Calibration Reduction for Through-time radial GRAPPA by Weights Compression

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Target Audience: Scientists and clinicians interested in highly-accelerated non-Cartesian imaging

Purpose: High acceleration factors with undersampled radial trajectories have previously been demonstrated with through-time radial GRAPPA (TT-rGRAPPA)[1]. This method estimates the radial GRAPPA weights by acquiring multiple fully-sampled reference frames that may imply long calibration scans - as long as several minutes - when multiple 2D slices are imaged. Therefore, reducing the duration of calibration scans is likely to increase clinical application of rGRAPPA techniques. Though the number of calibration frames may be decreased at the expense of image quality [1], a method for reducing calibration data requirements without affecting image quality is of interest. The purpose of this work is to shorten the calibration scan times aggressively by reducing the number of reference frames while reconstructing clinically acceptable images using an alternative calibration method involving the compression of the GRAPPA weights.

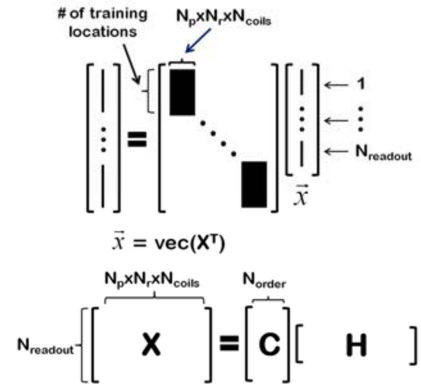

Figure 1: Modified radial GRAPPA calibration

Theory: A unique GRAPPA kernel is calibrated for each missing k-space sample from multiple occurrences over segments of k-space, as introduced in the original radial GRAPPA formulation [2], in addition to calibrating over multiple reference frames, making it a hybrid through-time/through-k-space calibration process. Since the weights for neighboring k-space locations are calculated from overlapping k-space regions, their values are expected to be very similar. Hence, we hypothesize that it is possible to parameterize the GRAPPA weights with smoothly varying functions over k-space, which can be modeled with an orthogonal basis of order (N_{order}) much smaller than the number of individual weight sets to be calculated -- a similar approach has been shown to produce reasonable results for Cartesian GRAPPA in a PROPELLER sequence [3]. In this work, we limit the modeling of weights to only the readout direction (as the variation in kernel geometry, hence the weights, along that direction is much smaller than that along the azimuthal direction). For a GRAPPA kernel of size $N_p x N_r$ (number of points in readout x number of points in azimuthal direction), the number of GRAPPA weights to be estimated for each unsampled k-point is $N_p x N_r x N_{coils}$. As shown in Figure 1, a vector $\vec{x}$ of length $N_p x N_r x N_{coils} x N_{readout}$ can be constructed by stacking the weights for each readout point of a radial spoke together. Rewriting $\vec{x}$ as $\vec{x}$ = vec($\mathbf{X}^\mathbf{T}$), it is possible to set **X** an orthogonal basis of size N_{order} such that **X = C H,** where **C** consists of the first N_{order} columns of the discrete cosine transform (DCT) matrix. Thus, the calibration problem is reduced from estimating the actual weights **X** to estimating the "pseudo-weights" **H**, where the number of unknowns is reduced by $N_{gain} = N_{readout}/N_{order}$ where $N_{readout}$ is the total number of sample points in one readout.

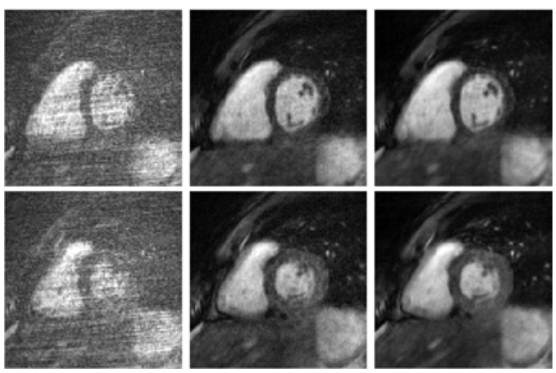

Figure 2: Images of end-diastolic (top-row) and end-systolic (bottom row) cardiac phases acquired in a normal subject. Left: TT-rGRAPPA with 6 calibration frames. Middle: Proposed calibration with 6 frames. Right: TT-rGRAPPA with 36 frames.

Methods: Normal subjects (N=3) were imaged with IRB approval at 1.5T (Avanto, Siemens Medical Systems, Erlangen, Germany) using the standard body and spine coils (15 receiver channels). Free-breathing cardiac imaging was performed using the product balanced steady-state free precession real-time sequence (FOV: 220 mm, resolution: 1.53x1.53x8.0 mm^3, TR: 3.1 ms, BW: 849 Hz/pix). Up to thirty six fully-sampled (144 radial spokes) calibration frames were acquired prior to the acquisition of 9-fold (R=9) undersampled (16 radial spokes) real-time image frames with 58 ms temporal resolution. Radial GRAPPA weights were calibrated with both the conventional method and the proposed method by varying number of calibration frames from 3 to 36, and images were reconstructed.. A 3x2 GRAPPA kernel and 8x2 (read x proj) k-space segment were used for the calibrations. N_{order} = 24 was tested, yielding a weights compression factor of $N_{gain} > 11$ (for 288 readout samples with 2x oversampling). Normalized RMSE values were computed for 100 reconstructed images relative to the reference (36 frames) TT-rGRAPPA reconstruction.

Results: Figure 2 shows that the proposed calibration technique enables the calibration of weights with only 6 frames. Image quality was significantly improved compared to the original TT-rGRAPPA method using the same number of frames for calibration. RMSE is less than 4% when more than 4 calibration frames are used in the proposed calibration (Fig. 3).

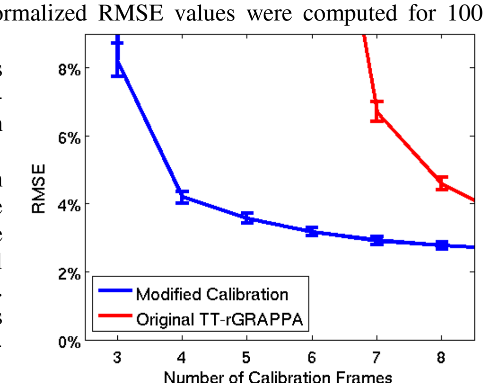

Figure 3: Mean RMSE over 100 frames. Bars indicate standard deviations.

Discussion/Conclusion: By compressing the rGRAPPA weights set, the proposed calibration method not only shortens the calibration scans significantly, but also serves the real-time image reconstruction process, where GPUs are commonly used for low-latency reconstructions [4]. Size reduction in the weights may help reduce memory requirements on limited GPU resources as well as data transfer speeds between device and host memory during real-time reconstructions [5]. Further compression of the GRAPPA weights may be possible by combining other data dimensions (e.g. projections, coils) to achieve higher gains. This method should also be applicable to 3D TT-rGRAPPA [6].

References: [1] Seiberlich et al., *Magn Reson Med* 2011. [2] Griswold et al., *ISMRM* 2003. [3] Skare et al., *Magn Reson Med* 2008. [4] Saybasili et al., *ISMRM* 2012. [5] Saybasili et al., *ISMRM* 2012 [6] Seiberlich et al., *ISMRM* 2013. **Funding:** Siemens, NIH/NIBIB R00EB011527.