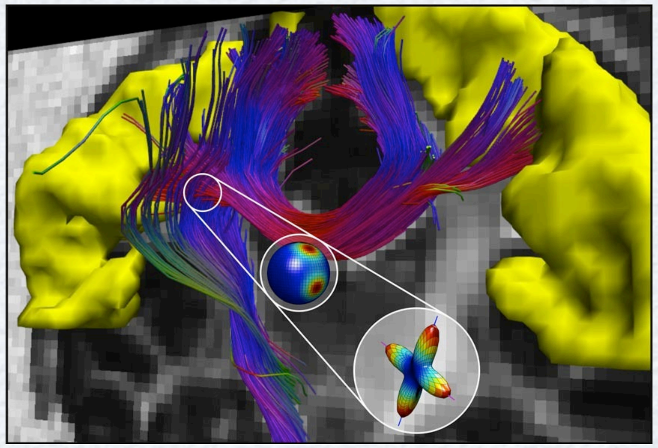
University of Guanajuato CIMAT A.C
México



HRCh 2013

FROGS TEAM REPORT

Alonso Ramírez-Manzanares (alram@cimat.mx)
Angel Ramón Aranda Campos (arac@cimat.mx)
Mariano J.J. Rivera Meraz (mrivera@cimat.mx)
Jesús Omar Ocegueda Gonzalez(omar@cimat.mx)

THE NAME

- "Guanajuato" means "place of frogs" in the native languaje.

OUR TEAMS

- Then we registered 3 teams
  - FROGS
    - (Alonso, Ramón, Mariano, Omar)

  - BLUE DART FROGS
    - (Omar, Mariano)

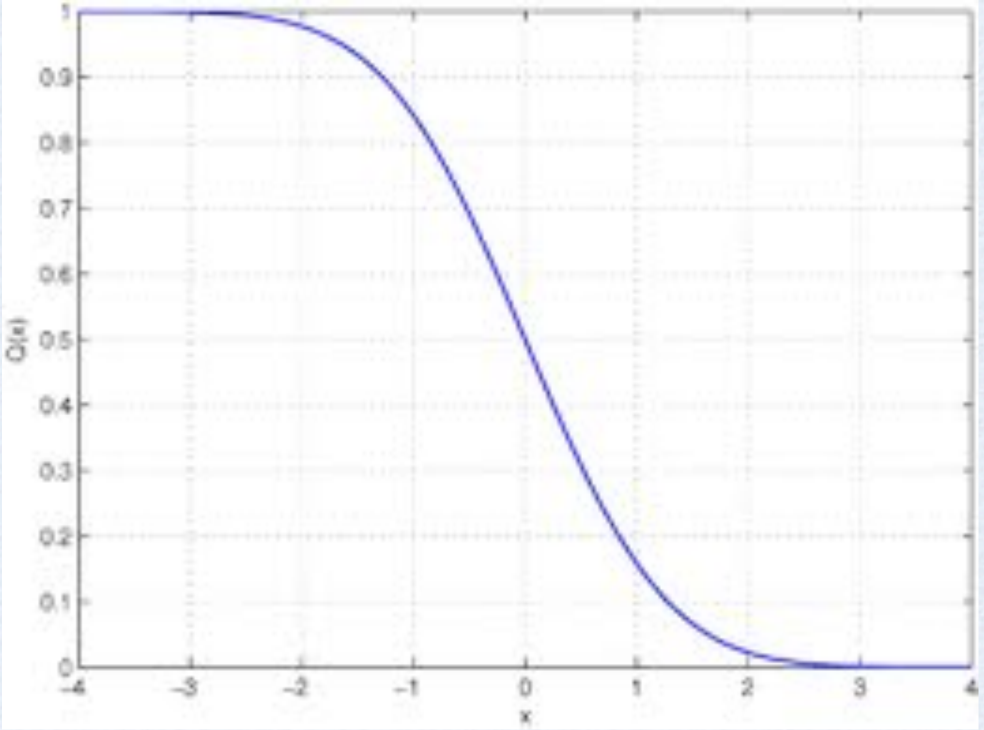
  - DIFFUSION WATER-FROGS
    - (Ramón, Mariano Alonso)

DATA

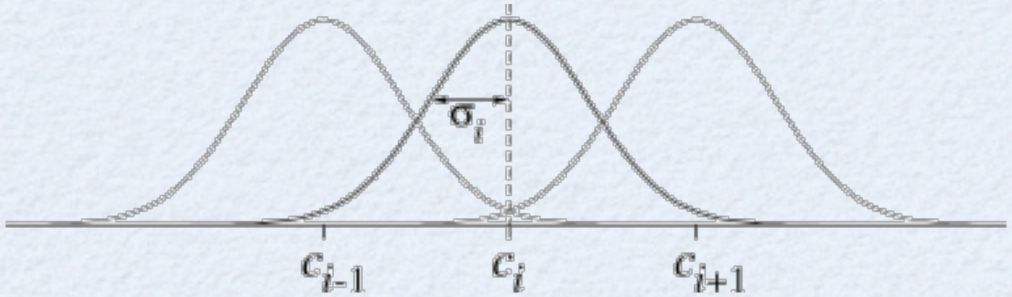
- The 3 teams submited results within the HARDI-Like Class, 64 DEO, b=3000.

