User-Independent Optimization of Spherical Deconvolution

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Introduction: Spherical deconvolution [1] is an elegant method for estimating the orientation of multiple white matter fibers on a voxel-by-voxel basis from high-angular resolution diffusion imaging (HARDI) [2]. The fiber orientations are characterized by a fiber orientation distribution (FOD) function. However, deconvolution methods are highly susceptible to noise and thus require filtering or regularization. The filter properties or regularization must be optimized in order to achieve a balance between resolution and noise immunity. Generalized cross validation (GCV) can be used to optimize regularization of FODs in a user-independent, voxel-by-voxel fashion [3]. In this contribution, we apply GCV to the negative-peak regularization method introduced by Tournier et al [4] (GCV-NEG) and compare the results to GCV used in conjunction with gradient-norm regularization [3] (GCV-GRAD). User-independent optimization contributes to the robustness of the regularization while facilitating comparison between methods.

Theory: In spherical deconvolution, diffusion-weighted signal, S, is modeled as the convolution of the FOD, F, and a response function, R, which is the signal profile of an individual white matter fiber: $S(\theta,\varphi)=R(\theta,\varphi)\otimes F(\theta,\varphi)$. Upon decomposition of the signal profile into spherical harmonics, the convolution becomes a matrix product of corresponding coefficients: $s = rf$. The FOD can be determined by simultaneously minimizing the chi-square of the fit of the signal and a regularization function: $f=\min_{\lambda}\{||Yrf\text{-}S||+\lambda||Lf||\}$, where Y is a matrix of spherical harmonics, L is a matrix representing the regularization function, and λ is the regularization parameter. A small chi-square indicates an accurate fit to the data, but with high sensitivity to noise. The regularization function is chosen to be large for a noisy fit, and λ determines the tradeoff between the accuracy of the fit and the effects of noise. In this contribution, we compare two regularization functions: one reflects the amplitude of spurious negative peaks in the FOD [4], and the other reflects the smoothness of the FOD via the integral of the norm of the gradient. For each case, λ is chosen in a user-independent fashion by GCV [3].

Methods: Diffusion-weighted images were acquired in a healthy volunteer [128x128 matrix, 384x384mm FOV, 31 slices, 3mm thick, TE/TR=115/5600msec, partial Fourier factor=5/8, b-value=3000sec/mm^2, 71 gradient directions chosen by Coulomb repulsion [5] with 8 b=0 acquisitions interspersed at regular intervals, 4 repeats, SNR~30 on b=0 images in white matter]. Motion correction was performed by determining the orientation of b=0 images by AFNI [6], interpolating coordinates for intervening b=3000 images, and coregistering the image volumes before averaging. The response function was determined from the 300 voxels exhibiting the highest anisotropy [1]. The regularization matrix, L, was calculated for negative peak regularization [4] and gradient-norm regularization [3]. λ was optimized by GCV using a freely available MATLAB package [7].

