Adaptive Averaging of Non-Identical Image Series in the Wavelet Space

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Purpose: Signal averaging is often necessary to improve image quality if the inherent signal intensity is low. In this work, we investigate a method for SNR improvement that reduces noise by averaging over a series of images with varying contrast in the wavelet space. The method is implemented such that the image intensities and object features initially covered by noise are maintained, which is mandatory for a subsequent quantitative analysis. It is here referred to as "Adaptive Wavelet-based Enhancement of Signal Over Multiple Experiments" (AWESOME). An explorative investigation of its performance is performed using qMTI (quantitative magnetization transfer imaging) data. They contain a series of high-resolution images (Z-spectra) with varying intensity (depending on saturation amplitude and offset) that would typically require signal averaging to obtain sufficient SNR for parameter fitting. It is shown that the proposed method achieves significant SNR improvements without degradation of the quantitative signal information and comes with the added advantage of saving scan time.

Methods: *MRI scans:* qMTI data were taken from previously acquired *post-mortem* marmoset brain scans a 3T [1,2,3]. Briefly, 38 image volumes (200 µm nominal isotropic resolution) were recorded with a 3D FLASH sequence and pulsed off-resonance saturation with varying amplitude and offset. For regular off-line complex signal averaging, experiments were repeated 6 to 16 times, depending on the expected signal intensity. Images were registered linearly to the first image and phase-corrected.

Adaptive averaging: Images are transformed into the wavelet space applying 'symlet8' wavelet transformation [4] from the MatLab Wavelet Toolbox (4.12). Three levels for the 3D wavelet decomposition are applied and all following steps are performed separately for 7 feature directions (3 main axes, 3 plane diagonals, and the space diagonal) per level, in the following referred to as FDL. *Step 1:* Calculating a normalized intensity map per FDL for each image in units of RMS of the FDL's background, assuming the background represents mostly noise in the higher frequency levels. *Step 2:* Creating a set of averaged FDLs over the image series. The averaged FDLs already show a decreased intensity of features in the background and maintained features of the brain resulting from the phase correction of the images. Because the phase of features is maintained in the wavelet transformation, the effect on features representing noise is comparable to averaging of complex images. *Step 3:* Calculating the phase difference of the FDLs of each image with the averaged set of FDLs for each feature and calculating a transfer map from a transfer function varying between 1 (feature) and −1 (inverted feature) with 0 representing pure noise. It is derived from the phase difference and furthermore refined by considering the normalized intensity map per FDL. *Step 4:* The transfer maps are used as a mixing ratio for each FDL with the averaged set. The normalized intensity maps are used to estimate the contribution of each FDL of the series to the averaged one, assuming that brain features add up constructively or, if opposite in the sign, destructively to the averaged one, and the noise mostly cancels out. The estimation of the contribution is additionally used to modulate the averaged features in intensity and sign to be as close as possible to the original brain features hidden in noise before the last step. *Step 5:* Choosing the levels to be handled by the adaptive averaging procedure. The original FDLs get fused with the averaged features using the mixing ratio and the contribution estimation to create FDLs for each image of the series with reduced noise, original high intensity features and ideally well-estimated low intensity brain features. *Step 6:* Wavelet reconstruction is applied on the new FDLs to rebuild the 3D image series.

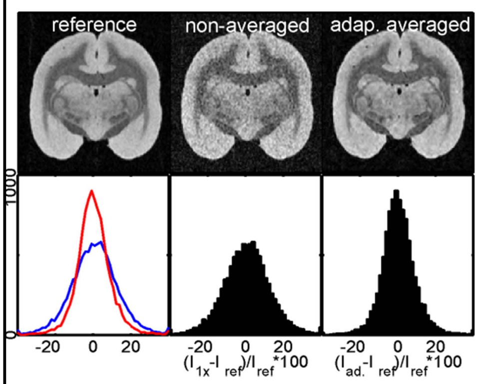

Figure 1: qMTI data (top row) and frequency distribution of the relative difference to the reference data for non-averaged (blue and bottom middle) and adaptively averaged data (red and bottom right).

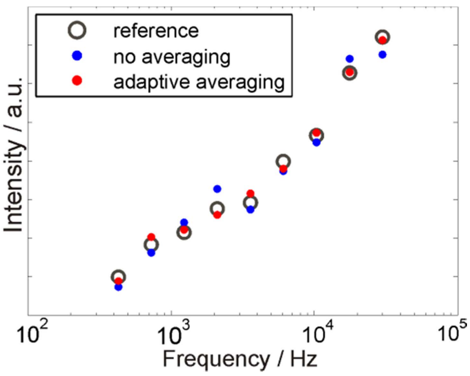

Figure 2: z-spectra of reference data, non-averaged data, and adaptively averaged data from a single white-matter voxel demonstrating the preservation of signal

Results and Discussion: The results obtained in a selected slice are shown in Figure 1 (top). To evaluate the performance of the method, we compared reference data obtained by regular averaging (N=9) to data without averaging (N=1) and adaptively averaged data integrating the information from all acquisitions of the z-spectrum. Images processed with AWESOME demonstrate reduced contamination by noise. Hidden features in non-averaged data were regained and cleaned from noise. As a quantitative criterion, the relative difference to the reference data was computed. It can be considered as the error in the data, assuming averaged data represent "true" values (gold standard). The frequency distribution of this error is Gaussian (Figure 1, bottom row) for both non-averaged and adaptively averaged data (σ^{non-av}=15.71%, $\sigma^{adap-av}$=10.14%). Note that a reduction of σ is expected due to averaging. In Figure 2, the z-spectrum (ω_1=7000 rad/s) of a single voxel in white matter is shown. The intensity is not significantly altered over the entire offset range but is closer to the reference data compared to the non-averaged data.

Conclusion: The proposed method shows improved SNR results as expected for regular averaging, however, without the need of identical repetitions as it can be applied to images with different contrast. Gains in SNR were approximately 40% (i.e., equivalent to doubling the number of scans) for experimental data and even higher with simulated data (results not shown).

References: [1] R. Müller et al. *Proc. ISMRM* 21: 4366, 2013. [2] H. Marschner et al. *Proc. ISMRM* 22: 3336, 2014. [3] H. Marschner et al. *Proc. ISMRM* 22: 208, 2014. [4] I. Daubechies. Ten Lectures on Wavelets, SIAM (1992). [5] D.K. Müller et al. *J. Magn. Reson.* 230: 88-97 (2013).