Self-calibrating Coil Sensitivity Profiles for Parallel Imaging based on Anisotropic Diffusion

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Abstract—Calibration of the spatial sensitivity functions of coil arrays is a crucial element in parallel magnetic resonance imaging (PMRI). In order to overcome the sensitivity miscalibration errors introduced by pre-scan calibration method and decrease the total examination time, a new self-calibrating method for estimating the coil sensitivity profiles was proposed in the paper. From a fully-sampled central region of a variable-density k-space acquisition, the sensitivity calibration images were directly extracted, and then were adaptively smoothed by a new anisotropic diffusion scheme to extract encoding effects of coil sensitivities. When the estimated coil sensitivity profiles were applied to reconstruct the full Field-Of-View image from the uniformly under-sampled MR data when under-sample rate was greater than 2, the experimental results showed that the quality of reconstruction image was evidently improved. Therefore, this self-calibrating method for calculating sensitivity profiles is suitable for much faster imaging in parallel magnetic imaging. Meanwhile, the paper suggest that the suitable number of central k-space lines for generating the internal reference images should be chosen between 8 to 20.

Index Terms—parallel magnetic resonance imaging, self-calibrating, anisotropic diffusion, sensitivity profiles

I. INTRODUCTION

Parallel magnetic resonance imaging (PMRI), known as parallel imaging, is a rapid acquisition technique considered to be one of the modern revolutions in the field of MRI. The technique simultaneously samples the reduced k-space data and uses the information from multiple receivers to reconstruct full Field-Of-View (FOV) image. In parallel imaging, since a certain amount of the spatial encoding, traditionally achieved by the phase-encoding gradients, is substituted by evaluating data from several coil elements with spatially different coil sensitivity profiles, the choice of sensitivity calibration strategy is at least as important as the choice of reconstruction strategy [1].

The most common solution to the problem of coil sensitivity calibration has been to measure sensitivities directly using one or more low-resolution calibration images. This calibration step can prolong total examination time, partially counteracting the benefits of decreased acquisition time associated with PMRI. It also introduces a possible source of error into the PMRI reconstruction, as it is difficult to ensure that the patient and coil array will be in the same positions during both the calibration scans and the accelerated data acquisitions.

In fact, PMRI techniques do not require a separate sensitivity reference scan, but can derive the necessary information directly from the accelerated data itself [2]. Through the use of self-calibrating scans that contain an internal sensitivity reference, the sensitivity error calibrations may be avoided. The AUTO-calibrating SImultaneous Acquisition of Spatial Harmonics (AUTO-SMASH) technique [3] is one example of a self-calibrating approach. In AUTO-SMASH, a small number of additional k-space lines are acquired in addition to the usual under-sampled acquisition, and these additional lines determine the weights necessary to reconstruct missing k-space lines. The variable-density AUTO-SMASH (VD-AUTO-SMASH) approach [4] expands and improves upon the AUTO-SMASH concept by acquiring a central block of k-space lines which are used in the reconstructed image itself, as well as in the calibration process. However, neither AUTO-SMASH nor VD-AUTO-SMASH make optimal use of the fully acquired central lines. The variable-density AUTO-SMASH (VD-AUTO-SMASH) approach [4] expands and improves upon the AUTO-SMASH concept by acquiring a central block of k-space lines which are used in the reconstructed image itself, as well as in the calibration process. However, neither AUTO-SMASH nor VD-AUTO-SMASH made optimal use of the fully acquired central lines. In addition, the use of calibration information in these reconstructions was applicable only to SMASH-like reconstructions, and could not be applied in a straightforward manner to the wide variety of other PMRI reconstruction techniques currently available, such as the generalized encoding matrix(GEM) reconstructions[5].

In this paper, the fully-sampled central k-space lines were extracted and Fourier-transformed to produce a low-
resolution image, which might be used as a sensitivity reference image. Due to the transverse magnetization distribution, Gibbs ringing artifacts and noise in the reference images, the paper would use a new anisotropic diffusion method proposed by us to extract the encoding effects of coil sensitivities, which can be used in any PMRI technique requiring such information, including both SMASH-like and SENSE-like approaches. In combination with a generalized parallel reconstruction algorithm, the benefits and the superiorities of this self-calibration method were demonstrated by the generalized reconstruction method for phantom and brain imaging.

