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ROBUST AUTOCALIBRATED LORAKS FOR EPI GHOST CORRECTION

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Abstract

Nyquist ghosts are a longstanding problem in a variety of fast MRI experiments that use echo-planar imaging (EPI). Recently, several structured low-rank matrix modeling approaches have been proposed that achieve state-of-the-art ghost-elimination, although the performance of these approaches is still inadequate in several important scenarios. We present a new structured low-rank matrix recovery ghost correction method that we call Robust Autocalibrated LORAKS (RAC-LORAKS). RAC-LORAKS incorporates constraints from autocalibration data to avoid ill-posedness, but allows adaptation of these constraints to gain robustness against possible autocalibration imperfections. RAC-LORAKS is tested in two challenging scenarios: highly-undersampled multi-channel EPI of the brain, and cardiac EPI with a double-oblique slice orientation. Results show that RAC-LORAKS can provide substantial improvements over existing ghost correction methods, and potentially enables new imaging applications that were previously confounded by ghost artifacts.

Index Terms

Structured low-rank matrix recovery; echo-planar imaging; constrained MRI reconstruction

1. INTRODUCTION

Echo-planar imaging (EPI) is one of the fastest and most popular MRI pulse sequences, but is prone to Nyquist ghost artifacts due to systematic mismatches between the data acquired with different gradient polarities and/or different shots [1]. These mismatches lead to periodic inconsistencies in k-space, which give rise to undesired aliasing artifacts (“Nyquist ghosts”) along the phase encoding dimension.

Perhaps the most common approach to EPI ghost correction is to acquire additional navigator information that enables estimation and model-based correction of systematic linear phase differences that often exist between different gradient polarities and shots [1]. While these approaches can work well in certain scenarios, there are a variety of important contexts in which higher-order eddy currents, concomitant magnetic fields, asymmetric gradient delays, and other effects lead to modeling violations that confound model-based

ghost correction. Although certain advanced methods can be more successful in a subset of these cases [2], there are still many challenging scenarios (e.g., double-oblique cardiac imaging) where existing approaches remain unsatisfactory.

Low-rank modeling of Toeplitz/Hankel-structured k-space matrices has been proposed as a powerful constraint in both the early days of constrained MRI [3] and the recent reconstruction literature [4–9]. These models enable the use of classical support, phase, parallel imaging, and sparsity constraints, but without the substantial prior information or calibration data that is often required by classical methods. Recently, these structured low-rank matrix approaches have been adapted to obtain state-of-the-art EPI ghost correction [10–14]. In our previous investigations [13, 14], we observed that a novel EPI reconstruction formulation based on a combination of LORAKS [6] and Autocalibrated LORAKS (AC-LORAKS) [15] was especially effective. However, a potential limitation of this AC-LORAKS approach was the need for high quality autocalibration (ACS) data [14], which may be hard to acquire in the presence of strongly time-varying subject/scanner behavior and strong concomitant fields.

In this work, we propose and evaluate a generalization of the previous AC-LORAKS method that is designed to be more robust to imperfect ACS data. We refer to this new approach as Robust AC-LORAKS (RAC-LORAKS), and our evaluations demonstrate that it often succeeds in quite challenging scenarios where other correction methods fail.

2. ROBUST AUTOCALIBRATED LORAKS

The following subsections review our previous AC-LORAKS approach [13, 14] and describe our new RAC-LORAKS approach. For simplicity, our descriptions will assume the context of single-channel single-shot EPI, noting that the generalization to the multi-channel and/or multi-shot case is straightforward [14]. In the single-channel single-shot context, we are interested in estimating $\mathbf{k}^+$ and $\mathbf{k}^-$, the vectors of Nyquist-sampled Cartesian k-space data corresponding to the positive and negative readout gradient polarities. Due to the nature of EPI sampling, each of these vectors will be subsampled during data acquisition, and as in previous approaches [10,13,14], our goal will be to estimate the missing entries while enforcing strict consistency with the measured data. We use $\mathbf{k}$ to denote the concatenation of $\mathbf{k}^+$ and $\mathbf{k}^-$.

