

An adaptive regularization of Richardson Lucy spherical deconvolution to reduce isotropic effects

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Introduction

Spherical deconvolution has demonstrated promising results in resolving complex fibre orientation distributions (FOD) in white matter from HARDI data [1] [2] [3]. Recently, the spherical deconvolution approach based on a modified Richardson Lucy algorithm (RL) [3][4] has shown good results in terms both of angular resolution and noise stability, with less unphysical spurious spikes than other methods [4]. However, in real in-vivo dataset, it is not possible to characterize different brain regions homogeneously in terms of noise stability. In fact, even with high SNR_{b=0} datasets, in regions with partial volume effect between white matter and isotropic tissues, the number of unphysical spurious orientations increases. A possible solution is to apply different levels of regularization depending on the voxel [5]. Standard regularization techniques usually improve solutions in terms of noise stability at the expense of angular resolution. In this work, we show preliminary results of an adaptive regularization approach to reduce unphysical FOD components without affecting angular resolution.

Theory

In RL algorithms, the iteration number is commonly used as regularization parameter. In fact, stopping the algorithm before full convergence prevents that spurious components increase excessively, due to noise amplification [4]. In RL algorithms it is also possible to add regularizing terms in the iterative procedure to bias the algorithm towards a smoother solution [6]. In order to apply an adaptive regularization on each FOD components, we modified this approach introducing an amplitude-depending factor, \mathbf{r} , in the regularizing term. The main points are : a) to apply a strong regularization on smaller FOD components, more likely due to noise effects, preventing, in this way, amplification of spurious spikes as iterations proceed; b) to apply a lighter or no regularization on higher FOD components, preserving angular resolution of the main fibre orientation components. In matrix-vector notation, the algorithm, for the k -th iteration, can be written as :

$$\mathbf{f}^{(k+1)} = \mathbf{f}^{(k)} \frac{\mathbf{H}^T \mathbf{s}}{\mathbf{H}^T \mathbf{H} \mathbf{f}^{(k)}} + \lambda \mathbf{r} (\mathbf{D} \mathbf{f}^{(k)}) \quad \text{with} \quad \mathbf{r} = \left(1 - \frac{(\mathbf{f}^{(k)})^v}{(\mathbf{f}^{(k)})^v + \eta^v}\right)$$

where \mathbf{f} is the estimated fibre orientation vector, \mathbf{s} is the HARDI sampled data vector, \mathbf{H} is the corresponding circulant matrix [4], λ and \mathbf{D} are the regularization parameter and the smoothing operator, respectively, as in [6]; \mathbf{r} is a vector which controls the level of smoothing for each fiber orientation component; η acts as a threshold value and v is a parameter related with the amplitude of the transition curve from full regularization and no regularization. The starting condition $\mathbf{f}^{(0)}$ is always set as an improbable (spherical) fibre orientation.

Methods

Simulations : Three-compartment configurations with different volume fractions were simulated : two identical anisotropic compartments ($D=[1.5 \ 0.3 \ 0.3] \cdot 10^{-3} \text{ mm}^2/\text{s}$, $f_1=f_2=0.5, 0.25$) crossing at 60° and one isotropic compartment ($D=0.8 \cdot 10^{-3} \text{ mm}^2/\text{s}$, $f_3=0, 0.5$) . SNR_{b=0} was set equal to 20.

In vivo: A normal brain was acquired on a 3T Philips Intera scanner (Philips Medical System, Best, The Netherlands) with: TE/TR=118/2000 ms, FOV=240x240 mm, slices=5, slice thickness=2.5 mm, matrix=128x128, NEX=4, SENSE factor=2, bvalue=3000 s/mm², DW-directions=92.

Deconvolution was performed both for simulation and in-vivo data with the standard RL approach and with the proposed method imposing a tensor equal to $[1.7 \ 0.2 \ 0.2] \cdot 10^{-3} \text{ mm}^2/\text{s}$ as fibre response and 200 algorithm iterations [4]. Regularization parameters were setup empirically.