II. THEORY AND METHODS

A. Sensitivity Reference Images Extraction

Coil sensitivity varies slowly as a function of spatial position, and low-resolution in-vivo images suffice to form sensitivity references [6]. Thus, valid coil sensitivities can be determined from the fully sampled central region of a variable-density acquisition, and the Fourier transformation of the central k-space lines for any given component coil produces a low-resolution reference image.

\[
I^\text{ref}_l(\vec{r}) = [\hat{\rho}(\vec{r}) C_l(\vec{r})]^{\text{low-res}} \approx \rho^{\text{low-res}} C_l(\vec{r}) \quad (1)
\]

Here \(\rho(\vec{r})\) denotes the distribution of transverse magnetization, and \(C_l(\vec{r})\) represents the complex-valued component coil sensitivity. The “low-res” superscript indicates that use of only the central k-space positions results in a low-resolution measurement of the full product of \(\rho(\vec{r})\) and \(C_l(\vec{r})\). As shown in (1), a certain approaches might be taken to remove the magnetization distribution \(\rho^{\text{low-res}}(\vec{r})\) and isolate the encoding effects of pure coil sensitivities.

In order to represent the dominant spatial variations of individual coil sensitivity for accurate PMRI reconstructions, a sufficient number of fully sampled central k-space lines will be clearly required to extract the internal reference images. However, truncation of high spatial frequency components of transverse magnetization \(\rho(\vec{r})\) can result in Gibbs ringing artifacts in the extracted reference images \(B_l^\text{ref}\). Consequently, the PMRI reconstruction interprets varying degrees of Gibbs ringing as actual features of the sensitivities, and corresponding sensitivity-mismatch artifacts can result. This effect can be alleviated by fully sampling a region at the center of k-space that is large enough to minimize Gibbs ringing. For a fixed outer reduction factor (ORF), acquiring more fully sampled lines at the center of k-space reduces the Gibbs ringing, but at the price of reducing the net acceleration factor and increasing the acquisition time associated with PMRI.

In this paper, in order to generate the freestanding sensitivity reference images for use with arbitrary PMRI reconstructions, the variable-density data acquisition schemes were adopted shown as Fig.1. Here, k-space was effectively split into two regions: a central region in which all phase-encode lines were fully sampled, and an outer region in which the lines were under-sampled in the manner typical of traditional PMRI data acquisition.

![Figure.1 A sample variable-density k-space trajectory made up of a regularly undersampled outer portion and a fully sampled inner portion. The inner portion may be used as a low-resolution in vivo sensitivity reference for PMRI reconstructions.](image)

For the experiments described below, the central lines of k-space in each variable-density acquisition were extracted and Fourier transformed to yield unaliased low-resolution images of the plane being imaged. These low-resolution images would be used as an internal sensitivity reference, from which the coil sensitivity were extracted by anisotropic diffusion method and then inhomogeneous scale was corrected to obtain the sensitivity profiles.

B. Determination of Sensitivity Maps by Anisotropic Diffusion Method

As shown in (1), since the sensitivity reference images \(I^\text{ref}_l\) were directly extracted from the fully sampled central k-space lines, Gibbs ringing artifacts because of truncation of high spatial frequency components of \(\rho(\vec{r})\) and the distribution of transverse magnetization \(\rho^{\text{low-res}}(\vec{r})\) might lie in these internal reference images. The paper would consider the problem of estimating coil sensitivity maps \(C_l(\vec{r})\) from the sensitivity reference images \(I^\text{ref}_l\) as a problem of adaptive smoothing image, and use anisotropic diffusion method to smooth \(I^\text{ref}_l\) to alleviate the Gibbs ringing artifacts and isolate the information about the spatial frequency content of the coil sensitivities. Meanwhile, in order to equal and appropriately homogeneous scaling the coil sensitivity maps [7], the individual coil reference images after adaptively smoothed would be divided by the “sum-of-squares” of these images.

