Merging squared-magnitude approaches to DWI denoising: An adaptive Wiener filter tuned to the anatomical contents of the image

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Abstract

We present a new method for denoising of Diffusion Weighted Images (DWI) that shares several desirable features of state-of-the-art proposals: 1) it works with the squared-magnitude signal, allowing for a closed-form formulation as a Linear Minimum Mean Squared Error (LMMSE) estimator, a.k.a. Wiener filter; 2) it jointly accounts for the DWI channels altogether, being able to unveil anatomical structures that remain hidden in each separated channel; 3) it uses a Non-Local Means (NLM)-like scheme to discriminate voxels corresponding to different fiber bundles, being able to enhance the anatomical structures of the DWI. We report extensive experiments evidencing the new approach outperforms several related methods for all the range of input signal-to-noise ratios (SNR).

Challenges and trade-offs in DWI denoising

CH1 A proper denoising filter must deal with the low-to-very-low SNR of DWI volumes, effectively reducing the bias and the variance in the raw signal coming from the Rician acquisition noise.

CH2 It should combine the joint information present in all the DWI channels to account for the actual diffusion structure of the tissues.

CH3 It should preserve the fine details in small fiber bundles.

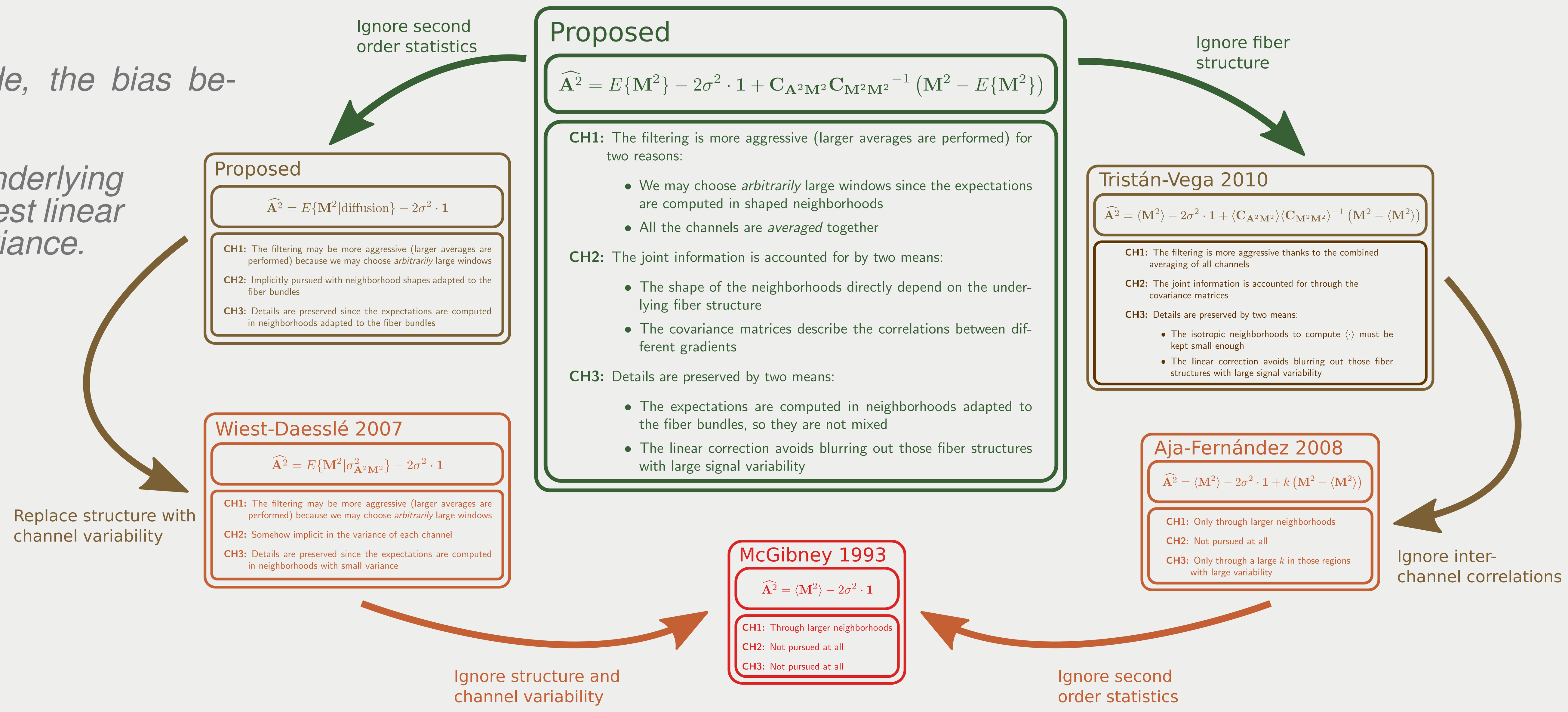
Our general model for the estimation of the squared magnitude of Rician noise-corrupted DWIs

By estimating the squared magnitude, the bias becomes signal-independent.

