SNR-Adaptive k-Space Filtering for Autocalibrated Parallel Image Reconstruction

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Introduction

Parallel MRI (P-MRI) with GRAPPA reconstruction [1] has been widely used in various MRI applications. However, the technique is less applicable for P-MRI with high reduction factors due to residual aliasing artifacts and substantial noise amplification. These problems can be resolved to some extent by using multi-dimensional auto-calibrating techniques such as GARSE [2]. However, noise amplification is still noticeable in the images reconstructed by GARSE from highly undersampled data. All of these autocalibrating methods calculate the reconstruction coefficients from the central k-space region and apply them to recover the missing k-space lines in the outside region of k-space. The noise amplification is caused when the coefficients from the high SNR region are applied to the very low SNR region. The reconstructed k-space lines have increased noise that can be readily evaluated when noise variance in individual coil data and reconstruction coefficients are known. In this study, a filter has been developed to process the k-space lines reconstructed by auto-calibrating techniques (GRAPPA or GARSE) to reduce the noise amplification for imaging with high reduction factors.

Methods

First, the GARSE method is used to recover the missing k-space lines according to the Eq. (1).

$$S_i\left(\vec{k}\right)=\sum_{j=1}^{N_C}\sum_{\hat{\vec{k}}\in\Omega_k} a\left(i, j, \hat{\vec{k}}\right)S_j\left(\hat{\vec{k}}\right) \qquad (1)$$

$$F(k)=\frac{\left|I_s\left(\vec{k}\right)\right|^2}{\left|I_s\left(\vec{k}\right)\right|^2+\sigma^2} \qquad (2)$$

Where $S_i(\vec{k})$ is the missing k data, $S_j(\hat{\vec{k}})$ is the acquired k data, a is the reconstruction coefficient, and Ω_k is the neighborhood of the acquired $\hat{\vec{k}}$. The Wiener filter is a linear filter for images degraded by additive noise. It is usually applied in the frequency domain. Therefore, the Wiener filter F is defined in k-space according to Eq (2) where the noise energy σ^2 in k-space is assumed to be constant, and $\left|I_s\left(\vec{k}\right)\right|^2$ is the signal energy. Second, the average energy $\overline{E(k_r)}$, which is a function of the radius k_r, is calculated from the reconstructed k-space data and is fitted to the smooth function. Because the signal and noise are hard to separate in k-space, the SNR adaptive filter F_i is defined in Eq. (3) according to the Wiener filter equation and applied in Eq. (4)

$$F_i(k_r)=\sqrt{\frac{\overline{E_i(k_r)}-\sigma_{im}^2+\sigma_i^2}{\overline{E_i(k_r)}}} \qquad (3)$$

$$\hat{S}_i(\vec{k})=F_i\left(k_r(\vec{k})\right)S_i(\vec{k}) \qquad (4)$$

where i is for the different coil, σ^2_i is the noise energy from the acquired data, σ^2_{im} is the noise energy in the reconstructed data and is calculated by using Eq. (1) and σ^2_i. The cross section profile of this SNR adaptive filter is shown in Fig. 1. This filter is multiplied only with those recovered missing k-space lines according to Eq. (4). The final images are reconstructed from these SNR-adaptive filtered k-space data.

Brain images were acquired on a 3T Trio MRI scanner (Siemens Medical Solutions, Erlangen, Germany) using the eight-channel head coil (Medical Devices, Waukesha, WI) and a RF-spoiled gradient echo pulse sequence. The imaging parameters were: TR=40 ms, TE=10 ms, FOV=256 mm, imaging matrix = 256×256. The reduced data were created by undersampling the complete datasets. The proposed technique was tested for a reduction factor R=4 and Nref =24 because the noise amplification is greatest for high reduction factors.

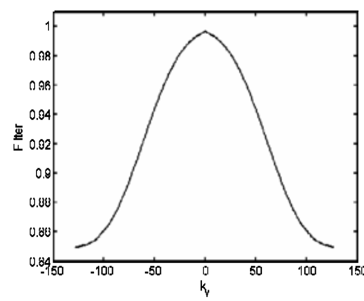

Fig. 1. The typical cross section profile of the SNR adaptive filter for GARSE.

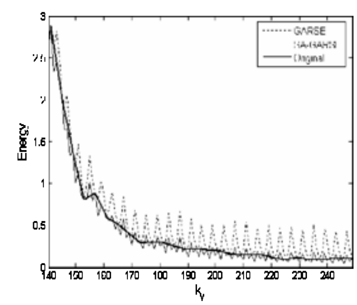

Fig. 2. The energy curves for the different methods.

Results

The energy curves of GARSE, SNR-adaptive GARSE and the original k-space are plotted in Fig. 2 after summing along the readout direction. The large deviation between GARSE and original is apparent due to the noise amplification. After applying the SNR-adaptive filter, the deviation is apparently reduced. The images reconstructed from k-space data recovered by GRAPPA and GARSE and with and without processing by the SNR-adaptive filter are shown in Fig. 3. (a) is the reference image reconstructed from the full sampled dataset. (b) is the image reconstructed using GARSE and applying the filter. (c) is the image only using the GARSE reconstruction. (d) is the image using GRAPPA and applying the filter. (e) is the image only using the GRAPPA reconstruction. The SNR adaptive filter can reduce the noise due to noise amplification in the reconstruction, but can not suppress the aliasing artifact.

Acknowledgments

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Reference

1. Griswold MA, et. al. Magn Reson Med 2002;47:1202-10.; 2. Kholmovski EG, Samsonov AA. ISMRM. 2005, p. 2672.

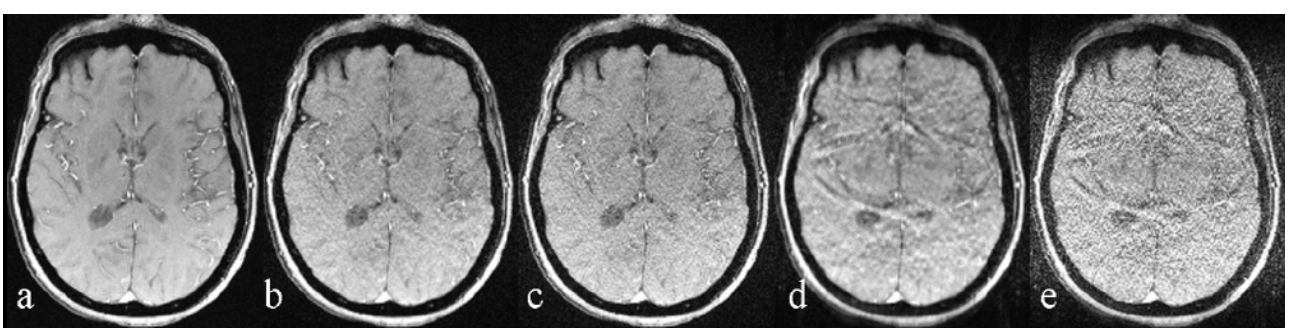

Fig. 3. (a) the reference image, (b) the SNR-adaptive weighted GARSE image, RMS=0.88 (c) the GARSE image, RMS=1.16 (d) the SNR-adaptive weighted GRAPPA, RMS=1.46, (e) The GRAPPA image, RMS=3.25. The images are in the same scale.