## A Rapid Self-Calibrating Radial GRAPPA method using Kernel Coefficient Interpolation

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Introduction: A generalized autocalibrating partially parallel acquisition (GRAPPA) method for radial k-space sampling is presented that calculates kernel weights without acquiring or synthesizing calibration data [1-3] and without regridding to a Cartesian grid [4].

2-Neighbor Error Map

6-Neighbor Error Map

**Methods:** In the first step, GRAPPA kernels are calculated for datapoints k at radius rand angle  $\theta$ . Neighboring datapoints  $k_i$  from adjacent projections of k, with relative shifts  $\Delta k_i$  are used to fit coefficients  $w(\Delta k_i)$ . For notational simplicity, we will adopt a convention where the coil dependence of the weights w is implicit. In order to obtain enough equations to solve the linear system fitting the GRAPPA kernel weights, datapoints from the neighborhood r -  $\Delta r$  to r + $\Delta r$  and  $\theta$  -  $\Delta \theta$  to  $\theta$  + $\Delta \theta$  around k are used for inversion. Here, it is assumed that the k-space shifts within this small segment of kspace are constant such that one unique set of GRAPPA kernel coefficients for one relative shift  $\Delta k$  can be obtained. This is repeated for all radial directions with varying relative shifts. In the second step, new coefficients  $w^*(\Delta k_v^*)$  are interpolated for new relative shifts  $\Delta k_{\nu}^*$ , where  $k_{\nu}^*$  denotes the  $\nu^{th}$  acquired neighbor of an unacquired datapoint  $k^*$  that lies between acquired projections. In this step, the kernel weights for each k-space shift within a wedge  $\Delta\theta$  are interpolated from all derived kernel weights within that same wedge, exploiting the translational invariance in the radial direction. In the third and final step, the interpolated weights are used to reconstruct projections positioned between acquired projections, thus effectively increasing the sampling density.

This study was approved by our institutional review board and written consent was obtained from each subject. Four healthy subjects were scanned in the axial plane at the liver, and one volunteer was scanned in the axial plane at the brain. A high-resolution calibration phantom was scanned in the axial plane. Datasets used 400 projections at 512 points per projection at double FOV for full Nyquist sampling, and were then subsequently undersampled 2, 4, and 8 times to produce datasets with 200, 100, and 50 projections, respectively. The size of the grappa kernel and the size of the fitting neighborhoods ( $\Delta\theta$  by  $\Delta r$ ) were varied to find those parameters yielding minimal reconstruction error (see below). Comparisons were made to calibrated GRAPPA reconstructions using the full 400 projection dataset as calibration data, similar to prior literature [2], but using the same radial and angular segmentation for the derivation of the local kernel weights. All comparisons are reported as the total power error (TPE) between accelerated image and reference image [2].

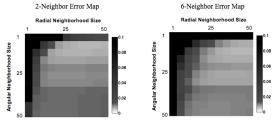
**Results:** The optimal angular and radial neighborhoods for inversion were found to be 10 angular segments by 45 radial segments for a 6-neighbor GRAPPA kernel (Fig. 1). Typical reconstructions are shown in Fig. 2 and Fig. 3. Error for each method for all volunteers is shown in Fig. 4. Good agreement was seen between the presented self-calibrated GRAPPA method and calibrated GRAPPA. Self-calibrated GRAPPA added up to 12.6% more processing time in MATLAB.

**Conclusion:** A rapid self-calibrating radial GRAPPA algorithm is developed that performs all computations in k-space, without the need to compute coil sensitivity maps, perform segmentation, grid to Cartesian space, or generate synthetic calibration data. Significant reductions of aliasing artifact are achieved, generating image quality and reconstruction speeds comparable to GRAPPA calibrated from fully sampled training data with low overall image error.

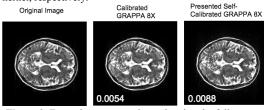
## References

[1] Griswold M, Heidemann R, Jakob P. Direct parallel imaging reconstruction of radially sampled data using GRAPPA with relative shifts. ISMRM, Toronto, Canada 2003. [2] Arunachalam et al. MRM 2007;57(5):931-938. [3] Huang et al. MRM 2007;57(6):1075-1085. [4] Seiberlich N, Breuer F, Heidemann R, Blaimer M, Griswold M, Jakob P. Magn Reson Med 2008;59(5):1127-1137.

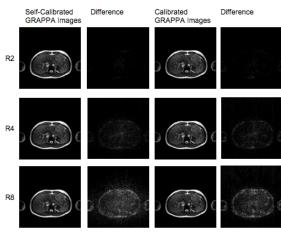
**Figure 4**. Total power error comparing each GRAPPA method and acceleration factor against the fully sampled image, for all 4 volunteers and phantom image.



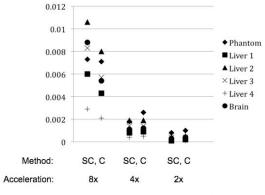
**Figure 1**. Error maps varying  $\Delta\theta$  and  $\Delta r$  for kernel inversion, using a 2-neighbor kernel and a 6-neighbor kernel, respectively.



**Figure 2**. Example reconstructions, showing the fully sampled image, calibrated, and the presented self-calibrated radial GRAPPA method. TPE overlaid.



**Figure 3**. Rows: acceleration factors 2, 4, and 8. Columns: self-calibrated GRAPPA, difference, calibrated GRAPPA, difference.



SC = Self-Calibrated, C = Calibrated