

# Riemannian Median and Its Applications for Orientation Distribution Function Computing

Jian Cheng<sup>1,2</sup>, Aurobrata Ghosh<sup>1</sup>, Tianzi Jiang<sup>2</sup>, Rachid Deriche<sup>1</sup>

<sup>1</sup>Athena, INRIA Sophia Antipolis, France

<sup>2</sup>LIAMA, NLPR, Institute of Automation, Chinese Academy of Sciences, China

INSTITUT NATIONAL  
DE RECHERCHE  
EN INFORMATIQUE  
ET EN AUTOMATIQUE

INRIA

centre de recherche SOPHIA ANTIPOLIS - MÉDITERRANÉE

LIAMA



## Introduction

The geometric median is a classic robust estimator of centrality for data in Euclidean spaces, and it has been generalized in analytical manifold in [1]. Recently, an intrinsic Riemannian framework for Orientation Distribution Function (ODF) was proposed for the calculation in ODF field [2]. In this work, we prove the unique existence of the Riemannian median in ODF space. Then we explore its two potential applications, median filtering and atlas estimation

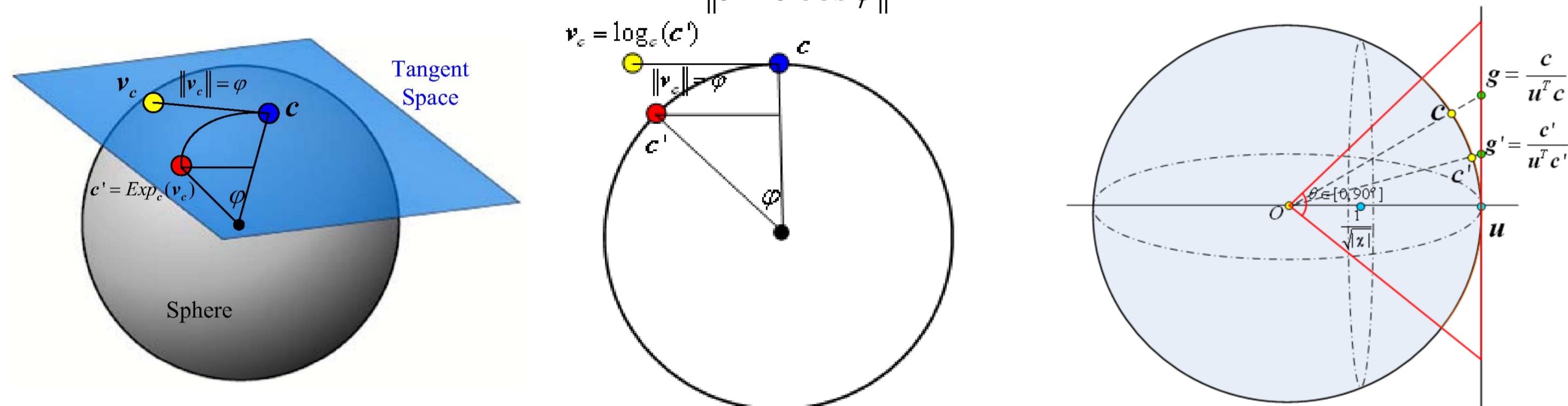
## Riemannian framework for ODFs

### I. PDF family via orthonormal basis representation [2]

$$p(\mathbf{x} | \mathbf{c}) = \left( \sum_{i=1}^K c_i B_i(\mathbf{x}) \right)^2 \quad \sum_{i=1}^K c_i^2 = 1 \quad \sum_{i=1}^K c_i B_i(\mathbf{x}) \geq 0$$