2.1. Review of AC-LORAKS for EPI Ghost Correction

Our previous AC-LORAKS EPI ghost correction approach estimates $\mathbf{k}^+$ and $\mathbf{k}^-$ according to [13,14]:

$$\hat{\mathbf{k}} = \underset{\mathbf{k}}{\operatorname{argmin}} \left\| \mathbf{N} \mathcal{P}_C \pm (\mathbf{k}) \right\|_F^2 + \lambda_s J_r(\mathcal{P}_S \pm (\mathbf{k})) \quad (1)$$

subject to strict data consistency constraints on $\mathbf{k}$. In this expression, the operator $\mathcal{P}_{C^\pm}(\cdot)$

forms a concatenated matrix defined by $\mathcal{P}_C \pm (\mathbf{k}) \triangleq [\mathcal{P}_C(\mathbf{k}^+) \mathcal{P}_C(\mathbf{k}^-)]$ the $\mathcal{P}_C(\cdot)$ operator

constructs a Toeplitz-structured matrix (known as the LORAKS C-matrix [6, 7]) out of the k-space data, the operator $\mathcal{P}_C \pm (\cdot)$ forms a concatenated matrix defined by

$\mathcal{P}_S \pm (\mathbf{k}) \triangleq [\mathcal{P}_S(\mathbf{k}^+) \mathcal{P}_S(\mathbf{k}^-)]$, and the $\mathcal{P}_S(\cdot)$ operator constructs Toeplitz/Hankel-structured matrix (known as the LORAKS S-matrix [6, 7]) out of the k-space data. The C-matrix is known to have approximately low-rank whenever the image has small support in the image domain, and its multi-channel version [4, 5, 7] will also have low-rank whenever an appropriate form of inter-channel correlation exists in multi-channel k-space data. The S-matrix is known to have approximately low-rank in the same circumstances as the C-matrix, but will have even further reduced rank if the image possesses smoothly varying phase.

In Eq. (1), $J_r(\cdot)$ denotes a non-convex low-rank promoting penalty function that is equal to the Frobenius norm of the residual after rank- r approximation [6] and λ_s is a regularization parameter. The $\mathbf{N}$ matrix contains an orthonormal basis for an estimate of the approximate left nullspace of the C-matrix, which is obtained from ACS data [4, 15]. In our implementation [13, 14], the ACS data was obtained using a standard temporally-encoded EPI prescan protocol that provides fully-sampled k-space data for each readout gradient polarity [16]. This approach assumes that the $\mathbf{N}$ matrix estimated from the ACS data will provide a good estimate of the approximate left nullspace for subsequent conventional EPI data acquired at potentially much-later time points.

The first term of Eq. (1) can be viewed as imposing support and parallel imaging constraints that have been learned from the ACS data on $\mathbf{k}^+$ and $\mathbf{k}^-$ independently. The second term additionally imposes smooth phase constraints on the reconstructed images (with the phase potentially very different from the ACS data) and encourages the existence of correlation between $\mathbf{k}^+$ and $\mathbf{k}^-$, in addition to further encouraging support and parallel imaging constraints. Note that we have previously proven that using some form of prior information (e.g., the first term in Eq. (1)) is a necessity for good EPI ghost correction using a structured low-rank matrix model [14]. If the second term of Eq. (1) (and variations thereof) is considered by itself, it will have infinitely many minimizers.

Despite obtaining good results with the previous ACLORAKS ghost correction method in several complicated single-channel and multi-channel scenarios [13, 14], its performance depends on the quality of the available ACS data and the consistency between the ACS data and conventional EPI data (which may be acquired at a potentially much-later time point). We have observed that both of these factors can confound the performance of this approach in certain challenging practical applications.

