Robust DTI Noise Level Estimation Improves RESTORE Tensor Estimation

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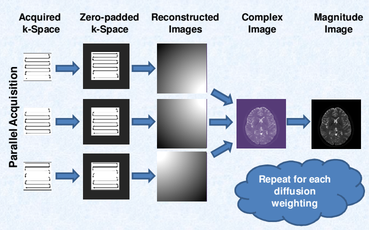
INTRODUCTION

- Noise standard deviation (NSD) estimation in DTI plays a crucial role in determining outliers, fitting likelihood-based tensor models, and estimating the reliability of measured quantities.
- NSD 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.
- 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.

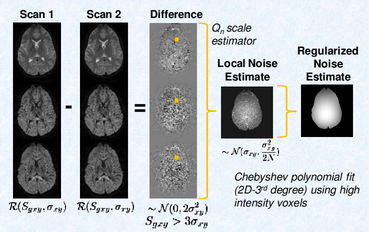
We develop a new estimation approach based on noise invariance to diffusion weighting and demonstrate that this technique improves the RESTORE method of outlier rejection and tensor estimation.

ROBUST ESTIMATION OF NOISE STANDARD DEVIATION (NSD)

Noise Propagation Model



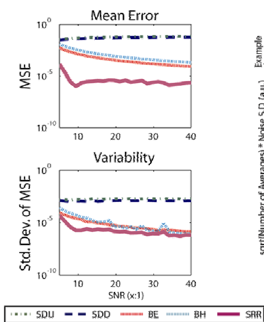
Proposed NSD Estimation Method



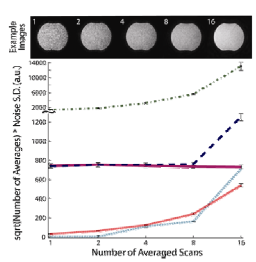
- For voxels with high signal intensity, the observed distribution is approximately Gaussian [3]. The NSD varies spatially, but does not depend on the diffusion weighting. Differences between repeated observations with the same diffusion weighting are also approximately Gaussian, but with zero mean and two-fold increased variance.
- Accordingly, we form an estimator for the local NSD level based on the Q_n scale estimator (a robust standard deviation statistic) over the set of difference images [4]. To extrapolate the NSD to low SNR voxels and to improve robustness against artifacts, we regularize the initial NSD from high SNR voxels using a coil sensitivity model based on Chebyshev polynomial regression with a third degree two-dimensional polynomial [5].

VALIDATION

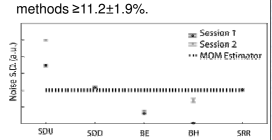
Simulation.
In simulation incorporating spatial variability and artifacts, the proposed method exceeded the performance of the standard approaches.

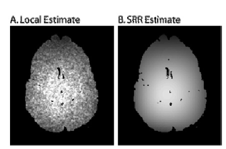


Phantom.
SNR should precisely correlate with the inverse of the square root of the number of averages (top row). The proposed method showed an R^2=0.99, while other methods exhibited R^2<0.95.



In vivo.
Estimates were spatially consistent with best available ground truth estimates (~5%). Mean estimate with proposed method within 1.7±0.9%, while other methods ≥11.2±1.9%.





SDU Standard deviation of uniform region
BE – Background Estimator based on Rayleigh distributions
SRR – Spatially regularized Robust – Proposed Method
SDD – Standard deviation of difference region
BH – Brummer's Histogram method

METHOD AND RESULTS

A realistic ground truth model was established by a standard method of moments estimator based on the 2nd and 4th 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.

NSD Estimation Impacts RESTORE

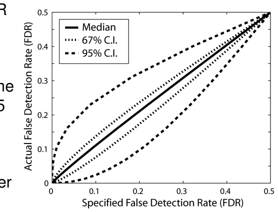
The proposed NSD method consistently led to more accurate estimates when compared against traditional. When used with RESTORE, the improved noise estimate reduces the number of both false rejections (exclusion of voxels without artifact) and true rejections (exclusion of voxels with simulated artifact) while reducing tensor MSE.

Noise Level Estimation Method	*Estimated Noise (a.u.)*	*Pct. False Rejections*	*Pct. True Rejections*	*Relative 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**
2nd/4th 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

APPLICATIONS EXPLOITING SPATIALLY VARYING NSD ESTIMATES

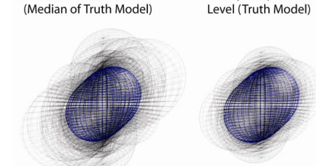
OUTLIER REJECTION

Spatially variable noise impacts outlier rejection. Given a desired FDR (horizontal axis), one may choose a rejection threshold based on the data and NSD. If one assumes a constant NSD equal to the mean within the brain, but the NSD is actually spatially variable, then the realized FDR (vertical axis) will be spatially variable as indicated by the median and confidence intervals (C.I.). At a very modest FDR of 0.05 (excluding 5% of good data, indicated by gray arrow), the expected difference between intended and actual FDR is 78% (95% range: 0.0056-0.186). If one used a single NSD for outlier rejection, in some regions 19% of the non-outlier voxels would be excluded while in other regions less than 0.6% of non-outlier voxels would be excluded.



MAXIMUM LIKELIHOOD TENSOR ESTIMATION

Error in maximum likelihood tensor estimation is reduced by accounting for spatially varying NSD. Each plot shows 25 estimates (light gray) based on a single simulated ground truth tensor (blue). The above tensor was chosen to be representative as it has the closest to the mean difference in error between the methods within the field of simulated tensors. Both tensor estimates with the median NSD (A) and locally adaptive NSD (B) were reconstructed from the same simulated datasets. Reduced error can be appreciated by noting the closer spacing of tensor outlines to the truth model.



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DISCUSSION

- The proposed NSD estimator 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 can 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.

With the widespread use of parallel imaging methods, the proposed noise standard deviation estimator has far wider utility beyond diffusion tensor imaging.

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