Robust DTI Noise Level Estimation Improves RESTORE Tensor Estimation

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Introduction: Noise level estimation in DTI plays a crucial role in determining outliers, fitting likelihood-based tensor models, and estimating the reliability of measured quantities. However, noise level estimation methods developed for other magnetic resonance techniques are often inappropriate for DTI acquisitions. For example, noise level cannot be directly computed from background regions with protocols using background suppression (e.g., CLEAR) or exhibiting spatially varying noise due to parallel imaging or variable coil sensitivity (e.g. SENSE). DTI images are commonly up-sampled by zero-padding the Fourier coefficient images, so the local noise structure is highly correlated. Thus, noise level estimation from local regions is difficult. Spatial variability and correlation limit the applicability of both the single image (based on background intensities) and double image (based on moments of Rician random variables) methods [1]. When the noise level specified for the RESTORE tensor estimation method is too low, too much data is excluded and the error rate suffers [2]. Conversely, when the noise level is specified too high, artifacts are not excluded and the error rate increases. Thus, accurate noise level specification is crucial. We develop a new estimation approach based on noise invariance to diffusion weighting and demonstrate that this technique improves the RESTORE method of outlier rejection and tensor estimation.

Methods: In contrast to previous approaches, our method exploits repeated pairs of acquisitions while remaining robust against correlations in image intensity. For voxels with high signal intensity, the noise distribution is approximately Gaussian [3]. The mean intensity varies by spatial location as well as by diffusion weighting. However, the noise level (e.g., variance) of this distribution varies spatially, but does not depend on the diffusion weighting. Thus, the differences between repeated observations with the same diffusion weighting are also approximately Gaussian, but with zero mean and two-fold increased variance. Since the distribution of the difference of Gaussian random variables does not depend on the original mean, the set of differences from the reference and DW images may be treated as repeated observations from the same distribution. Accordingly, we form an estimator for the local noise level based on the Q_n scale estimator (a robust standard deviation statistic) over the set of difference images [4]. The estimate is corrected for the increased standard. To extrapolate the noise field to low intensity voxels and to improve robustness against artifacts, we regularize the initial noise field using Chebyshev polynomial regression on non-background voxels with a third degree two-dimensional polynomial to create physically realistic noise level estimates. Chebyshev polynomials are numerically stable and have been previously used to model coil sensitivity profiles, which are dominant factors in determining the spatial characteristics of noise level [5].

A realistic ground truth model was established by a standard method of moments estimator based on the 2^{nd} and 4^{th} Rician moments using 22 acquisitions of a single control subject acquired in three sessions over a two week period at 1.5T (5 averaged b_0's, 30 diffusion weighted acquisitions) (**Fig.1A**). The proposed noise level estimation method was compared against existing methods in simulation using band limited Gaussian noise added in quadrature. Simulated acquisitions were developed based on the ground truth tensor model. To simulate artifacts, the intensity of one diffusion weighted image was randomly decreased by a factor of ten. The median level noise estimate over the brain was used to seed the RESTORE algorithm as implemented in CAMINO [6]. The mean squared error (MSE) of tensors estimated by RESTORE was evaluated when initializing the noise level by each of the estimation methods. For comparison, simulations were run with the noise level set to twice the truth model.

Results: Our method of noise level estimation consistently led to more accurate estimates when compared against traditional estimators based on background intensity (single image), second moments (double image), 2^{nd} and 4^{th} Rician moments, and an artificially high noise level (2*Truth Model) (**Table 1**). The truth model closely resembles (**Fig. 1A**) our intermediate local noise level estimate (**Fig. 1B**), while our final estimate (**Fig. 1C**) removes the impacts of vessels and artifact prone regions. The alternative methods produce a single noise level measure for the entire slice (**Fig. 1DEF**), all three of which are lower than the true noise level over most of the brain. When used with RESTORE, the improved noise estimate reduces the number of both false rejections (exclusion of voxels without artifact) and true rejections (exclusion of voxels with simulated artifact) while reducing tensor MSE.

Discussion: Our noise estimation procedure improves noise level estimation accuracy, does not depend on spatial correlations or the existence of a background region, and is robust against background suppression. It addresses complexities with spatially correlated noise, which is common in DTI due to up-sampling and interpolation. With the widespread use of parallel imaging methods, this noise level estimator – while specifically developed for tensor estimation– could also have far wider utility beyond diffusion tensor imaging. Our noise level estimation method could be readily adapted to work when more than two repeated scans are acquired (the sample standard deviation can be taken for each diffusion weighting and the median of these estimates is used) or when a single scan is acquired (a tensor can be fit at each voxel and the sample standard deviation taken over the residuals). In summary, our method is fully automated and robustly improves outlier identification leading to improved tensor estimation.

Fig 1. Noise Level Estimates (1 Example)

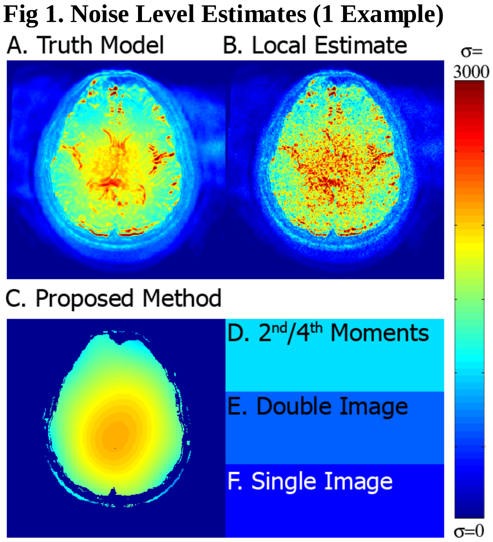

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Table 1. Impact of Noise Level Estimation on RESTORE

Noise Level Estimation Method	*Estimated Noise (a.u.)*	*Pct. False Rejections*	*Pct. True Rejections*	*Relative Tensor MSE w/ RESTORE*
Truth Model	1521	1.0 ± 0.01	80.9 ± 0.3	1.00
Proposed Method	1633 ± 16	0.6 ± 0.04	79.9 ± 0.5	0.99 ± 0.01
$2^{nd}/4^{th}$ Moments	1014 ± 9	5.9 ± 0.17	85.6 ± 0.2	1.11 ± 0.01
Double Image	631 ± 3	19.1 ± 0.14	89.8 ± 0.1	1.26 ± 0.01
Single Image	363 ± 1	39.0 ± 0.1	97.5 ± 0.1	1.49 ± 0.01
2*Truth Model	3042	0.0 ± 0.0	56.4 ± 1.5	1.00 ± 0.01