2.2. Proposed RAC-LORAKS for EPI Ghost Correction

Rather than completely trusting the approximate nullspace obtained from the ACS data as in the previous approach, our new RAC-LORAKS approach estimates the $\mathbf{N}$ matrix that is as consistent as possible with the ACS data while also being as consistent as possible with the conventionally-acquired EPI data that we are trying to reconstruct. The main assumption here is that if there are mismatches between the ACS data and the conventionally-acquired EPI data, we can potentially use the conventionally-acquired data to learn and correct for these mismatches. Formally, RAC-LORAKS solves the following optimization problem:

$$\{\hat{\mathbf{k}}, \hat{\mathbf{N}}\} = \arg \min_{\{\mathbf{k}, \mathbf{N}\}} \left\| \mathbf{N} \mathcal{P}_C \pm (\mathbf{k}) \right\|_F^2 + \lambda_s J_r(\mathcal{P}_S \pm (\mathbf{k})) + \lambda_c \left\| \mathbf{N} \mathcal{P}_C \pm (\mathbf{k}_{acs}) \right\|_F^2 \quad (2)$$

subject to the constraint that $\mathbf{N}$ has orthonormal rows (i.e., $\mathbf{N}\mathbf{N}^H = \mathbf{I}$, where $\mathbf{I}$ is the identity matrix) as well as strict data consistency constraints on $\mathbf{k}$. In this expression, $\mathbf{k}_{acs}$ is the vector of measured ACS data, and λ_c is a regularization parameter that controls the extent to which the ACS data is trusted when estimating $\mathbf{N}$. Note that Eq. (2) is identical to Eq. (1), except that we have added a new term to our objective function and allowed $\mathbf{N}$ to vary. In the limit as $\lambda_c \rightarrow \infty$, the estimate of $\mathbf{N}$ will be determined solely by the ACS data, and the RAC-LORAKS formulation from Eq. (2) reduces to the AC-LORAKS formulation from Eq. (1).

We solve the optimization problem in Eq. (2) by observing that the optimal solution $\hat{\mathbf{k}}$ to Eq. (2) must also be the solution to the lower-dimensional optimization problem:

$$\hat{\mathbf{k}} = \underset{\mathbf{k}}{\operatorname{argmin}} J_{r'}(\left[\mathcal{P}_C \pm (\mathbf{k}) \quad \sqrt{\lambda_c} \mathcal{P}_C \pm (\mathbf{k}_{acs}) \right]) + \lambda_s J_r(\mathcal{P}_S \pm (\mathbf{k})) \quad (3)$$

subject to strict data consistency constraints on $\mathbf{k}$. In this expression, r' denotes the number of rows of $\mathbf{N}$ (i.e., the desired dimension of the approximate left nullspace of the $\mathbf{C}$ matrix). Equation (3) has an identical form to optimization problems considered in previous LORAKS work [6,7]. In this work, we find a local minimum of Eq. (3) using the majorize-minimize algorithm from [6].

While both Eq. (2) and Eq. (3) are nonconvex and potentially subject to local minima, our empirical evaluations suggest that the solution we obtain is not very sensitive to the initialization of the algorithm. In this work (as well as many previous LORAKS papers that solve similar nonconvex optimization problems [6, 7]), we use a simple zero-filled initialization to first optimize the AC-LORAKS optimization problem from Eq. (1). Subsequently, we use this AC-LORAKS solution as an initialization for solving the RAC-LORAKS optimization problem from Eq. (3).

In our implementation, the rank parameters r' and r are chosen by plotting the singular values of $\mathcal{P}_C \pm (\mathbf{k}_{acs})$ and $\mathcal{P}_S \pm (\mathbf{k}_{acs})$ and selecting the points where the singular value curves start to flatten out.

3. EVALUATION OF RAC-LORAKS

RAC-LORAKS was evaluated in two challenging *in vivo* imaging scenarios.

The first case seeks to reconstruct an image from highly-accelerated multi-channel *in vivo* gradient echo EPI brain data. Accelerated data was acquired prospectively on a Siemens (Erlangen, Germany) 3T Prisma Fit using a standard product 32-channel receiver array. The imaging parameters were: FOV = 220 mm × 220 mm; matrix size 128×128; 5 slices; slice

thickness = 3 mm; TR = 2 sec; TE = 35 msec; acceleration factor $R = 6$; ACS data: 96 lines, 12 temporally-encoded segments (using the prescan protocol discussed in Sec. 2.1). We note that this acceleration factor is very high for the EPI trajectory (which has 1D undersampling), and is expected to be beyond the capabilities of most image reconstruction methods.

