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Model-based Iterative Reconstruction for Single-shot EPI at 7T

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Abstract

Purpose—To describe a model-based reconstruction strategy for single-shot echo planar imaging (EPI) that intrinsically accounts for k-space non-uniformity, Nyquist ghosting, and geometric distortions during rather than before or after image reconstruction.

Methods—Ramp-sampling and inhomogeneous B₀ field-induced distortion cause the EPI samples to lie on a non-Cartesian grid, thus requiring the non-uniform fast Fourier transform (NUFFT). Additionally, a 2D Nyquist ghost phase correction without the need for extra navigator acquisition is included in the proposed reconstruction. Coil compression is also incorporated to reduce the computational load. The proposed method is applied to phantom and human brain MRI data.

Results—The results demonstrate that Nyquist ghosting and geometric distortions are reduced by the proposed reconstruction. The proposed 2D phase correction is superior to a conventional 1D correction. The reductions of both artifacts lead to improved temporal signal-to-noise ratio (tSNR). The virtual coil results suggest that the processing time can be reduced by up to 75%, with a mean tSNR loss of only 3.2% when using 8-virtual instead of 32-physical coils for 2-fold undersampled data.

Conclusion—The proposed reconstruction improves the quality (ghosting, geometry and tSNR) of EPI without requiring calibration data for Nyquist ghost correction.

Keywords

Model-based reconstruction; Nyquist ghost; geometric distortion; single-shot EPI

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Introduction

High magnetic field strengths such as 7T and above allow functional magnetic resonance imaging (fMRI) with increased sensitivity for the detection of brain activation based on the blood-oxygen-level-dependent (BOLD) effect. The improved sensitivity is caused by an increase in the signal-to-noise ratio (SNR) due to higher tissue magnetization and by a super-linear increase of the BOLD effect with field strength (1). A fast imaging technique is also required for fMRI to follow the hemodynamic changes occurring in seconds. Echo-planar imaging (EPI) (2), especially single-shot EPI, has been the most common imaging technique used in fMRI. This sequence can successfully capture the BOLD contrast with relatively high temporal resolution.

However, EPI suffers from geometric distortions caused by different off-resonance factors such as B0 field inhomogeneity and eddy current effects (3,4). These distortions cause a difficulty to co-register the acquired EPI with other anatomical data. Moreover, inaccurate timing of the sampling relative to the switched gradient, temporal asymmetries in the analogue filter, or inhomogeneities in the static field cause phase modulation of alternate lines in k-space that are acquired under opposite readout gradients. This phase modulation generates a ghost image shifted by $N/2$ pixels in the phase encoding direction (so-called Nyquist ghost) (5). This artifact is a great concern for fMRI, especially when it is large in amplitude, because it could potentially project the ghosted BOLD activation into regions located half a field-of-view (FOV) away (6). Furthermore, temporally unstable Nyquist ghosting will also compromise the temporal signal-to-noise ratio (tSNR). At higher magnetic field strengths, the abovementioned artifacts become more apparent because local variations in magnetic field are larger, and such variations cause severe phase distortions in the magnetization (7).

Several approaches can be applied to mitigate geometric distortions. For instance, shimming can reduce the field inhomogeneity prior to imaging (8,9), ramp sampling, which involves data acquisition also on the up- and downslope of the readout trapezoid, can reduce the readout time and echo spacing, and parallel imaging techniques (10-12) can decrease the effective echo spacing by the acceleration factor. Moreover, the remaining distortions can be alleviated after the image reconstruction using a voxel shift map (VSM). Such VSMs are generally calculated from double-echo gradient recalled echo (GRE) (13), point spread function (PSF) (14,15), or model-based (16) techniques. The Nyquist ghosts can be corrected by 1D or 2D phase corrections. A 1D non-phase-encoded navigator (1D-Nav) is commonly used on clinical systems, which involves a non-phase-encoded two- or three-lobed readout that is played out immediately after each excitation to estimate the offset between odd and even k-space lines (5). Recently, the phased-array ghost elimination (PAGE) method (17) was proposed to remove Nyquist ghosting through parallel imaging methods such as SENSE (11). The separation of EPI data into positive and negative echo sets can remove Nyquist ghosting by introduction of a factor of two undersampling. These sets can be reconstructed separately using SENSE. In PAGE, images are combined coherently using a weighted summation derived from the point spread function. In cases where the point spread function needs to be estimated, the weighting coefficients can be derived from a time averaged covariance matrix for each pixel. Alternatively, the image

