Iterative, field-inhomogeneity compensated image reconstruction for MRI with Z-shim gradients

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susceptibility Abstract—Magnetic artifacts, including both image distortions and signal losses, exist near air/tissue interfaces in the ventral brain in standard blood oxygenation level dependent (BOLD) functional magnetic resonance imaging (fMRI). Several correction methods have been developed to compensate for image distortion artifacts. However, signal losses still remains a significant issue in fMRI, especially in the orbital frontal cortex and amygdala. Signal losses result from through-plane gradients induced by magnetic field inhomogeneity, which cause spin dephasing within a voxel. Although several acquisition-based approaches exist to address the signal losses, they require increased acquisition time or patient customization. In this work, we propose to build a statistical estimation model that includes the effects of magnetic field gradients (both within-plane and through-plane gradients) and uses an iterative reconstruction algorithm to reconstruct images corrected for both magnetic field distortion and signal losses. We combine our reconstruction approach with a recently proposed MRI sequence that acquires spiral-in and spiral-out images with a Z direction (through-plane) shimming gradient in between to enhance the compensation for signal losses. Therefore we extend our forward model of the MR signal to include the physics of Susceptibilityinduced magnetic Field (SF). Susceptibilityinduced magnetic Field Gradients (SFG), and the application of the data acquisition technique with Z-Shim Gradients (ZShG). The results show that not only signal distortions but also significant signal losses can be compensated by considering both the modeling of field-inhomogeneity effects along with the acquisition with ZShG.

Keywords—fMRI, field inhomogeneity, susceptibility, iterative reconstruction, Z-Shim gradients, spiral

I. INTRODUCTION

For functional magnetic resonance imaging (fMRI) with blood oxygenation level-dependent (BOLD) contrast, the long readout times make the functional scan sensitive to magnetic inhomogeneity. Without compensation, the susceptibility differences near air/tissue interfaces, especially at the ventral brain (e.g. above the sphenoid and frontal sinuses), will induce field inhomogeneity which leads to susceptibility artifacts including image geometric distortions and signal losses.

Several methods exist for compensating the susceptibility-induced magnetic field (SF) inhomogeneity. Non-iterative, Fourier-based correction methods (e.g. Conjugate Phase [1], etc.) can compensate for image distortion artifacts, but susceptibility-induced signal losses are not addressed by these methods. Signal losses result from susceptibility-induced magnetic field gradients (SFG), which cause spin dephasing within a voxel [2, 3]. Although several acquisition-based approaches (e.g. Hardware-Shim, Tailed RF pulses, Thinner Slices, etc.) exist to address the signal losses, they require increased acquisition time or patient customization. A natural alternative is to build a statistical estimation model and use iterative algorithm to perform reconstruction while modeling the SFG that lead to signal losses. Our previous work builds a physical model that accounts for both within-plane gradients and through-plane gradients of the field inhomogeneity to correct for geometric distortions and signal losses [2, 3, 4, 5].

When the SFG are too large, the signal losses will be too severe so that the signals will be too weak to be extracted from the noise. In this case, we might benefit from additional information gathered during data acquisition. The Z-shim gradients (ZShG) technique in data acquisition has been introduced to reduce susceptibility artifacts [6], but with a cost of increased scan time. A recently proposed method of ZShG single-shot MR imaging for spiral scan trajectory, which combines spiral-in and spiral-out with a ZShG in between, would decrease the acquisition time considerably [7].

In this work, we introduce an iterative, inverse approach to reconstruct fMRI image for compensating the susceptibility artifacts based on building model with physics of SF, SFG, and the application of the acquisition technique with ZShG.

II. THEORY

A. Signal Models

In MRI scan, the measurements of raw data are noisy samples of the signal

$$y_i = s(t_i) + \varepsilon_i, \qquad i = 1, \dots, L_s \tag{1}$$

where $s(t_i)$ is the complex MR signal at time t_i during the readout; ε_i is the complex white Gaussian noise at time t_i which is introduced during the data acquisition; L_s is the number of k-space samples.