Without a better knowledge of the underlying signal, the Wiener filter provides the best linear estimator from its mean value and variance.

Somehow related works:

- G. McGibney, “Unbiased signal-to-noise ratio measure for MR images,” Med. Phys., vol. 20, pp. 10771078, 1993.
- S. Aja-Fernández, “Restoration of DWI data using a Rician LMMSE estimator,” IEEE Trans. Med. Imag., vol. 27, pp. 13891403, 2008.
- N. Wiest-Daesslé, “Non-Local Means variants for denoising of diffusion-weighted and diffusion tensor MRI,” in Procs. of MICCAI, ser. LNCS, vol. 4792, 2007, pp. 344351.
- A. Tristán-Vega, “DWI filtering using joint information for DTI and HARDI,” Med. Imag. Anal., vol. 14, pp. 205218, 2010.

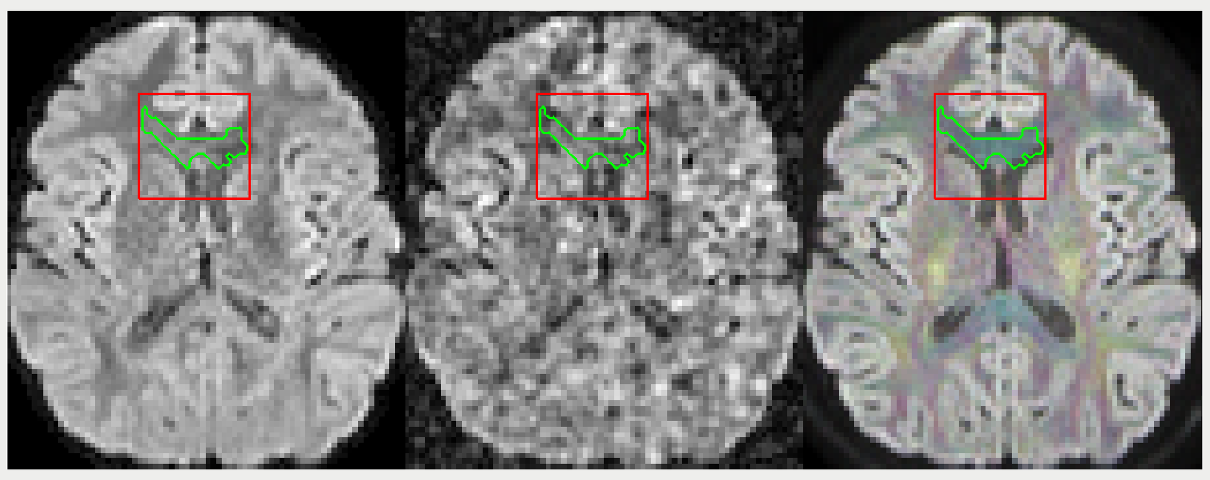


Implementation details

- The covariance matrices are parametrically estimated assuming the channels are fully correlated [10]:

$$\mathbf{C}_{\mathbf{A}^2\mathbf{M}^2} = \varsigma\langle\mathbf{A}^2\rangle_{\mathcal{N}}\langle\mathbf{A}^2\rangle_{\mathcal{N}}^T;$$
$$\mathbf{C}_{\mathbf{M}^2\mathbf{M}^2} = \varsigma\langle\mathbf{A}^2\rangle_{\mathcal{N}}\langle\mathbf{A}^2\rangle_{\mathcal{N}}^T + 4\sigma^2\text{diag}(\langle\mathbf{A}^2\rangle_{\mathcal{N}}) + 4\sigma^4 I_N.$$

- The adaptive expectations $\langle\cdot\rangle_{\mathcal{N}}$, together with $E\{\mathbf{M}^2\}$, are estimated as NonLocal Means-like averages, whose weights are computed over a RGB map obtained from the projections of the DWIs onto three independent unit directions:



$$\langle M^2(\mathbf{x}_i)\rangle_{\mathcal{N}} = \frac{1}{Z}\sum_{l\in\mathcal{N}}\exp\left(-\frac{d(\mathbf{x}_i,\mathbf{x}_l)}{h\cdot\alpha^2}\right)M^2(\mathbf{x}_l);$$
$$\frac{d(\mathbf{x}_i,\mathbf{x}_l)}{\alpha^2} = \frac{1}{\sigma^2}\frac{d_R(\mathbf{x}_i,\mathbf{x}_l)+d_G(\mathbf{x}_i,\mathbf{x}_l)+d_B(\mathbf{x}_i,\mathbf{x}_l)}{\sum_{i=1}^N w_{R_i}^2+\sum_{i=1}^N w_{G_i}^2+\sum_{i=1}^N w_{B_i}^2}.$$