A well-known method of adaptive smoothing is the anisotropic diffusion scheme proposed by Perona and Malik [8], named as P-M model, by which the smoothing process is formulated by a partial differential equation (PDE). This equation is the function of the scale-space parameter \(t\), where the larger values \(t\) corresponds to images at coarser resolutions.

Given the internal reference images \(I^\text{ref}_l(x, y)\), its smoothed versions comprised of a family of images \(I(x, y; t)\), and the scale-space variable \(t\) parameterizes the amount of smoothing. For \(t=0\), \(I(x, y; 0)\) is initialized to \(I^\text{ref}_l(x, y)\); for \(t>0\), \(I(x, y; t)\) is obtained by solving an evolution equation as (2):

\[
I_t = \nabla \cdot \left( \frac{\nabla I(x, y; t) V}{\nabla V I} \right) = \epsilon(x, y; t) \Delta I + \nabla \cdot \nabla I \quad (2)
\]

With respect to the scale-space variables \(t\), \(\epsilon\) denotes the divergence operator. \(\nabla\) and \(\Delta\) are respectively the gradient and Laplacian operators. \(\epsilon(x, y; t)\) is the diffusion coefficient. A suitable choice of \(\epsilon(x, y; t)\) determines the reliability of adaptive smoothing.

Adaptive smoothing by (2) must satisfy a certain criteria: causality, piecewise smoothing and immediate...
localization. If the edge position in image \( I(x,y,t) \) is estimated by gradient of the image, the diffusion coefficient \( e(x,y,t) \) could be a function of the magnitude of the gradient as expressed in (3).

\[
e(x,y,t) = g(|\nabla I(x,y,t)|) \tag{3}
\]

When smoothing within a region, in preference to smoothing across the boundaries, the diffusion coefficient \( e(x,y,t) \) should be set to be 1 in the interior of each region and 0 at the boundaries. The smoothing would then take place separately in each region with no interaction and 0 at the boundaries. The smoothing would then take place separately in each region with no interaction and 0 at the boundaries.

\[
\text{Calculating Coil Sensitivity Profiles}
\]

C. A New Solution to Anisotropic Diffusion Model for Calculating Coil Sensitivity Profiles

Perona and Malik gave an inexact discretization scheme of (2):

\[
I^t_{ij} = I^t_{ij} + \lambda (e_N \nabla_N I + e_E \nabla_E I + e_S \nabla_S I + e_W \nabla_W I)_{ij} \tag{5}
\]

Here \( \lambda \leq 0.25 \) for the numerical scheme to be stable, greater \( \lambda \) results in the faster diffusion. N, S, E, W are the mnemonic subscripts for North, South, East, and West, and the symbol \( V \) indicates the nearest-neighbor differences.

Derived from (2), nonlinear diffusion model as (6) will be used for adaptive smoothing the internal reference images in this paper.

\[
\frac{\partial I}{\partial t} = e(I_{xx} + I_{yy}) + e_x I_x + e_y I_y \tag{6}
\]

The solution to nonlinear model (6) will be derived when the function \( g(\bullet) \) is defined by (4).

\[
I(t+1) = I(t) + \lambda (e(I_{xx} + I_{yy}) + e_x I_x + e_y I_y) \tag{7}
\]

\[
I(t+1) = I(t) + \lambda (g(|\nabla I| I_{xx} + I_{yy}) + \frac{g(|\nabla I|)}{K^2} (I^2_{xx} + I^2_{yy}))
\]

\[
- \frac{g(|\nabla I|)}{K^2} (I^2_{xx} + I^2_{yy} + 4I_x I_y) \tag{8}
\]

It could be seen that the nonlinear diffusion went along eight directions: north, south, east, west, northwest, northeast, southwest and southeast.

