

## Correlation-based reconstruction using coil sensitivity information and image content similarity

Yu Li<sup>1</sup>, Feng Huang<sup>2</sup>, Wei Lin<sup>2</sup>, Randy Duensing<sup>2</sup>, and Charles L. Dumoulin<sup>1</sup>

<sup>1</sup>Imaging Research Center, Radiology Department, Cincinnati Children's Hospital Medical Center, Cincinnati, Ohio, United States, <sup>2</sup>Invivo Diagnostic Imaging, Philips HealthCare, Gainesville, Florida, United States

**Introduction:** A limitation on parallel imaging acceleration in clinical magnetic resonance imaging (MRI) is the spatial encoding capability of multi-channel coil sensitivity [1-3]. We have proposed a framework of "correlation-based reconstruction" in order to overcome this limit by converting high-speed imaging reconstruction to the estimation of correlation functions that may include multiple data correlation mechanisms underlying parallel acquisition [4]. In the work presented here, we used the previously reported framework to investigate whether coil sensitivity information and image content similarity can synergistically benefit correlation-based reconstruction for a static MRI scan.

**Theory:** Figure 1(a) shows the k-space model for correlation-based reconstruction [4]. The least square solution to the linear filters  $\{u_i(k), i=1,2,\dots,N\}$  for reconstruction of an arbitrary channel  $m$  in Figure 1 can be resolved from a set of linear equations given by:

$$\sum_{i=1}^N \sum_{k' \in [k | u_i(k') \neq 0]} c_{ij}(k'-k) t_s(k'-k) u_i(k') = c_{mj}(-k), \quad j, k \in \{j, k | u_j(k) \neq 0\}$$

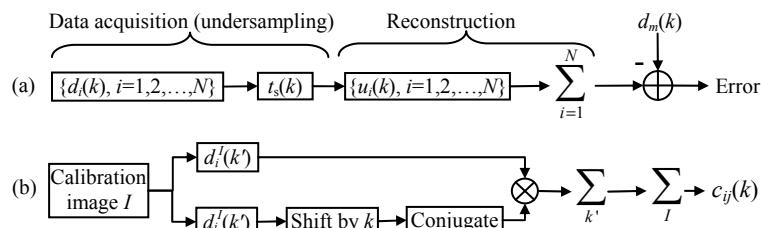
where  $t_s(k)$  is a previously determined undersampling trajectory, and  $c_{ij}(k) = \text{sum}\{\{d_i(k')\} \cdot \text{conjugate}[d_j(k'+k)]\}_{\text{over } k'}$  represents the auto- or cross-channel correlation functions, which can be estimated using the ensemble summation approach shown in Figure 1(b). This ensemble summation allows for the use of both coil sensitivity information and image content similarity provided by multiple calibration images in correlation-based reconstruction.

**Methods and Materials:** A brain imaging experiment was conducted using an 8-channel head coil array and a 3T clinical MRI scanner. Two sets of axial imaging data were acquired with full Fourier encoding using a T<sub>1</sub>-weighted SE (FOV 240×240 mm, matrix 64×64, TR/TE 630/7 ms, flip angle 30°, 32 slices with 4 mm thickness and 4 mm gap) and a T2-weighted TSE sequence (FOV 240×240 mm, matrix 256×256, TR/TE 3000/80 ms, TSE factor 16, flip angle 90°, 10 slices with 4 mm thickness and 8 mm gap). The phase encoding direction was left-right. The first set of low-resolution data (64×64) was used as calibration (as in SENSE approach). The second set of high-resolution data (256×256) was manually undersampled with a series of reduction factors  $R=2, 3, \dots, 8$ . The undersampled data were used to simulate the real scan data in image reconstruction. Correlation-based reconstruction was compared with GRAPPA (calibrated from 24 ACS lines) and SENSE (calibrated from the low-resolution imaging data).

