard estimation



Standard + LE spatial prior

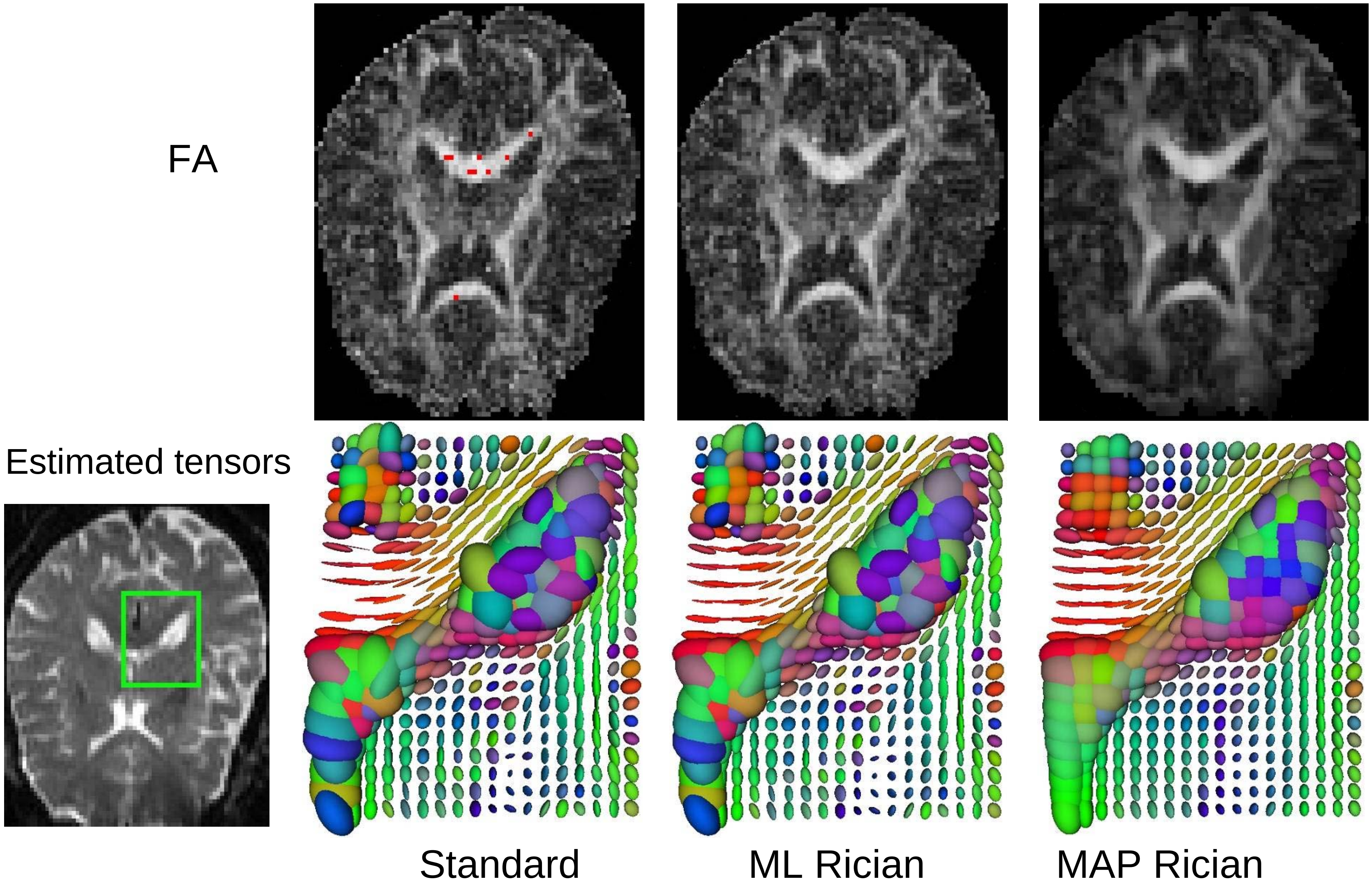


Rician ML



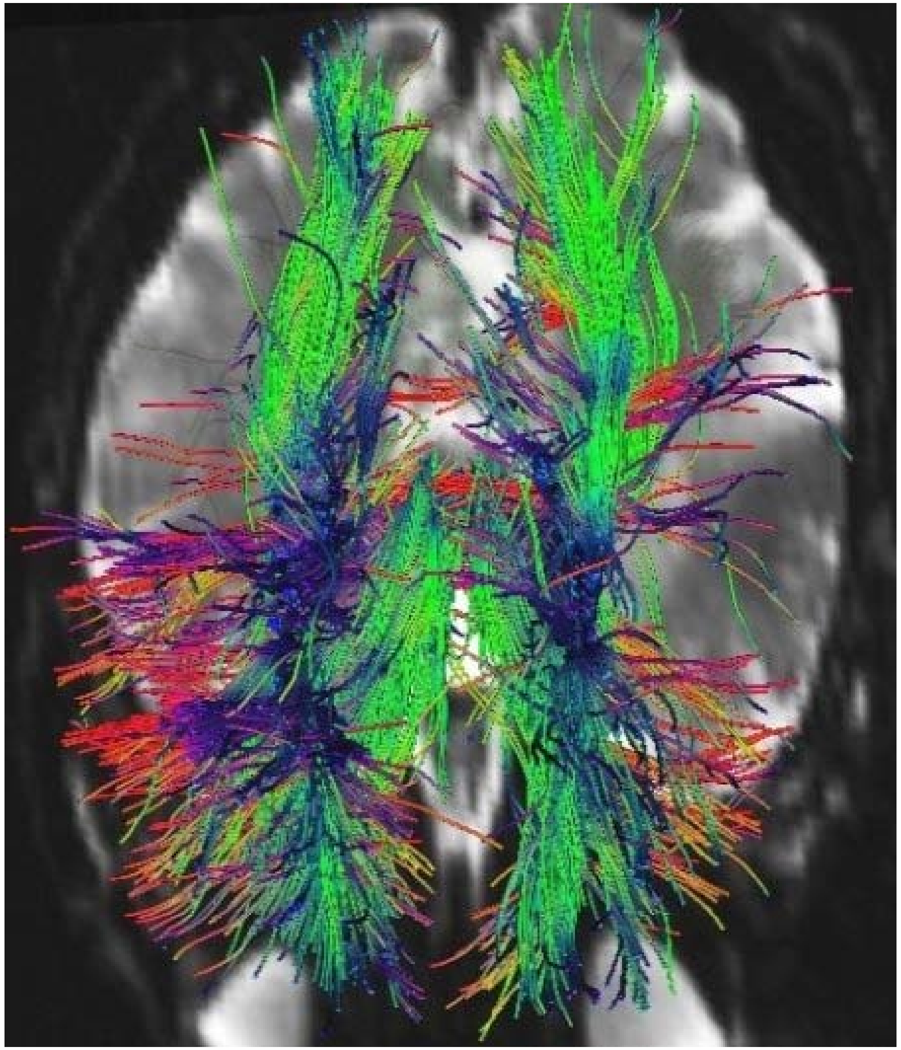
