An automatic method for change detection in serial DTI-derived scalar images

H. Boisgontier[1,2], V. Noblet[1], F. Heitz[1], L. Rumbach[2,3], J.-P. Armspach[2]

[1]LSIIT, UMR CNRS-ULP 7005, Strasbourg, France,
[2]LINC, UMR CNRS-ULP 7191, Strasbourg, France,
[3]Service de Neurologie, CHU Minjoz, Besançon, France

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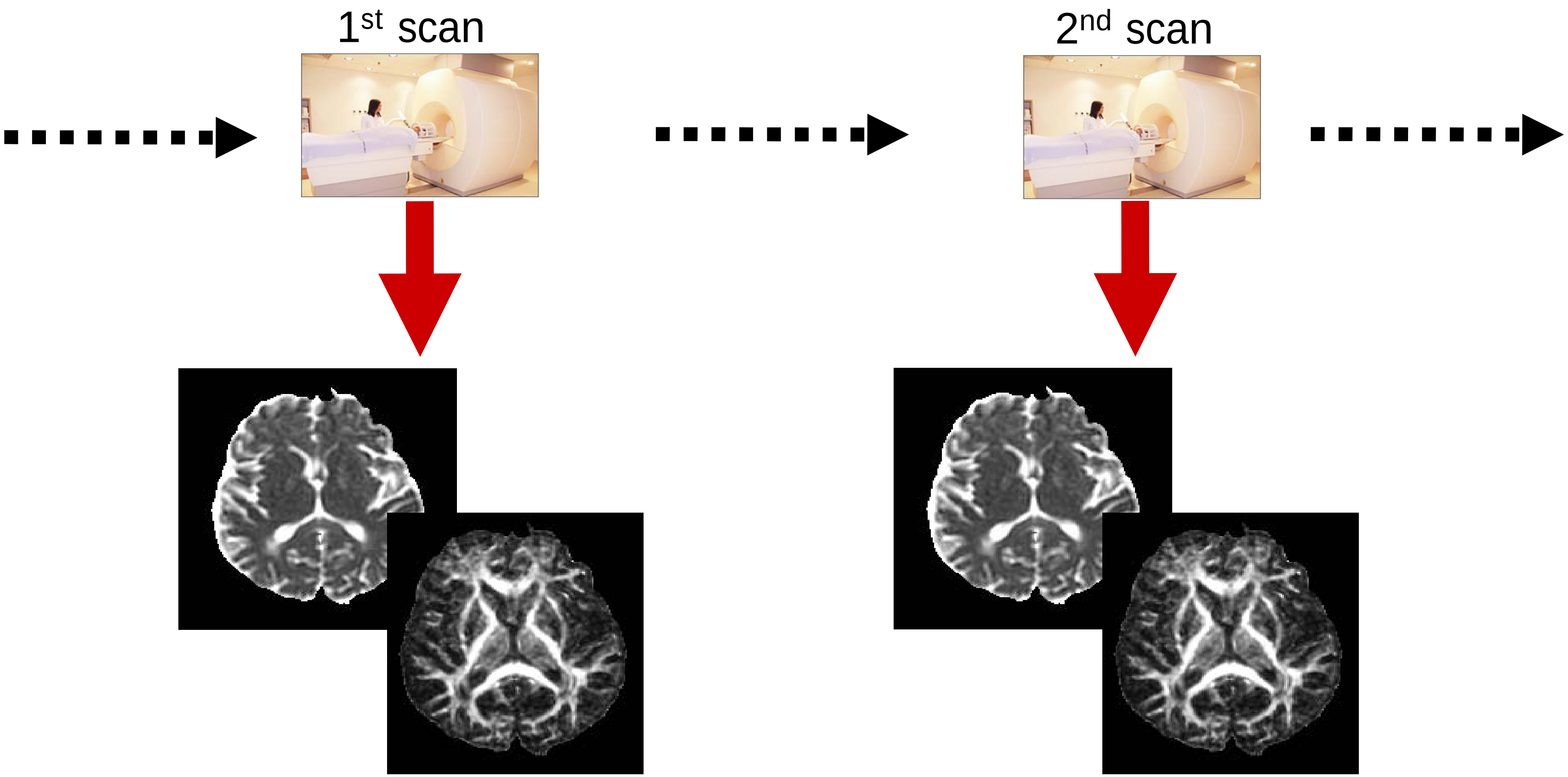
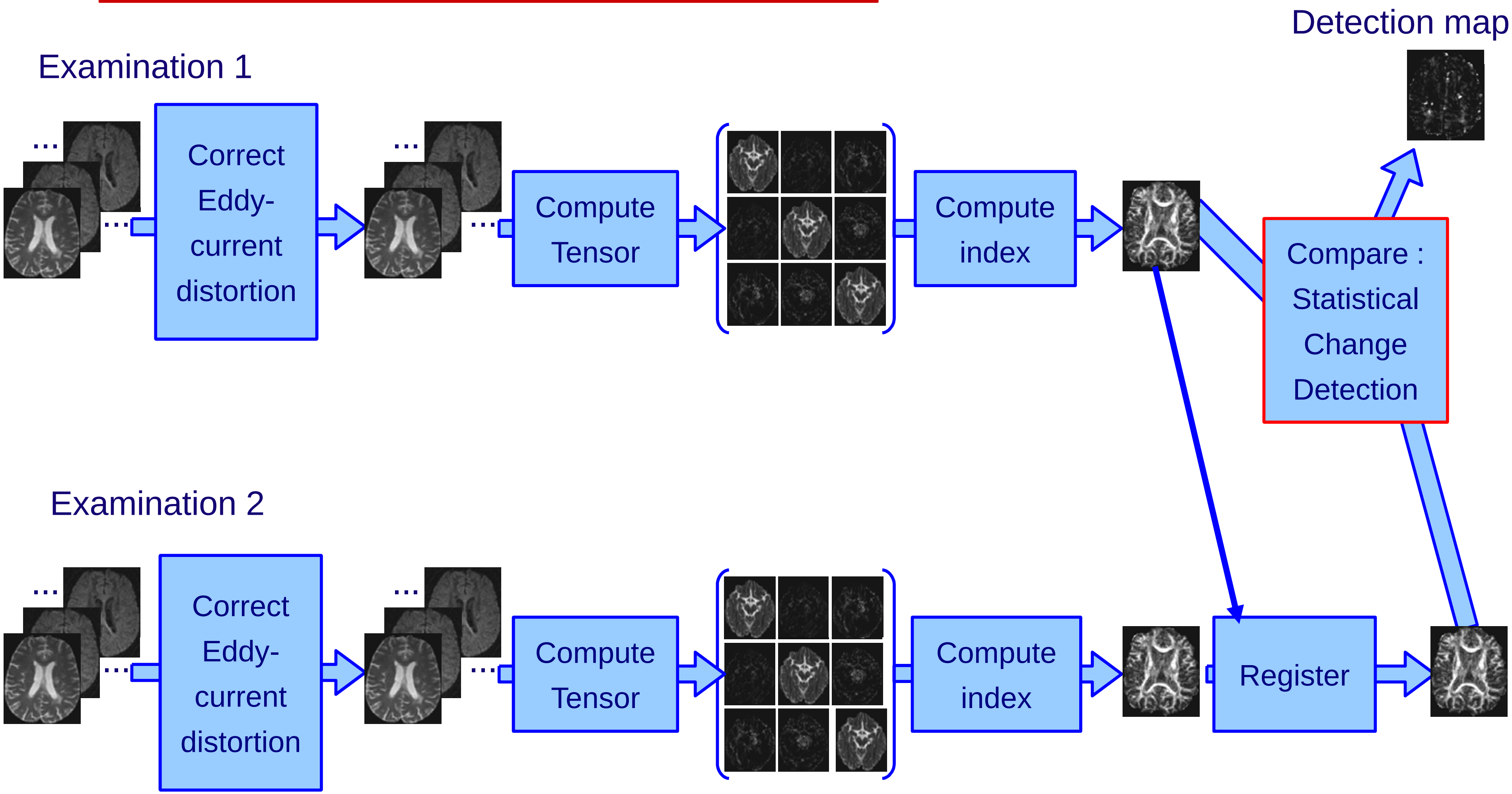
Objective