Diffusion Basis Functions (DBF), TMI, 2007

- The DBF model is based on Regularization By Using a Overcomplete Dictionary of Atoms

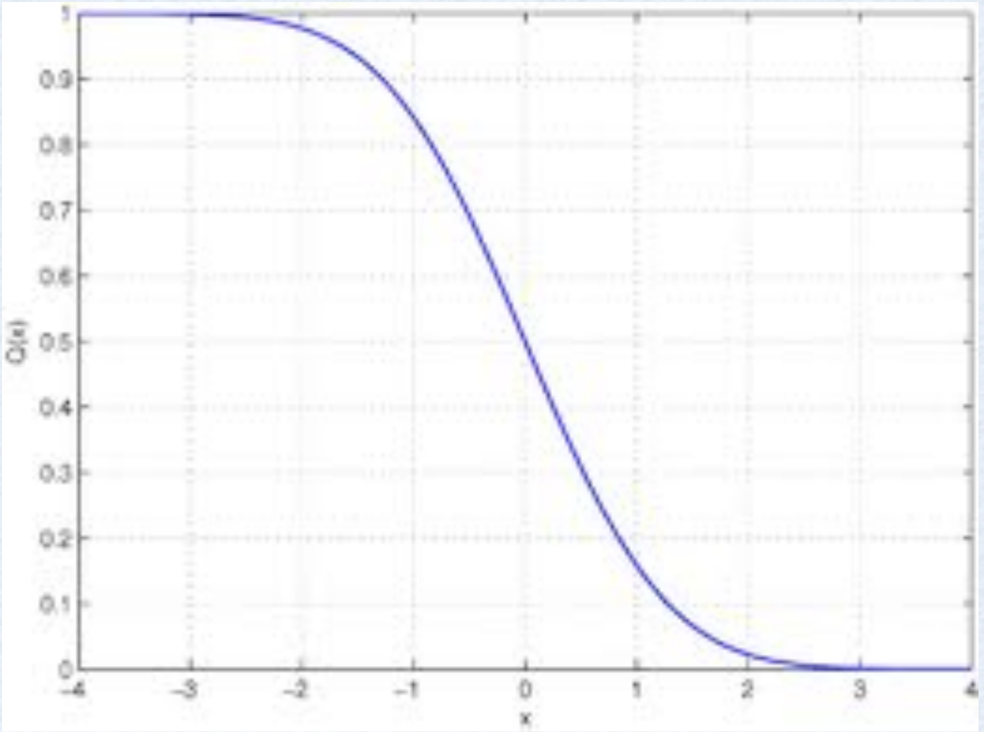


$$f(x) \approx \sum_{i=1}^{N} \alpha_i \phi_i(\sigma_i, c_i)$$



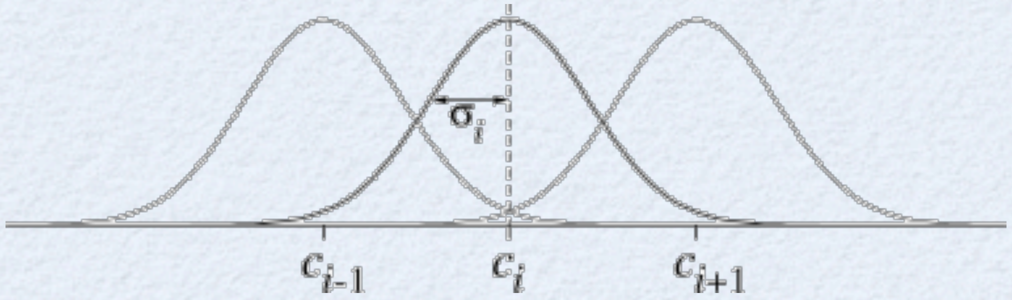
Diffusion Basis Functions (DBF), TMI, 2007

- The DBF model is based on Regularization By Using a Overcomplete Dictionary of Atoms



