A Nonlinear GRAPPA Method for Improving SNR

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INTRODUCTION

GRAPPA [1] reconstructs the missing *k*-space data by a linear combination of the acquired data using a set of weights obtained through calibrations. Several methods have been proposed in recent years to improve GRAPPA using localized coil calibration and variable density sampling [2], multicolumn multiline interpolation [3], regularization [4,5], reweighted least square [6], high-pass filtering [7], cross validation [8], iterative optimization [9], multi-slice weighting [10], etc. In this abstract, a nonlinear GRAPPA method is proposed to address the poor SNR of GRAPPA at high reduction factors. The method is motivated by the fact that nonlinear filtering usually outperforms linear ones in denoising [11]. For example, TV regularization as a nonlinear method is superior to the linear Tikhonov regularization for SENSE reconstruction [12]. The proposed method uses a nonlinear combination of the acquired *k*-space data to estimate the missing data. The experimental results demonstrate that the proposed method is able to improve the SNR of GRAPPA at high reduction factors.

THEORY

GRAPPA reconstruction can be considered as a linear filtering process when the weights are obtained. In the proposed method, we add additional high order terms of a polynomial in GRAPPA so that it becomes a nonlinear filtering process. Specifically, the missing *k*-space data is reconstructed by $S_j\left(k_y + r\Delta k_y, k_x\right) = \sum_{l=1}^{L}\sum_{b=-N_b}^{N_a}\sum_{h=-H_l}^{H_r}\sum_{n=1}^{N} w_{j,r}\left(l,b,h,n\right)\times S_{n,l}\left(k_y + bA\Delta k_y, k_x + h\Delta k_x\right)$, where $S_{n,l}\left(k_y,k_x\right) = S_l^n\left(k_y,k_x\right) / \max_{k_y,k_x} \left| S_l^n\left(k_y,k_x\right)\right|$ is the *n*th power of the original *k*-space data, but is normalized by its largest magnitude. Compared to the original GRAPPA formulation, the proposed method has one additional summation over all orders *n* to incorporate high-order constraints for accurate estimation. By using polynomial as the nonlinear representation, the computation is still as simple as the linear case. The order *N* can be tuned to define the polynomial for the best reconstruction. The least squares technique is used to solve the over-determined equation. Other improved GRAPPA methods (e.g. [6],[7]) that are compatible with the proposed method can also be combined to improve reconstruction.

METHOD

We tested the proposed method on a set of *in vivo* data acquired on a 3T commercial scanner (GE Healthcare, Waukesha, WI) with a four-channel head coils (axial plane, 4 coils, 256x256 matrix). The data were acquired with Nyquist rate and used for reconstructing the reference image. The data were then manually down-sampled with a reduction factor of 4 and 64 ACS lines at the central *k*-space. Images were reconstructed using both the conventional GRAPPA and the proposed nonlinear GRAPPA. The neighboring four blocks and three columns were used along the k_y and k_x directions for reconstructing the missing data. The order of nonlinear GRAPPA was chosen to be 5. For comparison, GRAPPA reconstructions using the same net reduction factor of 2.29 but different combinations (4× with 64 ACS and 3× with 40 ACS) were also obtained.

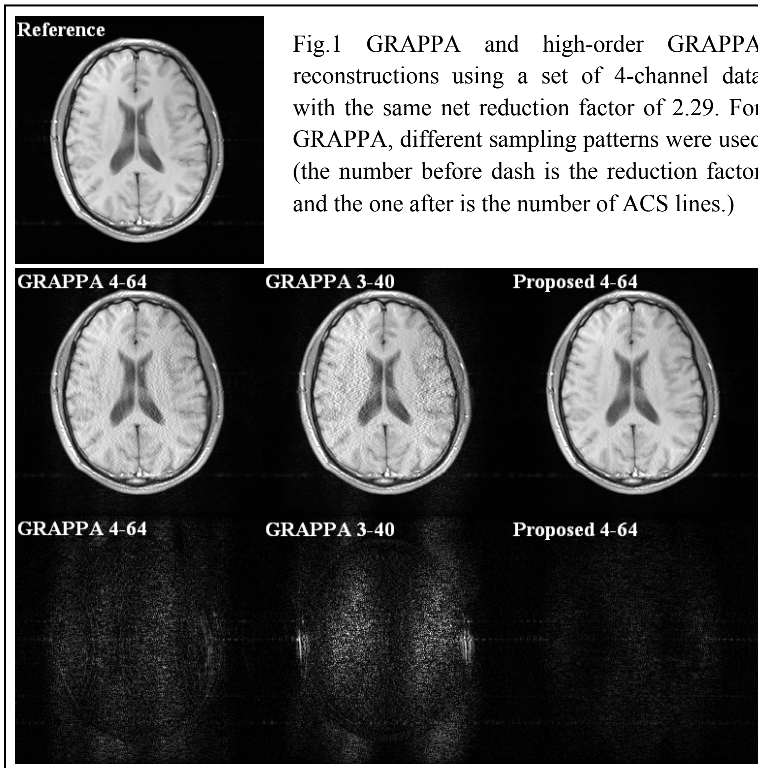

Fig.1 GRAPPA and high-order GRAPPA reconstructions using a set of 4-channel data with the same net reduction factor of 2.29. For GRAPPA, different sampling patterns were used (the number before dash is the reduction factor and the one after is the number of ACS lines.)

RESULTS AND DISCUSSION

The figure left shows the reference image and reconstructed images by GRAPPA and nonlinear GRAPPA. Compared to GRAPPA reconstructions with different combinations for the same net reduction factor, the proposed method improves the reconstruction quality in terms of SNR. The proposed method performs similarly with different orders of 3, 4, 5, and 6.

CONCLUSION

We have presented an improved GRAPPA method via a nonlinear combination of the acquired *k*-space data. Experimental results demonstrate the method can effectively reduce the noise in conventional GRAPPA. The method is expected to find applications when noise becomes serious in GRAPPA.

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