=> Detect significant changes between diffusion-weighted scalar images

General scheme



Statistical change detection

We consider the Generalized Likelihood Ratio Test (GLRT):

Likelihood ratio under 2 hypothesis:

- H_0: there is no significant change between images I_1 and I_2.
- H_1: there is a significant change between images I_1 and I_2.

$$GLRT = \frac{p(I_1|\widehat{\theta}_1)\ p(I_2|\widehat{\theta}_2)}{p(I_1|\widehat{\theta}_0)\ p(I_2|\widehat{\theta}_0)}$$

I_1 and I_2 are considered as realizations of random variables drawn according to parametric probability density functions:

- with the same parameters θ_0 under assumption H_0
- with two sets of different parameters $\theta_1 \neq \theta_2$ under assumption H_1

Bosc's method

Bosc *et al* (Neuroimage, vol 20 (2), pp 643-656, 2003) use a similar framework for detecting MS lesion evolution in conventional multimodal MRI sequences

<u>Hypothesis</u>:

- Intensities are modeled as a constant value μ in a window W_s of 3×3×3 voxels
- additive stationary Gaussian noise

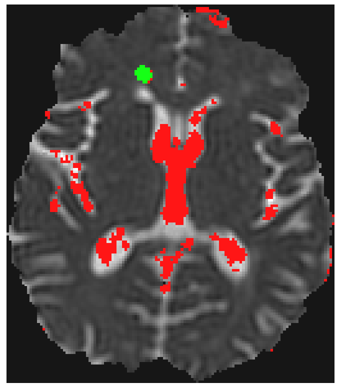
$$\log GLRT(s) \propto \frac{\left(\mu_2^{W_s} - \mu_1^{W_s}\right)^2}{\sigma^2}$$

Bosc’s method

However, Bosc’s approach fails when coping with DTI-derived scalar images because of the non-stationarity of noise.

MD

FA



MD

Proposed approach

We propose to account for the non stationarity of the noise by estimating a variance at each voxel:

$$GLRT(\mathrm{s}) = \frac{\sigma_0^2(\mathrm{s})}{\sqrt{\sigma_1^2(\mathrm{s})\ \sigma_{\mathbf{2}}^{\mathbf{2}}(\mathrm{s})}} \exp^{\frac{(I_1(\mathrm{s})-\mu_{\mathbf{0}}(\mathrm{s}))^{\mathbf{2}}+(\mathbf{I_2}(\mathrm{s})-\mu_{\mathbf{0}}(\mathrm{s}))^{\mathbf{2}}}{2\ \sigma_0^2(\mathrm{s})}}$$

Estimation of the variance is done using the method described in
Chang *et al*, Magnetic Resonance in Medicine, vol 57(1), pp 141 - 149, 2007

Variance estimation (1/2)

Variance on the tensor elements is obtained as a by-product of least squares estimation:

$$Y = AX$$

$$X = [D_{xx}, D_{yy}, D_{zz}, D_{xy}, D_{xz}, D_{yz}]^t$$

$$Y = [1/b \ \log(S_0/S_1), \cdots, 1/b \ \log(S_0/S_N)]^t$$

$$A(i,:) = \left[g_{i;x}^2, g_{i;y}^2, g_{i;z}^2, 2g_{i;x}g_{i;y}, 2g_{i;x}g_{i;z}, 2g_{i;y}g_{i;z}\right]$$

$$\widehat{X} = (A^t A)^{-1} A^t B$$

$$\Sigma_X = \sigma^2 (A^t A)^{-1} \quad \text{with} \quad \sigma^2 = \frac{1}{N}(Y - A\widehat{X})^t (Y - A\widehat{X})$$

Variance estimation (2/2)