- The self-similarity of the patches used to compute the NLM weights is computed from the local mean value and gradients of each RGB channel, bursting the efficiency of the regular NLM (a speedup of ×20 may be reached [12]):

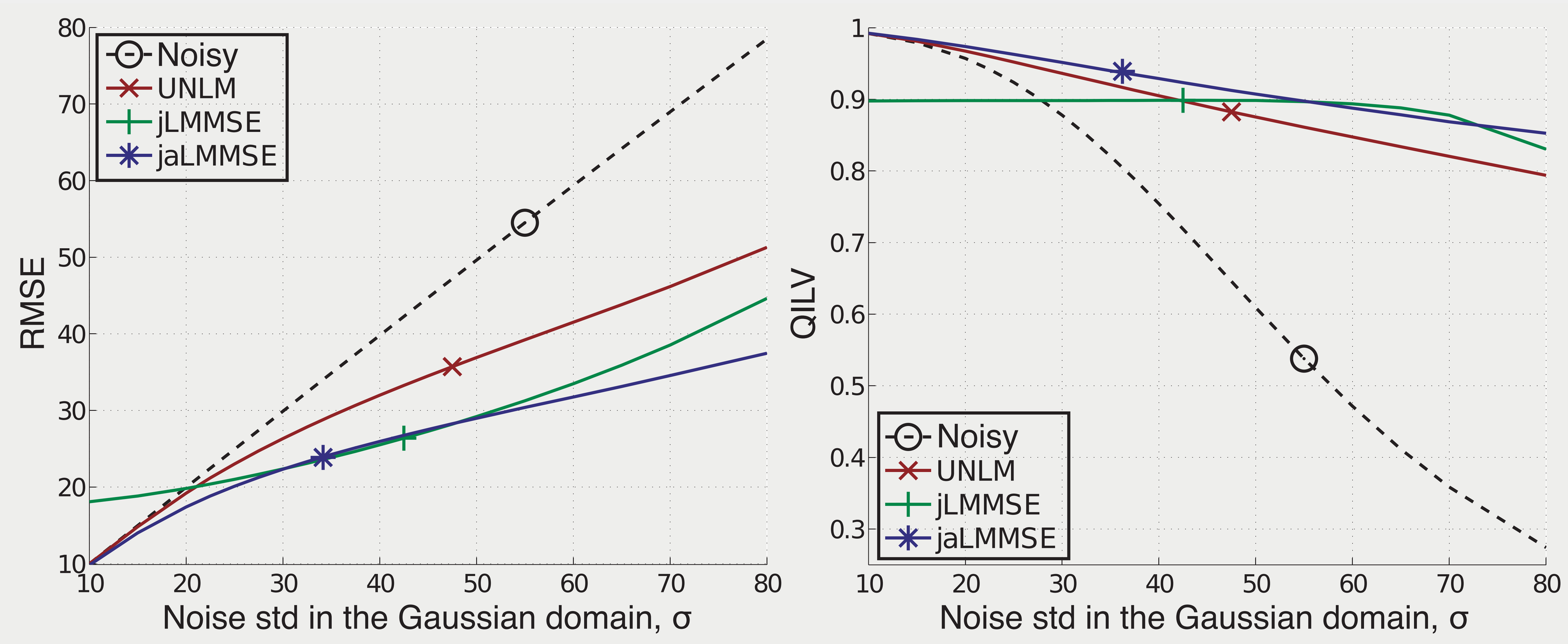
$$d_R(\mathbf{x}_i,\mathbf{x}_l) = \frac{\left|\overline{R}(\mathbf{x}_i)-\overline{R}(\mathbf{x}_l)\right|^2}{h/h_{\text{eff}}} + \sum_{k=1}^{3}\delta_k\frac{|R_k(\mathbf{x}_i)-R_k(\mathbf{x}_l)|^2}{h/h_{\text{eff}}},$$

Download and use! Features:

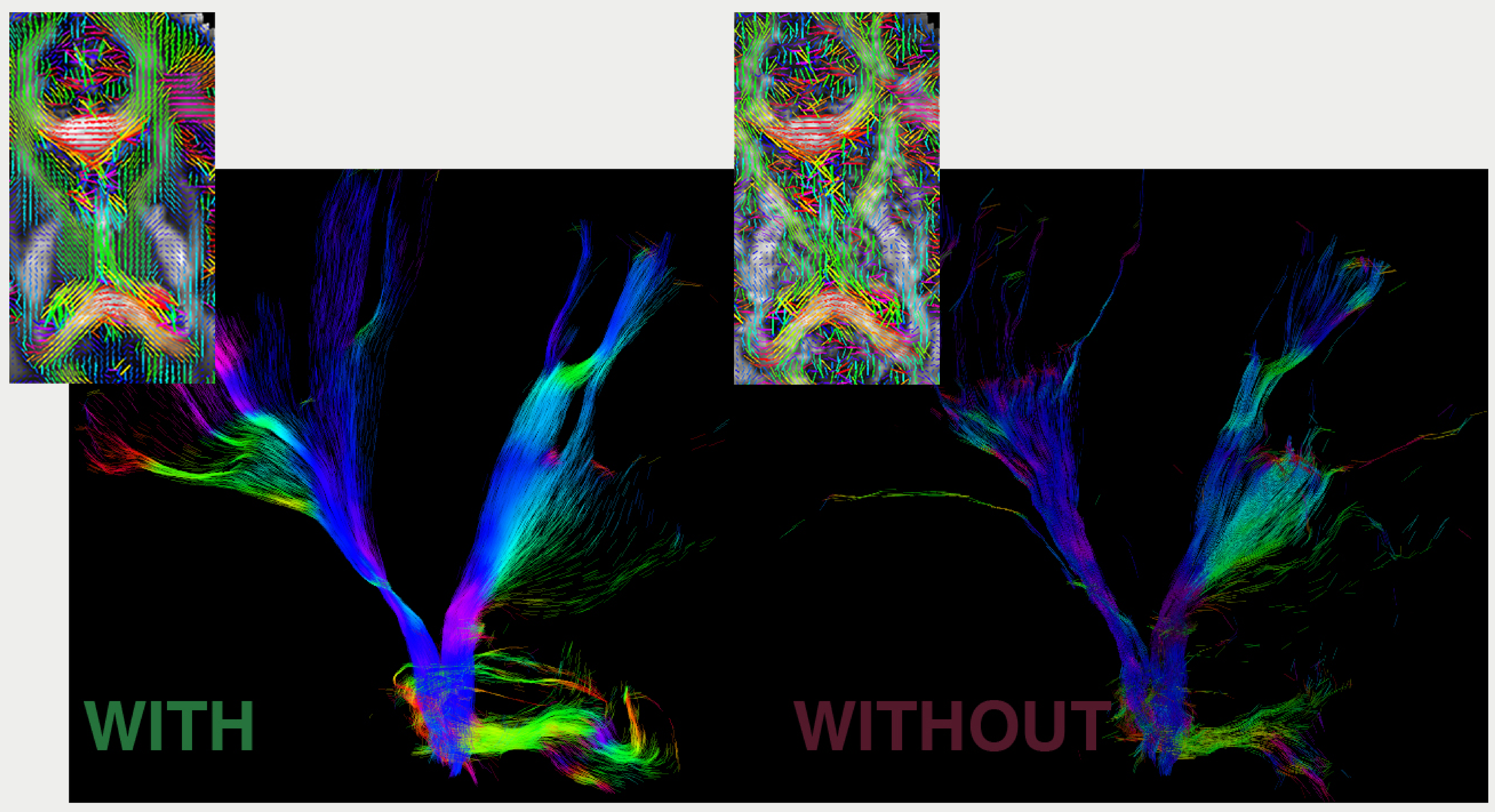
- Optimized C++/ITK open-source implementation.
- Built-in stationary noise-power estimation.
- Standalone console application and 3-D Slicer plugin available.
- Full source code or multi-platform pre-compiled binaries available.

http://www.nitrc.org/projects/jalmmse_dwi

Some examples (check the full paper for further results)



- Realistic phantom based on regularized real data [13]
- White matter masking by FA thresholding
- MSE describes how well noise is removed
- QILV describes how well details are preserved [15]



References

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12 A. Tristán-Vega, V. García-Pérez, S. Aja-Fernández, and C.-F. Westin, “Efficient and robust nonlocal means denoising of MR data based on salient features matching,” Comput. Meth. Prog. Biomed., vol. 105, pp. 131–144, 2012.

13 A. Tristán-Vega and S. Aja-Fernández, “Design and construction of a realistic DWI phantom for filtering performance assessment,” in Procs. of MICCAI, ser. LNCS, vol. 5761, 2009, pp. 951–958.

15 S. Aja-Fernández, R. San-José-Estépar, C. Alberola-López, and C.-F. Westin, “Image quality assessment based on local variance,” in Procs. of IEEE EMBC, New York, USA, 2005, pp. 4815–4818.

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