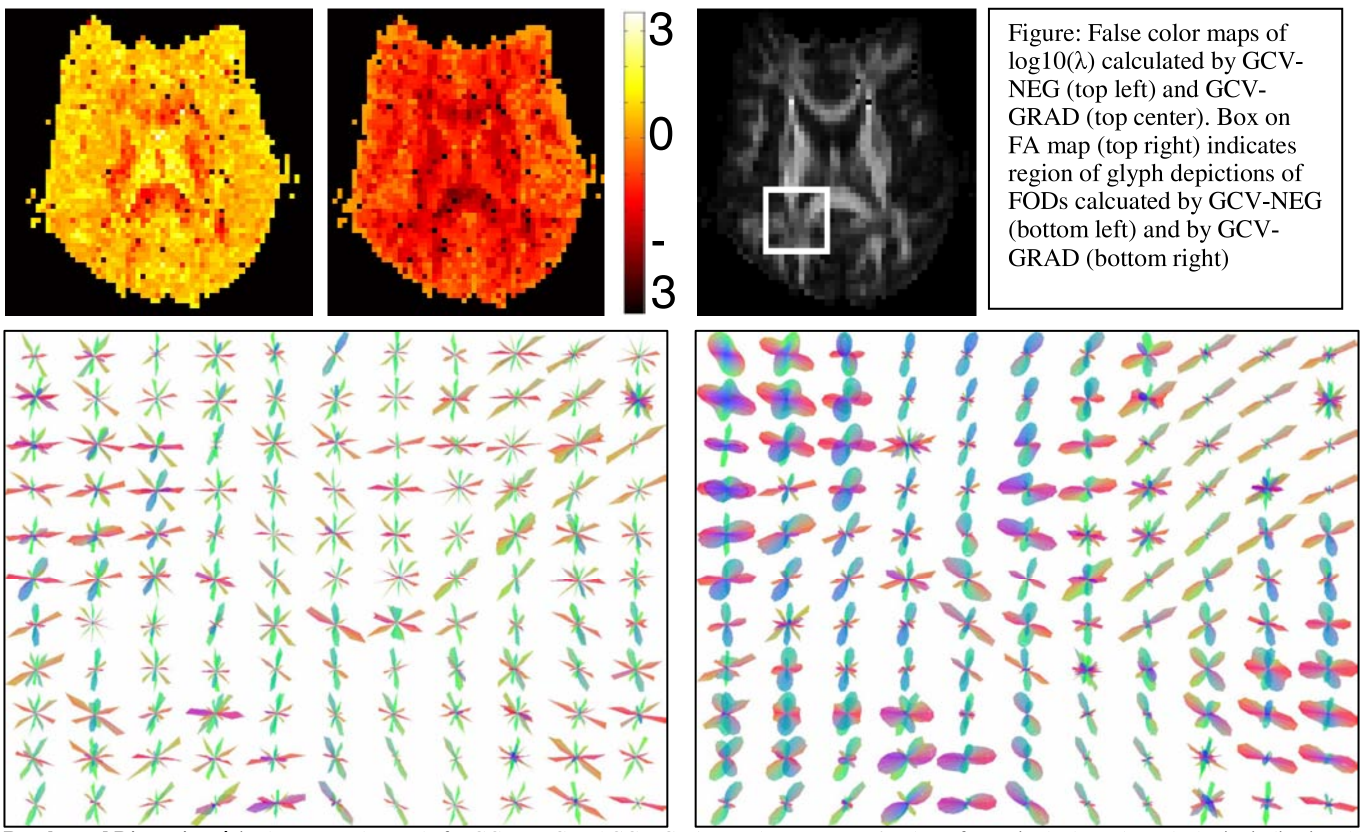

Figure: False color maps of log10(λ) calculated by GCV-NEG (top left) and GCV-GRAD (top center). Box on FA map (top right) indicates region of glyph depictions of FODs calcuated by GCV-NEG (bottom left) and by GCV-GRAD (bottom right)

Results and Discussion: λ is shown on a log scale for GCV-NEG and GCV-GRAD, and ranges over 6 orders of magnitude throughout the brain, indicating that user-independent optimization of λ by a method such as GCV is necessary for objective regularization of FOD calculations. Choice of a single value of λ for all voxels leads to severe under- or over-regularization in different regions, corresponding to undesirably high sensitivity to noise or loss of angular resolution, respectively. Magnified glyph representations of FODs indicate that, while GCV-NEG provides higher resolution in regions of individual and crossing fibers, gradient-norm regularization produces fewer spurious peaks in regions of low anisotropy. L-curve estimation was used in place of GCV for optimization of λ, and led to similar results when combined with gradient-norm regularization but severe over-regularization with negative-peak regularization.

Conclusion: We show that user-independent optimization of regularization by GCV leads to a large range of regularization parameter, indicating its necessity for reliable calculation of FODs by spherical deconvolution. Other optimization methods [6] and regularization functions may prove more effective than the ones investigated here. It remains to be seen how the degree of regularization affects reliability of fiber-tracking.

References:[1] Tournier JD et al. Neuroimage 23:1176-1185 (2004). [2] Tuch DS et al. ISMRM 7:321 (1999). [3] Sakaie KE and Lowe MJ. Neuroimage:Epub Oct 6 (2006). [4] Tournier JD et al. ISMRM 13:384 (2006). [5] Jones et al. MRM 42:515-525 (1999). [6] Cox RW. Computers and Biomedical Research 29:162-173 (1996) [7] Hansen PC. Numerical Algorithms 6:1-35 (1994).