A DUAL-POLARITY GRAPPA KERNEL FOR THE ROBUST RECONSTRUCTION OF ACCELERATED EPI DATA

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ABSTRACT
The quality of high-resolution Echo Planar images of the human brain has improved greatly in recent years, enabled by novel multi-channel receiver coil arrays and parallel imaging. However, in regions with local field inhomogeneity, EPI artifacts limit which parts of the brain can be imaged successfully. In this work, we present evidence that certain image artifacts can be attributed to nonlinear phase errors that are present in regions of local susceptibility gradients and certain coil array elements. Because these phase errors cannot be corrected with conventional Nyquist ghost correction, we propose a new method that integrates ghost correction with parallel imaging reconstruction. The proposed Dual-Polarity GRAPPA method operates directly on raw EPI data to estimate k-space data from the under-sampled acquisition while simultaneously correcting inherent EPI phase errors. We present examples of this method successfully removing strong phase-error artifacts in high-resolution 7T EPI data.

Index Terms— EPI, Nyquist Ghost Correction, parallel imaging, fMRI, Artifact Correction

1. INTRODUCTION
Echo planar imaging (EPI) is widely used in functional, diffusion, and perfusion MR imaging of the brain. However, EPI is vulnerable to multiple artifacts, including geometric distortions and Nyquist ghosting. Many of these artifacts can be traced to local field inhomogeneity, gradient hardware imperfections, and induced eddy currents. EPI ghost correction algorithms seek to correct the differences that exist between data sampled on positive readout gradients (RO+) versus negative readout gradients (RO−). The difference between the two readouts is typically modeled as a scalar and first-order phase correction in image space [1]. However, nonlinear phase differences have been reported in certain imaging scenarios, e.g. in surface coil arrays [3].

Accelerated parallel imaging (pMRI) methods are often employed with EPI to shorten the echo train, and subsequently reduce the geometric distortion that arises from local field inhomogeneity. pMRI reconstruction methods are fundamentally driven by models of the acquisition process. When the pMRI model does not accurately describe the actual imaging system, image quality can degrade. When reconstructing accelerated EPI data, such models necessarily include the need for EPI ghost correction. Image quality can suffer when the ghost correction is imperfect and/or inconsistent between the pMRI calibration data and the acquired data

To address the need for non-linear phase correction and impose ghost correction consistency in the pMRI reconstruction process, we propose here to embed the ghost correction within a GRAPPA [3] reconstruction model. Specifically, we seek to incorporate the RO+/RO− phase error correction within the pMRI data recovery process. This is achieved by introducing a Dual-Polarity GRAPPA (DPG) kernel that is applied directly to the raw EPI data. A secondary benefit of this approach is that higher-order ghost correction terms—beyond the simple scalar and linear correction sought by most methods—are successfully modeled by the DPG kernel. This results in a dramatic improvement in overall image quality compared to methods that apply ghost correction and pMRI reconstruction separately, and enables high-quality images to be consistently produced from highly-accelerated EPI data.

2. METHODS
GRAPPA can be described analytically as generating a target point in k-space, \( \hat{k}[x, y, c] \), from a weighted linear combination of source points

\[
\hat{k}[x, y, c] = \sum_{i=0}^{N_x-1} \sum_{j=0}^{N_y-1} \sum_{\ell=1}^{N_c} c_{ij\ell} k[x', y', \ell]
\]

where \( c_{ij\ell} \) are the GRAPPA reconstruction weights, \( k[x', y', \ell] \) are the source data with \( x' = x + i - (N_x-1)/2, \ y' = y + r(j - N_y/2) + s, \ r \) is the distance between sampled k-space lines at \((x, y)\), \( s \) is the distance from target to source data, \( \{N_x, N_y\} \) are the extent of the GRAPPA kernel along the \( k_x \) and \( k_y \) direction, respectively, and \( N_\ell \) is the number...
of receive coils. This model is illustrated in Fig. 1(a), for a kernel of size $N_x = 5$ and $N_y = 4$, with source points shown in gray and the target point shown in black. The GRAPPA weights, $c_{ij\ell}$, are determined by constructing a linear system from the Auto Calibration Signal (ACS) data that are sampled at the Nyquist rate (e.g. fully-sampled, non-accelerated). Using ACS data, one can train a particular GRAPPA kernel by learning the weights that map from known source data points to known target data points within the ACS data. Once determined, the weights are then used to synthesize missing data in subsequent under-sampled MRI acquisitions.