magnitude may be estimated non-coherently as the root-sum-of-squares in case of unknown weighting coefficients.

The conventional EPI reconstruction pipeline involves phase correction to remove Nyquist ghosts, k-space gridding to account for non-uniform k-space (ramp) sampling, k-space to image transformation, and geometric distortion correction. When considering the steps above, certain aspects may be investigated to further improve the reconstruction quality. First, the efficiency of Nyquist ghost correction highly depends on the accuracy of the phase reference. For example, the widely used 1D-Nav based correction often results in images with high residual ghosts even in fully sampled or moderately accelerated data (18). The artifacts can be suppressed more efficiently by 2D correction, but an additional full k-space reference scan is required to measure the 2D phase information (19-21). Second, GRAPPA (10) and SENSE (11) are widely used for reconstructing undersampled EPI data. GRAPPA has been found to perform more robustly (22,23) and have better noise distribution properties than SENSE (24). SENSE is sensitive to numerical errors or errors in sensitivity profiles. Although an EPI-based calibration provides a fairly matched geometry, it is inferior in terms of SNR and tSNR compared to a FLASH-based calibration (25). Nevertheless, FLASH-based calibration may create residual artifacts related to the geometric mismatch (26). Applying distortion correction in post-processing may be unable to reduce the residual artifacts related to the geometric mismatch. However, SENSE-based reconstruction provides flexibility in modeling physical phenomena directly (27-29) that may be not corrected sufficiently by post-processing techniques. Recently, regularized SENSE reconstructions (30,31) have been shown to improve the sensitivity and specificity of fMRI to detect brain activation. However, some conventional corrections, such as data gridding and phase corrections are still prerequisite for these regularized techniques.

In this study, we improve the accuracy of SENSE-based EPI reconstruction without acquiring calibration data for Nyquist ghost correction. All physical effects mentioned above are integrated into a single forward model rather than considering them separately. Two models are introduced herein, namely, Model-I and Model-II. Model-I aims to generate the individual even and odd complex-value images that are used to estimate a 2D phase map. This phase information is then fed into the proposed augmented Model-II to obtain the artifact-free EPI. The effectiveness of the proposed method is demonstrated through phantom and human brain studies. The ghost-signal-ratio (GSR) and the temporal signal-to-noise ratio (tSNR) are used to evaluate the efficiency of the proposed Model-based reconstruction. The main contributions of this work are as follows:

1. Develop a single forward model that includes the effects of the inhomogeneous B0 field-induced geometric distortion, the ramp sampling (k-space non-uniformity), and the opposite polarity readout gradient induced phase error.
2. Determine a full 2D phase difference map from the acquired EPI data itself; the even- and odd-phase images are reconstructed separately, and then used to estimate the 2D phase map.
3. Reduce the computational load using coil compression approach.

Methods

The Proposed EPI Signal Model-I

It is assumed that the phase difference between even and odd signals is unknown. In principle, the phases are already absorbed in the individual even or odd signal that can be reconstructed by using conventional reconstruction techniques. However, to obtain accurate phase images, an appropriate signal model is required. In this work, we model the individual even and odd EPI signals at any coil element j acquired with ramp sampling and under the presence of B0 inhomogeneity as:

$$s[\kappa_x, \kappa_y]^{j,+} = \iint \nu(x, y)^+ \cdot c(x, y)^j \cdot e^{-i(A[\kappa_x]x + \kappa_y \cdot \psi[y])} dx dy \quad [1]$$

