De-noising of diffusion-weighted MRI data by averaging of inconsistent input data in wavelet space

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Synopsis

Diffusion Weighted Images datasets with high spatial resolution and strong diffusion weighting are often deteriorated with low SNR. Here, we demonstrate the feasibility of a recently presented repetition-free averaging based de-noising (AWESOME). That technique reduces noise by averaging over a series of N images with varying contrast in wavelet space and regains intensities and object features initially covered by noise. We show that high resolution DWIs are achievable in a quality that almost equals to that obtained from 6fold complex averaging.

Purpose

Signal averaging can improve the image quality at the cost of substantially prolonged scan times and susceptibility to motion due to the requirement of repeated acquisitions. This is particularly important in diffusion-weighted MRI (dMRI) targeted at high spatial resolutions and/or strong diffusion weighting.[1] Recently, a de-noising technique referred to as 'AWESOME' has been proposed that reduces noise by 'averaging' of complex data in wavelet space.[2] It permits to use image series acquired with different parameters (e.g., echo times) as input without the need for repeated acquisitions. Application to relaxation studies demonstrated that the quantitative information was preserved in the de-noised images while object features initially covered by noise were regained. Here, we investigated if this technique might be beneficial in dMRI.

Methods

Acquisition: A data set acquired previously[1] on a 3T scanner (Skyra CONNECTOM, Siemens Healthcare, Germany) with a gradient strength of 300mT/m and a custom-built 64-channel head coil was made available. In particular, it consisted of a single-refocused dMRI scan in a healthy subject employing the following parameters:[5,6] 1.2mm isotropic resolution, FoV=210x210mm, 98 slices, partial Fourier=6/8, TR/TE=4600ms/54ms, GRAPPA=3, SMS=2. Six repetitions of 128 diffusion directions at b=5000s/mm^2 were recorded along with 10 interspersed b=0 images.

Phase correction: Slice-wise background phase maps were calculated in Matlab based on artificial neural networks, Figure 1.

Complex averaging and distortion correction: Six repetitions of phase-corrected complex images were averaged as detailed elsewhere.[1] These high-SNR data served as reference in diffusion model fits and as image quality target for the de-noising algorithm.

AWESOME de-noising: The details of AWESOME have been described elsewhere.[2] In short, it operates in the wavelet space of complex MR images. To each voxel a dedicated filter described by a multi-parametric function is applied. These parameters are derived from a series of images of the same slice or volume, whereby the contrast of those images may vary. The filter parameters depend on the characteristics of the noise contaminations, on the mean value of the series, and on certain experimental conditions, such as, magnetization preparation by the pulse sequence, image distortion, subject motion, and SNR. The derivation of the filter parameter is a crucial step that is performed for each experiment. In particular, motion may disturb the filter function, requiring sophisticated motion correction.
To minimize the need for interpolation from motion or distortion corrections, images from a single repetition of 128 diffusion directions were clustered in 10 groups, with only subtle subject movement in each set. Then, the 16 parameters of the AWESOME filter function were optimized by global non-linear minimization (Matlab) of the mean squared difference between de-noised volumes and the 6x complex averaged reference volumes. Thus, for each subset a unique filter function was derived. As all filters indicated similar performance, we may assume that a general filter function can be obtained for the given type of input images, e.g., by choosing the mean of the parameters.

dMRI processing: dMRI data were processed using the standard FSL[5] diffusion tensor imaging (DTI) preprocessing pipeline.

Results

Three data sets were analyzed: (i) a “noisy” data set from the non-averaged first repetition (1xAV); (ii) a de-noised data set from the identical repetition after application of AWESOME (1xDN), and (iii) a reference data set obtained from all six repetitions after traditional averaging of the complex images (6xAV). An example of magnitude images recorded at b=5000 is shown in Figure 2. The results of the dMRI analysis results are summarized in Figure 3, showing fractional anisotropy (FA) maps and color-coded directional FA values. In addition, a more sophisticated ball-and-stick model (FSL)[6] was applied to extract information on multiple fiber orientations. Results for the color-coded direction of the second peak are presented in Figure 4 demonstrating substantial improvements for assessing crossing fibers.

