Improved Noise Performance Using Regionally Optimized Reconstruction for Partially Parallel Imaging

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Introduction: In SENSE [1], an unfolding matrix is resolved from a set of linear equations based on the correlation of a few pixels that are superimposed onto one another in the reduced FOV/aliased image. Due to the ill-conditioning problems, the resolved unfolding matrixes may amplify the noise at some positions in image-space and this "pixel by pixel" reconstruction method considerably suffers from g-factor noise. In this study, a "region by region" reconstruction method is introduced by taking advantage of the spatial correlation of the unfolding matrixes for neighboring pixels. By this method, the entire image space can be divided into many small regions and the pixels in a small region and those that are superimposed onto this region can be reconstructed by resolving a common set of equations. Compared with the conventional SENSE, this method can reduce the ill-conditioning problems and improve the noise performance in the regions where g-factors are high. Compared with GRAPPA, this method minimizes the least-square error in reconstruction regionally instead of globally and hence gives better image quality in the regions where g-factors are low.

Theory: In SENSE, a pixel can be reconstructed by the multiplication of a row vector of the unfolding matrix and a column vector consisting of the image values at the corresponding superimposed position in the N-channel aliased images. This reconstruction can be more generally represented by the weighted summation of the N-channel aliased images as shown by Eq. 1, where m(x,y) is the reconstructed image, N is the number of coils, a_i(x,y) represents the aliased image acquired from the ith channel, and u_i(x,y)'s are the weights for the reconstruction of the pixel at the position (x,y). In this work, we introduce a constraint that these weights are spatially smooth. This is reasonable because these weights are dependent on the smooth coil sensitivity profiles. Accordingly, a set of low-order polynomials can be used to approximate these weights within a small region in image space as shown in Eq. 2, where k_{ij}'s are the polynomial coefficients, and *RUC* represents the region under consideration, which is consisted of multiple neighboring pixels. The entire FOV can be divided into many small *RUC*s. The optimal coefficients k_{ij}'s for each *RUC* can be calibrated from either auto-calibration signals or pre-scan data by the minimization of least square error function defined in Eq. 3, where ψ_{ij} is the noise correlation between the ith and jth channel, the superscript * represents the conjugate operation, α_{RUC} is the Lagrange multiplicator to balance the noise amplification and reconstruction error within the *RUC*, X(x,y) is a low-resolution image from the calibration data, and a_i^X(x,y) is an aliased image by downsampling the calibration data from the ith channel. The first term starting with the factor α_{RUC} in Eq. 3 is equivalent to that used in SENSE for regularization of inverse matrix [3]. The minimization of Eq. 3 requires its partial derivative with respect to the coefficients k_{ij}'s equal to zero. This will generate a set of linear equations and the optimal coefficients can be resolved by the calculation of pseudo-inverse. With the optimal coefficients, Eqs. 1 and 2 can be used to reconstruct the image within one *RUC* and the entire image can be reconstructed region by region.

$$m(x,y) = \sum_{i=1}^{N} u_i(x,y)\, a_i(x,y) \quad (1)$$

$$u_i(x,y) = k_{i1} + k_{i2}x + k_{i3}y + k_{i4}xy \quad for \ (x,y)\in RUC, i = 1,2,\ldots,N \quad (2)$$

$$\varepsilon_{RUC} = \sum_{(x,y)\in RUC} \left\{ \alpha_{RUC} \sum_{i=1}^{N}\sum_{j=1}^{N} \left(k_{i1}+k_{i2}x+k_{i3}y+k_{i4}xy\right)\psi_{ij}\left(k_{j1}+k_{j2}x+k_{j3}y+k_{j4}xy\right)^{*} + \sum_{i=1}^{N}\left|\left(k_{i1}+k_{i2}x+k_{i3}y+k_{i4}xy\right)a_i^X(x,y) - X(x,y)\right|^2 \right\} \quad (3)$$

Methods: Brain, spine, breast and cardiac images were collected using multiple-channel coil arrays. The acquired data were fully sampled in k-space. Only the partial k-space data were used for reconstruction. Auto-calibration signals were used as the calibration data. The same partial k-space data were used for the regionally optimized reconstruction and GRAPPA with a kernel size of 4×5. The reconstructed images were compared. Noise amplification was investigated by comparing the SENSE g-factor maps with the error maps, which were the difference images between the reconstructed images and the reference images calculated by the Fourier transform of the fully sampled data. The reconstruction error was defined as the ratio of the power of an error map to that of the reference image.