Rician MAP

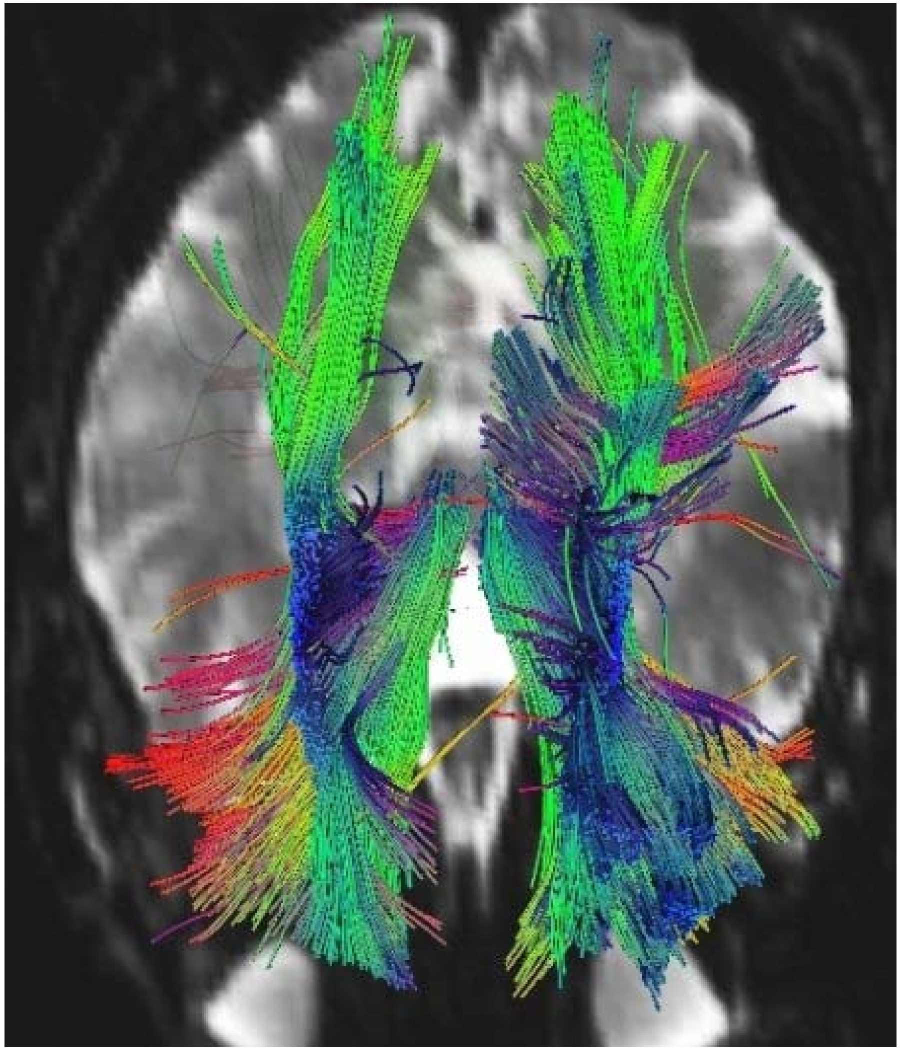
Results on Clinical DTI of the Brain with 7 directions