Discussion

The results after AWESOME de-noising approached the SNR obtained with 6x complex averaging, however, with some degradation in detail sharpness. Information on fiber orientation and presence of crossing fibers were preserved as demonstrated by comparison with the reference data with striking improvements especially in inferior regions. In conclusion, application of AWESOME to dMRI may offer the potential to produce reliable quantitative results with low-SNR input data that result from application of very large b-values or high spatial resolution. This is achieved without the need of averaging over repeated (identical) acquisitions yielding a substantial reduction in scan time.

Acknowledgements

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References

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Figures

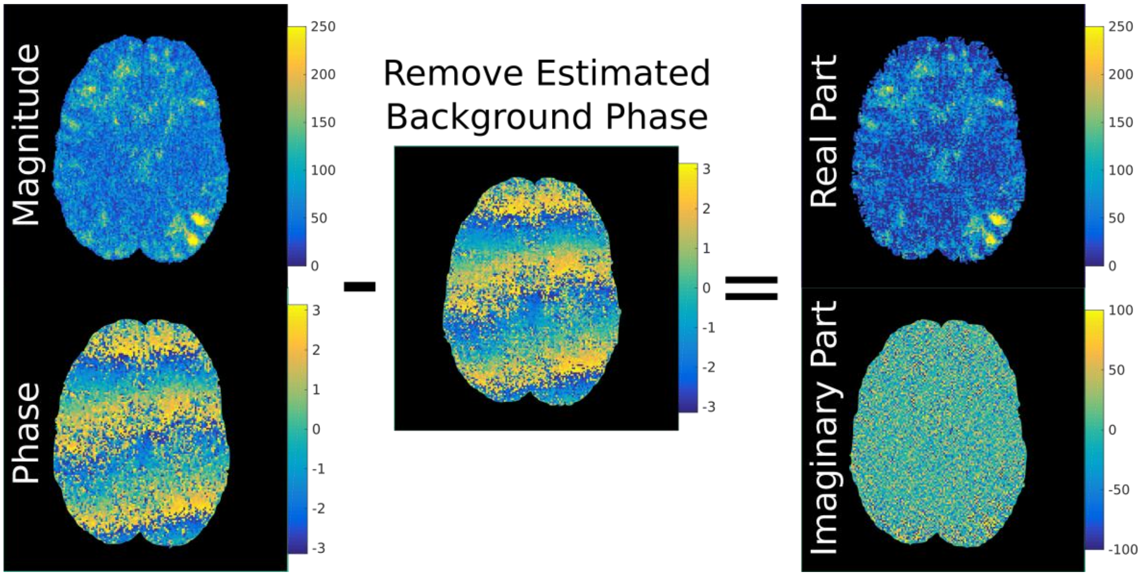

Figure 1: Phase correction of background phase using NAR neural networks; the estimated background phase offers a stable phase correction as visible in the imaginary part, containing mostly random noise.

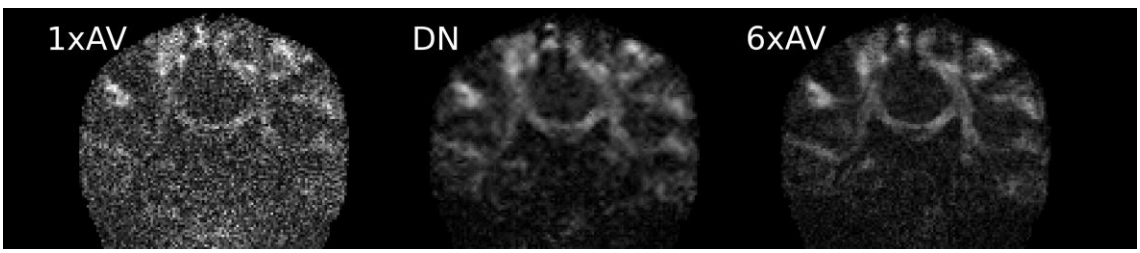

Figure 2: Magnitude images of original, de-noised and 6x complex averaged data. The adjusted de-noising algorithm largely reproduces the results obtained with 6x complex averaging, with a subtle loss of sharpness, which is presumably due to differently distorted (uncorrected) input images.

