A fast Principal Direction Imaging method from Diffusion Weighted Images

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Introduction

Diffusion tensor imaging requires at least 6 gradient directions. From the tensor, we can compute diverse quantities, such as FA, MD, principal direction PD, and non-principal directions. Fibre tracking can be performed from the principal direction information. A method for PD imaging has been proposed in 2002 (1) using diffusion tensor tomography. This, however, requires iterative methods, and measurements with non-stationary gradients. Here we suggest a method to short-cut the acquisition of principal directions for applications where we are mostly interested in the PD. As this has 2 parameters, (azimuth and elevation), plus a 3rd parameter for the diffusivity, it would appear that 3 gradient directions would be enough. In order to remove some sign ambiguities, we use a 4th direction. We investigate how good the PD estimation is in different conditions. The method investigated here uses the measurements as standard DT-MRI, except that fewer gradients are necessary, thus reducing overall scan time.

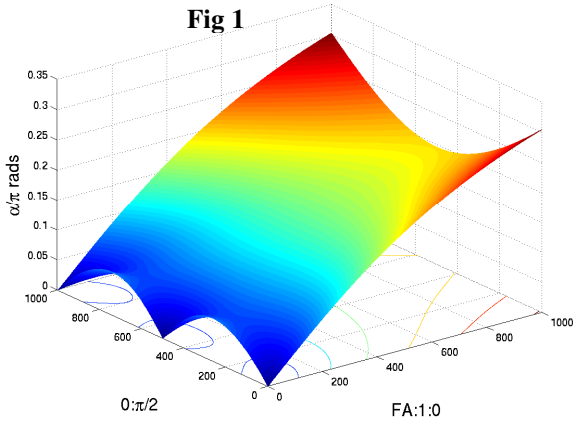
Method

The standard model for Stejskal-Tanner diffusion represents the diffusion weighted images as $s_0\ exp(-b\ \mathbf{g}^t\mathbf{D}\mathbf{g})$ where $\mathbf{g}$ is the corresponding direction of the diffusion gradient. $\mathbf{D}$ is assumed to be a 6 parameter diffusion tensor, with parameters $[\mathbf{D}_{xx},\mathbf{D}_{yy},\mathbf{D}_{zz},\mathbf{D}_{xy},\mathbf{D}_{xz},\mathbf{D}_{yz}]$. These parameters are not very geometric, and another parametrisation is via eigenvalue-eigenvectors: this more unusual way to write the tensors amounts to writing $\mathbf{D} = \lambda_1\ \mathbf{e}_1\mathbf{e}_1^t + \lambda_2\ \mathbf{e}_2\mathbf{e}_2^t + \lambda_3\mathbf{e}_3\mathbf{e}_3^t$, where $\mathbf{e}_i$ is eigenvector, λ_i eigenvalue. Good tensors for tracking are the ones where lambda1 is much bigger than λ_2, and λ_3, an extreme would be $\lambda_2=\lambda_3=0$. Thus, when we make the admittedly extreme assumption that tensors represent a single direction, we replace the model above by the new model $\mathbf{D} = \lambda\mathbf{e}\mathbf{e}^t$. In other words, we interpret the log of the diffusion weighted images as being the squares of the components of the PD. $-log(s_i/s_0)/b = \lambda(\mathbf{g}_i^t\mathbf{e})^2$.

Of course, this is a crude model, and fitting this to the data leads to one difficulty, as can be seen by assuming that the gradient directions are the x-y,z axes. We then have an estimate of the squared components x^2, y^2, z^2 of the principal direction. There are up to overall plus-minus signs 4 possible solutions: $[x,y,z],[-x,y,z],[x,-y,z],[x,y,-z]$. To discriminate between them, we use a 4th direction and compare the values from the fitted model with it, and pick the choice of sign which fits best.

Clearly, if the input tensor is not perfectly needle-like, *i.e* all eigenvalues are non-zero, this estimate of the direction will be incorrect. In the **Results** section, we investigate the error of such estimates.

Fig 1



Results

Figure 1 shows the error as function of changing anisotropy, and tensor direction, for a tensor of the form diag([10,*a*,*a*]) where *a* varies from 0 to slightly less than 10 (at exactly 10 obviously, the principal direction is not defined anymore), thus varying FA from 1 to 0, and where the tensor direction is rotated in the xy-plane from 0 to 90 degrees. The error (vertical axis) is $\text{acos}(\mathbf{e}^t\mathbf{e}_0)/\pi$ where $\mathbf{e}_0$ is the true tensor eigenvector for the largest eigenvalue, and $\mathbf{e}$ is the PD estimated using our method. We also used an in vivo tensor image to construct a simulation as follows. We create pseudo-DWI images by resampling the tensor on the 3+1 gradient directions mentioned above, and compute the PDs from this. Figure 2a shows the correct eigenvector, coded on following usual conventions. Figure 2b shows the estimated PDs, while in Fig 2c we shows the PDs after noise was added to the pseudo-DWIs.These have a mean of 0.42, and the noise was randomly distributed with mean 0, std 0.1.

Discussion: Our method does not require any modification to standard diffusion imaging, except a *reduction* of the number of required gradient directions. From the data shown here, the method seems robust, and it would allow to perform fibre tracking. Potential applications would be to cardiac diffusion, where specific interest is in the fibre architecture, where anisotropy would be traded for any possible speed-up. Unlike HARDI our model is used to reduce the number of directions acquired, however it has in common the assumption thatthe response function is needle-like.. The gradients direction used here were chosen just for convenience, it may be that to get maximum gradient strength a better choice would be parallel to [1 1 1], [1 1 -1], [1 -1 1], [-1 1 1].

Ref: [1] Panin et al *Physics in Med. And Biol* **47** (2002) 2737-2757.