$$s[\kappa_x, \kappa_y]^{j,-} = \iint \nu(x, y)^- \cdot c(x, y)^j \cdot e^{-i(A[\kappa_x]x + \kappa_y \cdot \psi[y])} dx dy \quad [2]$$

where $c(x, y)^j$ is the coil sensitivity of channel j . $\nu(x, y)^+ = p(x, y) \cdot e^{-i\phi(x, y)^+}$, and $\nu(x, y)^- = p(x, y) \cdot e^{-i\phi(x, y)^-}$ are complex-valued images, comprising 2D magnitude (p) and 2D phase ($e^{i\phi^+}$, $e^{i\phi^-}$), respectively. It is assumed that 2D phase differences measured between the 2D phase images from even and odd echoes are due to hardware imperfections, such as eddy-currents, imperfect sampling time, imperfect gradient shapes and field inhomogeneity, along the readout and phase encoding directions. $\psi[y]$ is the distortion field mapping physical to distorted coordinates due to B0 inhomogeneity which commonly considers only shifts in the phase encoding direction. $A[k_x]$ denotes the k-space coordinates according to the non-uniform k-space ramp sampling trajectory.

The reconstruction goal in Eq. 1 and Eq. 2 is to produce an image residing on a Cartesian grid from non-uniformly spaced, noisy k-space samples. The recovery of a continuous domain object from finite measurements is ill-posed. In practice, a discrete-to-discrete formulation (27) is commonly suggested. Using the basic principle of this formulation, Eq. 1 and 2 can be discretized and modeled as a linear system:

$$s^{j,+} = M^+ E C^j \nu^+ + n^+ \quad [3]$$

$$s^{j,-} = M^- E C^j \nu^- + n^- \quad [4]$$

where M^+ and M^- are the binary sampling masks (1=sampled, 0=otherwise). The noise (n) in MRI is considered white Gaussian (29). The matrix $E = e^{-i(A[k_x]r_x + k_y \cdot \psi[r_y])}$ is denoting the Fourier matrix that accounts for k-space non-uniformity due to the ramp sampling in the

readout direction and image distortion caused by B0 inhomogeneity in the phase encoding direction. The direct computation of E is computationally intensive. Instead, the NUFFT-based operators (32) are commonly used as:

$$E \approx (G_{\Lambda} F_{\Lambda} D_{\Lambda}) iF [D_{\psi} F_{\psi} G_{\psi}] \quad [5]$$

where G_{ψ} is an oversampled interpolation that maps the undistorted image in regular grids onto the finer distorted grids $\psi[r_y]$. F_{ψ} is an oversampled FFT. D_{ψ} indicates a deapodization operator that accounts for the blurring introduced by G_{ψ} . The inverse FFT (iF) transforms the k-space back to image domain. G_{Λ} denotes a gridding operator that maps oversampled k-space data in uniform grids onto the actual k-space trajectory $\Lambda[k_x]$. D_{Λ} defines a deapodization that accounts for the blurring introduced by G_{Λ} . Note that the three operators within the square and round brackets are commonly referred to as NUFFT type-I and type-II, respectively.

In the model-based reconstruction (27), the desired even and odd images corresponding to Eq. 3 and 4 are iteratively reconstructed by minimizing the cost functions:

$$\mathcal{J}_1^+(\nu^+) = \|\nu^+ - A_1^+(\nu^+)\|_2^2 + \lambda \|\mathbf{L}\nu^+\|_2^2, \text{ with } A_1^+ = \sum_{j=1}^{N_c} \mathbf{M}^+ \mathbf{E} \mathbf{C}^j \quad [6]$$

$$\mathcal{J}_1^-(\nu^-) = \|\nu^- - A_1^-(\nu^-)\|_2^2 + \lambda \|\mathbf{L}\nu^-\|_2^2, \text{ with } A_1^- = \sum_{j=1}^{N_c} \mathbf{M}^- \mathbf{E} \mathbf{C}^j. \quad [7]$$

The Tikhonov regularization with tri-diagonal (1 -2 1) regularization matrix ($\mathbf{L}$) is used to reduce noise and stabilize the solution at high iteration counts. The tri-diagonal matrix was found to provide smoother solutions than an identity matrix (results not shown). This is advantageous for the regions with strong distortion. The regularization parameter (λ) is a positive integer.