Results: Fig. 1 gives the plots of reconstruction error against the reduction factor. It can be seen that the regionally optimized reconstruction gives less error than GRAPPA, especially at high reduction factors. Fig. 2 gives an example of breast imaging with a reduction factor of 4. It can be seen that the error map of the regionally optimized reconstruction are more uniform than the SENSE g-factor map, which implies that the noise amplification due to high g-factors is efficiently suppressed. Obviously, GRAPPA can also suppress the noise amplification at high g-factor regions, but generates more error than the regionally optimized reconstruction in low g-factor regions. Figure 3 shows an example of brain imaging with a reduction factor of 4. It can be seen that the image from the regionally optimized reconstruction is visibly better than the GRAPPA image.

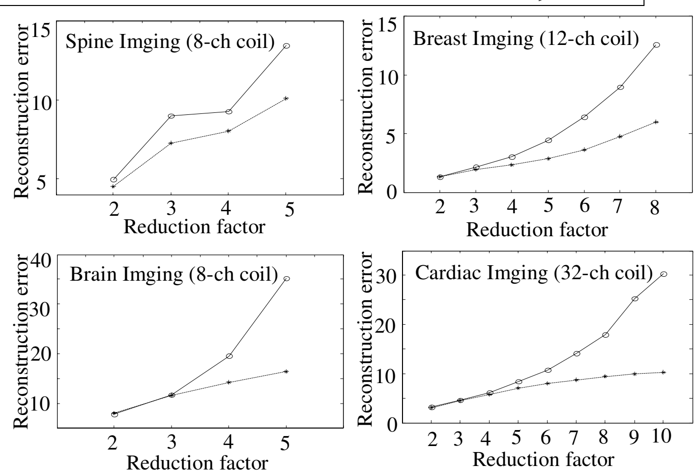

Fig. 1. Reconstruction error in percentage for different imaging applications, 'o', GRAPPA; '*', Regionally optimized reconstruction

Discussion and Conclusion: Regionally optimized reconstruction use the spatial correlation of neighboring pixels to reduce the ill-conditioning problems. Accordingly, noise amplification is suppressed at those positions where g factors are high. Even though this costs a little increase of noise at their neighbors, the total noise in the entire local region is minimized. In the regions where g-factors are low, SENSE is optimum because of the pixel by pixel optimization in reconstruction. The regionally optimized reconstruction is a very good approximation to SENSE in low g-factor regions because every *RUC* can be very small. This is different in GRAPPA: GRAPPA operates in k-space and the reconstruction is optimized over the entire image-space. As a result, the reconstruction over the entire FOV may be degraded by the severe ill-conditioning at a small number of positions. For this reason, regionally optimized reconstruction has better performance than GRAPPA in low g-factor regions, as shown in Fig. 2(c) and (d). In conclusion, regionally optimized reconstruction is an efficient way to improve the noise performance in partially parallel imaging and can be used in general imaging applications.

Reference: 1). Prussmann , K.P. et. al., MRM 42: 952-962 (1999). 2). Griswold, M. A. et. al., MRM 47:1202-1210 (2002). 3) King KF, et. al., ISMRM 2001, p1771.

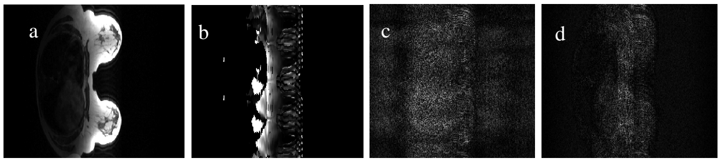

Fig. 2 An example of breast imaging. (a) Reference image; (b) SENSE g-factor map; (c) Error map of GRAPPA; (d) Error map of regionally optimized reconstruction.

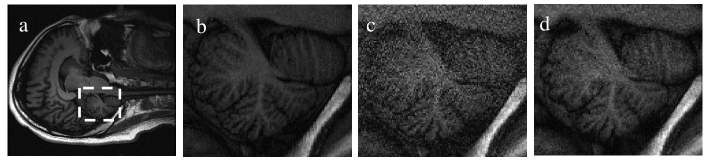

Fig. 3 An example of brain imaging. (a) Whole image; (b), (c) and (d) are zoomed images in the region marked by white box in (a). (b) Reference image; (c) GRAPPA; (d) Regionally optimized reconstruction.