### II. The intrinsic Riemannian framework for ODF computing [2]

- Fisher metric [6]:  $g_{ij} = 4 \int_{S^{K-1}} \partial_i \sqrt{p(\mathbf{x} | \mathbf{c})} \partial_j \sqrt{p(\mathbf{x} | \mathbf{c})} d\mathbf{x} = 4 \delta_{ij}$
- Geodesic:  $d_{g_{ij}}(p(\cdot | \mathbf{c}), p(\cdot | \mathbf{c}')) = d_{\delta_{ij}}(\mathbf{c}, \mathbf{c}') = \arccos(\mathbf{c}^T \mathbf{c}')$
- Exponential map:  $Exp_{\mathbf{c}}(\mathbf{v}_{\mathbf{c}}) = \mathbf{c}' = \mathbf{c} \cos \varphi + \frac{\mathbf{v}_{\mathbf{c}}}{\|\mathbf{v}_{\mathbf{c}}\|} \sin \varphi$ , where  $\varphi = \|\mathbf{v}_{\mathbf{c}}\|$
- Logarithmic map:  $Log_{\mathbf{c}}(\mathbf{c}') = \mathbf{v}_{\mathbf{c}} = \frac{\mathbf{c}' - \mathbf{c} \cos \varphi}{\|\mathbf{c}' - \mathbf{c} \cos \varphi\|} \varphi$ , where  $\varphi = \arccos(\mathbf{c}^T \mathbf{c}')$



### III. Properties of parameter space (PS) [2]

- PS is a **closed convex**
- PS is contained in a **convex cone with 90°**
- The **projection** of any  $\mathbf{u}$  on the uniform ODF  $\mathbf{c}$  is more than  $\frac{1}{\sqrt{4\pi}}$
- Weighted Riemannian mean **uniquely exists**  $m_w = \arg \min_{f \in PS} \sum_{i=1}^N w_i d(f, f_i)^2$

## Weighted Riemannian Median

- Definition:**  $\mu_w = \arg \min_{f \in PS} \sum_{i=1}^N w_i d(f, f_i)$
- Uniquely exists** if one of the two conditions is satisfied [1]
  - the sectional curvatures of M are non-positive
  - the sectional curvatures of M are bounded by  $\Delta > 0$  and  $diam(U) < \pi / (2\sqrt{\Delta})$** , where  $U$  is the convex set which contains  $\{x_i\}$  and  $diam(U)$  is the diameter of  $U$
- A Weighted Riemannian median **uniquely exists** in PS because of condition (b)
- No close form. Numerical algorithm [1]:

#### Algorithm 1: Weighted Riemannian Median

**Input:**  $f_1, \dots, f_N \in PS^K$ ,  $\mathbf{w} = (w_1, \dots, w_N)'$ ,  $w_i \geq 0$ ,  $i = 1, 2, \dots, N$ ,  $\sum_{i=1}^N w_i = 1$ .

**Output:**  $\mu_w$ , the *Weighted Frechet Mean*.

Initialization:  $\mu_w^{(0)} = \frac{\sum_{i=1}^N w_i f_i}{\|\sum_{i=1}^N w_i f_i\|}$ ,  $k = 0$

Do

$$q_i = w_i d(\mu_w^{(k)}, x_i) / \sum_{i=1}^N w_i d(\mu_w^{(k)}, x_i), \quad v_{\mu_w^{(k)}} = \sum_{i=1}^N q_i Log_{\mu_w^{(k)}}(f_i)$$

