Estimation of spatially variable Rician noise map in diffusion MRI

Jelle Veraart[1], Jeny Rajan[1], Ronald R Peeters[2], Alexander Leemans[3], Stefan Sunaert[2], and Jan Sijbers[1]

[1]*Vision Lab, University of Antwerp, Antwerp, Belgium,* [2]*Dept. Radiology, University Hospitals of Leuven, Leuven, Belgium,* [3]*Image Sciences Institute, University Medical Center Utrecht, Utrecht, Netherlands*

TARGET AUDIENCE: Scientists working in the field of diffusion MRI.

PURPOSE: Diffusion magnetic resonance imaging (dMRI) is widely used to quantify water diffusion in biological tissue. The accuracy of diffusion model-specific measures will be limited if not accounting for the statistical distribution of the magnitude dMRI data, which has typically low SNR. The prior knowledge of the underlying noise parameters thus allows more accurate dMRI analyses. Most of the existing noise estimation methods can be classified as methods that use background regions or the image object itself to estimate the noise parameter. Background-based methods often fail due to the suppression of the background signal by the scanner, image artifacts (e.g. ghosting), or spatially varying noise. The object-based methods often rely on a Gaussian approximation of the noise, a sufficiently high spatial resolution such that a (non)local set of voxels with similar neighborhoods can be found to fit a noise distribution, repeated measurements, or a spatially uniform distribution of the noise level. dMRI, however, suffers from a restricted spatial resolution and involuntary subject and/or brain motion causing misalignments between multiple measurements to become more likely. In addition, the noise is generally spatially varying due to the use of parallel imaging techniques. We here propose a new strategy with low assumptions on the diffusion weighted (DW) data that allows for the voxelwise estimation of the noise level.

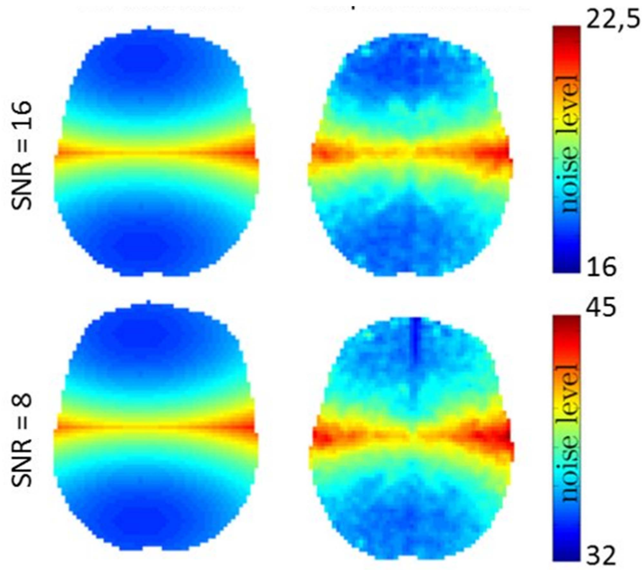

Fig. 1: In the left column, the reference noise maps were shown. The average noise maps using the proposed estimator based on the DW images with b = 2500 s/mm2 were shown in the right column, respectively. Contrast was kept constant for visual comparison purposes.

METHODS: Koay et al. showed that the noise level could be computed if the mean and standard deviation (SD) of the rice distributed variable is known or can be estimated [1]. In dMRI, the magnitude mean can be estimated by linearly fitting spherical splines to the data. Furthermore, 3D wavelet decomposition delves data into different spatio-frequency bands. The high frequency (HHH) sub-band is mainly composed of coefficients corresponding to the noise, and as such, the sub-band was previously used to estimate the magnitude SD using the MAD estimator [2]. The MAD estimator should, however, only be used if the magnitude noise properties are spatially or temporally invariant. If DW measurements are not repeatedly acquired, the condition is not fulfilled. However, we avoid the need for repeated measurements by commuting the median operator and Koay's iterative correction, which is monotonic. The accuracy of our noise map estimator was evaluated during a simulation experiment**:** We simulated accelerated (R=2) whole brain DW. Phantom images were derived from a diffusion atlas. In addition to 12 non-DW images, a single b-shell was sampled from the atlas: Jones60 directions at b = 2500 s/mm^2. Eight-channel k-space data was slice-by-slice calculated as the Fourier transform of each individual coil image, which is the noise-free DW image modulated by a normalized coil sensitivity map. Complex, Gaussian noise was added to the k-space data and all odd phase encoding k-space lines were suppressed before mSENSE reconstruction. For a real data experiment (12 repetitions of non DW images, 60 x b = 1000 s/mm^2, 60 x b = 2500 s/mm^2, 12 repetitions of 1 x b = 3000 s/mm^2) we had to define a heuristic reference map on the real data to evaluate our noise map estimation approach. As a *bronze* standard, we adopted the strategy proposed by Maximov et al. [3]. Their strategy relies on the acquisition of repeated measurements and can, thus, be applied on the b = 0 s/mm^2 as well as on the b = 3000 s/mm^2 DW images. Our method was subsequently applied on the b = 1000 s/mm^2 and b = 2500 s/mm^2 shell.