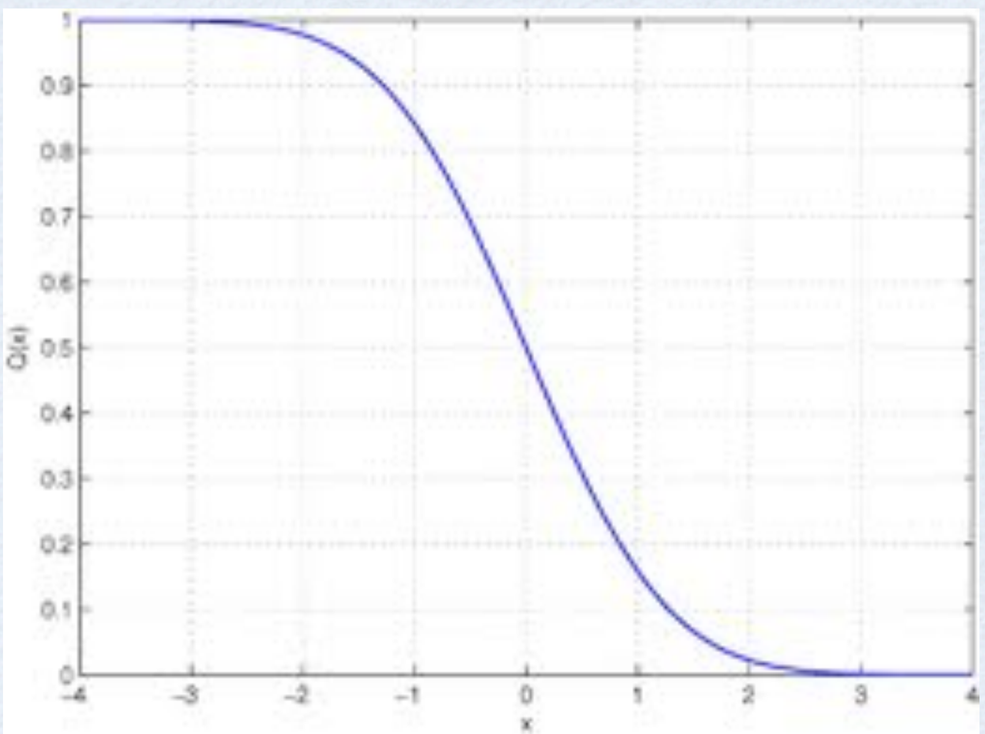
$$f(x) \approx \sum_{i=1}^{N} \alpha_i \phi_i(\sigma_i, c_i)$$

$$\mathbf{x} = \mathbf{\Phi}\alpha$$



Diffusion Basis Functions (DBF), TMI, 2007

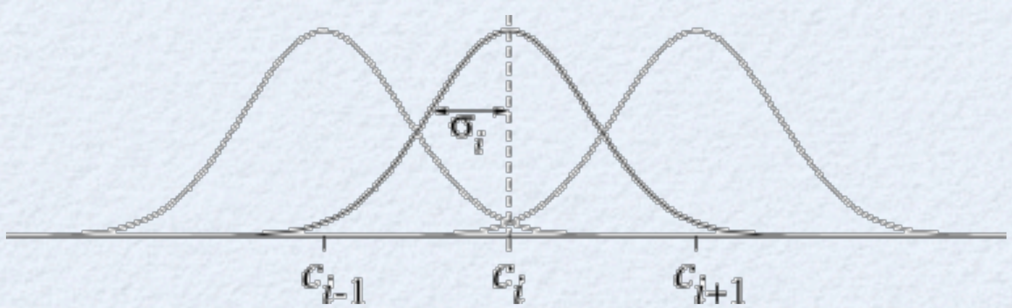
- The DBF model is based on Regularization By Using a Overcomplete Dictionary of Atoms