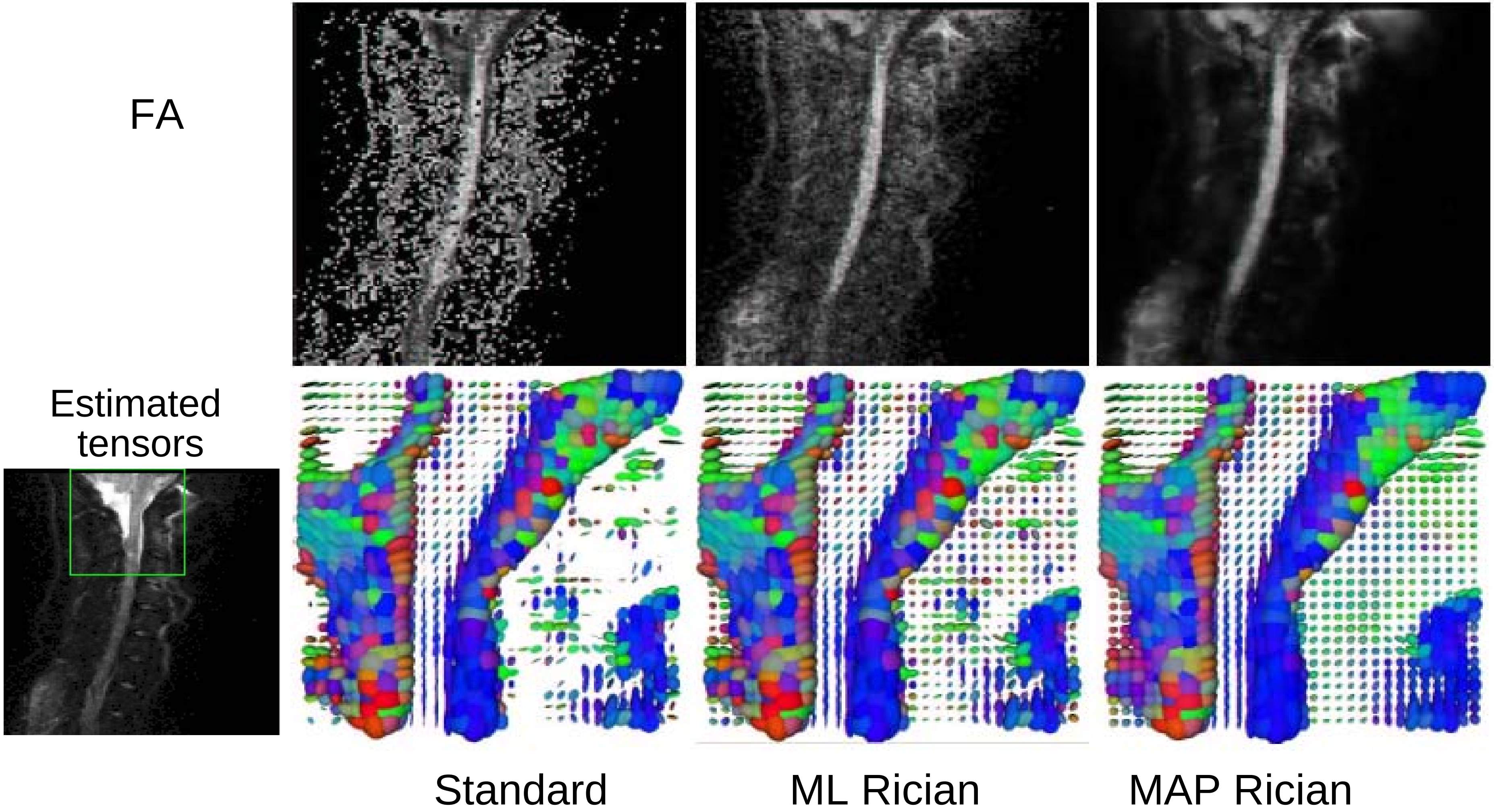
[Fillard, Arsigny, Pennec, Ayache ISBI'06, TMI 26(11) 2007]

