Quality Analysis of DTI Images

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Introduction: Diffusion Tensor Imaging (DTI) is a Magnetic Resonance Imaging (MRI) method for observing the macro-level anisotropic diffusion of water molecules, which allows the extraction of white matter brain fibers. The noise level and artifacts in Diffusion Weighted Images (DWI) may lead to an incorrect or bad quality fiber tracking. There are many factors affecting the quality of fibers, such as scan parameters, resolution, the type of coil and etc… These factors, along with the lack of ground truth images/fibers, make assessing the quality of fiber tracking, a challenging problem. In this work, we propose a probabilistic framework that enables us to judge the quality of a DTI scan by examining the log-likelihood of its Fractional Anisotropy (FA) map, based on a non-parametric distribution learnt from a training set.

Materials: Diffusion Tensor Images from three subjects, were acquired with a 3T whole body MR-scanner (Achieva, Philips Medical Systems) using a SENSE head coil with the following acquisition parameters: TR=2604ms, TE=68ms, FOV=230, matrix=128x128, axial slices=20, slice thickness=3mm, NSA=2, b=1000, number of gradient directions=6. For each volunteer, 24 scans with the same parameters are carried out to build the distributions. To reduce motion artifacts, the images were first coarsely registered manually and then an automatic registration process is carried out to obtain a fine correspondence. The last step of motion correction was tensor-to-tensor registration. For both the registration and fiber tracking, we used the 3D Slicer and the statistical analysis part was implemented with MATLAB 7 (Mathworks, Boston, MA).

Methods: To judge the quality of DTI, we followed the bootstrapping idea, developed in [1]. The scans from two volunteers are used for training and the other volunteer for testing. The training images are first filtered with a Rician bias correction filter [2] to reduce the noise in low signal regions. Then two scans from the same patient are combined into a single image set to obtain data with two volumes for b=0 (baseline) and two volumes for each gradient directions, yielding 12 set for each subject. Then 1000 new samples are generated in the following way: for each new sample, two baseline volumes were drawn with replacement from the training set, for the new baseline positions, and two DWI volumes were drawn again with replacement for each gradient, from the corresponding gradient volumes in the training set. Then FA maps for each new sample were computed and used to build a distribution for each voxel. The histograms of FA values from the new samples were used as probability distribution functions (pdf) and 90% confidence intervals (CI) were computed. When a new DTI scan is encountered, it was first registered to one of the volumes in the training (again both manually and automatically) and the computed FA maps were used to compute the log-likelihood of the new sample with respect to the distributions from the training phase. The total likelihood is $L = \sum_i^N \log(P(FA_i))$ where N is the number of voxels.

Results: The algorithm is currently able to discriminate normal and noisy images. When we used the data from the third subject, the quality indicator (likelihood) was not significantly different from the ones in the training set, which was also the case visually in terms of fiber tracking. The log-likelihood of such images was on the average -1.5E+3. For this reason, we artificially added Rician noise, with standard deviation of 20, to the test set, which resulted in a significant drop in the likelihood to -1.95E+3.

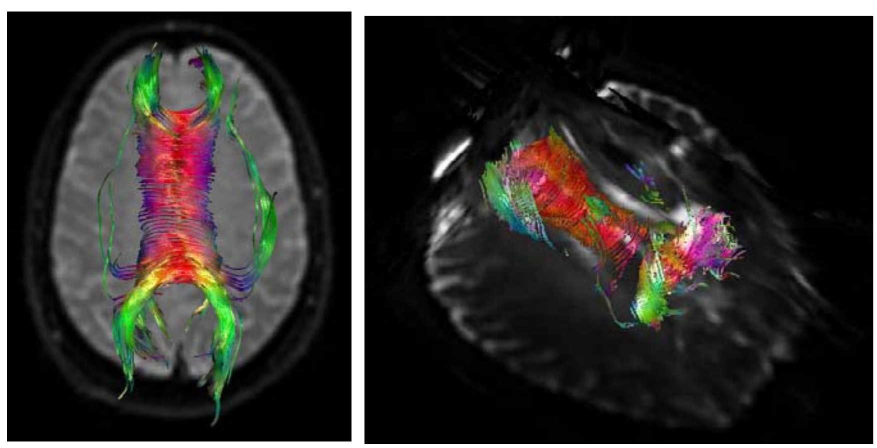

Figure 1. Fiber tracking with -1.5E+3 likelihood on the left. Fiber tracking with -1.95E+3 likelihood on the right.

Discussions: The accuracy of the algorithm will improve with more scans and more volunteers, making the distributions more exact. Another approach to the problem besides the one demonstrated above is to use a t-test for comparing the quality of 2 DTI or to use MANOVA to test if several DTI scans have the same quality. However, the bottleneck in this approach is the correctness of the registration process. Currently, it is possible to compare the images with the same resolution and the same number of gradients but we are working on solving this problem by up-sampling the low resolution tensors by using interpolations in Riemannian manifolds of positive-definite matrices.

References:

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