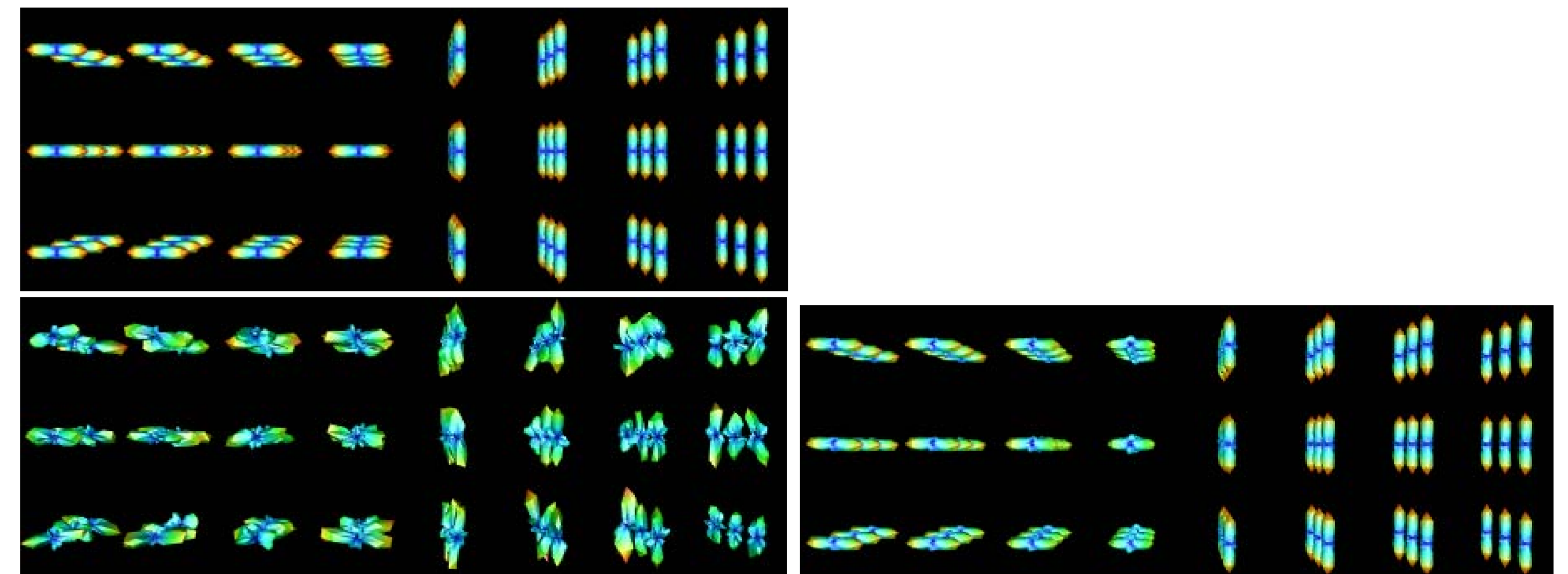
$$\mu_w^{(k+1)} = Exp_{\mu_w^{(k)}}(v_{\mu_w^{(k)}})$$

$k = k + 1$

while  $\|\mu_w^{(k)}\| > \varepsilon$

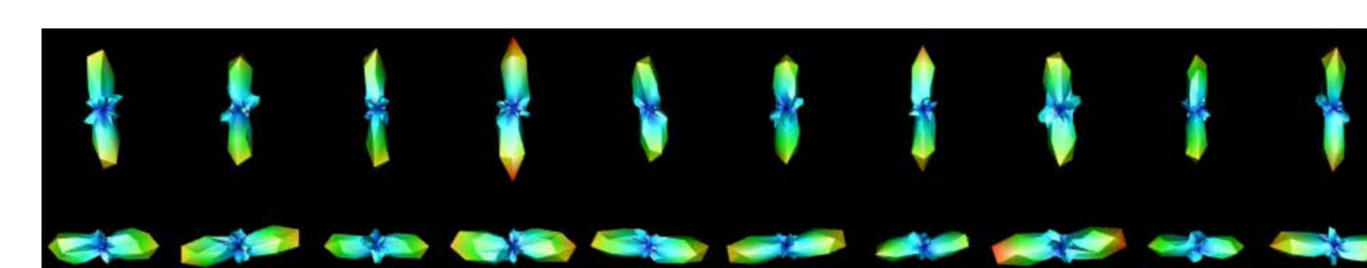
## Median Smoothing

- Edge-preserving smoothing**
- Experiment on synthetic data (Gaussian noise on tangent space)