Impact on Fiber Tracking



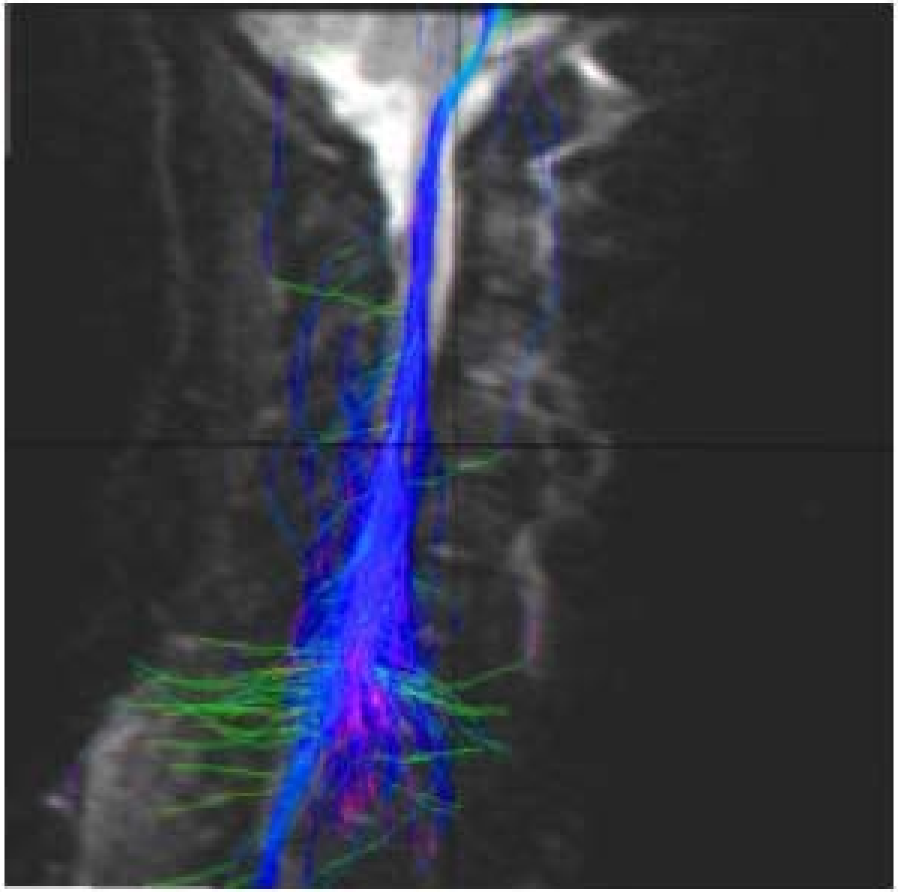


Clinical DTI of the spinal cord

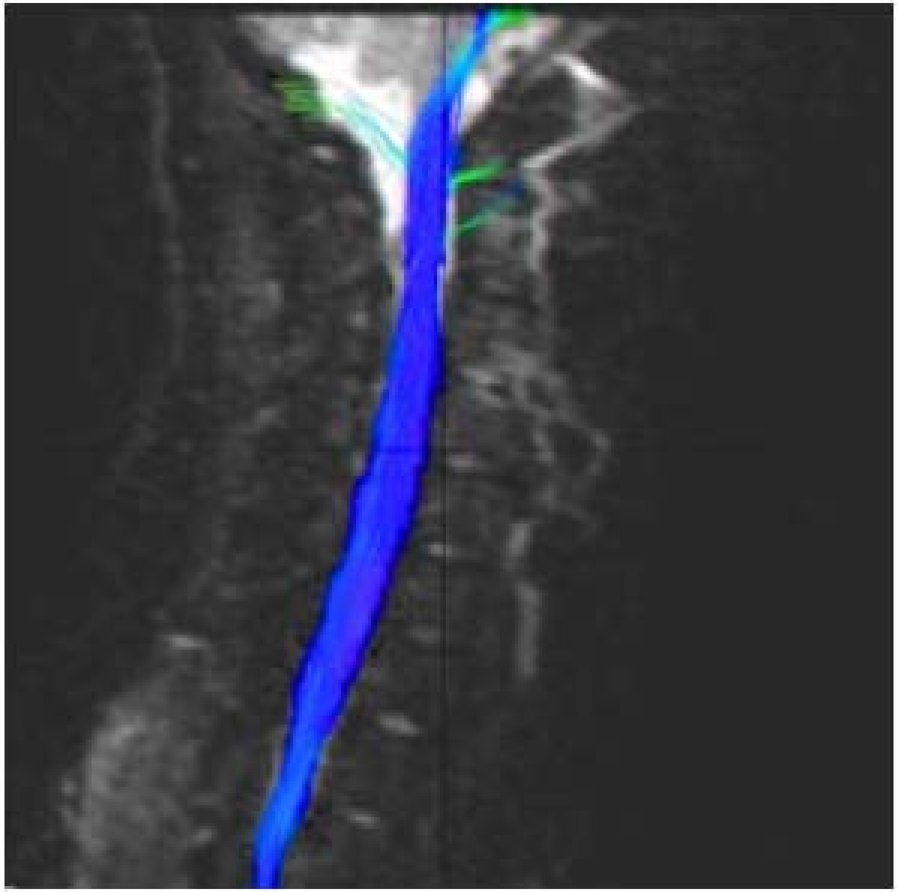


[Fillard, Arsigny, Pennec, Ayache ISBI'06, TMI 26(11) 2007]