$$f(x) \approx \sum_{i=1}^{N} \alpha_i \phi_i(\sigma_i, c_i)$$

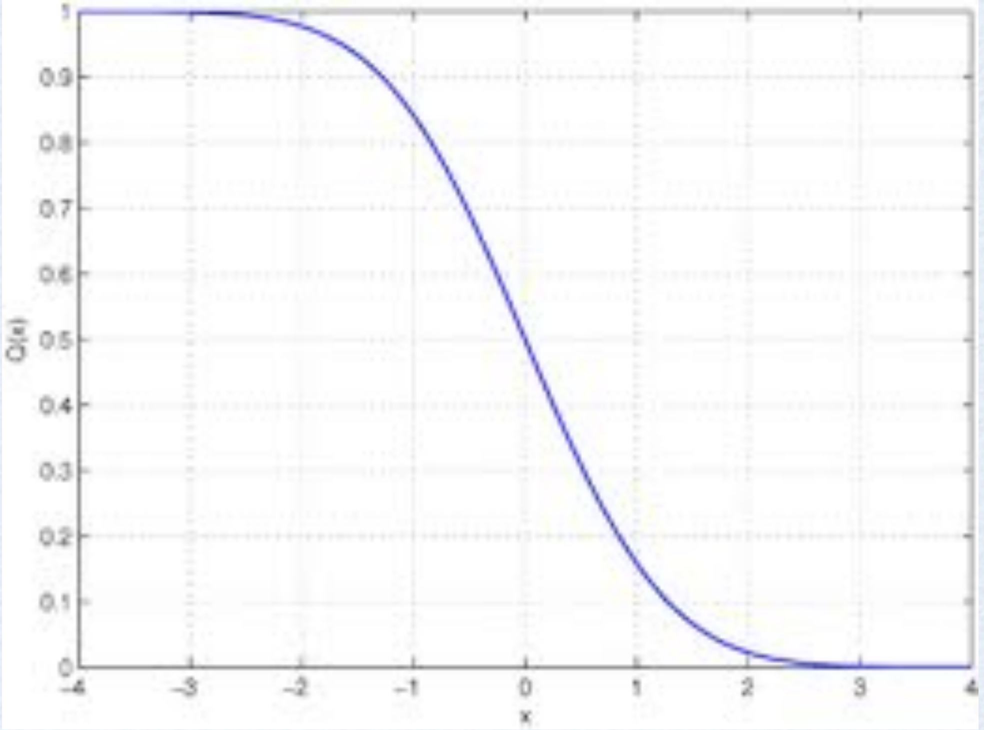
$$\mathbf{x} = \mathbf{\Phi}\alpha$$

$$||\mathbf{A}\ (\Phi\alpha) - \mathbf{b}||^2 + \lambda||\alpha||_1$$



Diffusion Basis Functions (DBF), TMI, 2007

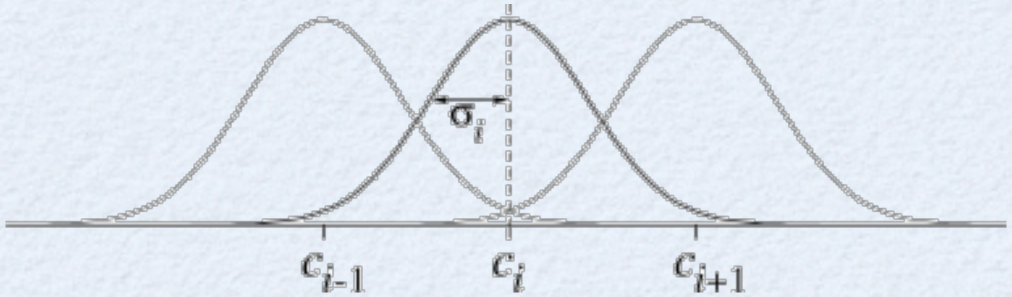
- The DBF model is based on Regularization By Using a Overcomplete Dictionary of Atoms



$$f(x) \approx \sum_{i=1}^{N} \alpha_i \phi_i(\sigma_i, c_i)$$

$$\mathbf{x} = \boldsymbol{\Phi}\alpha$$

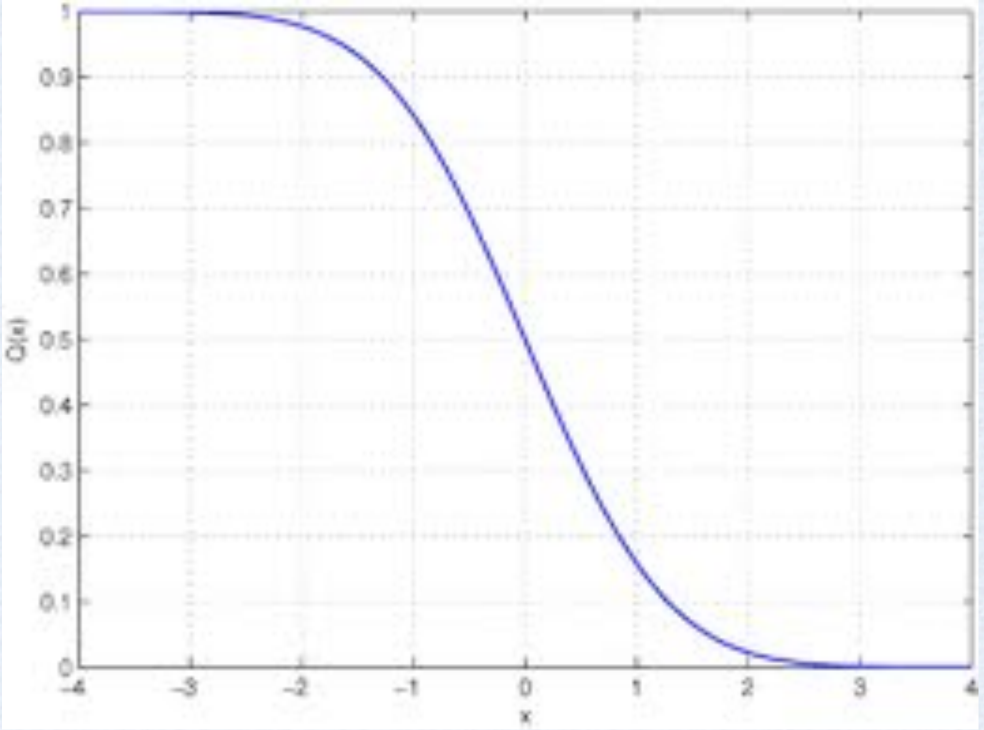
$$||\mathbf{A}\ (\Phi\alpha) - \mathbf{b}||^2 + \lambda||\alpha||_1$$