The covariance matrix is propagated to the eigenvalues of X

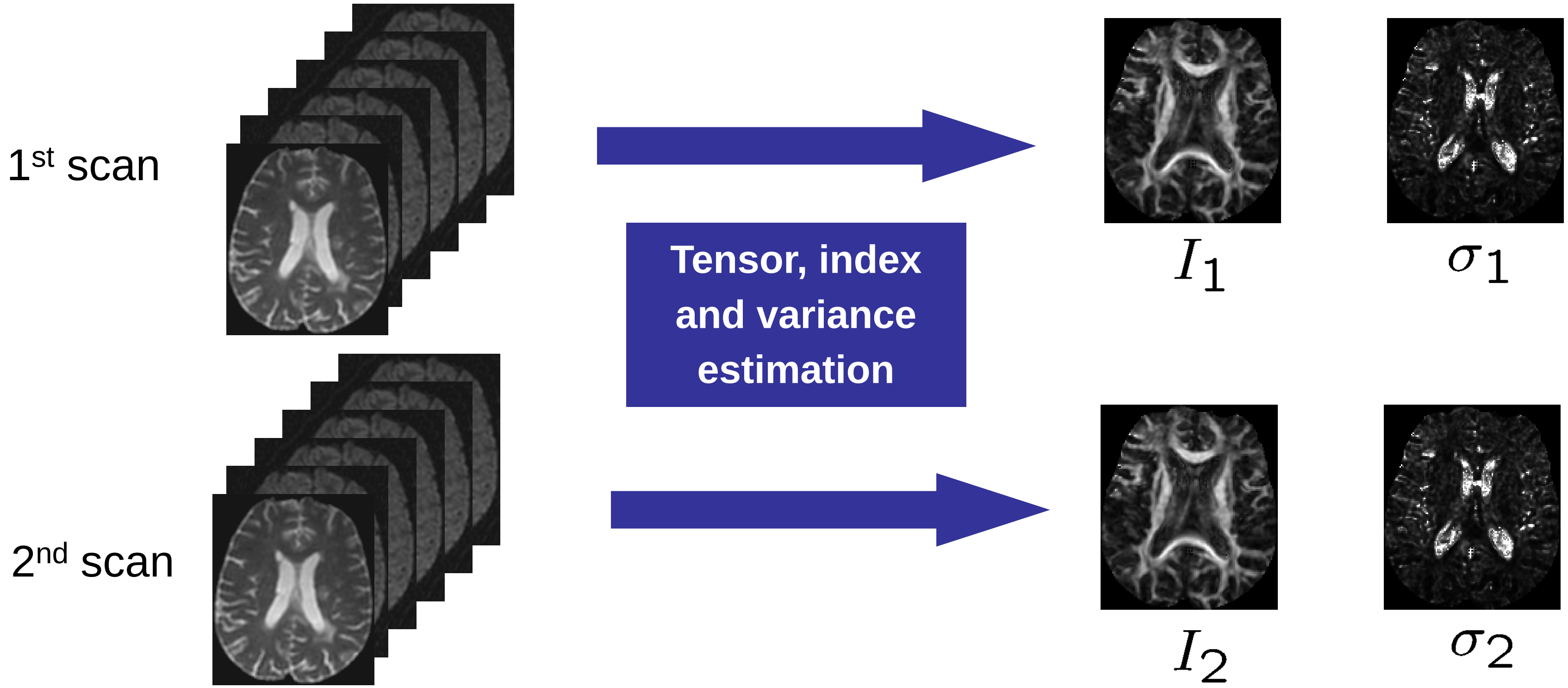
$$\Sigma_\lambda = R \; \Sigma_X \; R^t$$