Clinical DTI of the spinal cord: fiber tracking



Standard



MAP Rician

[Fillard, Arsigny, Pennec, Ayache ISBI'06, TMI 26(11) 2007]

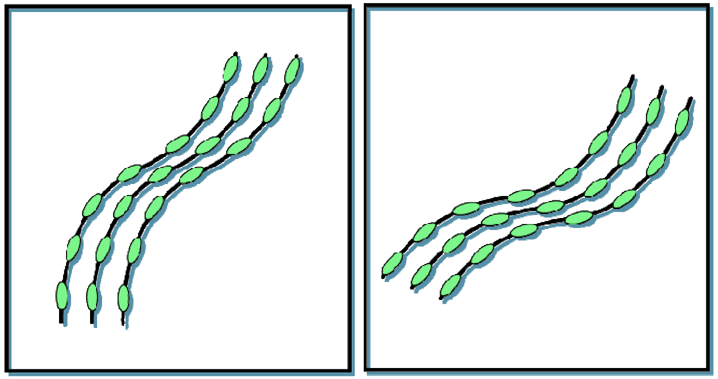
Content

DTI Registration Challenges

Similarity metric:

- Tensor comparison (distance)

$$C(\phi) = \int dist^2\left(\Sigma_1(x), (\phi * \Sigma_2)(x)\right)$$



Deforming tensor images

- Tensor interpolation (resampling)
  - Local linear approximation using the Jacobian:
    $\phi(x+v) \approx \phi(x) + J(x).v$ with $J(x) = D\phi(x)$
  - Affine action: $J*\Sigma = J.\Sigma.J^t$ does not preserve eigenvalues
- Tensor re-orientation [Alexander TMI 20(11) 2001]: $J*\Sigma = R(J).\Sigma.R(J)^t$
  - Finite-Strain (FS): Clostest rotation $R(J) = (J.\ J^t)^{-½}\ J$
  - Preservation of Principal Directions (PPD)

References on Tensor registration

Image metric based on Transformation Invariant Features

- No reorientation [Guimond’02, Leemans’05, Park’05, Ziyan’07]

Euclidean metric on the full tensor

- Preservation of Principal Directions
  - Elastic, PPD with approx grad (R(J) not differentiated) [Alexander and Gee CVIU 77(2), 2000]
  - LDDMM with exact PPD differential [Cao et al MMBIA 2006]
- Finite-Strain
  - Parameters are locally affine transformation [Zhang et al. MedIA 10(5) 2006 & TMI 26(11) 2007]

DT-REFinD: Diffusion Tensor Registration with Exact Finite-Strain Differential

[Thomas Yeo, et al. DTI Registration with Exact Finite-Strain Differential. ISBI'08]

Tensor interpolation/metric

- Euclidean and Log-Euclidean (Arsigny ’06)

