Robust GRAPPA Reconstruction and Its Evaluation with Perceptual Difference Model (PDM)

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Introduction

GRAPPA [1] is a popular SMASH-type parallel imaging reconstruction technique. It allows one to extract the sensitivity information, or the fitting coefficients from the acquired ACS (Auto Calibration Signal) lines, and reconstruct the missing k-space lines from these coefficients. GRAPPA uses standard least-squares to get the "fitting" coefficients. We hypothesize that there are errors resulting from this estimation can be reduced using robust fitting techniques. We call this approach Robust GRAPPA. So as to easily test a variety of independent variables (image data set, noise, reduction factor, etc.) as a function of the type of robust estimation technique, we quantify image quality using a Perceptual Difference Model (PDM) [2-3] and evaluate 7,500 images.

Methods

In parallel imaging, data are acquired at the Nyquist rate in the center of k-space (the so-called calibration region), and in the outer k-space data are acquired every ORF (Outer Reduction Factor) lines. With GRAPPA reconstruction, the first step is to estimate the fitting coefficients by a least-squares algorithm. Blocks of signals from all the coils are used to fit a single ACS line in one coil. Each block is composed of one line of measured signal and ORF -1 lines of missing signal. Fitting coefficients are typically obtained using a pseudo-inverse matrix operation. The second step is to reconstruct the missing k-space signals in outer k-space. By applying the same equation at a different k-space location, with known fitting coefficients and acquired signal, one can reconstruct the missing k-space lines by direct matrix multiplication. Using a least squares method to solve the over-determined equations, GRAPPA considers every data point in the calibration region equally in the reconstruction. To improve the fitting accuracy, we have implemented the two different Robust Grappa techniques below.

Slow Robust GRAPPA. We used the *iteratively re-weighted least squares* algorithm [4], as implemented in robustfit.m, a MATLAB routine. In this algorithm, the weight of each datum at each iteration is calculated by applying the bi-square function to the residuals from the previous iteration. Effectively, outliers are given less weight in the final estimate. This process is very time-consuming.

Fast Robust GRAPPA. This simplified approach computes quickly. An initial least-squares fit is performed, and residuals are calculated. The largest residuals are labeled as "outlier" data. Outliers are effectively removed by setting their weights to zero, and another least squares fit is performed, giving the final estimated coefficients. Instead of hundreds of least square fits, the least-squares operation is done twice. The algorithm contains a single parameter, the outlier ratio, O_r, the fraction of data points deemed to be "outliers."

Experiments and Results

In the experiment, five different image datasets with different anatomy (brain and heart) and resolution were used. For each dataset, full-sampled data were acquired and used to reconstruct the reference image. Image data were sub-sampled data with different reduction factors and reconstructed with conventional GRAPPA and Robust GRAPPA algorithms, with different outlier ratios. These test images were compared to the high quality reference image using PDM. Results from a typical dataset are shown in Figure 1 for one coil. As compared with regular GRAPPA, the Robust GRAPPA techniques reduce noise and artifacts. There is little difference between the slow and fast techniques with regard to both reconstructed image and k-space data (Figure 1).

We used PDM to help determine a suitable O_r value for fast Robust GRAPPA. For this experiment, ORF was set as 4; the number of ACS lines was varied to change the total reduction factor from 1.5 to 3.0; and o*R* was varied from 0% to 50%. Fast Robust GRAPPA becomes conventional GRAPPA when $O_r = 0$. The PDM score changes with different outlier ratios and total reduction factors are shown in Figure 2. The best outlier ratio across R values was at about 8%, but PDM changed little for OR values between 5% and 10%. Other datasets gave similar results.

Conclusion

Fast Robust GRAPPA greatly improved fitting accuracy and reconstructed image quality. Results were very similar to those from Slow Robust GRAPPA. This application again demonstrates the advantages of applying PDM to systematically optimize parallel imaging.

Reference:

[1] Griswold M, et al., MRM 47:1202–1210, 2002.
[2] Salem K, et al., JEI 11(2), 224– 235, 2002.
[3] Huo D, et al., ISMRM 2005, p2455.
[4] Huber, P.J. (1981), Robust Statistics, New York: Wiley

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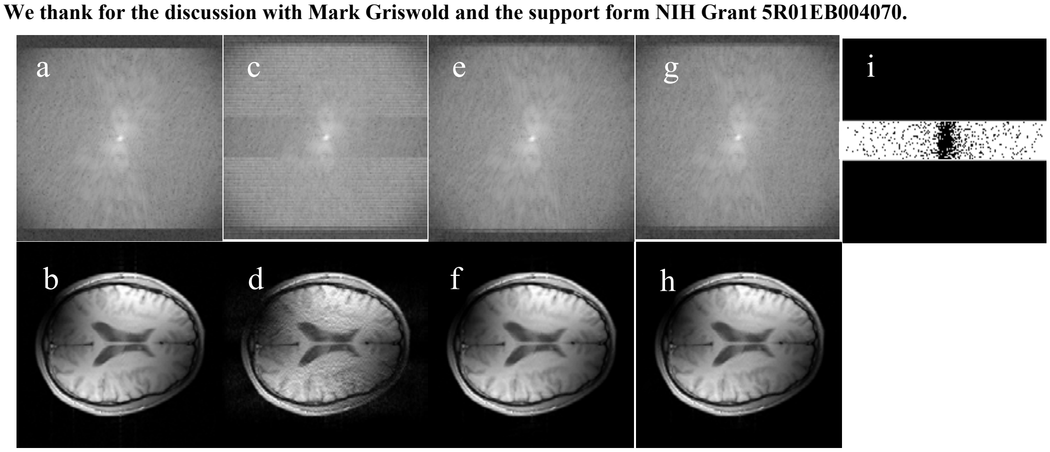

Figure 1. Test images with different reconstruction method. The log of the original k-space data from one of the surface coils is shown in (a); the corresponding image is shown in (b). GRAPPA reconstructed k-space data are shown (c), and the image is shown in (d). Slow Robust GRAPPA gives improved k-space data (e) and image (f). Fast Robust GRAPPA gives almost the same k-space data (g) and image (h); eliminated points are shown in (i) as black points.

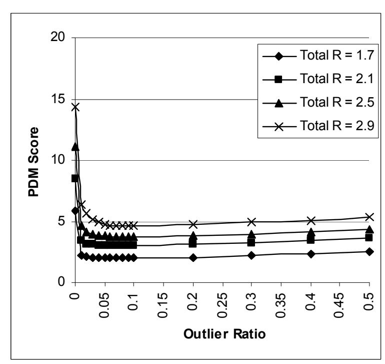

Figure 2. PDM as a function of outlier ratio and reduction factor.