In theory, interleaved data drawn from all of the ACS segments for a common polarity readout, either RO+ or RO-, should be free of Nyquist ghosts. In practice, however, phase incoherence between the different segments results in undesirable ghost artifacts in the ACS image for each polarity as can be observed in Fig. 1. These artifacts are particularly visible in the phase images. Figure 1 shows the results of applying RAC-LORAKS ghost correction to this data. For comparison, results are also shown in cases with no compensation of the mismatch between different gradient polarities (“Uncorrected”), the state-of-the-art Dual-Polarity GRAPPA (DPG) method [2], the MUSSELS approach [11,12], and our previous AC-LORAKS approach [14]. The results demonstrate that RAC-LORAKS achieves high reconstruction quality without any visibly noticeable ghost artifacts. All of the other methods demonstrate very noticeable artifacts.¹

The second case demonstrates the performance of RAC-LORAKS in an unaccelerated mid-short axis cardiac EPI image. Images were acquired using an inner volume spin-echo EPI sequence on a GE Signa HDx 3T scanner with a 8 channel cardiac coil [17]. The imaging parameters were: FOV = 280 mm $\times$ 140 mm; matrix size 128 $\times$ 64; slice thickness = 10 mm; TR = 55 msec; TE = 32.9 msec; velocity cutoff 5cm/s; ACS data: 40 lines, 2 temporally-encoded segments. In this case, the temporally-encoded ACS data yields considerable ghost-artifacts as can be observed in the RO+ ACS image in Fig. 2. The RO- image shows similar artifacts, but is not shown for brevity. Removing these artifacts from the ACS data is difficult with conventional methods, which leads to corresponding errors for the previously proposed ghost correction methods. However, the RAC-LORAKS method provides a phase-correction bridge between the ACS and sub-sampled data, yielding substantially lower artifacts.

4. DISCUSSION AND CONCLUSION

We have proposed a new EPI ghost correction method called RAC-LORAKS, which generalizes a previous method we proposed based on the AC-LORAKS framework. Our new method does not trust the nullspace information learned from ACS data as strictly as the previous method did, which enables it to overcome signal-phase incoherence in the segmented EPI data that form the ACS calibration data. Our results presented two different yet very-challenging practical scenarios and demonstrate that RAC-LORAKS can be substantially more successful than current state-of-the-art ghost correction methods. We believe that RAC-LORAKS is a powerful approach to EPI ghost correction that is broadly applicable across a range of different application contexts, and may also be an enabling technology for applications like double-oblique cardiac EPI where conventional navigator-based ghost correction frequently fails and high-quality ACS data is also challenging to

¹While DPG and MUSSELS have been shown to work well in previous literature [2, 11, 12], the data we show here has a substantially higher acceleration factor than was considered in previous evaluations of these methods.

acquire. While we considered RAC-LORAKS in the context of EPI ghost correction, we believe that the same approach may be useful for dealing with imperfect ACS data in more general applications.

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Fig. 1. (top) Magnitude and (bottom) phase images corresponding to the (first two columns) ACS data and (remaining columns) image reconstruction results obtained from highly-accelerated multi-channel EPI data ($R = 6$, 32-channels). The red arrow indicates the phase encoding direction.

Fig. 2.

Magnitude images corresponding to the (first column) positive gradient polarity image of the ACS data and (remaining columns) image reconstruction results obtained from unaccelerated double-oblique cardiac EPI data. The first six columns are windowed to highlight the appearance of ghost artifacts, while the last column shows a more standard intensity window for reference, using the same RAC-LORAKS image as in the sixth column. The red and yellow arrows indicate the phase encoding direction and a ghost artifact location, respectively.