Tensor reorientation

- Finite Strain with Exact Differential

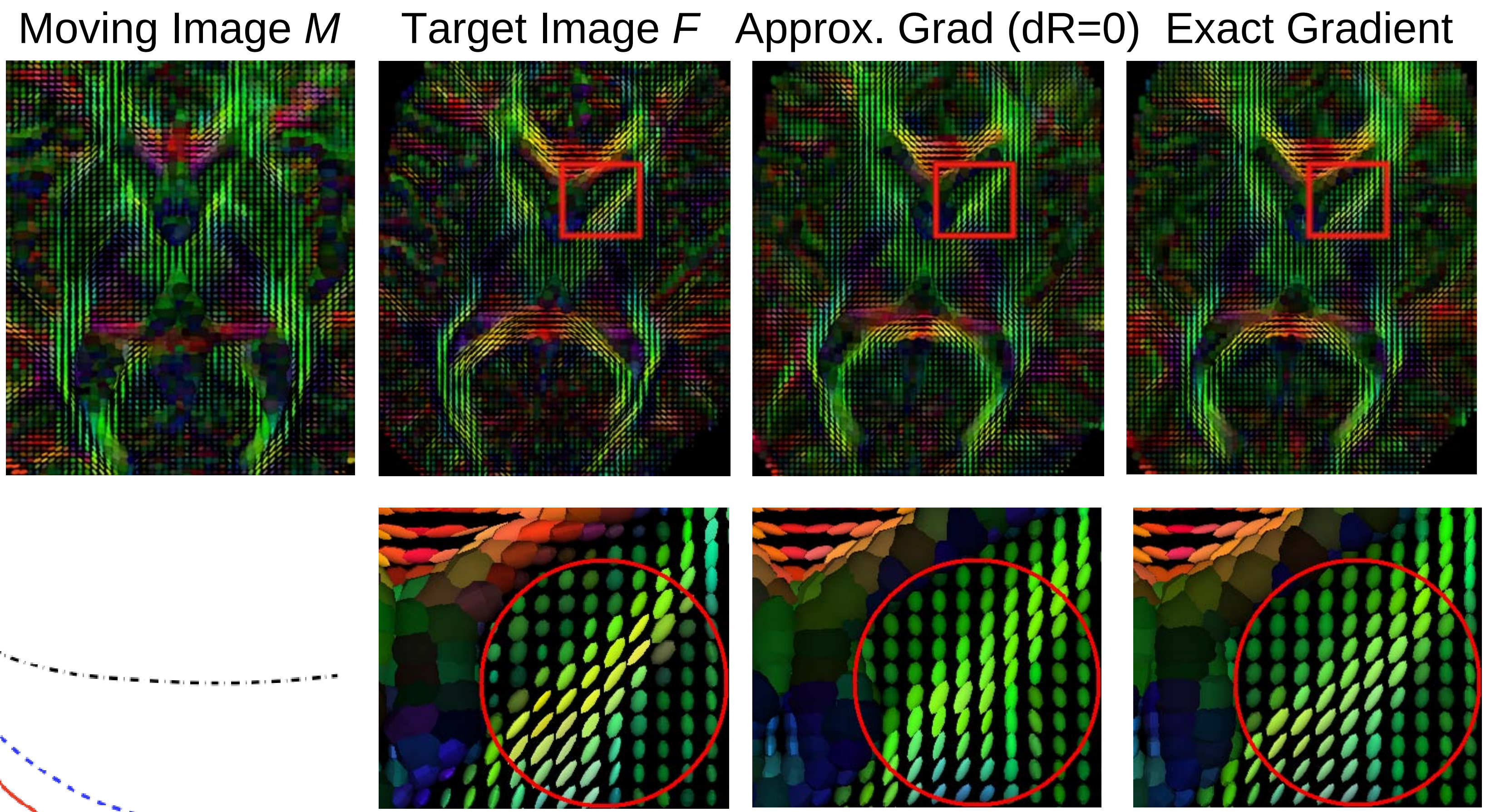
Deformation model

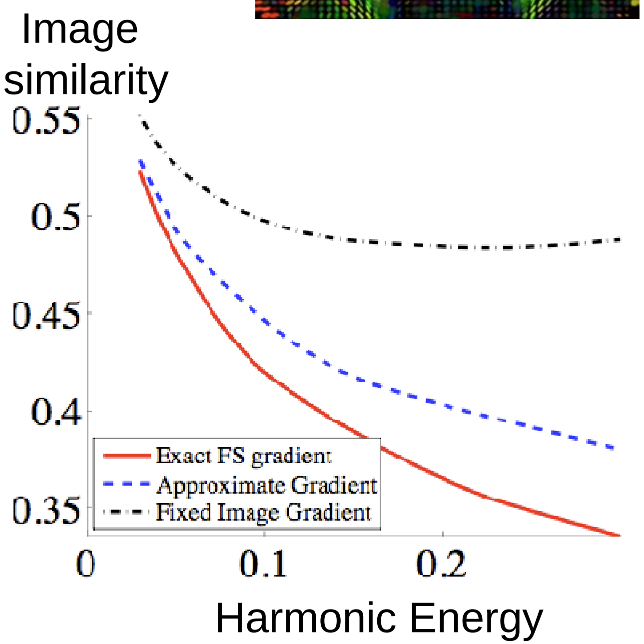
- Iterated one parameter diffeomorphisms
- Diffeomorphic Demons [Vercauteren MICCAI’07]

