COMBINING COMPRESSED SENSING AND NONLINEAR GRAPPA FOR HIGHLY ACCELERATED PARALLEL MRI

Yuchou Chang[1], Kevin F. King[2], Dong Liang[3], and Leslie Ying[1]

[1]*Electrical Engineering, University of Wisconsin - Milwaukee, Milwaukee, Wisconsin, United States,* [2]*Global Applied Science Laboratory, GE Healthcare, Waukesha, Wisconsin, United States,* [3]*Shenzhen Institutes of Advanced Technology, Chinese Academy of Sciences, Shenzhen, China, People's Republic of*

INTRODUCTION: To accelerate conventional MRI, both parallel imaging (pMRI) [1,2] and compressed sensing (CS) [3] have been used to reduce the number of acquired data. Several methods have been developed to combine CS and pMRI for even higher speed of reconstruction [4-7]. Among these methods, CS-GRAPPA has the benefit of decoupling CS and GRAPPA without the need for coil sensitivities. However, noise and errors from the CS step can propagate and be amplified in GRAPPA. We recently developed a nonlinear GRAPPA (NLGRAPPA) approach [8] that can suppress the GRAPPA noise significantly. In this work, we propose to integrate CS and NLGRAPPA (named CS-NLGRAPPA) to improve CS-GRAPPA reconstruction. The NLGRAPPA step can reduce the amplification of noise and errors in CS reconstruction. Experimental results using phantom and in vivo data demonstrate that the proposed CS-NLGRAPPA method can significantly improve the reconstruction quality over the CS-GRAPPA at high net reduction factors (around 4).

THEORY AND METHOD: The sampling pattern for the proposed method has two parts. The first part is the same as the sampling used in CS-SENSE [4]. Specifically, a variable-density random sampling scheme [3] is employed to further undersample the data along the phase encoding direction that is already undersampled in pMRI, as shown in Fig. 1 from (a) to (b), where the white lines represent the sampled *k*-space locations. The other part acquires the fully sampled auto-calibration signal (ACS) at the central *k*-space. The union of the undersampled (Fig. 1 (b)) and ACS data (Fig. 1 (c)) produces the ultimate sampling pattern as shown in Fig. 1 (e) for the proposed method. The net reduction factor is calculated by the total number of acquired lines divided by the number of lines when full sampling is employed.

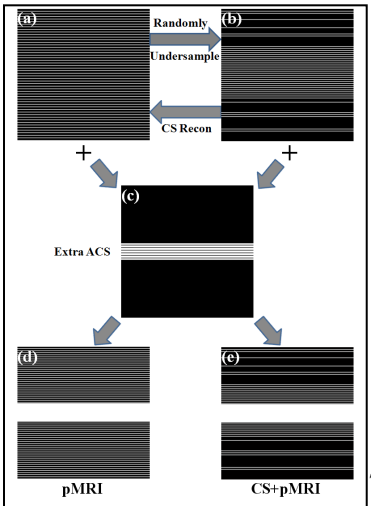

Figure 1. Sampling pattern of pMRI and proposed CS+pMRI method.

The proposed method carries out CS and NLGRAPPA reconstructions sequentially. In the CS step, the uniformly undersampled data are reconstructed from the randomly undersampled data as shown in Fig. 1 from (b) to (a). To this end, CS is used to reconstruct the aliased image in each channel and then Fourier transformed to obtain the uniformly undersampled *k*-space data. Specifically, we solve $\arg\min_{\mathbf{f}_l^A}\left\{\left\|\mathbf{F}^u\mathbf{f}_l^A-\mathbf{d}_l^u\right\|_2^2+\lambda_1\left\|\boldsymbol{\psi}\mathbf{f}_l^A\right\|_1+\lambda_2\mathrm{TV}\left(\mathbf{f}_l^A\right)\right\}$ (1) where the first term denotes the data consistency and the other two terms enforce the sparseness constraint with $\mathbf{f}_l^A$ being the unknown vector for the aliased reduced FOV image from the *l*-th channel to be reconstructed. In the NLGRAPPA step, the ACS data in Fig. 1 (c) are used

$$S_j\left(k_y+r\Delta k_y,k_x\right)=w_{j,r}^{(0)}\times 1+\sum_{l=1}^{L}\sum_{b=B_1}^{B_2}\sum_{h=H_1}^{H_2}w_{j,r}^{(1)}(l,b,h)\times S_l\left(k_y+bR\Delta k_y,k_x+h\Delta k_x\right)+\sum_{l=1}^{L}\sum_{b=B_1}^{B_2}\sum_{h=H_1}^{H_2}w_{j,r}^{(2,0)}(l,b,h)\times S_l^2\left(k_y+bR\Delta k_y,k_x+h\Delta k_x\right)+ \quad (2)$$