In this work we seek to embed EPI ghost correction within GRAPPA by employing a dual-polarity GRAPPA kernel—where one half of the kernel draws from EPI source data sampled on $RO^+$ and the other half draws from EPI data sampled on $RO^-$. This necessitates a split in the GRAPPA analytic model, as

$$\hat{k}_{x,y,c} = \sum_{i=0}^{N_x-1} \sum_{j=0}^{N_y-1} \sum_{\ell=1}^{N_z} w_{ij\ell} k_{x', y'', \ell}$$

$$+ \sum_{i=0}^{N_x-1} \sum_{j=1,3,5,\ldots}^{N_y-1} \sum_{\ell=1}^{N_z} w_{ij\ell} k_{x', y'', \ell}. \quad (2)$$

with $y'' = y + 2r(j - N_y/2) + s$. This model is illustrated in Fig. 1(b), for a kernel of size $N_x = 5$ and $N_y = 4$, with source points shown in gray and the target point shown in black. We emphasize that the data, $k$, in Eq. 2, are EPI data prior to ghost correction. To emphasize the ghost correction character of the DPG kernel in the figure, the $RO^+$ and $RO^-$ source points are depicted as distinct from the target sampling grid and offset from the sampling grid in the $k_x$ direction.

The method to train weights for the DPG kernel is similar to standard GRAPPA, with some additional sorting of the EPI data. First, the ACS data are derived from a set of temporally encoded reference data—in which the fully-sampled reference data are acquired twice, with a standard readout polarity then with a readout of opposite polarity—in order to acquire both $RO^-$ and $RO^+$ training data. In the experiments below, the ACS data consisted of segmented multi-shot EPI with the number of segments equal to the acceleration factor. To generate ghost-free target data, this ACS data was sorted and processed using GESTE [4] for segmented data as described in [5]. To generate $RO^+$ and $RO^-$ source data, the acquired ACS data was sorted by acquisition readout polarity. Together, the $RO^+$, $RO^-$, and ghost-free target data were used to train the DPG reconstruction parameters. After training, fully-sampled images were generated from accelerated data by applying the DPG kernels directly to the raw EPI data. Note that in DPG, in order to perform ghost correction on the sampled lines, every k-space line is synthesized as a linear combination of acquired lines. This is in contrast to standard GRAPPA methods where only skipped lines are synthesized.

For comparison, images representative of the current state-of-the-art were generated using the Local Phase Correction (LPC) method of Feiweier [6] for ghost correction of the accelerated EPI data. Conventional GRAPPA parameters were generated using the ghost-free target data described previously. The ghost correction parameters identified by the LPC algorithm were first applied to the raw accelerated EPI data to correct the shift between the $RO^+$ and $RO^-$ k-space lines, then GRAPPA was applied to the ghost corrected data.

The results below were generated from data acquired on a Siemens 7T whole-body scanner equipped with SC72 body gradients and a custom-made 32-channel brain array receive coil and a birdcage transmit coil [7]. The gradient-echo EPI sequence employed a custom FLEET-GESTE [8] pre-scan implementation to enable temporal encoding of the ACS calibration data. Data were acquired using two typical high-resolution, accelerated single-shot gradient-echo EPI protocols: one with nominal $1.5\times1.5$ mm$^2$ in-plane voxel size, $TE/TR/BW/matrix/flip = 25$ ms/2000 ms/1776 Hz/pix/128$\times$128/75$^\circ$, no partial-Fourier, a nominal echo-spacing of 0.67 ms, $R = 3$ acceleration, 126 refer-