and then to FA or MD

$$\begin{aligned}
\sigma^2_{MD} &= \sigma^2_{\lambda_1} + \sigma^2_{\lambda_2} + \sigma^2_{\lambda_3} + 2\ \sigma^2_{\lambda_{12}} + 2\ \sigma^2_{\lambda_{13}} + 2\ \sigma^2_{\lambda_{23}} \\
\sigma^2_{FA} &= \sigma^2_{\lambda_1}\left(\frac{\partial FA}{\partial \lambda_1}\right)^2 + \sigma^2_{\lambda_2}\left(\frac{\partial FA}{\partial \lambda_2}\right)^2 + \sigma^2_{\lambda_3}\left(\frac{\partial FA}{\partial \lambda_3}\right)^2 \\
&+ \ 2\ \sigma^2_{\lambda_{12}}\frac{\partial FA}{\partial \lambda_1}\frac{\partial FA}{\partial \lambda_2} + 2\ \sigma^2_{\lambda_{13}}\frac{\partial FA}{\partial \lambda_1}\frac{\partial FA}{\partial \lambda_3} + 2\ \sigma^2_{\lambda_{23}}\frac{\partial FA}{\partial \lambda_2}\frac{\partial FA}{\partial \lambda_3}
\end{aligned}$$

GLRT: H_1 hypothesis

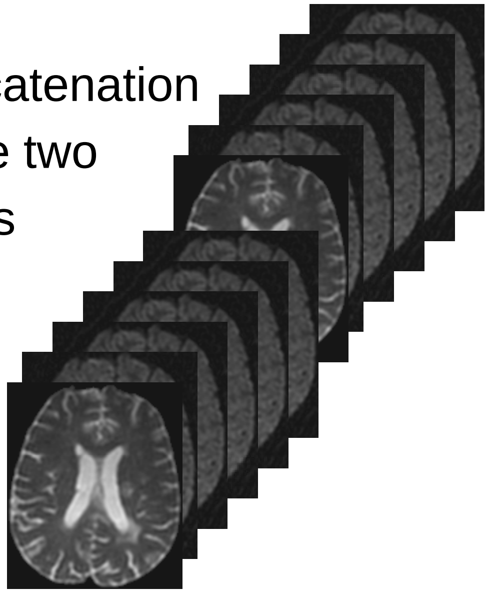
$$GLRT(\mathrm{s}) = \frac{\sigma_0^2(\mathrm{s})}{\sqrt{\sigma_1^2(\mathrm{s})\ \sigma_2^2(\mathrm{s})}} \exp^{\frac{(I_1(\mathrm{s})-\mu_0(\mathrm{s}))^2+(\mathbf{I_2}(\mathrm{s})-\mu_0(\mathrm{s}))^2}{2\ \sigma_0^2(\mathrm{s})}}$$



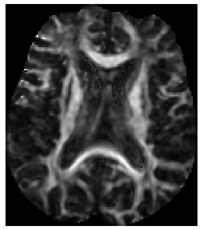
GLRT: H_0 hypothesis

$$GLRT(\mathbf{s}) = \frac{\sigma_0^2(\mathbf{s})}{\sqrt{\sigma_1^2(\mathbf{s})\ \sigma_2^2(\mathbf{s})}} \exp^{\frac{(I_1(\mathbf{s}) - \mu_0(\mathbf{s}))^2 + (\mathbf{I_2}(\mathbf{s}) - \mu_0(\mathbf{s}))^2}{2\ \sigma_0^2(\mathbf{s})}}$$

