IMAGE RECONSTRUCTION FROM PHASED-ARRAY MRI DATA BASED ON MULTICHANNEL BLIND DECONVOLUTION

H. She[1], R. Chen[1], D. Liang[2], Y. Chang[2], and L. Ying[2]
[1]Department of Electrical and Computer Engineering, University of Utah, Salt Lake City, Utah, United States, [2]Department of Electrical Engineering and Computer Science, University of Wisconsin-Milwaukee, Milwaukee, Wisconsin, United States

INTRODUCTION

A typical method to reconstruct the original image from multiple images acquired using a phased array coil without knowledge of the sensitivity functions is the sum-of-squares (SoS) method [1, 2]. However, the assumption under the SoS method usually fails, which causes the reconstructed image to be dark at locations further away from all coils. The non-uniformity of the image intensity greatly complicates further automatic analysis such as registration and tissue segmentation [3]. To address this issue, methods [4, 5] have been proposed to reconstruct both the original image and the sensitivity functions jointly. These methods are all based on the image domain. In this paper, we propose a new approach to jointly estimate the image and sensitivity functions in *k*-space. The approach is based on a multichannel blind deconvolution (MBD) framework. Both simulation and *in vivo* experimental results demonstrate that the proposed method reconstructs images with more uniform intensity than the SoS method does.

THEORY AND METHOD

The acquired *k*-space image from channel *i* is equal to the circular convolution of the sensitivity function of channel *i* and the original image in *k*-space i.e. $\mathbf{y}_i = \mathbf{H}_i\mathbf{g}$, (1) where $\mathbf{y}_i$ is a vector consisting of acquired *k*-space data from channel *i*, $\mathbf{H}_i$ is the 2D circular convolution matrix constructed from the *i*th sensitivity function in *k*-space, **g** is a vector consisting of original image in *k*-space. Under the MBD framework, we assume both $\mathbf{H}_i$ and **g** are unknowns to be solved for. In addition to data consistency, we also have the cross relationship $\mathbf{Y}_i\mathbf{h}_j = \mathbf{Y}_j\mathbf{h}_i$ (2) described in [6], where $\mathbf{Y}_i$ is 2D circular convolution matrix constructed from the acquired k-space data from channel *i*, $\mathbf{h}_i$ is a vector consisting of the *i*th sensitivity function in *k*-space. Based on the cross relationship, we propose a regularized MBD method. The method finds the optimum *k*-space data **g** and the sensitivity functions $\mathbf{h} = (\mathbf{h}_1^T \dots \mathbf{h}_P^T)^T$ by minimizing the energy function $E(\mathbf{g},\mathbf{h}) = \sum_{i=1}^{P}\|\mathbf{H}_i\mathbf{g}-\mathbf{y}_i\|^2 + \alpha\|\mathbf{Y}\mathbf{h}\|^2 + \beta\|\mathbf{F}^{-1}\mathbf{g}\|_{\mathrm{TV}} + \gamma\sum_{i=1}^{P}\|\mathbf{F}^{-1}\mathbf{h}_i\|_{\mathrm{TV}}$ (3), where **Y** is composed of all 2D circular convolution matrix $\mathbf{Y}_i$ as described in [6], $\mathbf{F}^{-1}$ is the inverse Fourier transform matrix, ***P*** is the number of coils. The first term in the energy function is for data consistency; the second one combines all cross relationships in Eq. (2); and the last two terms are for total variation (TV) regularization [7, 8] constraining both the image and sensitivity functions to be smooth in the image domain. To solve the optimization problem, we use an alternative minimization method [4, 9], which alternatively minimizes the energy function with respect to **g** and **h**. It is worth noting that without the two regularization terms, there are an infinitely many solutions that make the first two terms on the right-hand side of (3) zero. We can verify that the SoS solution, in particular, is one of such solutions.

RESULTS

Both simulation and *in vivo* experiments were carried out to evaluate the proposed method. In simulation, an MR image is used as the original image. The simulated *k*-space data were generated by taking the Fourier transform of the original image weighted by a set of eight sensitivity functions. The sensitivity functions were simulated using the Biot-Savart law [10]. The image is reconstructed using both the SoS and the proposed method. The parameters used in the simulation are $\alpha = 1$, $\beta = 10^3$, and $\gamma = 10^3$, with a random initial guess for both the image and sensitivity functions. We set large values of β and γ to impose the constraint that the image function and sensitivity functions are spatially smooth. The reconstructions are shown in Figure 1. It is seen that the center of the SoS reconstruction is darker and has a lower contrast than that of the proposed method. In *in vivo* experiment, the data were collected from a GE 3T scanner (Waukesha, WI) with a four-channel head coil and a 3D T_1-weighted spoiled gradient echo sequence (T_E = minimum full, T_R = 7.5ms, FOV = 24 × 24 cm, matrix = 256 × 256, slice thickness = 1.7mm). The parameters for the proposed method were $\alpha = 1$, $\beta = 10^3$, and $\gamma = 10^{10}$. Both SoS and the proposed reconstructions are shown in Figure 2. It is seen that the intensity of the reconstruction by the proposed method is more uniform across the whole image compared with the SoS reconstruction.

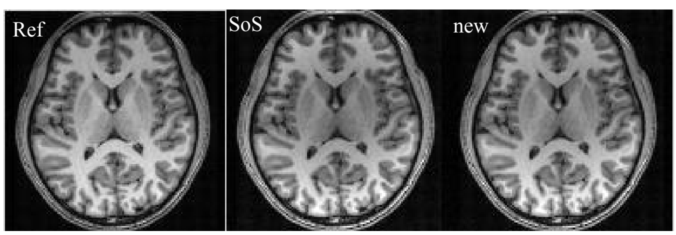

Figure 1. Reconstruction from a set of 8-channel simulation data (128 × 128). Compared with the original image (labeled as "Ref"), the center of SoS reconstruction is darker than that of proposed method (labeled as "new").

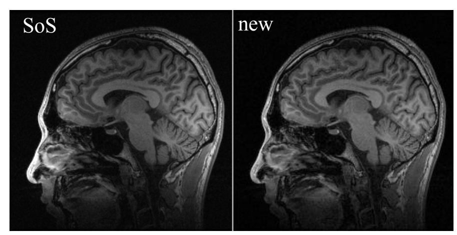

Figure 2. Reconstructions from a set of 4-channel *in vivo* data (256 × 256). Note the intensity of the proposed method is more uniform than that of SoS reconstruction.

CONCLUSION

We propose a novel regularized MBD method to reconstruct the original image from multichannel phased-array MRI data. Simulation and *in vivo* experimental results demonstrate that the proposed method can improve the uniformity of the image intensity over the conventional SoS method. The method is expected to be useful in applications where the assumption for SoS reconstruction fails.

REFERENCE

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