$$\min_{\alpha} ||\alpha||_1$$

Diffusion Basis Functions (DBF), TMI, 2007

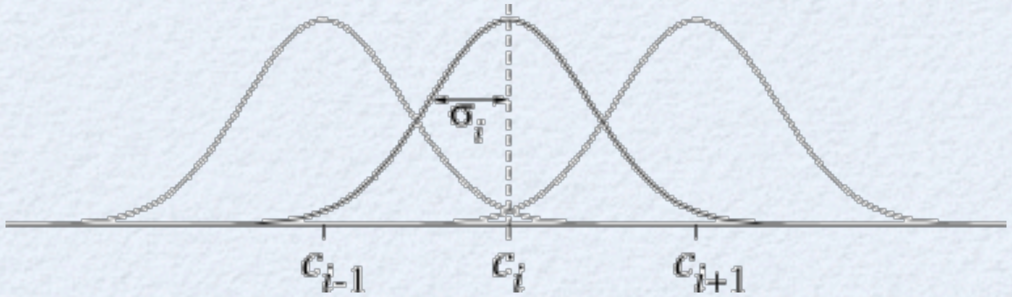
- The DBF model is based on Regularization By Using a Overcomplete Dictionary of Atoms



$$f(x) \approx \sum_{i=1}^{N} \alpha_i \phi_i(\sigma_i, c_i)$$

$$\mathbf{x} = \mathbf{\Phi}\alpha$$

$$||\mathbf{A}\ (\Phi\alpha) - \mathbf{b}||^2 + \lambda||\alpha||_1$$



$$\min_{\alpha} ||\alpha||_1$$

$$\text{s.t.}\ \ A(\Phi\alpha) - b = 0$$

DBF MODEL

- Based on the GMM or Multi-Tensor

$$S_i = S_0 \sum_{j=1}^{J} \beta_j \exp\left(-b g_i^T T_j g_i\right)$$

- We precompute this part as

- Such that the model is

DBF MODEL

- Based on the GMM or Multi-Tensor

$$S_i = S_0 \sum_{j=1}^{J} \beta_j \exp\left(-b g_i^T T_j g_i\right)$$

- We precompute this part as

- Such that the model is

DBF MODEL

- Based on the GMM or Multi-Tensor

$$S_i = S_0 \sum_{j=1}^{J} \beta_j \exp\left(-b g_i^T T_j g_i\right)$$

- We precompute this part as

$$\phi_{i,k} = S_0 \exp\left(-b g_i^T \bar{T}_k g_i\right)$$

- Such that the model is

DBF MODEL

