Robust Diffusion Tensor Estimation by Maximizing Rician Likelihood

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Introduction: Diffusion tensor imaging (DTI) is widely used to characterize white matter in health and disease. Previous approaches to the estimation of diffusion tensors have either been statistically suboptimal or have used Gaussian approximations of the underlying noise structure, which is Rician in reality. The most prevalent tensor estimation method, the log-linear minimum mean squared error (LLMMSE) approach [1], assumes independently, log-Gaussian noise. Sijbers et al. [2] presented an ML approach for Rician bias compensation of single MR images, and Koay et al. [3] demonstrated an exact solution and extended the method for images from multiple coils. Jones et al. [4] presented an estimation method that incorporates noise level estimation. Salvador et al. [5] reviewed distribution assumptions and described a weighted least squares procedure for addressing non-Gaussianity. These methods do not take into account either (1) the propagation of Rician noise into the tensor domain or (2) the dependence between observed attenuations caused by the use of common reference scans. These systematic differences can cause quantities derived from these tensors — e.g., fractional anisotropy and apparent diffusion coefficient — to diverge from their true values, potentially leading to artifactual changes that confound clinically significant ones. Recent developments with Diffusion Tensor Estimation by Maximizing Rician Likelihood (DTEMRL) showed that tensor estimation can be performed by considering the joint distribution of all observed data in the context of an augmented tensor model that accounts for Rician noise [6]. This abstract presents a robust extension of DTEMRL (rDTEMRL) designed to improve reliability in low SNR and artifact prone applications.

Methods: To improve numeric stability and to prevent non-physical solutions, DTEMRL incorporates a robust characterization of positive definite tensors and an estimator of underlying noise variance specifically developed for repeated DTI acquisitions. We observe the most common modes of failure for DTEMRL are due to extreme value observations (outliers). With limited data, the strict ML approach favors selection of an incorrectly high noise level, which, in turn, corrupts tensor estimates. To address this problem, we make three modifications to the original algorithm. First, we generalize the noise estimation procedure to operate on a single DTI acquisition as follows: a tensor is fit with LLMMSE at each voxel, the sample standard deviation is taken over the residuals, and this is regularized with a coil sensitivity model. Next, we introduce Gaussian priors on the noise level based on the estimated noise field with a Bayesian *a posteriori* approach. The mean of the prior is set to the estimated noise level while the standard deviation of the prior is proportional to the square of the SNR, so that the impact of the prior diminishes at high SNR. Finally, we utilize a Huberized (truncated) likelihood measure to reduce the impact of artifacts on tensor estimation. The truncation point is determined adaptively from the likelihood distribution, and set to exclude observations that fall outside two standard deviations from the median likelihood.

Simulation experiments were performed with prolate tensors (i.e., tensors with identical second and third eigenvalues). The maximum (parallel) diffusivity was set to $2\text{x}10^{-3}$ mm^2/s and the radial diffusivities were adjusted to create tensors with fractional anisotropies of 0, 0.2, 0.5, and 0.8. Artifacts were simulated by randomly attenuating one diffusion weighted (DW) image by a factor of 10. Simulated DTI studies were conducted at a b-value of 1000 s/mm^2 with 30 DW and 5 non-averaged reference images. Additionally, 22 repeated *in vivo* scans (acquired over 3 days) of a control subject (male, 24 y/o) were individually analyzed with both LLMMSE and rDTERML. Briefly, the data were acquired with a spin echo EPI sequence (TR/TE=3632/100, 0.9375 in plane, 2.5 mm slice thickness) on a 1.5T system (Intera, Philips Medical Systems, Best, The Netherlands).

Results: Simulations indicated improved performance of rDTEMRL over LLMMSE in the absence of artifact (**Fig. 1A**) as low as 10:1 for gray matter (GM) like voxels (FA≤0.2) and 5:1 for white matter voxels (FA>0.2). In the presence of artifact, simulations demonstrate improvements in mean squared error across all noise levels studied (**Fig. 1B**). *In vivo* data (**Fig. 2**) show substantially improved performance in the major WM tracts. The degree of reliability improvement can be appreciated from **Fig. 3** (showing twenty two tensors estimated at a single location within the WM).

Discussion: rDTEMRL considerably improves the reliability of diffusion tensor estimates over the traditional methodology by exploiting the Rician noise distributions of MR data. The method is robust to low SNR and substantial artifact. As with DTEMRL, rDTEMRL does not use any spatial regularization in the estimation process, and it is possible that spatial regularization could further improve these results. An important question for further study is how rDTEMRL relates to other robust tensor estimation methods; understanding the relative benefits and tradeoffs between M-estimator methods could lead to improved robustness and performance across the SNRs.

References: [1] P. J. Basser and D. K. Jones. NMR Biomed, 15(7-8):456, 2002. [2] J. Sijbers and A. J. den Dekker. MRM, 51(3):586, 2004. [3] C. G. Koay and P. J. Basser. JMR, 179(2):317. [4] D. K. Jones and P. J. Basser. MRM, 52(5):979, 2004. [5] R. Salvador, et al. HBM, 24(2):144, 2005. [6] B. Landman et al. ICCV/MMBIA 2007.

Fig 1. Simulation: Relative Tensor Estimation Errors

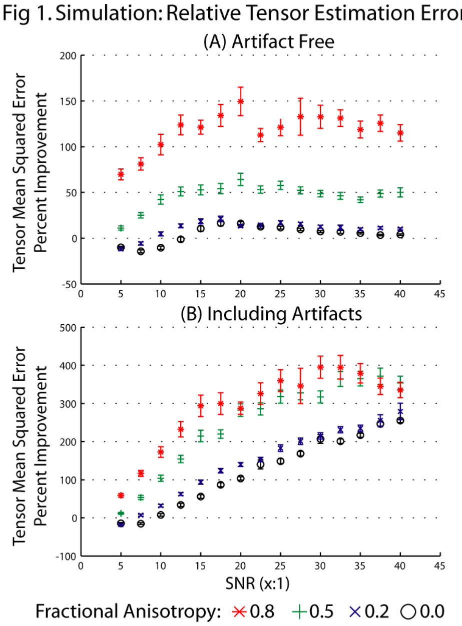

Fig 2. Tensor Variability LLMSE vs rDTEMRL

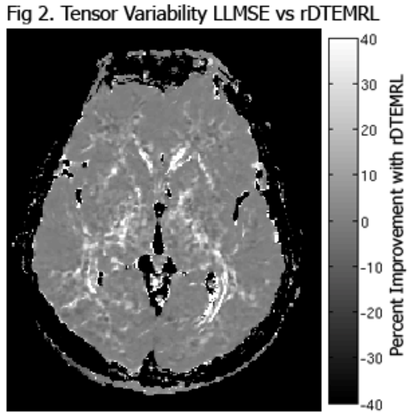

Fig 3. Reproducibility Example: 22 Repetitions of One WM Voxel