Based on the PAGE framework (17,33), both non-coherent (I^{nc}) and coherent (I^c) images can be computed from the images obtained by Eq. 6 and Eq. 7 as:

$$I^{nc} = \sqrt{\sum_{k=k1}^{k2} |\nu^k|^2} \quad [8]$$

k1 corresponds to even echo, k2 to odd echo

$$I^c = \nu^+ + e^{-i\Delta\varphi} \nu^-. \quad [9]$$

The 2D phase difference between even and odd echo images (φ) can be estimated using the complex-valued images obtained from Eq. 6 and Eq. 7 via Hermitian inner product.

$$\Delta\varphi = \text{angle}(\nu^{+*} \cdot \nu^-) \quad [10]$$

The notation $*$ denotes the complex conjugate.

The PAGE results may be degraded by g-factor-related noise enhancement due to an effectively doubled acceleration of the separate echo images. To prevent such noise enhancement, we include the φ map (obtained by Eq. 10) into Model-II.

The Proposed EPI Signal Model-II

To avoid the g-factor-related noise that generally enhances when the reconstruction is applied to even and odd echoes separately, the proposed discretized EPI signal incorporates both echoes into an augmented model:

$$s^j = \sum_{k=1}^2 (M^k E C^j \varnothing^k \nu + n^k), \quad [11]$$

where $\varnothing^k$ consists of a set of phase information $\{e^{i\varphi^k}$ for $k=1$, and $e^{i\varphi}$ for $k=2\}$. Once the phase map is obtained, the artifact-free EPI ν in Eq. 11 is reconstructed by minimizing the cost function:

$$\mathcal{J}_2(\nu) = \|s - A_2(\nu)\|_2^2 + \lambda \|L\nu\|_2^2, \text{ with } A_2 = \sum_{k=1}^2 \sum_{j=1}^{N_c} M^k E C^j \varnothing^k \quad [12]$$

Importantly, the 2D phase map obtained by Model-I (Eq. 6 and Eq. 7) must be distortion free. Otherwise, a geometric mismatch artifact may be visible in the image obtained by Model-II (Eq. 12). Therefore, the distortion correction needs to be considered in both models. Moreover, the same coil sensitivities are used for both to enable SENSE. A schematic diagram of the proposed reconstruction is shown in Figure 1.

Data Acquisition

Both phantom and in vivo experiments were performed on a whole-body 7T MRI scanner (Siemens Healthcare, Erlangen, Germany) equipped with a gradient coil type “SC72AB” (70mT/m and 200 T/m/s) using a 32-channel head coil (Nova Medical, Wilmington, MA,

USA). A spherical silicon-oil phantom (diameter 17 cm) was used. Seven healthy volunteers (2 females, 5 males, 31 ± 5 years old) were scanned after informed consent according to the IRB-approved protocol. All EPI scans with fifty time points were performed using the vendor provided EPI sequence that includes 1D non-phase-encoded navigator echoes before the EPI readout and trapezoidal gradients with ramp sampling. Double-echo GRE reference data were collected using the FLASH sequence and served to estimate the B_0 field maps and coil sensitivity profiles for offline reconstruction. The imaging parameters are summarized in Table 1.

Data Processing

The reconstruction was performed offline using MATLAB (version 14, The MathWorks Inc.). The NUFFT type-I, type-II and their adjoints were performed using Fessler's NUFFT package (34). The $2\times$ oversampling min-max optimized Kaiser-Bessel interpolation (32) was used for both types of NUFFT. Zero-padding was employed for all partial Fourier data.