- Based on the GMM or Multi-Tensor

$$S_i = S_0 \sum_{j=1}^{J} \beta_j \exp\left(-b g_i^T T_j g_i\right)$$

- We precompute this part as

$$\phi_{i,k} = S_0 \exp\left(-b g_i^T \bar{T}_k g_i\right)$$

- Such that the model is

$$S_i \approx \sum_{k=1}^{N} \alpha_k \phi_{i,k}$$

DBF MODEL

- Based on the GMM or Multi-Tensor

$$S_i = S_0 \sum_{j=1}^{J} \beta_j \exp\left(-b g_i^T T_j g_i\right)$$

- We precompute this part as

$$\phi_{i,k} = S_0 \exp\left(-b g_i^T \bar{T}_k g_i\right)$$

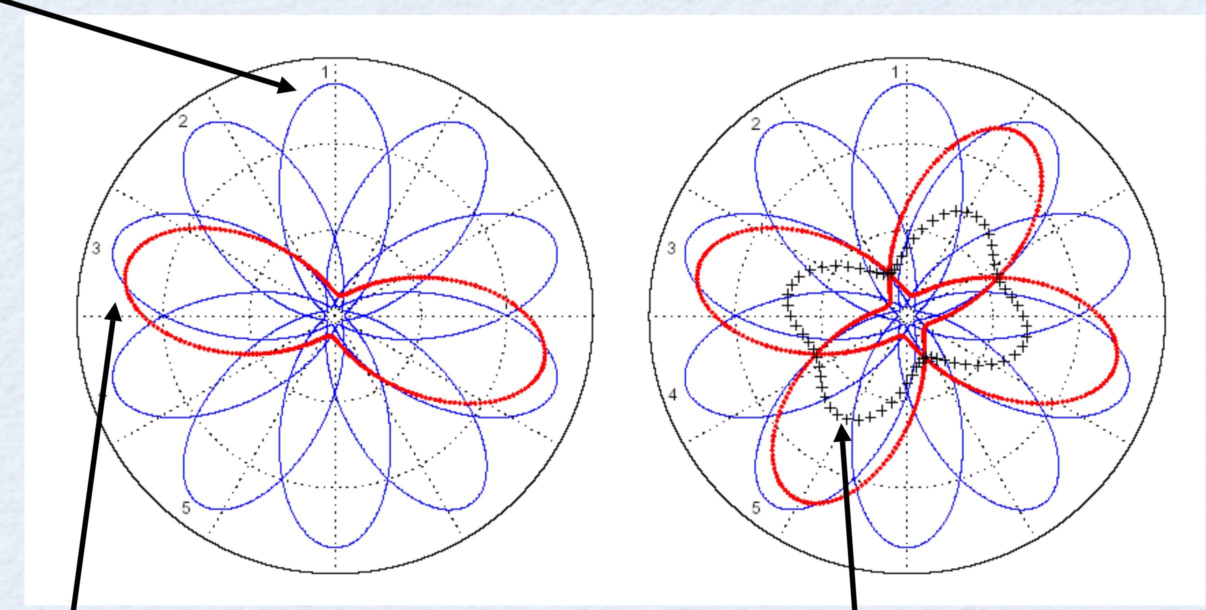
- Such that the model is

$$S_i \approx \sum_{k=1}^{N} \alpha_k \phi_{i,k} \quad \text{with } \alpha_k \geq 0$$

Naive 2D explanation

$$\Phi_{ij} = \exp\left(-b\,\mathbf{g}_i^T\,\bar{\mathrm{T}}_j\,\mathbf{g}_i\right)$$

Set of signals for the DBFs



MRI signal for a single fiber

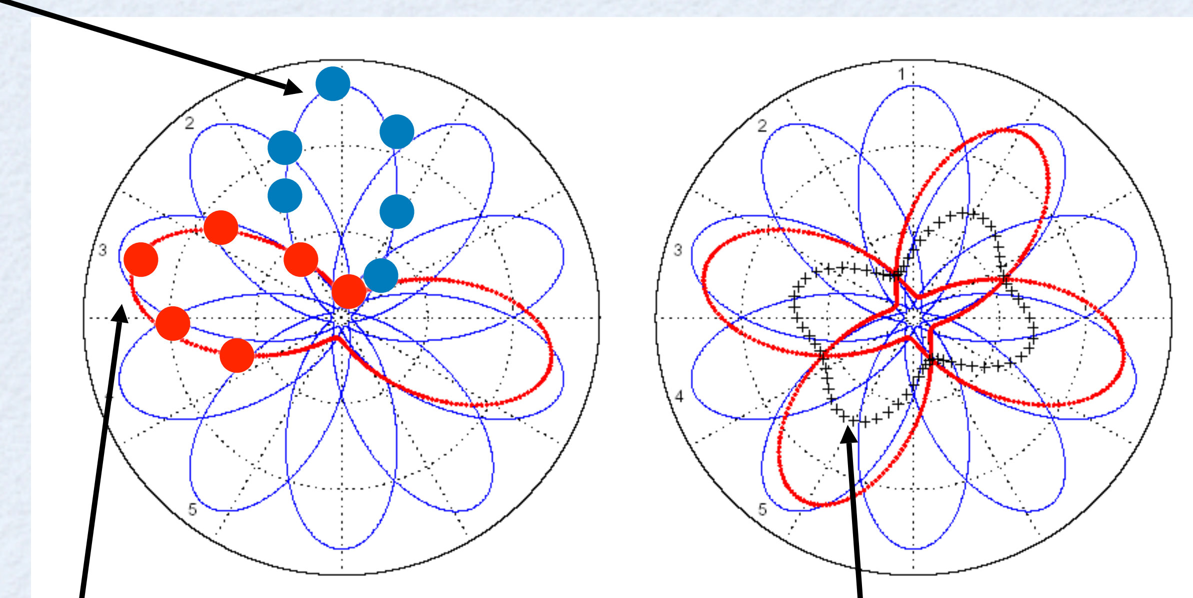
MRI signal for a 2 fiber crossing

$$S_i = S_0 \sum_{j=1}^{N} \alpha_j \Phi_{ij} + \eta_{ir}$$

Naive 2D explanation

$$\Phi_{ij} = \exp\left(-b\, \mathbf{g}_i^T\, \overline{\mathrm{T}}_j\, \mathbf{g}_i\right)$$