III. DATA ACQUISITION AND ANALYSIS

A. Simulation Data and In-Vivo Data Acquisition

Unaccelerated anatomical images of a standard resolution phantom were obtained from a 3T human using an 8-channel head array coil. Imaging parameters: echo time (TE)=3.45 ms, repetition time (TR)=2530 ms, TI=1100 ms, Flip angle=7deg, slice=20, slice thickness=1.33mm, measurement=1, FOV=256 mm. In our experiments, simulated B1 coil maps were calculated using Biot-Savart's law, and the fully sampled k-space data were obtained by inverse Fourier transforming the acquired unaccelerated images.

A in-vivo brain dataset was obtained from PULSAR (a matlab toolbox for parallel MRI) [11], which was acquired using MR systems with eight-channel head array and multi-channel receiver and from a healthy male volunteer with fast spoiled gradient-echo sequence, TR/TE=300/10 ms, RBW=16kHz, matrix size = 256×256, tip angle=15° and FOV = 22×22 cm. One fully sampled dataset was acquired in our study.

To simulate the under-sampled datasets in the manner typical of traditional PMRI data acquisition, the k-space data were decimated using reduction factors \( R=2, 3 \) and 4 for simulated and in-vivo data. Meanwhile, the central k-space data were fully sampled to generate the sensitivity reference images for self-calibration, and the numbers of central lines along phase-encode were 8, 12, 16, 20, 24. In the paper, the internal reference images would be smoothed by anisotropic diffusion method and image reconstructions were implemented by GEM reconstruction method in the MATLAB programming language.

B. Analysis

To quieter and faster reconstructing MR image in self-calibrating parallel imaging, two focal points would be studied in the paper. The first point was to demonstrate the availability of self-calibration. The number of fully sampled central lines, named as Ncenter, for estimating the coil sensitivity profiles would be 8, 12, 16, 20, 24. In consideration of effectively decreasing the acquisition time and meanwhile minimizing Gibbs ringing in sensitivity reference images, the optimal number of the central fully-sampled k-space lines along phase-encode would be analyzed on basis of the quality of reconstruction images. The second point was to test the effects of the coil sensitivity profiles adaptively smoothed by new anisotropic diffusion scheme (6) on the quality of reconstruction images. In the paper, two sets of coil sensitivity profiles would be used for comparative evaluation. One set of coil sensitivity profiles was called rough sensitivity map, and the other set was called AD sensitivity maps. The rough sensitivity profiles were directly estimated from the internal reference images, while the AD sensitivity maps were calculated from the sensitivity reference images adaptively smoothed by anisotropic diffusion scheme (6). They both were corrected for equal inhomogeneous scaling by their own “sos”.

In order to quantitative analysis above two points, Signal-to-noise ratio (SNR) and artifact power (AP) were calculated for each reconstructed image, which was reconstructed from the different under-sampling rate \( R=2, 3 \) and 4, also named acceleration factor, data for the simulated data and in-vivo brain data. However, the pure sensitivities are never explicitly calculated in the self-
calibrating reconstruction. For the purposes of comparative evaluation, we were not primarily interested in predicting the absolute SNR. Instead, we were interested in determining SNR normalized relative to an optimal image reconstructed from the corresponding unaccelerated acquisition, so the so-called pixel-to-pixel normalized SNR $S_{\text{SNR}}(\rho)$ would be used as (9) in the paper.

$$S_{\text{SNR}}(\rho) = \frac{1}{N_{\text{acquired}}^{\text{full}}} \left( \sum_{\rho} \left( \sum_{k} E_{\rho,k}^{1} \right)^{2} \sum_{l} \left( \sum_{k} E_{l,k}^{1} \right)^{2} \right)^{1/2} \left( \sum_{l} \left( \sum_{k} E_{l,k}^{1} \right)^{2} \right)^{1/2} \left( \sum_{\rho} \left( \sum_{k} E_{\rho,k}^{1} \right)^{2} \right)^{1/2}$$