RESULTS: Simulation experiment: The estimated noise maps were averaged over 50 trials and shown in Fig 1. A slight positive bias can be observed. When using a b = 2500 s/mm^2 shell for noise map estimation, the bias was 1.6% and 2.5% for SNR=16 and 8, respectively. Real data experiment: Our proposed method resulted in noise maps (Fig. 2) which correspond well with the bronze standard, both in terms of intensity and spatial distribution, especially, if we compare our results with the bronze standard – based on 12 repetitions – calculated from the b = 3000 s/mm^2 images. The noise map derived from the b = 0 s/mm^2 images is clearly affected by pulsation artefacts. This is mainly reflected in an increased noise level in regions surrounding the CSF. Strong edges (i.e. high frequent image information) in the DW images will show-through in the HHH sub-band. The effect is less pronounced if low SNR images (e.g., with high b-values) are used for noise map estimation.

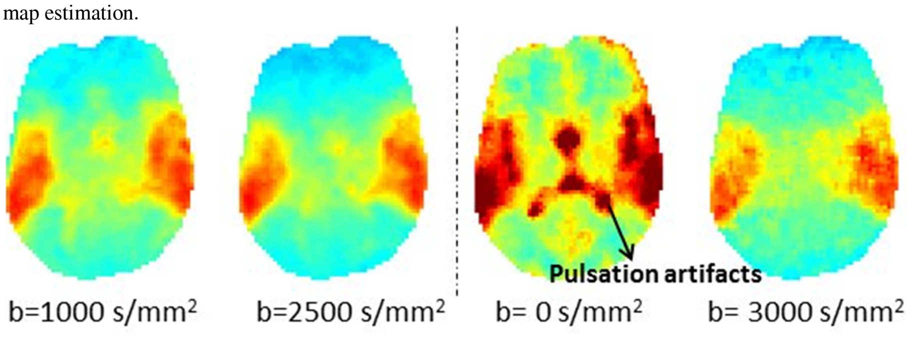

Fig. 2 Our proposed noise map estimator, applied to the b = 1000 mm^2/s images and b = 2500 mm^2/s images, was compared to a bronze standard, calculated from the b = 0 mm^2/s repetitions or b = 3000mm^2/s repetitions.

DISCUSSION/CONCLUSION: The development of a noise map estimation strategy is of utmost importance when aiming for more accurate dMRI analyses. For the real data experiments, the estimated noise map corresponds very well with the bronze standard, which was constructed with a recently proposed technique based on repeated measurements [3]. In a clinical setting, that approach, however, has two clear limitations: (a) the acquisition of repeated measurements (preferably with high b-value) will further lengthen the scan time, (b) misalignment between repeated measurements, which will cause the bronze standard to become erroneous, is much more likely to occur for a patient than for an instructed healthy volunteer. For noise map estimation, the highest b-value shell is preferably used. In those images, the HHH sub-band is the least corrupted with residual signal, which originates in high image gradients. One might benefit from further suppressing the HHH sub-band's residual signal. Coupé et al. already suggested to threshold the gradient magnitude of low frequency sub-band to create a mask for high gradient regions [2]. Importantly, the proposed noise map estimator relies on the assumption of an identical Gaussian noise map for all uncorrected DW images.

REFERENCES: [1] Koay, C.G. and Basser, P.J.. (2006) JMR 179(2):317-22 [2] Coupé, P. et al., 2010. Medical image analysis, 14(4), 483-93 [3] Maximov et al. (2012) Med Imag Anal 16:536-548