## Atlas Estimation

- Robust Statistics**, breakdown point
- Experiment on outlier effect

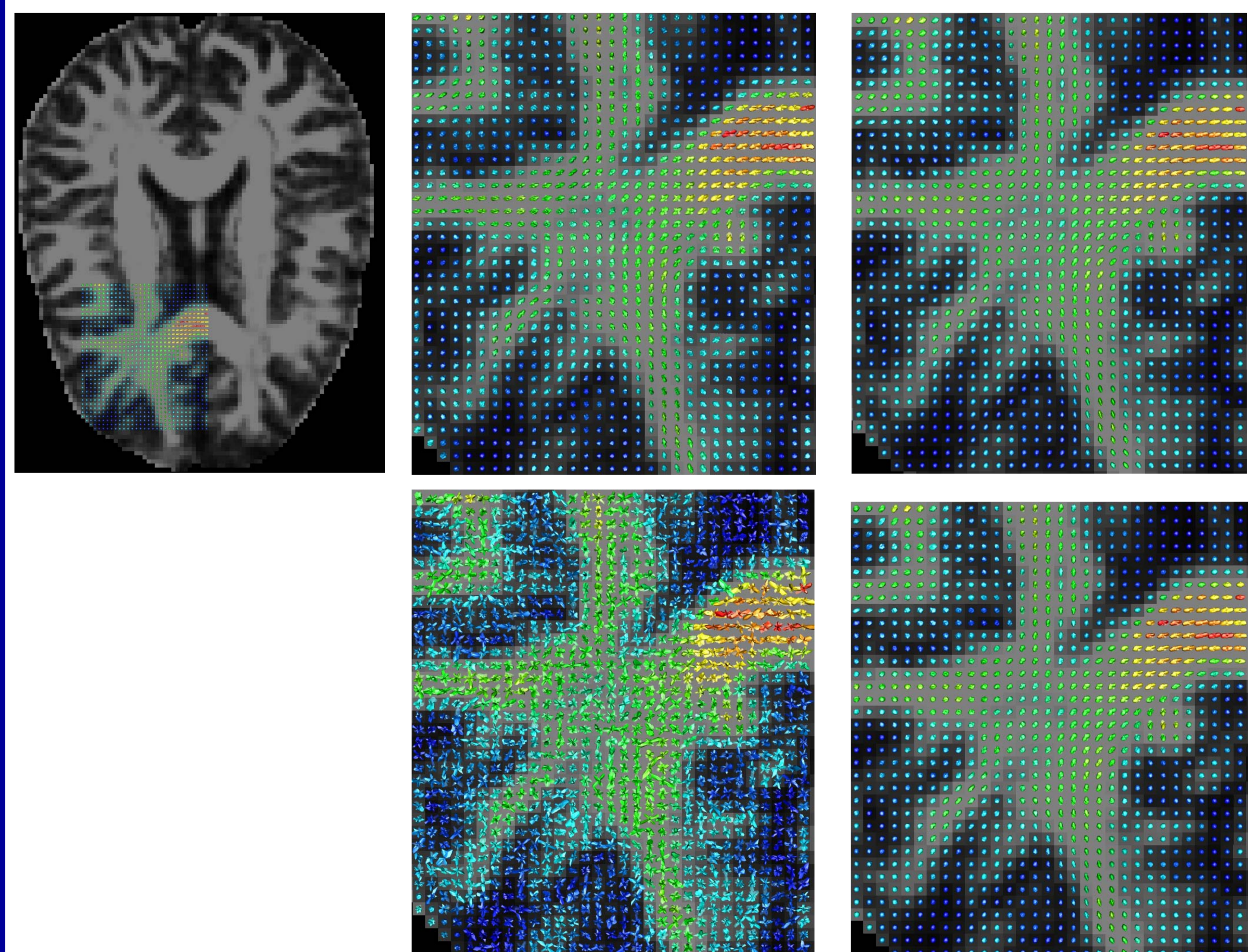


Left: regular ODFs, outliers;

Right: Euclidean mean, Riemannian mean, Riemannian median

### Atlas Estimation on five subjects

- Affine registration on all DWIs**
- Affine matrix from the registration on the image without diffusion via FSL**
- re-orientate the gradient directions via the finite strain (FS) [4]**



From left to right, first row: a slice of estimated atlas; ODF field in ROI for one subject; ODF field of the estimated atlas, second row: ODF field in ROI with Gaussian noise in Riemannian space (std=0.1) for one subject; ODF field of estimated atlas from the data with noise.

## References

- P. T. Fletcher, Suresh Venkatasubramanian, Sarang Joshi: *The geometric median on Riemannian manifolds with application to robust atlas estimation* NeuroImage 2009(45) S143-S152
- Jian Cheng, Aurobrata Ghosh, Tianzi Jiang, Rachid Deriche: *A Riemannian Framework for Orientation Distribution Function Computing*. MICCAI 2009
- Iman Aganj, Christophe Lenglet, Guillermo Sapiro: *ODF reconstruction in q-ball imaging with solid angle consideration*. ISBI 2009
- David S. Tuch: *Q-ball imaging*. Magnetic Resonance in Medicine 2004(52) 1358-1372
- D. C. Alexander, C. Pierpaoli, P. J. Basser, J. C. Gee: *Spatial Transformations of Diffusion Tensor Magnetic Resonance Images*. IEEE Transactions On Medical Imaging 2001(20)
- Pennec, X., Fillard, P., Ayache, N.: *A Riemannian framework for tensor computing*. International Journal of Computer Vision 2006(66) 41-66