Set of signals for the DBFs



MRI signal for a single fiber

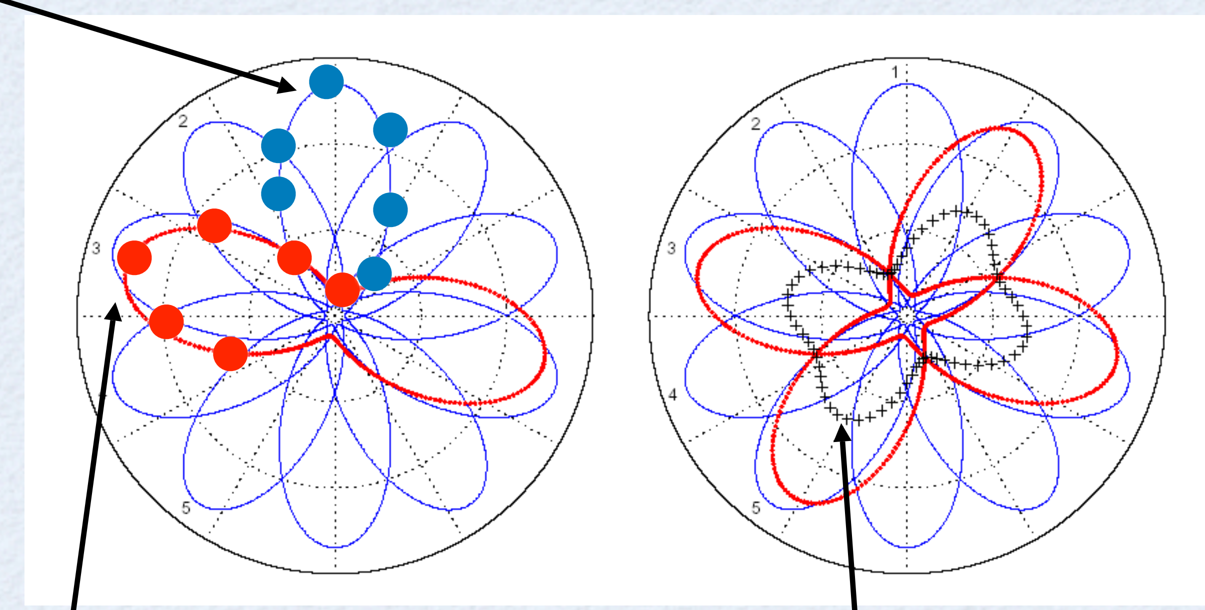
MRI signal for a 2 fiber crossing

$$S_i = S_0 \sum_{j=1}^{N} \alpha_j \Phi_{ij} + \eta_{ir}$$

Naive 2D explanation

$$\Phi_{ij} = \exp\left(-b\, g_i^T\, \bar{T}_j\, g_i\right)$$

Set of signals for the DBFs



MRI signal for a single fiber

MRI signal for a 2 fiber crossing

$$S_i = S_0 \sum_{j=1}^{N} \alpha_j \Phi_{ij} + \eta_{ir}$$

with $\alpha_k \geq 0$

Solvers

$$s = \sum_{i \in \Gamma} \alpha_i \phi_i + \eta = \Phi\alpha + \eta$$

A redundant dictionary of atoms (non-orthogonal functions)

Rectangular Matrix N >> M

The problem can be stated as:

$$\min \|\alpha\|_1 \quad \text{subject to} \quad \Phi\alpha = s \qquad \alpha \geq 0$$

or

$$\min_{\alpha} \quad U(\alpha) = \|\Phi\alpha - S\|_2^2 \qquad \text{subject to} \quad \alpha \geq 0$$

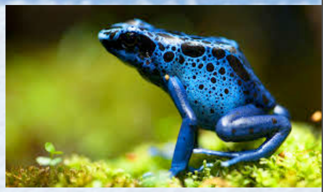
DFB UPDATE FOR THE HRC

- We participate with this method on the HRC2012. This year we submit the same method as a base of comparison.
- Modifications: We smooth the DW-MR signals