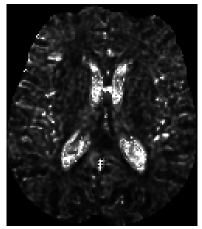
Concatenation of the two scans



Tensor, index and variance estimation

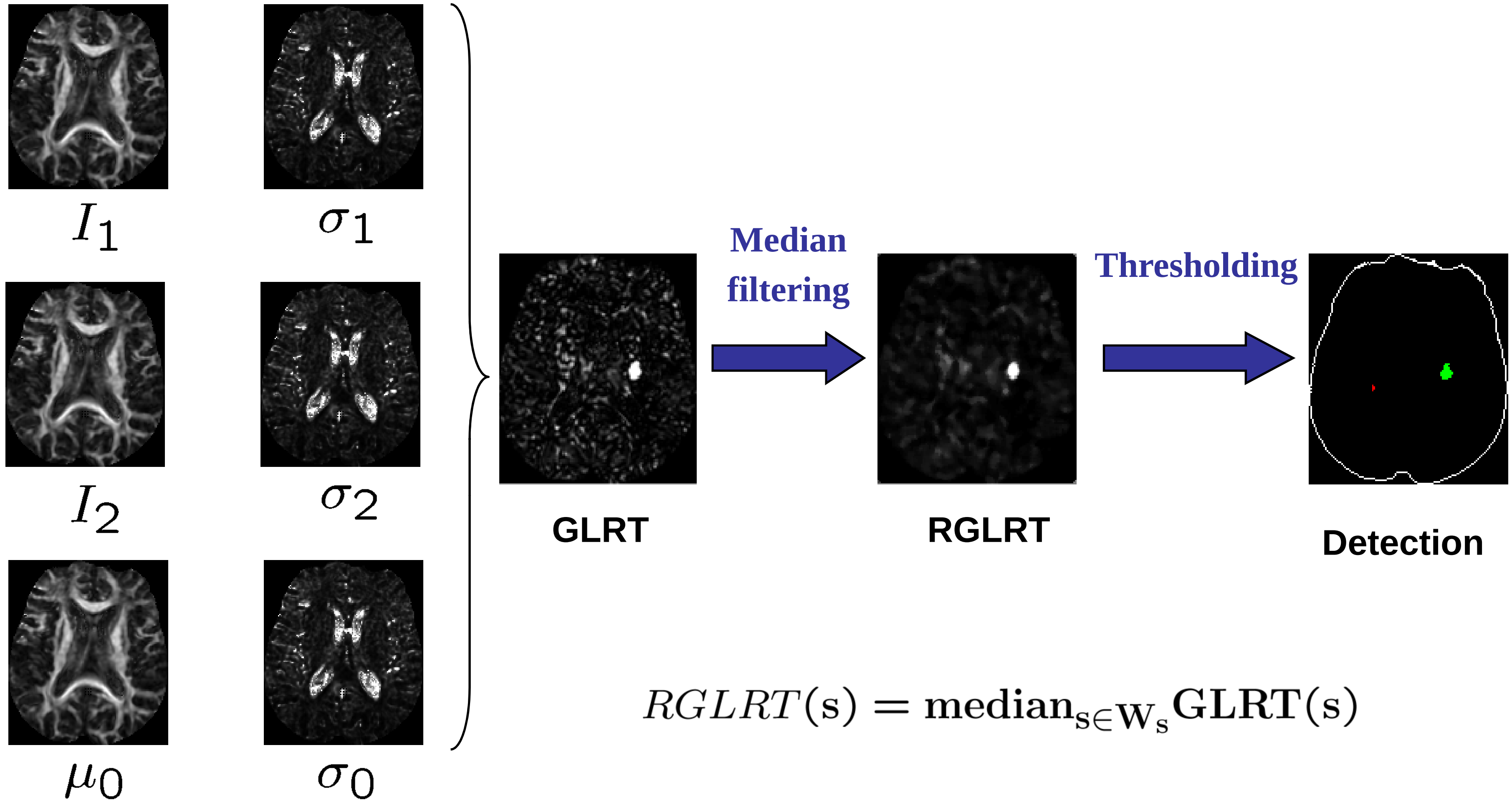


μ_0



σ_0

Spatial information



$$RGLRT(\mathbf{s}) = \mathbf{median}_{\mathbf{s} \in \mathbf{W_s}} \mathbf{GLRT}(\mathbf{s})$$

Validation

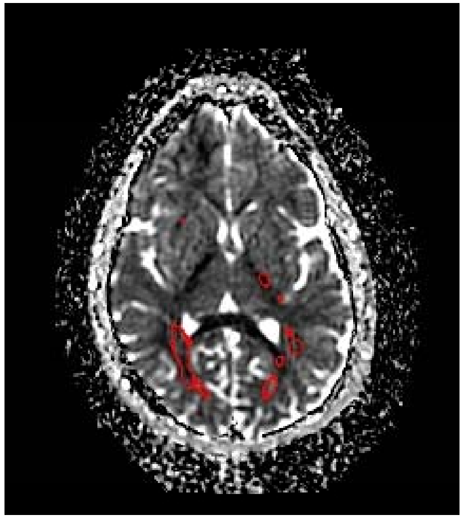
- Validation of such method is difficult due to the lack of ground truth
- Even for experts, it is difficult to detect changes in DT-images
- We resort to simulation of MS lesion appearance