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**Fig. 1.** (a) Traditional GRAPPA model. (b) Proposed dual-polarity GRAPPA (DPG) reconstruction model. The dot shading corresponds to: light-gray : source points; black : target point; Traditional GRAPPA generates missing k-space data from a single data set. Our DPG approach splits the kernel between RO$^+$ and RO$^-$ EPI data, and embeds the ghost correction step with the DPG kernel parameters. For simplicity, the coil dimension is not shown.
ence lines, 37 slice-interleaved, 1.5-mm thick axial slices (no gap); and one with nominal 1.1×1.1 mm² in-plane voxel size, TE/TR/BW/matrix/flip = 26 ms/2000 ms/1512 Hz/pix/174×174/75°, no partial-Fourier, a nominal echo-spacing of 0.79 ms, R = 4 acceleration, 128 reference lines, 34 slice-interleaved, 1.1-mm thick axial slices (no gap). For both protocols, 4 dummy measurements were included immediately prior to the accelerated image series to allow the longitudinal magnetization to achieve steady-state; for FLEET-GESTE ACS data a constant flip angle of 10° was employed with 5 RF preparation pulses.

The temporal stability of our algorithm was assessed via calculation of Time-series SNR (tSNR) [9]. First, rigid-body motion correction was performed with the AFNI [10] command 3dvolreg [11, 12] using the middle time-point as a reference. tSNR maps were then generated from the motion-corrected data by dividing the temporal standard deviation by the temporal mean after linear detrending.

### 3. RESULTS

Fig. 2 shows the phase difference between the RO⁺ and RO⁻ navigator signals in the R = 3 data that are typically acquired prior to the EPI echo train. The images show the phase difference over multiple coils or slices, with the signal for a particular coil and slice highlighted in each sub-figure. Although the phase difference in hybrid (x-kz) space is commonly modeled as linear, we have found that in regions of local field inhomogeneity—such as above the paranasal sinuses and ear canals—there often exist significant components that are non-linear along the z direction. The non-linearity in these signals can bias the phase correction parameter estimation, which leads to model mismatch between the corrected data and the ACS data used for pMRI calibration. This mismatch commonly appears as interference patterns or “ripples” in images reconstructed from accelerated EPI data.

Figs. 3 and 4 show both LPC+GRAPPA and DPG images reconstructed from the R = 3 and R = 4 7T data, respectively. The axial LPC+GRAPPA images show significant rippling in the upper right quadrant, which corresponds to a brain region just above the paranasal sinuses. This artifact is present in a number of slices, as seen in the circled region of the LPC+GRAPPA sagittal reformatted images shown at the bottom of each figure. In contrast, the DPG kernel reconstructions show significantly lower levels of these interference pattern artifacts, demonstrating that the DPG method is better able to compensate for non-linear phase errors in these slices.

The tSNR maps generated from the R = 3 data are shown in Fig. 5. The images show that the sensitivity and stability of the DPG-reconstructed time-series data is as good or better than that of the LPC+GRAPPA data.

### 4. DISCUSSION AND SUMMARY

We have presented a method to reconstruct images from subsampled multi-channel EPI data by embedding the ghost correction step within the pMRI reconstruction process. This approach removes the possibility of biased ghost correction from adversely impacting the pMRI reconstruction. As seen in the Results, even a small amount of estimate error in the phase correction coefficients can produce significant ripple artifacts in the accelerated images. Although the method originally described by Feiweier [6] allows for higher-order phase correction via fitting nonlinear basis functions to the phase differences that may also remove these artifacts, appropriate basis sets are difficult to determine a priori.

In this work we employed a novel DPG kernel for pMRI reconstruction. Given a kernel of sufficient size, the flexibility provided by the GRAPPA parametrization ensures that higher-order phase errors in the EPI data can be correctly compensated. We have shown that this can be beneficial when imaging brain regions near air-tissue interfaces particularly
when using a large number of receiver channels at ultra-high field.

5. REFERENCES


Fig. 3. A comparison of LPC+GRAPPA and DPG images from R=3x accelerated 32-channel 7T data.

Fig. 4. A comparison of LPC+GRAPPA and DPG images from R=4x accelerated 32-channel 7T data.

Fig. 5. Comparison of tSNR maps for the 3x 7T data