Fast and accurate

- 15 minutes,128x128x60, Xeon 3.2GHz
- Better tensor alignment

Exact vs approximate FS gradient

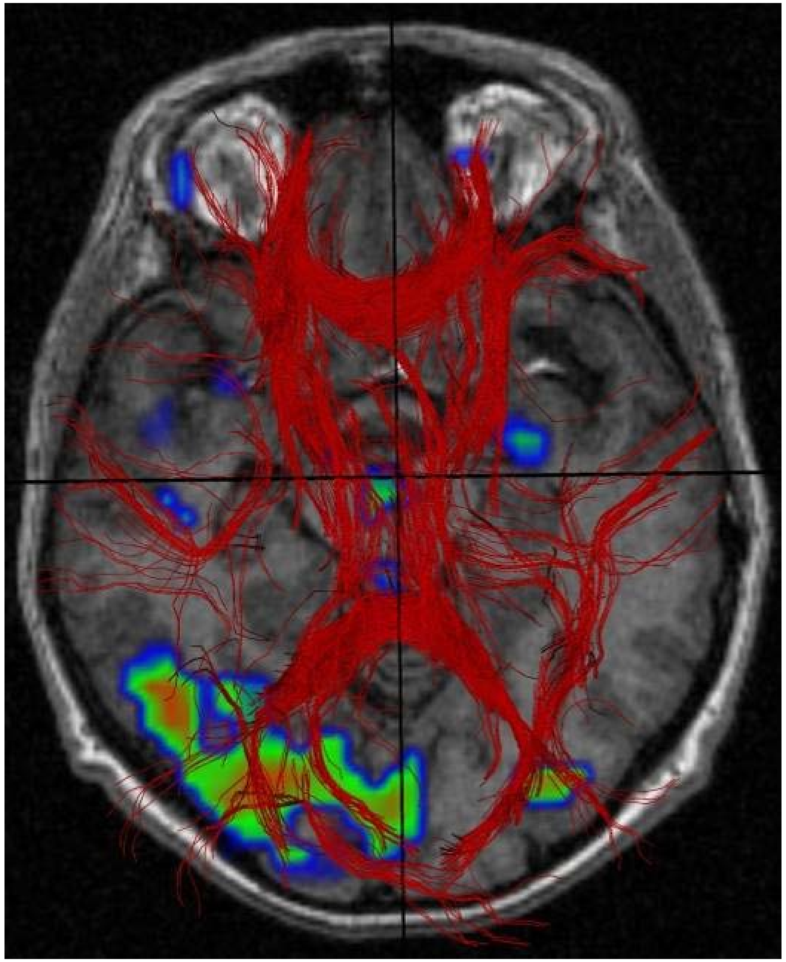




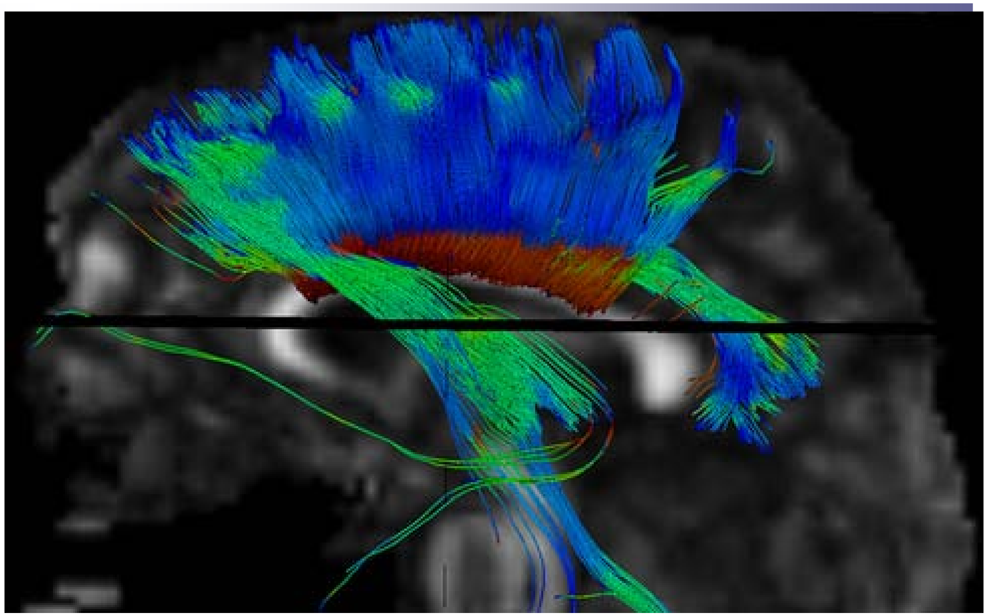
*** DTI data courtesy of Denis Ducreux, MD, Bicêtre Hospital, Paris, France**


Freeware
Announcement
MedINRIA
• Powered by ITK & VTK
• DICOM support
• DTI Analysis, Fiber Bundling
• Image Registration and Fusion
NEW Tensor Registration
with Diffeomorphic Demons
www-sop.inria.fr/asclepios/software/MedINRIA
INRIA
vtk
itk