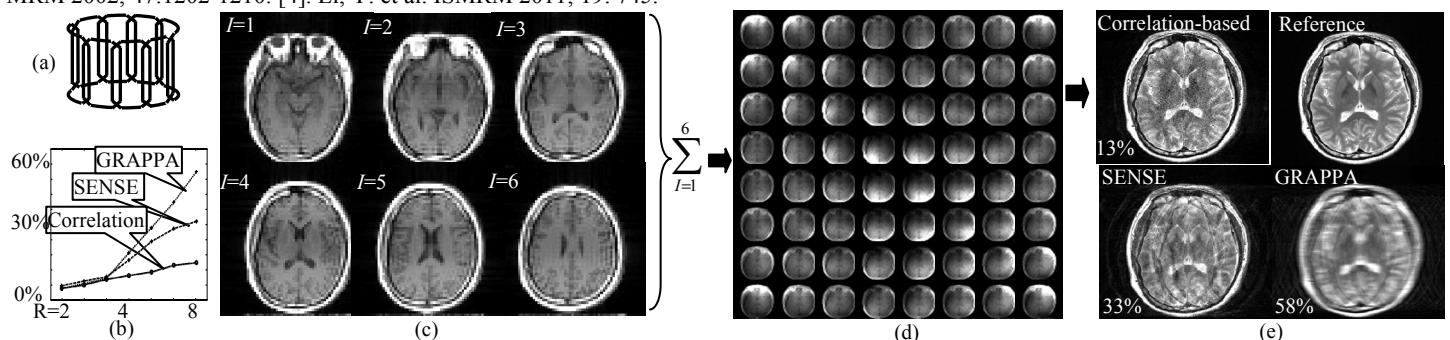
**Results and Discussion:** As shown in Figure 2(a), the head coil array used in this work has at most 4 elements in any direction and this number is the maximal parallel imaging acceleration factor allowed on a clinical scanner using this coil array. Consequently, it can be seen that GRAPPA and SENSE perform well when  $R \leq 4$  while the errors increase fast when  $R > 4$  (Figure 2b). In comparison, correlation-based reconstruction gives acceptable reconstruction errors for reduction factors from 2 to 8. In the reconstruction example ( $R=8$ ) given by Figures 2(c)-(e), correlation functions were estimated from 6 calibration images with different contrast and around the location of the image to be reconstructed (reference image). The ensemble summation of the correlation functions estimated from all 6 calibration images reduces the incoherent information in calibration data, providing data correlation needed for reconstruction. By bringing both coil sensitivity information and image content similarity into image reconstruction, correlation-based reconstruction preserves image information well with only 32 phase encoding lines ( $R=8$ ). The low image quality provided by SENSE and GRAPPA using the same amount of data demonstrates this acceleration is beyond the parallel imaging acceleration limit permitted by the 8-channel coil array. It was also found that the robustness of correlation-based reconstruction increases as the number of calibration images (requires  $>3$  in this experiment) in ensemble summation. The use of a small number of calibration images may introduce unwanted information about image contrast and anatomical structure in the estimated correlation functions, manifesting as destructive image artifacts in reconstruction. In this work, the use of multiple calibration images for ensemble summation in the estimation of correlation functions removes the necessity for iterative algorithm proposed in our previous work [4], providing simplicity for clinical translation.

**Conclusions:** It was found that high-speed image reconstruction can be successfully implemented using correlation functions estimated from multiple calibration images with the same or different contrast and at the same (or approximately the same) scan location. This implies that the similarity in both coil sensitivity and image content provides useful information for correlation-based reconstruction. By introducing an ensemble summation method in the estimation of correlation functions, correlation-based reconstruction provides a generic approach to overcoming parallel imaging acceleration limit posed by a coil array in static MRI.

**Reference:** [1]. Sodickson, D.K. et al., MRM 1997, 38: 591-603. [2]. Pruessmann, K.P. et al., MRM 1999, 42: 952-962. [3]. Griswold, M. A. et al., MRM 2002, 47:1202-1210. [4]. Li, Y. et al. ISMRM 2011; 19: 745.



**Figure 1.** (a) k-space model for correlation-based reconstruction: Estimate of channel  $m$  from all channels.  $N$ : channel number;  $d_i(k)$ : data from channel  $i$ ;  $t_s(k)$ : undersampling trajectory for imaging acceleration;  $u_i(k)$ : linear filter for reconstruction. (b) Estimation of correlation functions by ensemble summation over multiple calibration images.  $d_i^I(k)$ : data from channel  $i$  in calibration image  $I$ .



**Figure 2.** Experimental results in brain imaging: (a). Coil layout for multi-channel data acquisition. (b) Root-Mean-Squared errors (RMSE) in SENSE, GRAPPA and correlation-based reconstruction for  $R=2,3,\dots,8$ . (c) Low-resolution calibration images for estimating correlation functions (Figure 1b). (d) Estimated auto-and cross-channel correlation functions in image space (8×8 image matrix). (e) Comparison of correlation-based reconstruction, SENSE and GRAPPA with  $R=8$  in reference to the image from fully-sampled data. Correlation functions in (d) bring the information from all 6 calibration images into correlation-based reconstruction.