For a 2D data acquisition, the signal $s(t_i)$ at each t_i can be written as

$$s(k_{x}(t_{i}), k_{y}(t_{i}), k_{z}(t_{i})) = \iiint f(x, y)e^{-i\omega(x, y, z)t_{i}}$$
$$\cdot e^{-i2\pi[k_{x}(t_{i})x + k_{y}(t_{i})y + k_{z}(t_{i})z]}dxdydz \quad (2)$$

where f(x,y) is a function of the object's transverse magnetization at location (x,y) in the selected slice; $\omega(x,y,z)$ is the map of field inhomogeneity including both the within-plane gradient (x, y-direction) and through-plane gradient (*z*-direction), which can be determined by a pre-scan; $k_x(t)$ and $k_y(t)$ is the kspace trajectory along *x* and *y* directions, and $k_z(t)$ represents the application of ZShG.

B. Basis expansion

Our MR imaging reconstruction challenge is to estimate the object f(x,y) that closely matches the measurements of raw data y_i $(i=1,...,L_s)$. From equation (2), we know that this is an ill-posed problem, because f(x,y) is a continuous function but measurements vector $\mathbf{Y}=[y_1, ..., y_{Ls}]$ is discrete since we only have finite samples. We proceed by parameterizing the object f(x,y) and field inhomogeneity map $\omega(x,y,z)$ in terms of basis functions $\phi(x,y)$ as follows

$$f(x, y) \approx \sum_{n=0}^{N-1} \sum_{m=0}^{M-1} f_{mn} \phi(x, y)$$
(3)
$$\omega(x, y, z) \approx \sum_{n=0}^{N-1} \sum_{m=0}^{M-1} \left(\omega_{mn} + X_{mn} \frac{x - x_m}{\Delta_x} + Y_{mn} \frac{y - y_n}{\Delta_y} + Z_{mn} \frac{z - z_{mn}}{\Delta_z} \right) \phi(x, y)$$
(4)

where (x_m, y_n) is the in-plane center of each voxel; ω_{mn} is the off-resonance frequency for each voxel (in rad/sec); X_{mn} , Y_{mn} are the within-plane gradients and Z_{mn} is the through-plane gradient within each voxel (in rad/(sec·cm)); Δ_x , Δ_y are the in-plane dimensions of each voxel; M, N are the numbers of in-plane voxels along x and y directions respectively; here we use a 2D rectangle function as the basis function

$$\phi(x, y) = rect_2\left(\frac{x - x_m}{\Delta_x}, \frac{y - y_n}{\Delta_y}\right)$$
(5)

Substituting Eq. (3)-(5) into the signal model in Eq. (2) and simplifying yields

$$s(k_{x}(t_{i}),k_{y}(t_{i}),k_{z}(t_{i})) = \Phi(k_{x}(t_{i}),k_{y}(t_{i}),k_{z}(t_{i}))e^{-i2\pi k_{z}(t_{i})z_{0}}$$
$$\cdot \sum_{n=0}^{N-1} \sum_{m=0}^{M-1} f_{mn}e^{-i\omega_{mn}t_{i}}e^{-i2\pi [k_{x}(t_{i})x+k_{y}(t_{i})y]}$$
(6)

where z_0 is the slice location in through-plane direction; $\Phi(k_x(t_i), k_y(t_i), k_z(t_i))$ is the 2D Fourier Transform of the basis function of $\phi(x,y)$ combined with the effects of the gradients of field inhomogeneity, which can be written as

$$\Phi(k_x(t_i), k_y(t_i), k_z(t_i)) = sinc\left(k_x(t_i)\Delta_x + \frac{X_{nm}t_i}{2\pi}\right)$$
$$\cdot sinc\left(k_y(t_i)\Delta_y + \frac{Y_{nm}t_i}{2\pi}\right)sinc\left(k_z(t_i)\Delta_z + \frac{Z_{nm}t_i}{2\pi}\right)$$
(7)

In our case, the effect of through-plane gradient Z_{mn} and the effect of Z-Shim gradient $k_z(t_i)$ are both modeled inside the third $sinc(\cdot)$ term. If the term $k_z(t_i)$ for effect of Z-Shim gradient is equal to zero, then the proposed model is equivalent to one of our previous approach described in [3].