Here, $N_{\text{acquired}}^{\text{full}}$, $N_{\text{acquired}}$ represent the unaccelerated and accelerated number of phase-encoded lines respectively. $E$ represents the sensitivity encoding functions, which are estimated from the internal reference images. It could be seen that

$$AP = \frac{\sum_{\rho} \left| \mu_{\rho}(\rho) - \left| I_{\text{reconstructed}}(\rho) \right| \right|}{\sum_{\rho} \left| \mu_{\rho}(\rho) \right|}$$

Note that a higher value of $AP$ represents increased artifact and reduced image quality. It should also be noted that the formula for $AP$ in (12) does not measure residual aliasing alone, but will include any difference in image intensity between $\mu$ and $I_{\text{reconstructed}}$. Thus, $AP$ should be regarded as upper bound on the artifact level in the PMRI reconstructions.

IV. RESULTS

A. Simulated Results

In the paper, the simulated data was used to demonstrate the potential availability of self-calibration in parallel imaging. In order to generate the sensitivity reference images, the fully-sampled central $k$-space lines, $N_{\text{center}}$, was respectively chosen 8, 12, 16, 20 and 24, and their unequal and inhomogeneous scale were corrected by their “sos”. Fig.2 showed the rough sensitivity maps extracted from central $k$-space data when $N_{\text{center}}$ was 16.

Due to the transverse magnetization distribution and Gibbs ringing artifacts in the low-resolution reference images, the paper used anisotropic diffusion method to extract the encoding effects of pure coil sensitivity from them. Fig.3 showed the AD sensitivity profiles, which were calculated by adaptive smoothing individual coil’s reference sensitivity images by (8) after 100 order iteration, meaning that scale-space parameter $t$ was 100, and the internal reference images were extracted from the fully-sampled data in $k$-space central 16 lines.

Using the coil sensitivity profiles shown as Fig.3, the full-FOV MR images showed as Fig.5 were respectively reconstructed from the uniform under-sampling data by using simulated B1 maps (left), rough sensitivity maps (middle) and the AD sensitivity maps (right) respectively when uniform under-sampling rate $R$ was 4.
GEM reconstruction method when under-sampling R was 2, 3, 4.

Table 1 list means of the normalized SNR of reconstruction images respectively from the uniform under-sampling data and under-sampling rate was 2, 3 and 4. They used the rough sensitivity profiles and AD sensitivity maps, which were both calculated from the fully-sampled data in central k-space 8, 12, 16, 20 and 24 lines. For comparative analysis, means of normalized SNR of reconstructed images using b1 maps were 0.5312, 0.0837, 0.0455 respectively for reduction factor R=2, 3, 4.

**TABLE I**

<table>
<thead>
<tr>
<th>N*</th>
<th>ROUGH SENSITIVITY</th>
<th>AD SENSITIVITY*</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>R=2 R=3 R=4 R=2 R=3 R=4</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>0.5127 0.0845 0.0436 0.5141 0.1131 0.0566</td>
<td></td>
</tr>
<tr>
<td>12</td>
<td>0.5041 0.0831 0.0421 0.5073 0.1217 0.0588</td>
<td></td>
</tr>
<tr>
<td>16</td>
<td>0.4981 0.0859 0.0400 0.5057 0.1284 0.0572</td>
<td></td>
</tr>
<tr>
<td>20</td>
<td>0.4985 0.0878 0.0388 0.5067 0.1211 0.0576</td>
<td></td>
</tr>
<tr>
<td>24</td>
<td>0.5065 0.0851 0.0409 0.5123 0.1229 0.0554</td>
<td></td>
</tr>
</tbody>
</table>

AD SENSITIVITY*: calculated by adaptive smoothing the individual coil’s low-resolution reference images by (8), where scale-space parameter \( t \) was 100 and \( \lambda \) was 0.25. The low-resolution reference images were extracted from fully-sampled k-space central data.

R*: Under-sampling rate.

N*: The number of fully sampled central k-space lines

**B. In-vivo results**

Fig. 6 showed AD coil sensitivity profiles calculated from the images, which were low-resolution reference sensitivity extracted from the fully-sampled data in k-space central 16 number of lines and then adaptively smoothed by (8) after 150 order iteration.