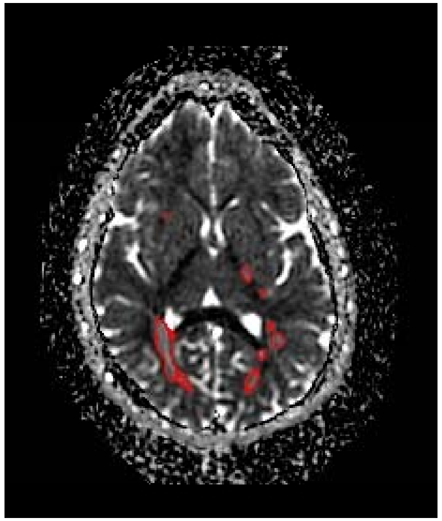
MS lesion simulation

Experimental studies have shown that demyelination leads to an increase of the radial diffusivity ($D_{\perp}$) in DW-images.

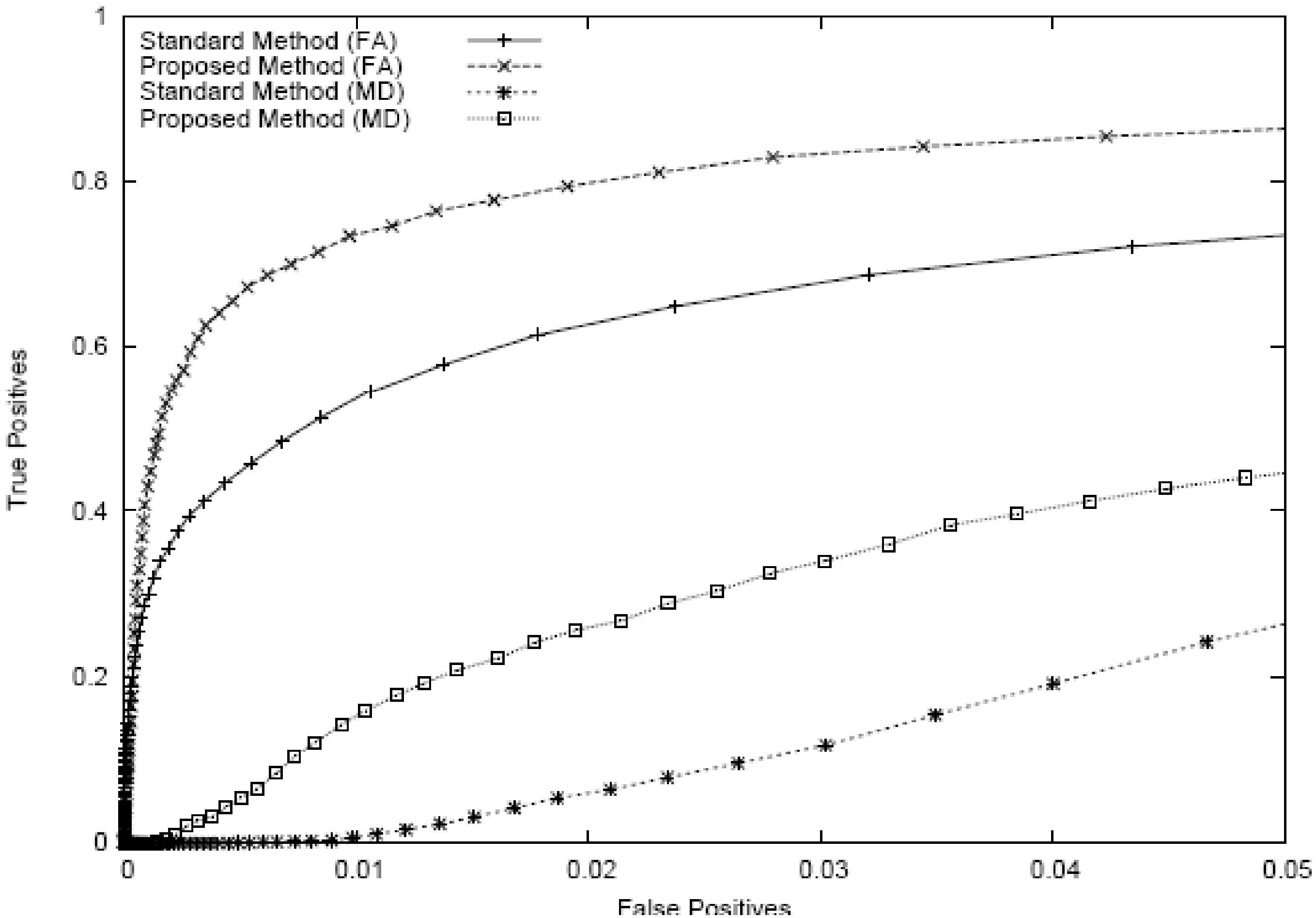
[Harsan *et al*, Journal of neuroscience research, vol 83(3), pp 392-402, 2006]