C. Iterative Algorithms



Fig. 1 – System Model

As shown in Fig.1, we can express the measured noisy samples in Eq. (1) in matrix-vector form:

$$\mathbf{y} = \mathbf{S} + \boldsymbol{\varepsilon} = \mathbf{A}\mathbf{f} + \boldsymbol{\varepsilon} \tag{8}$$

where **y** is the measured noisy data samples at the kspace locations arranged as a single column vector; **S** is the signal modeled as above; **f** is the object also as a single column vector; ε is the complex white Gaussian noise; **A** is the system matrix with dimension P×Q (where P is the number of raw data samples, Q is the number of spatial locations), which denotes the data acquisition procedure, with the elements a_{ij} shown as follows

$$a_{ij} = \Phi(k_x(t_i), k_y(t_i), k_z(t_i))e^{-i2\pi k_z(t_i)z_0}e^{-i\omega_j t_i} \\ \cdot e^{-i2\pi [k_x(t_i)x_j + k_y(t_i)y_j]}$$
(9)

Here, since we use two acquisitions (spiral-in and spiral-out with Z-Shim in between), our system matrix **A** is a stacked version, i.e. the system matrix **A**_{in} for an individual spiral-in acquisition (that includes SF map (SFM) and SFG map (SFGM), but without ZShG) is stacked on the top of a system matrix **A**_{out} for a spiral-out acquisition (with SFM, SFGM and ZShG explicitly modeled). The magnetic susceptibility (in both **A**_{in} and **A**_{out}) is in the term $exp(-i\omega_j t_i)$, while the magnetic susceptibility gradients (in both **A**_{in} and **A**_{out}) and Z-Shim gradient (in **A**_{out} only) are both modeled inside the term $\Phi(k_x(t_i), k_y(t_i), k_z(t_i))$ as described in Eq. (7).

The object **f** is estimated by minimizing a quadratic penalized least-square cost function $\Psi(\mathbf{f})$,

$$\hat{\mathbf{f}} = \underset{\mathbf{f}}{\operatorname{arg\,min}} \Psi(\mathbf{f})$$
$$\Psi(\mathbf{f}) = \frac{1}{2} \|\mathbf{y} - \mathbf{A}\mathbf{f}\|_{2}^{2} + \beta R(\mathbf{f})$$
(10)

where $\|\cdot\|_2$ is the 2-norm of a matrix (square root of sum of square of all the elements); β is the regulation parameter; and $R(\mathbf{f})$ is a regularization function, which penalizes the roughness of the estimated image to control noisy effect, as defined

$$R(\mathbf{f}) = \frac{1}{2} \left\| \mathbf{C} \mathbf{f} \right\|_2^2 \tag{11}$$

where the matrix **C** takes differences between inplane neighbouring voxels. This regularization function $R(\mathbf{f})$ can decrease the condition number of the image reconstruction and therefore speed convergence. We apply the iterative algorithm of conjugate gradients (CG) for minimizing the cost function $\Psi(\mathbf{f})$. The main operations are evaluating **A**x and **A**^{*}y (where ^{*} denotes the complex conjugate transpose) in each iteration [8].

III. METHODS AND RESULTS

To evaluate the proposed methods, we performed simulation, phantom and in vivo studies. Currently another commonly used method for susceptibility artifacts compensation is non-iterative reconstruction using SFM combined with ZShG. Therefore, we compared the results of this non-iterative method (Md1: NIT+SFM+ZShG) with our proposed iterative method (Md2: IT+SFM+SFGM +ZShG).