Using the coil sensitivity profiles as showed Fig. 6, the full-FOV MR images, showed as Fig. 7, were respectively reconstructed from the uniform under-sampled in-vivo data by GEM reconstruction method, where the under-sampling rate, named as R, was respectively 2, 3, 4.

Table 2 show means of normalized SNR of reconstruction images from uniform under-sampling data were showed in Table 2.

**TABLE II**

<table>
<thead>
<tr>
<th>N*</th>
<th>ROUGH SENSITIVITY</th>
<th>AD SENSITIVITY*</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>R=2 R=3 R=4 R=2 R=3 R=4</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>0.5784 0.1576 0.1145 0.5881 0.1653 0.1223</td>
<td></td>
</tr>
<tr>
<td>12</td>
<td>0.5859 0.1678 0.1255 0.5935 0.1744 0.1312</td>
<td></td>
</tr>
<tr>
<td>16</td>
<td>0.5810 0.1795 0.1291 0.5912 0.1891 0.1344</td>
<td></td>
</tr>
<tr>
<td>20</td>
<td>0.5906 0.2060 0.1446 0.5989 0.2096 0.1474</td>
<td></td>
</tr>
<tr>
<td>24</td>
<td>0.5984 0.2190 0.1582 0.6055 0.2171 0.1568</td>
<td></td>
</tr>
</tbody>
</table>

For comparative analysis, by using AD sensitivity profiles which were extracted from fully-sampled central k-space data when \( N_{center}=8, 12, 16, 20, 24 \), the mean normalized SNR of the reconstruction images from uniform under-sampling data were showed in Table 2.
V. DISCUSSION

The accuracy of coil sensitivity estimates is a major determinant of the quality of parallel magnetic resonance image reconstructions. Self-calibrating the coil sensitivity profiles can eliminate the need for an external sensitivity reference. From our study, we have confirmed that it is an effective method to extract spatial sensitivity information from data acquired during a variable-density PMRI scan. This approach eliminates calibration errors by providing sensitivities that are truly simultaneous with the target acquisition. Such an approach also eliminates the need for a separate calibration step, thereby reducing total examination time. Since self-calibrating reference sensitivity images contain their own “decoding key”, reconstructions of these scans are automatic and “portable”.

However, the sensitivity reference images in self-calibrating parallel imaging, which are directly Fourier transformed from the fully-sampled k-space data, might have the information of transverse magnetization distribution, Gibbs ringing and noise from the data acquisition. As a result, the coil sensitivity estimated from them should be inaccurate, with which the quality of the reconstruction image might be degraded. In order to remove transverse magnetization distribution, reducing Gibbs ringing and noise before calculating the coil sensitivity profiles. The anisotropic diffusion method by (8) was used to adaptively smooth the low-resolution reference images, and then AD sensitivity maps were calculated. As showed in Fig.3, the coil AD sensitivity profiles perfectly reflect the spatial information of receiver coils.

In Table.1 and Table.2, it could be seen that acceleration factor R is the main element of degrading the quality of reconstruction images. However, the exact coil sensitivity could partly alleviate this contradiction. As seen in Table.1, it was interesting that the quality of reconstruction image using B1 maps is lower than using self-calibrating rough sensitivity profiles when acceleration factor R is 3. When using AD sensitivity, mean of normalized SNR of reconstruction images were evidently improved. It also could be seen, for a fixed outer reduction factor (ORF), that the normalized SNR of reconstruction images varied with its using self-calibrating sensitivity profiles, which were extracted from the different fully-sampled k-space central data.

From this study, the following aspects could be taken into account when self-calibrating coil sensitivity profiles were calculated from central k-space data by anisotropy diffusion method:

(1) The number of fully sampled central lines for estimating the coil sensitivity profiles would be carefully chosen. In consideration of quieter and faster reconstructing MR image, it shouldn’t be necessary to acquire more fully-sampled phase-encoding central lines for generating the internal reference images. From the simulated study and in-vivo study, we proposed that \( N^\text{center} \) should be chosen from 12 to 20 and not higher than 20 in consideration of quieter and faster imaging.