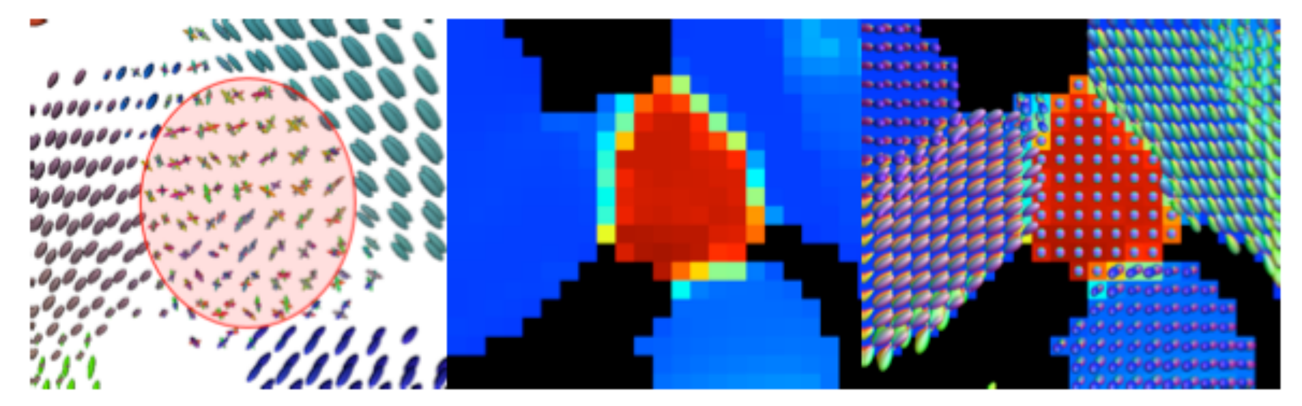
$$\hat{S}_r = \frac{1}{\#\mathcal{N}_r + 1}\left(S_r + \sum_{t:t\in\mathcal{N}_r} S_t\right)$$

- The ODF was computed on a contrasted solution, we increase the longitudinal diffusion and decrease the radial difussion.

Blue Dart Proposal



- A local coherence index was computed based on the PDDs of the multi-tensor solutions to identify potential water balls. Those regiones were filled with spheric ODFs.



- The team enforced the model at voxel *p* to explain not only the signal observed at voxel *p* but its neighbors.

$$\min_{\beta_p \in \Re^N} \sum_{q \in \mathcal{N}(p) \cup \{p\}} ||\Phi\beta_p - S_q||_2^2, \; s.t. \; \beta_p \geq 0,$$

- which can be shown to be equivalent to

$$\min_{\beta_p \in \Re^N} ||\Phi\beta_p - \bar{S}_p||_2^2, \; s.t. \; \beta_p \geq 0,$$ with $\bar{S}_p = \frac{1}{1+\mathcal{N}(p)} \sum_{q \in \mathcal{N}(p) \cup \{p\}} S_q$

Diffusion Water Frogs

- We computer a better estimation of the PDDs by computing a small rotation

$$\phi'_{i,k} = S_0 \exp\left(-b g_i^T R(\theta_k) \bar{T}_k R(\theta_k)^T g_i\right)$$

- Such that the problem-to-be-solved is

$$\begin{array}{ll} \min\limits_{\Theta,\alpha} & U(\Theta,\alpha) = \|\Phi(\Theta)\alpha - S\|_2^2 \\ \text{subject to} & \alpha \geq 0 \end{array}$$

-

- In order to simplify the problem we decompose

$$R(\theta_k) = X(\theta_{x,k})Y(\theta_{y,k})Z(\theta_{z,k}),$$

- and use approximations like

$$X(\theta_{x,k}) = X_k = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos(\theta_{x,k}) & -\sin(\theta_{x,k}) \\ 0 & \sin(\theta_{x,k}) & \cos(\theta_{x,k}) \end{bmatrix} \approx \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & -\theta_{x,k} \\ 0 & \theta_{x,k} & 1 \end{bmatrix}$$

  - which are valid for small angles.

- Finally, we solve for each rotation matrix

$$X(\theta_{x,k})Y(\theta_{y,k})Z(\theta_{z,k})$$

- iteratively.

- All the details in the paper:
  - SELF-ORIENTED DIFFUSION BASIS FUNCTIONS FOR WHITE MATTER STRUCTURE ESTIMATION, R.Aranda, M. Rivera and A. Ramirez-Manzananres, ISBI 2013.
    - WeCT4 Diffusion MRI II, 15:18

- Thank you very much for your attention

  - ¿Questions?

  - Alonso Ramirez-Manzanares (alram@cimat.mx)

A little announcement

- For those who would like to know Guanajuato, we are participating in the organization of the PSIVT'13:
- www.psivt.org/psivt2013/
- There is a Track on Biomedical Image Processing and Analysis

A little announcement

- For those who would like to know Guanajuato, we are participating in the organization of the PSIVT'13:
- www.psivt.org/psivt2013/