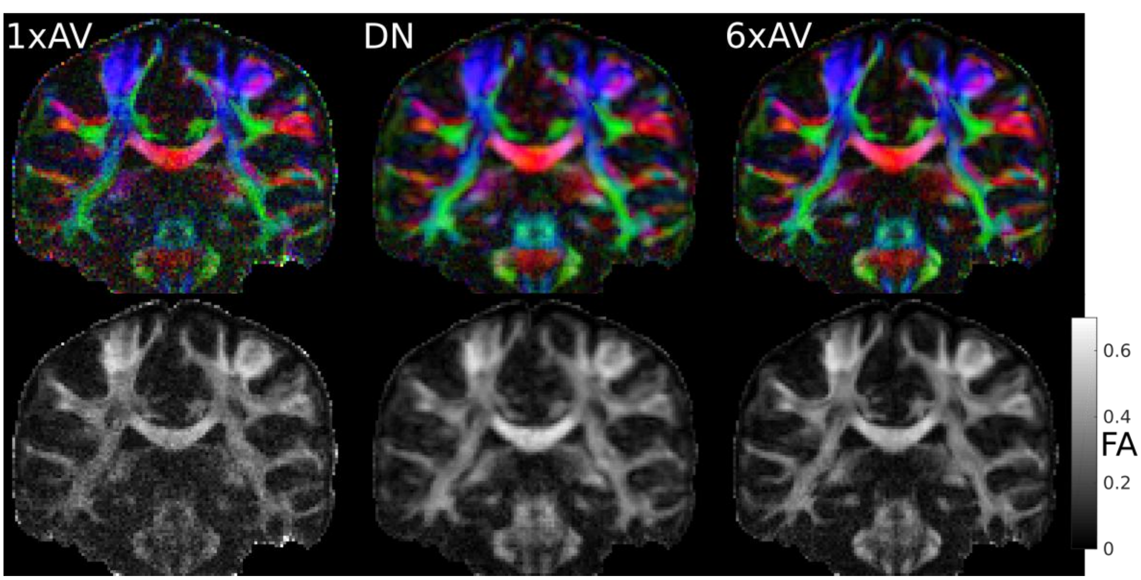

Figure 3: Color-coded FA for single repetition, de-noised, and 6x complex averaged data. De-noising substantially improves the FA estimates in areas of low SNR, e.g. pons, and overall yields similar values as the 6x averaged reference.

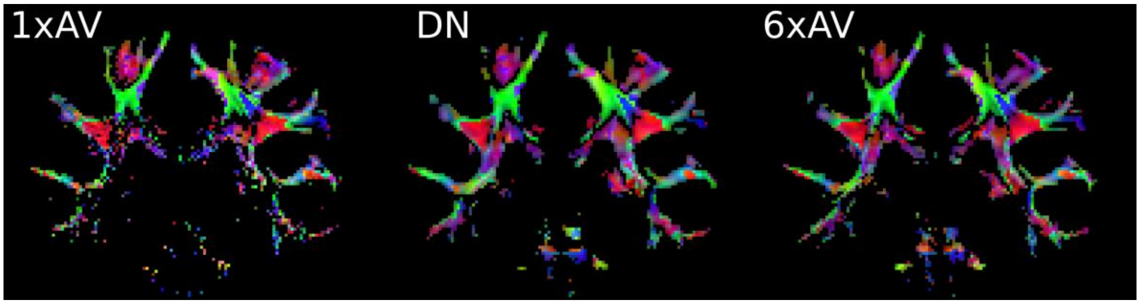

Figure 4: Secondary fiber orientation for single repetition, de-noised and 6x averaged datasets (threshold of 0.05 for anisotropic fiber fraction). De-noising yields comparable definition of secondary fibers as obtained with averaged dataset.