Denoising diffusion MRI data using a path algorithm strategy

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Introduction

One way to circumvent the typically low signal-to-noise ratio (SNR) in diffusion-weighted (DW) MRI datasets is to use denoising algorithms (e.g., [1,2,3]). While the advantage of this strategy is that it does neither increase the acquisition time nor requires a specific acquisition setup, it intrinsically relies on accurate estimation of noise properties i.e. type of noise distribution and its variance [4]. Algorithms which assume fewer hypotheses are thus likely to still be applicable in situations where clinical datasets are astray from the theoretical assumed noise distributions. To circumvent the need of reliably estimating such noise parameters, we extend the Non Local Spatial and Angular Matching (NLSAM) denoising approach [1] with a fast and efficient path algorithm strategy that does not explicitly rely on noise properties.

Methods

Theory: We adapted the available implementation of [1] to use a penalized *l1*-norm reconstruction (see **Eq.** 1) instead of a constrained *l1*-norm reconstruction (see **Eq.** 2). This allows for using path algorithms [5,6], which compute multiple values for the regularization factor, yielding different signal reconstructions with their associated linear models. However, by removing the explicit dependence of the regularization parameter on the noise level, a model selection strategy is now needed. To tackle this challenge, an unbiased estimation of the degrees of freedom for *l1*-regularized models has been developed [7], making it possible to rely on well known methods such as the Aikake information criterion (AIC) or the Bayesian information criterion (BIC) for optimal model selection.

$$\text{Eq. 1 } \min_x ||Ax - b||_2^2 + \lambda ||x||_1 \qquad \text{Eq. 2 } \min_x ||x||_1 \text{ s.t. } ||Ax - b||_2^2 \leq \lambda$$

Simulated DW data: We used the publicly available synthetic data from the ISMRM 2015 tractography challenge [8], which is a full brain dataset consisting of 32 DW images with b = 1000 s/mm^2 and one b = 0 s/mm^2 at a spatial resolution of 2 × 2 × 2 mm^3. Starting from the ground truth data, we added Rician distributed noise at various SNR, where $\mathrm{SNR} = \mathrm{mean(b0)} \,/\, \sigma^2$ with mean (b0) the mean intensity of the b = 0 s/mm^2 image and σ^2 the Gaussian noise variance.

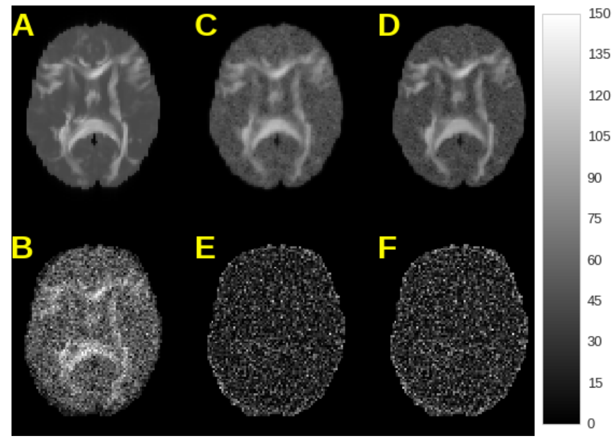

Figure 1: Denoising results for the synthetic dataset A) ground truth B) noisy input data C) nlsam path D) original nlsam E) removed noise from C) and F) removed noise from D). Noise is removed without affecting structure.

In vivo DW data: We used the publicly available in vivo dataset of [2], which contains 40 DW images with b = 1000 s/mm^2 and one b = 0 s/mm^2 image at a spatial resolution of 1.2 × 1.2 × 1.2 mm^3.

Analyses: To evaluate the performance of the proposed path denoising method, we qualitatively show the denoising result on the in vivo dataset and quantitatively evaluated both methods on the synthetic dataset with the structural similarity index (SSIM) and normalized root mean square error (NRMSE) computed on a slice of interest. We first corrected the Rician noise bias with the algorithm of [9] and processed the synthetic dataset with the default parameters of NLSAM (block size of 3x3x3 and 5 angular neighbors) and our modified NLSAM path version. We used the BIC as a selection criterion since it favors sparser models than the AIC, which is an underlying hypothesis of *l1*-norm optimization.

