Noise-Adaptive Nonlinear Filtering Technique for SENSE – Reconstructed Images

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SENSitivity Encoding (SENSE) reconstruction allows significant scan time reduction. The resulting images have amplified and spatially non-uniform noise level. Noise levels significantly increase at high reduction factors and for non-optimized coil geometries. In this work, we demonstrate that standard retrospective filtering methods are often non-optimal for SENSE images. We introduce a modified anisotropic diffusion filtering technique for denoising SENSE images. Our technique uses a noise matrix from the SENSE reconstruction to adjust filter behavior for optimal filtering of regions with different noise levels. The method produces fewer filtering artifacts for SENSE images than standard anisotropic diffusion filtering techniques while effectively denoising the entire image.

Introduction

Images reconstructed by SENSE [1] are characterized by increased and spatially non-uniform noise levels due to the reduced acquisition times, geometry factor and coil sensitivities. One way to improve image quality is to use postprocessing denoising techniques. Anisotropic diffusion filtering [2] was shown to be an efficient method for edge-preserving noise filtering of MRI images [3] and can be characterized as a diffusion process in image space:

$$\partial I(\boldsymbol{r}, t)/\partial t = \nabla(c(\boldsymbol{r}, t) \cdot \nabla I(\boldsymbol{r}, t))$$

where $c(\boldsymbol{r}, t) = f(\nabla I(\boldsymbol{r}, t), k)$ is a monotonically decreasing diffusion function of the local gradient and conductance parameter k [2]. k is usually chosen to be constant for a given MRI dataset [3]. While this choice is adequate for MRI data with a uniform noise distribution throughout the image, for SENSE-reconstructed data, such a choice leads to under-smoothing in the high noise areas and/or over-smoothing in the areas of low noise resulting in filtering artifacts. We have developed a new filtering method that uses a spatially variant noise map that is readily available from the SENSE reconstruction and can be used to locally adjust the conductance parameter for optimal filtering in all image areas with different noise levels.

Method

Standard SENSE reconstruction with Cartesian sampling yields *partial image noise matrix* [1]:

$$X = \frac{1}{n_k}(S^H \Psi^{-1} S)^{-1},$$

where is S and S^H is *the sensitivity matrix* and its Hermitian conjugate, Ψ is *the receiver noise matrix*, n_k is the number of sampling positions. Diagonal entries of the matrix yield the noise level in the unfolded pixels and off-diagonal entries describe noise correlation among the pixels. For smoothing purposes, noise correlation could be neglected, as the correlation occurs among distant pixels obtained from the SENSE reconstruction. Then, a spatially variant map of noise variances can be obtained from the main diagonal of the partial noise matrix during the reconstruction. For each pair of neighboring pixels *n* and *m*, we choose the conductance parameter to be proportional to the averaged value of noise standard deviation estimations at these pixels:

$$k_{nm} = w \cdot (\sigma_n^{noise} + \sigma_m^{noise})/2\,,\ 1.5 < w < 3$$

where weighting parameter w is constant for a given dataset. The resulting spatially variant conductance map is then used in anisotropic diffusion filtering iterations.

Results

Folded and reference images of a phantom (reduction factor R=4) and a human volunteer (R=2) were acquired on a 1.5T MR scanner (GE SIGNA, GE Medical Systems, Milwaukee, WI) using a 4-coil phased array and body coil and then reconstructed by the SENSE method [1]. The noise distribution map was obtained during the reconstruction. For phantom images, anisotropic diffusion filtering was first applied with the proposed spatially variant conductance map and next with a constant conductance parameter (Fig. 1). In the second case, the conductance parameter was estimated using central area of the noise map (Fig. 1-c) to provide equivalent filtering of the area in both cases. Figures 1-d and 1-e demonstrate significant noise reduction in the image filtered by the proposed method. Substantial object edge blurring differences can be observed between the initial image and the image filtered by standard anisotropic diffusion (Fig.1-g). However, the difference for noise-adaptive anisotropic diffusion filtering does not contain noticeable correlated features (Fig. 1-f). Figure 2 shows the results of noise-adaptive filtering of a T2-weighted image.

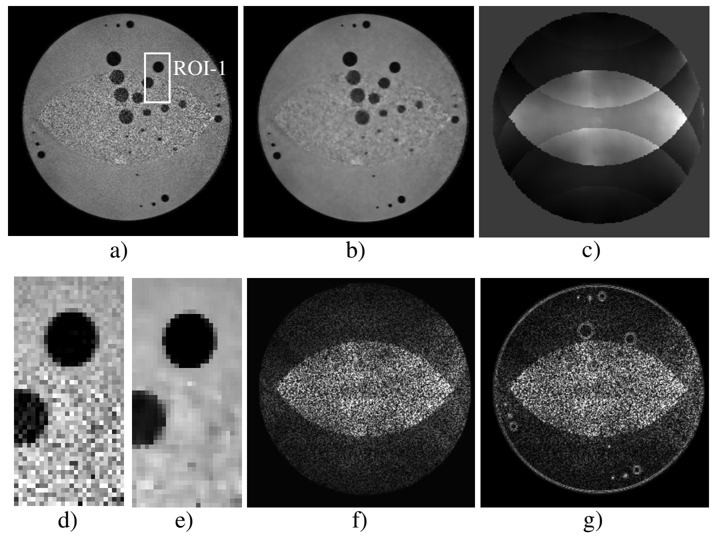

Figure 1. Filtering of phantom image. a) phantom image reconstructed by SENSE (R=4, phase encoding in vertical direction), b) filtered image, c) noise map, d) magnified region of interest ROI-1 for initial image, e) magnified ROI-1 for filtered image, f) difference between initial image and filtered by noise-adaptive anisotropic diffusion filter, g) difference between initial image and filtered by standard anisotropic diffusion filter.

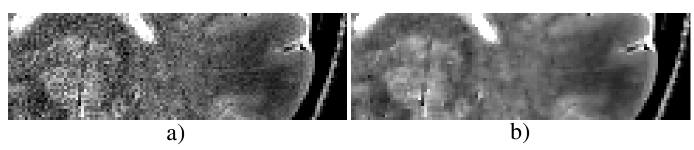

Figure 2. Filtering of T2 image. a) initial SENSE - reconstructed image (magnified part, R=2), b) image after 5 iterations of noise-adaptive anisotropic diffusion filter.

Discussion

The noise matrix from SENSE reconstruction can be efficiently used for optimization of standard denoising techniques for SENSE-reconstructed images. The proposed filtering scheme provides optimal denoising of SENSE-reconstructed images, which is not possible to achieve with standard anisotropic diffusion filtering techniques that utilize a constant conductance parameter. The proposed method is especially useful in cases of non-optimized coil configurations when geometry factor contribution to the noise map results in highly non-uniform noise distribution. Furthermore, the new method is of practical use at high foldover factors, when the noise component may significantly degrade the reconstructed image.

Acknowledgements

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References

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