Joint Image Reconstruction and Sensitivity Estimation in SENSE (JSENSE)

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INTRODUCTION

Most parallel imaging methods, such as SMASH (1) and SENSE (2), requires the sensitivity weighting function for each receiver channel for image reconstruction. The desired sensitivity functions are either derived from a set of reference images obtained in a calibration scan. A practical problem with this technique is that any misregistration from the calibration scan to the accelerated scan can create significant image artifacts, which is a major concern in dynamic imaging applications. Although the problem can be alleviated through either motion correction (3), or the use of self-calibration techniques (4), the estimated sensitivity functions are usually subject to spatial-varying noise and data truncation errors. Several techniques have been used to improve the sensitivities (2,5). However, these techniques primarily address the issue of noise, leaving the errors due to data truncation still unresolved. These sensitivity errors may be acceptable for small reduction factors, but can cause serious artifacts with increased reduction factor. In this paper, we propose a novel approach (JSENSE) that jointly estimates the coil sensitivities and reconstructs the desired image, taking advantage of the information from both the auto-calibrating data (ACS) and the reduced encodings.

METHOD

Similar to other auto-calibrating methods, we acquire some ACS lines. Instead of assuming the sensitivity functions estimated from these ACS data are exactly accurate, we introduce some degree of uncertainty. Specifically, we model the coil sensitivities as a polynomial function $s_l(\vec{r}) = \sum_{i=0}^{N} \sum_{j=0}^{N} a_{l,i,j} x^i y^j$ [1], where $(x, y) = \vec{r}$ denotes the location of a pixel, and $a_{i,j}$ is the coefficient of an order-N polynomial that is assumed unknown. Because of the smooth nature of coil sensitivity in general, a polynomial of low order is usually sufficient. Under this model, both the polynomial coefficients and the desired image are to be solved jointly. Since the noise in the acquired data is white Gaussian, we can jointly estimate the coefficients for coil sensitivities $\mathbf{a}$ and the desired image $\mathbf{f}$ by minimizing a cost function $\mathrm{U}(\mathbf{a,f})$. Specifically, this procedure is represented as $\{\mathbf{a,f}\} = \arg\min_{\mathbf{a,f}} \mathrm{U}(\mathbf{a,f}) = \arg\min_{\mathbf{a,f}} \left[\frac{1}{2} \left\| \mathbf{d} - \mathrm{M}(\mathbf{a,f}) \right\|^2 + \beta \mathrm{R}(\mathbf{f}) \right]$ [2], where $\mathrm{R}(\mathbf{f}) = \frac{1}{2} \left\| \mathbf{Af} \right\|^2$ denotes the regularization term that penalizes the discontinuities of the estimated image, $\mathrm{M}(\mathbf{a,f})$ is the encoding function which Fourier transforms the product of the desired image with the sensitivities modeled by a polynomial, and $\mathbf{d}$ is a vector formed by the acquired k-space data. For simplicity, we used a matrix $\mathbf{A}$ that takes differences between neighboring pixels. The parameter β is chosen to control noise but not to significantly affect the resolution of the image. Solving the joint optimization problem in Eq. [2] is computationally intensive. We resort to a greedy iterative algorithm. We alternate between updating the image and the polynomial coefficients of the coil sensitivities. Specifically, an initial set of sensitivities is estimated using the ACS data alone. With the sensitivities given, the image is reconstructed by minimizing the cost $\mathrm{U}(\mathbf{a,f})$ over $\mathbf{f}$ which, similar to GSENSE (6), can be solved by an iterative conjugate gradient algorithm. We then fix $\mathbf{f}$ and improve the sensitivity coefficients by minimizing the cost $\mathrm{U}(\mathbf{a,f})$ over $\mathbf{a}$. The relationship between $\mathbf{a}$ and the acquired data is linear, so the minimization can be achieved using the similar conjugate gradient method. The obtained coefficients are then plugged into Eq. [1] to update the sensitivities. The above procedure repeats until the cost function is less than a threshold.

RESULTS

The proposed approach has been tested on a number of real data set. Here we show a set of representative results for a 256 by 256 phantom image. The data was originally acquired in full with an eight-channel receiver coil. The reduced encodings are simulated with a reduction factor of 4 with 32 ACS lines. The image is reconstructed using the proposed algorithm, as shown in Fig. 1 (a). The order of the polynomial for coil sensitivities was chosen to be N=20. For comparison, Fig. 1 (b) shows the reconstructions using GSENSE, where the sensitivities were estimated using the ACS lines. It is seen that the proposed method is able to correct the sensitivity errors and improve the image reconstruction.

(a) (b)

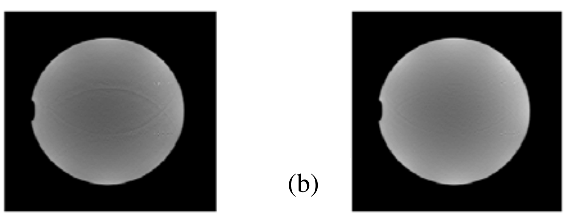

Fig. 1 (a) Reconstruction by GSENSE and (b) the proposed JSENSE method with 8 channels, reduction factor of 4, and 32 ACS lines.

DISCUSSION AND CONCLUSION

The proposed method can be easily adapted to arbitrary trajectories. It is especially advantageous for spiral or radial trajectories where the central k-space automatically satisfies Nyquist sampling rate even with partial acquisition, so that no additional encodings are needed. In addition, the polynomial model currently used in the method may be generalized to other models that can represent the spatial variation in sensitivities using a small number of model parameters. The proposed algorithm is expected to significantly improve the image reconstruction quality in parallel MRI, especially when a large number of coils are used to achieve high imaging speeds.

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