A. Simulation study

The goal of the simulation study is to examine the efficiency of the proposed methods for compensation of susceptibility artifacts induced by the field inhomogeneity. The noisy simulation data **y** was formed by constructing a high-resolution model of the human brain at a matrix size of 256×256 and then applying Eq. (2) to compute the signal **S** at the desired k-space locations with the white Gaussian noise ε .

To evaluate the quality of resulting image and efficiency for the proposed method, we calculated the normalized root-mean-squared errors (NRMSEs) in the region of interest (ROI) as follows

$$NRMSE = \frac{\left\|\mathbf{f}_{0} - \hat{\mathbf{f}}_{c}\right\|_{2}}{\left\|\mathbf{f}_{0}\right\|_{2}}$$
(12)

where \mathbf{f}_0 is the reference image; $\hat{\mathbf{f}}_c$ is the results of estimated images compensated with either of two methods. We compared the NRMSE₁ between reference image and result from the non-iterative method (Md1) on one side and the NRMSE₂ between reference image and result from the proposed iterative method (Md2) along with various values of iteration number R_n , also used non-compensated image (NC) as control standard to compare (shown in Fig. 2).



Comparison of the NRMSEs for the resulting image from non-iterative method (Md1: NIT+SFM+ZShG) and the resulting image from our iterative method (Md2: IT+SFM+SFGM +ZShG) along with iterations R_n . Where the green sign "-" shows the non-compensated image (NC) as control; the red sign "-" shows the NRMSE₁ between reference image and the non-iterative method (Md1); the blue sign " Δ " shows the NRMSE₂ between the reference image and out proposed iterative method (Md2).

As shown in Fig. 2, we examined the first 15 iterations of the NRMSEs for our iterative method. The proposed method (Md2) converges fast in the first several iterations, and already has lower errors after iteration 5 compared with the non-iterative method (Md1).

B. Phantom and in vivo study

For the phantom and in vivo study, the experiments were performed on a head-only Siemens Allegra 3T MRI scanner. The data scan parameters are given as follows: matrix size of 64×64 , field of view (FOV) of 24 cm, slice thickness of 4 mm, TR of 100 ms, TE of 35 ms, number of slices of 20.

The SFM was acquired using a pre-scan of multiecho gradient echo sequence with similar slice prescription, but twice the resolution in all directions, with TR of 200 ms, and TE of 10 and 12.46 ms. In the functional scanning, we use a straightforward spiral-in-and-out trajectory with ZShG, as described in [7]. The spiral-in trajectory, which starts k-space sampling from the peripheral region and ends at the center, can be joined immediately with the traditional spiral-out acquisition without significant



Fig. 3 (1) - Phantom study results



Fig. 3(2) – In vivo study results

In Fig3, for both (1) Phantom study results and (2) In vivo study results, First row (non-iterative methods):

(a) Non compensation (NC), (b) NIT+SFM, (c) NIT+SFM+ZShG (Md1). Second row (Iterative methods):

(d) Effect of ZShG, (e) IT+SFM+SFMG, (f) IT+SFM+SFMG+ZShG (Md2).

delay (delay time of 1.5 ms). The ZShG (4 mT/m for 1 ms) was inserted between the spiral in and out data acquisitions. Thus the spiral-in-and-out acquisition with ZShG would enhance the compensation for signal losses.

The results of image obtained from phantom and in vivo data are shown in Fig 3. We compared the results of non-iterative method (Md1) (Fig. 3 (c) in both (1) & (2)) with our proposed iterative method (Md2) (Fig. 3 (f) in both (1) & (2)). The results clearly shows that our proposed iterative method (Md2) with compensation of SFM, SFGM, and ZShG together have better image quality.

IV. CONCLUSIONS

The presented results show that the iterative reconstruction method combining the susceptibilityinduced magnetic field map (SFM), the gradients of field map (SFGM), with the Z-shim gradients (ZShG) in data acquisition, reduced susceptibility artifacts of both signal distortion and significant signal losses and the image quality was improved.

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