Results and Discussion

In Fig.1, simulations show that the presence of mixed configurations with both isotropic and anisotropic compartments increases spurious FOD components in comparison to a pure anisotropic configuration. On the other hand, the proposed regularization approach is able to effectively prevent an excessive amplification of spurious components. In Fig. 2, in-vivo results are shown (on the left standard RL, on the right regularized RL). In the regularized RL algorithm minor FOD components were removed preserving, at the same time, angular resolution of the main fibre orientations, as highlighted in yellow regions. It should be noted that, due to the linearity of the deconvolution problem, low amplitude signals from more isotropic voxels lead to smaller FODs and, consequently, a different regularization level is also applied depending on the voxel. In conclusion, these preliminary results suggest that the proposed method can improve RL spherical deconvolution in terms of noise stability preserving angular resolution.

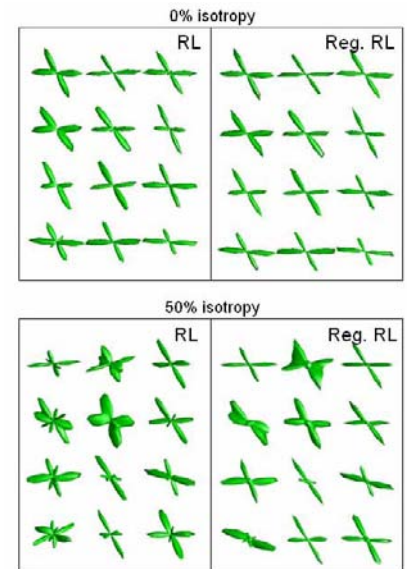


Fig. 1

Reference [1] Tournier JD *et al.* NeuroImage 23:1176-1185 (2004). [2] Alexander DC Proc IPMI (2005). [3] Dell'Acqua F *et al.* Proc. 27th IEEE EMB 1415-1418 (2005). [4] Dell'Acqua F *et al.* IEEE TBME (2007 - in press). [5] Sakaie KE *et al.* NeuroImage (2006 - in press). [6] Bratsolis E *et al.* A&A 375:1120-1128 (2001).

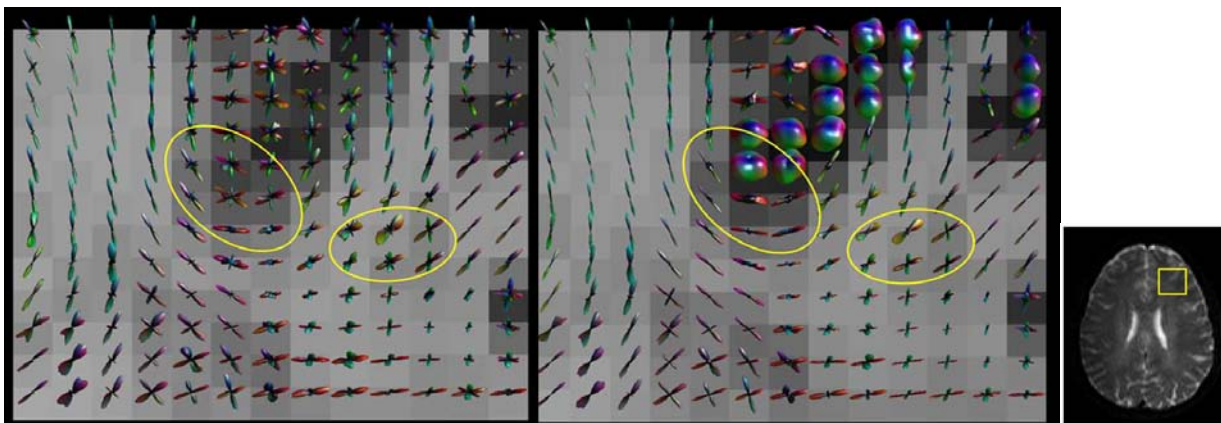


Fig. 2