(2) According to our experiment, during the process of anisotropic diffusion of the internal low-resolution reference images for estimating the coil sensitivity maps, the mean of g-map and AP of reconstruction image gradually decrease, that could be shown as Fig.8.

In Fig.8, the AD sensitivity maps were calculated from in-vivo internal reference images by (8) along with scale-space parameter \( t \) from 50 to 300, and the reference images were extracted from fully-sampled central k-space in-vivo data when \( N^\text{center} \) was chosen 16. When scale-space parameter \( t \) in (8) was 200, mean AP of reconstruction image from under-sampling in-vivo data of R=2, 3, 4 were respectively 0.2517, 0.4727, 0.5898. While using rough sensitivity profile, mean of AP of reconstruction image were respectively 0.2509, 0.4774, 0.5948. Since AP measures any difference between “true” image and reconstruction image, a lower value of AP inferred that reconstruction image much truly reflect MR image, so artifacts in reconstruction image were reduced. We considered the reason should be that their own “decoding key” information contained in the self-calibrating reference images was gradually extracted. In a conclusion, this self-calibrating sensitivity method could reduce any artifacts, not alone aliasing artifact.

(3) The coil sensitivity maps estimated by anisotropic diffusion of internal sensitivity image could improve quality of reconstruction image, but the isolated noise in the reconstructed image could not be eliminated. It can be seen in Fig.4, Fig.5 and Fig.7, that there are many noise scatters in reconstruction images. In order to reduce isolated noise in reference sensitivity images, we improved the value of parameter \( \lambda \) in (8). However, when parameter \( \lambda \) overrun 0.35, some noise scatters were more prominent, so we set \( \lambda \) to 0.25 in our study.

The P-M model proposed by Perona and Malik can adaptively smooth the image and preserve the edge properties well, but the problem of reducing isolated noise is not resolved satisfactorily. In order to overcome
the drawback of the P-M model, many researchers proposed improvements to eliminate the Gaussian noise while preserve the edge features [12][13]. However, by our test, the coil sensitivity maps calculated by these methods are so similar that the matrix inversion can not be implemented for reconstructing the image.

(4) As illustrated in Table.1, when the AD sensitivity maps were extracted from central k-space data of \( N_{\text{center}} = 8, 12, 16, 20, 24 \), the quality of reconstruction image using AD sensitivity was evidently higher than using rough sensitivity and simulated \( b1 \) maps when under-sampling rate \( R \) was 3, 4. In Table.2, mean of normalized SNR of reconstruction image using AD sensitivity profiles was evidently higher than using rough sensitivity, except for the sensitivity profiles extracted from central k-space data of \( N_{\text{center}} = 24 \). As a result, we could refer that this self-calibrating sensitivity profiles was suitable for faster imaging in parallel MRI.

(5) The edge condition for (8) must be cautious. In the study, the edge condition at frequency-encoding direction is different from the edge condition at phase-encoding direction. In consideration of Cartesian sampling, this study sets the edge conditions for (8) along x-direction and along y-direction as (11):

\[
\frac{\partial I(x_0, y_0)}{\partial x} = 0, \quad \frac{\partial I(x_0, y_0)}{\partial y} = -I(x_0, y_0)
\]

(11)

Here, \( I(x_0, y_0) \) is the edge pixels of the image \( I(x, y) \). The study showed that the edge condition for the gradient of \( I(x, y) \) can tremendously affect the coil sensitivity maps

IV. CONCLUSION

Parallel magnetic resonance imaging provides a quantum leap in speed for MRI scanners. The most important step in a practical parallel MRI implementation is to acquire the sensitivities of the various coil array elements. In the paper, we proposed a new self-calibrating sensitivity method for parallel imaging, and the obtained sensitivity profiles can be used in any PMRI technique requiring such information. In order to improve the quality of reconstruction image, the constrained reconstruction is generally shown to be an effective method [14][15][16]. However, modifying the values of the coil sensitivities can moderate the ill-conditioning of the matrix inversion for reconstructing image.

REFERENCES


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