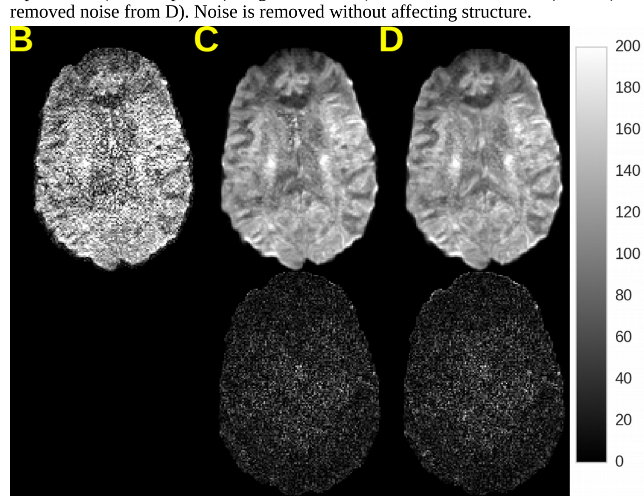

Figure 2: **Top** : Denoising results for the invivo dataset and **Bottom** : Removed noise from each image on B) noisy input data C) nlsam path D) original nlsam.

Results

Figure 1 shows **A)** the noiseless data, **B)** the noisy input data **C)** the denoised results for our NLSAM path version and **D)** the original NLSAM denoising. **Figure 2** shows the results of each algorithm and residuals on the in vivo dataset. **Figure 3** shows the SSIM and NRMSE for the synthetic data at various SNRs. In all studied cases, denoising improves the results over the original data and our path searching strategy improves upon the original NLSAM formulation in terms of NRMSE.

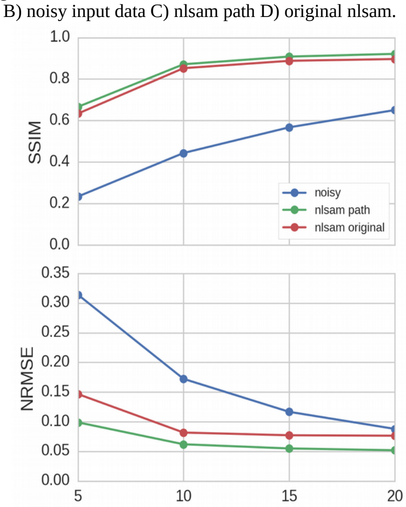

Figure 3: Structural similarity index (SSIM) and normalized root mean squared error (NRMSE) for various SNR on the synthetic dataset.

Discussion & Conclusion

We have shown how path searching algorithms can be used for efficiently denoising diffusion datasets without relying on an explicit estimation of the noise level. This estimation can be problematic to accurately perform in some scenarios e.g. the acquired data exhibit artifacts or the scanner applied some post-processing filter on the background image [4]. This approach is also about five times faster than the original constrained NLSAM algorithm with the use of warm start from previous solutions along the regularization path [6]. Since most denoising algorithms share an intrinsic dependence on the noise variance, this also means they cannot perform optimally on data where the noise estimation deviates from their theoretical assumptions. Algorithms which assume fewer hypotheses are thus likely to still be applicable in situations where clinical datasets are astray from the theoretical assumptions of each algorithm.

References: [1] St-Jean et al. 2016 Medical Image Analysis [2] Manjón et al. 2013 PLoS ONE [3] Becker et al. 2014 NeuroImage [4] Aja-Fernández et al. 2016 Springer International Publishing [5] Efron et al. 2004 Ann. Statist. [6] Friedman et al. 2010 Journal of statistical software [7] Zou et al. 2007 Ann. Statist.
[8] http://www.tractometer.org/ismrm_2015_challenge [9] Koay et al. 2009 Journal of Magnetic Resonance