$$\sum_{l=1}^{L}\sum_{b=B_1}^{B_2}\sum_{h=H_1}^{H_2-1}w_{j,r}^{(2,1)}(l,b,h)\times S_l\left(k_y+bR\Delta k_y,k_x+h\Delta k_x\right)\times S_l\left(k_y+bR\Delta k_y,k_x+(h+1)\Delta k_x\right)+\sum_{l=1}^{L}\sum_{b=B_1}^{B_2}\sum_{h=H_1}^{H_2-2}w_{j,r}^{(2,2)}(l,b,h)\times S_l\left(k_y+bR\Delta k_y,k_x+h\Delta k_x\right)\times S_l\left(k_y+bR\Delta k_y,k_x+(h+2)\Delta k_x\right)$$

for calibration and the uniformly undersampled data in Fig. 1 (a) obtained from the CS step are used for reconstruction of the final image. The unacquired *k*-space signal S_j is obtained by a nonlinear combination of the acquired *k*-space signals S_l weighted by coefficients *w* as given in Eq. (2), where the first term is a constant, the second term is the same as GRAPPA, and the rest are the second-order nonlinear terms.

RESULTS AND DISCUSSION: CS-NLGRAPPA method was evaluated on both phantom and *in vivo* data sets. An 8-channel phantom dataset was acquired using a Gradient Echo sequence (TE/TR = 10/100 ms, 31.25 kHz bandwidth, matrix size = 256×256, FOV = 250 mm^2). An 8-channel brain dataset was obtained using a 2D spin echo (SE) sequence (TE/TR = 11/700 ms, matrix size = 256 × 256, FOV = 220 mm^2). A set of cardiac cine images was acquired using a 2D trueFISP sequence (TE/TR=1.67/50.1 ms, bandwidth 903 Hz/pixel, 45 degree flip angle, 8mm slice thickness, 34 cm FOV in readout direction, 256x146 acquisition matrix) with a 12-channel cardiac coil but combined to 4 channels. The data were acquired with Nyquist rate and used for reconstructing the reference image. CS-GRAPPA and CS-NLGRAPPA were used to reconstruct images from data with an outer reduction factor (ORF) of 1.5 (CS) ×5 (NL/GRAPPA) and 42 ACS for phantom, ORF 1.7×4 and 36 ACS for brain, and ORF 2×4 and 40 ACS for cardiac dataset, respectively. Net reduction factors are 4, 3.93, and 4.12 respectively. Reconstructions are shown in Fig. 2. They demonstrate that CS-NLGRAPPA can suppress the noise and aliasing artifacts in CS-GRAPPA reconstruction at acceleration factors up to 4.12.

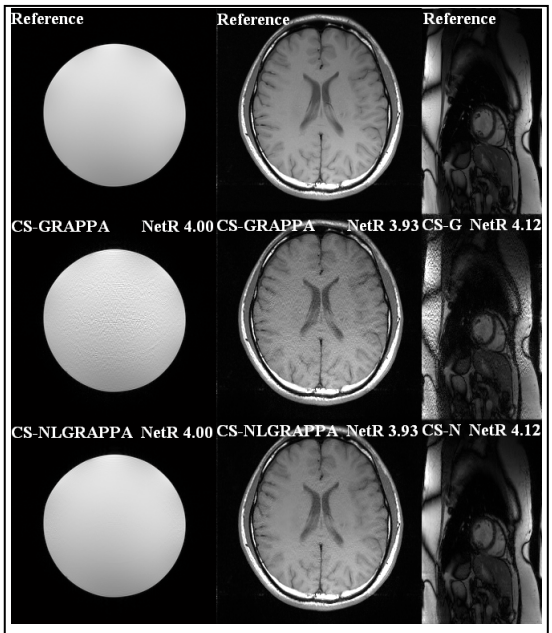

Figure 2. Recons of CS-GRAPPA and CS-NLGRAPPA.

CONCLUSION: We propose a novel method that combines CS with nonlinear GRAPPA sequentially for fast MRI. The experimental results demonstrate that the proposed CS-NLGRAPPA method is superior to the CS-GRAPPA method in suppressing both noise and artifacts when a high net reduction factor is used.

REFERENCES: [1] Pruessmann KP, et al, MRM 42:952-962, 1999. [2] Griswold MA, et al, MRM 47: 1202-1210, 2002. [3] Lustig M, et al, MRM 58:1182-1195, 2007. [4] Liang D, et al, MRM 62:1574-1584, 2009. [5] King K, et al, ISMRM, 2010, 4881. [6] Lustig M, et al, MRM 64:457-471,2010. [7] Liu B, et al, ISMRM, 2008, 3154. [8] Chang Y, et al, MRM, in print.