- Two scans of a healthy subject are considered
- The two last eigenvalues (corresponding to the radial diffusion) of the second examination are increased in several regions of Interest to simulate lesion apparitions

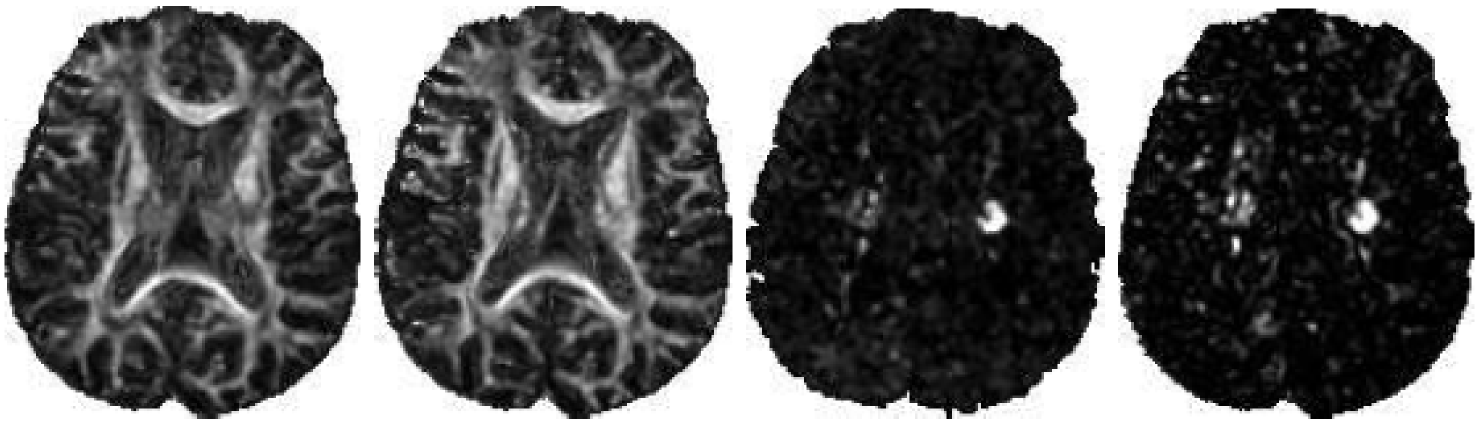




MS lesion simulation



Follow-up of MS patients



1st scan | 2nd scan | Proposed method | Standard method

Conclusion and perspectives

- Further validation should be done on real cases
- Automatic threshold selection: p-value estimation, multiple comparison problem
- Extension for multimodal detection
- Extension to tensor images and to other model of diffusion