Some results

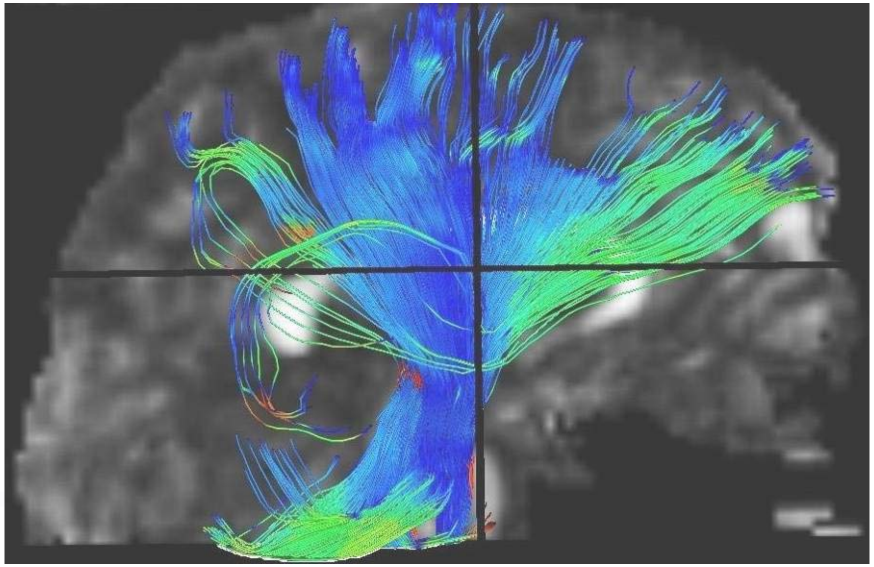


T1 + Activation map + fibers



Corpus callosum + cingulum

Corticospinal tract and
thalamo cortical connections



Conclusion & Perspectives

The Riemannian computing framework

- Integral or sum in M: minimize an intrinsic functional
  - Fréchet / Karcher mean
  - Filtering, convolution through weighted means
- The exponential chart is the basic tool
  - Gradient descent is geodesic walking
  - Intrinsic numerical scheme for Laplace Beltrami

Choice of the metric

- Log-Euclidean (faster than affine invariant) for tensors
- Cholesky or Procruste for rank deficient tensors?
- Design new metrics for HARDI and higher order tensors?

Conclusion & Perspectives

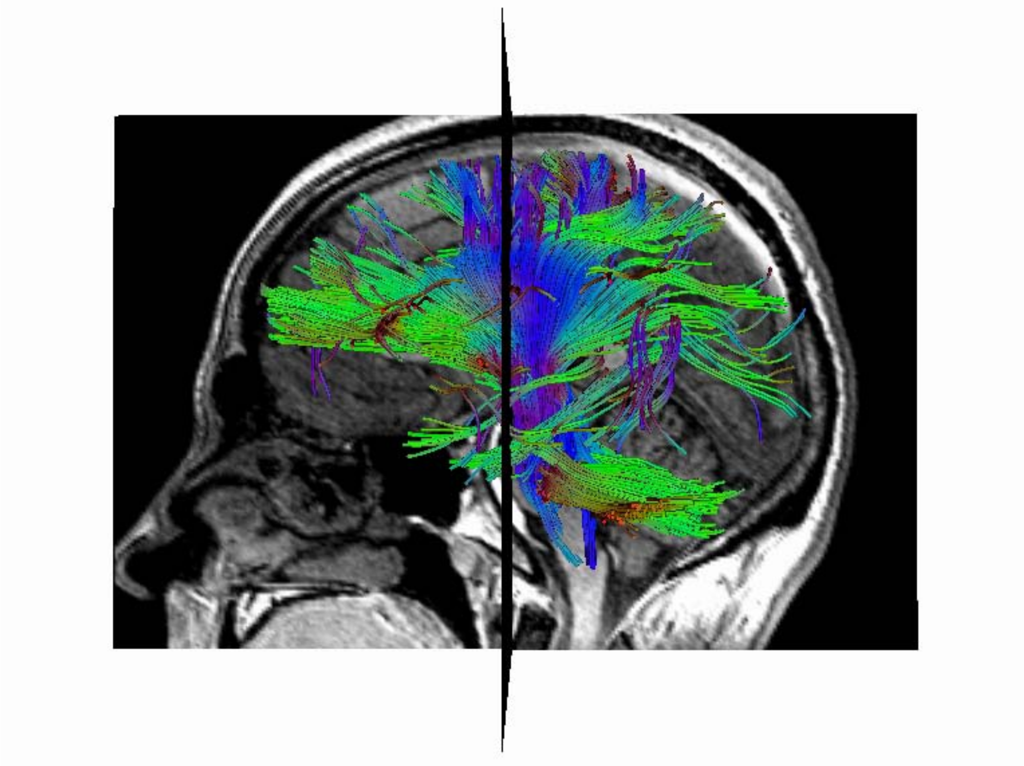
A consistent set of tools for

- Tensor Estimation
- Tensor Registration
- Statistical Atlas building

Computational anatomy challenges

- Probing the information highways of the brain with DMRI
- From tensors / HARDI to fiber statistics?

Thank You!



Riemannian DT-MRI processing with **MedINRIA**:

http://www.inria.fr/sophia/asclepios/software/MedINRIA.

Special thanks to Pierre Fillard for most of the illustrations!

Literature

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