For the conventional reconstruction pipeline, 1D phase correction (5) and 1D gridding (35) were applied before combining all coil images. Coil-combination by the root-sum-of-square method and iterative regularized SENSE were used for the fully sampled and the undersampled data, respectively. In this work, the abbreviations “Conv+DiCo” and “Conv” represented the conventional reconstruction with and without distortion correction, respectively. Note that the distortion correction was applied after image reconstruction using the standard method (36).

Phase unwrapping is required if phase wraps are presented in the ϕ image. Moreover, the raw ϕ map contains g-factor noise (11,37). Before taking ϕ into account, an image denoising technique was applied. In this work, we employed the wavelet-based toolbox (denC2D.m, (38)). This algorithm requires two parameters reflecting image noise and signal threshold. Specifically, the forward discrete wavelet transforms (DWT) over 4 scales is first applied to the noisy image. Then a soft thresholding is applied to the wavelet coefficients through all scales and sub-bands. After soft thresholding, the denoised image is obtained by an inverse DWT.

The Tikhonov regularization via conjugate gradient (CG) solver was employed in both conventional ($R > 1$) and the proposed Model-based reconstructions. The regularization parameters (λ) were manually adjusted based on visual perception. λ was fixed for the time series to avoid SNR variation. The optimal λ values for the proposed method were between 3×10^4 and 3.5×10^4 . The number of iterations was fixed at 20. The Jacobian determinant of the spatial transformation was applied in the final step after solving Eq. 6, 7, and 12.

Coil Sensitivity Estimation and Data Compression—We required accurate phase information from the individual undersampled even and odd signals as described in Model-I. In general, multi-channel phase reconstruction presents a difficult challenge because all channels have spatially varying phase offsets. A homogeneous reference scan, such as that from a body coil, is required to remove the coil-specific phase. In the absence of a body coil, the eigenvalue-based coil estimations (39,40) are usually used to address this problem. In this work, we applied the method introduced in (41), which employs a virtual body coil

concept (42). The reference channel that can replace the body coil is obtained by applying singular value decomposition (SVD) coil compression. The dominant singular vector (the first channel) is used as the reference. The Walsh method (39) and standard estimation (11) were applied to the compressed images to obtain the coil sensitivity maps. Note that the TE₁ data from the double-echo GRE were used to calculate the coil sensitivities. The aliased EPI was compressed using the eigenvectors derived from GRE at identical slice positions.

Voxel Shift Map—The VSM was estimated from double-echo GRE. The processing steps are as follows. First, the phase difference is calculated from two TE images as:

$$\Delta\varphi = \text{angle}\left(\sum_{j=1}^{N_c} I_{1j}^* \cdot I_{2j}\right) \quad [13]$$

where I_{1j} and I_{2j} are the TE₁ and TE₂ complex-valued images of coil element j , respectively. Second, $(\Delta\varphi)$ was used to estimate the B₀ field and the voxel shift maps via the FieldMap toolbox (SPM8). Since the VSM was obtained by the GRE images with matrix 112×112, a cubic interpolation was applied to up-sample the low resolution VSM to match the EPI with a matrix size of 160×160.

Ghost-to-Signal Ratio, Temporal Signal-to-Noise Ratio—To calculate the GSR, four regions of interest (ROIs) within the ghost and within the object (free of ghost), and one noise ROI (outside object and ghost) were drawn. The ghost-ROI was drawn in the Nyquist ghost area outside the brain/object with highest signal intensity. All ROIs are shown in Figure 2a. Each ROI covered 100 pixels. The GSR was calculated as:

$$\text{GSM} = \frac{1}{4} \sum_{i=1}^4 \left(\frac{NI_i - BI}{SI_i} \right) \quad [14]$$

where NI_i and SI_i are the mean of Nyquist ghost and signal intensities at ROI i , respectively. BI is the mean of background noise intensity at a chosen ROI.

The tSNR in EPI time-series images x_j was defined by;

$$\text{tSNR} = \frac{\mu}{\sigma} = \frac{\mu}{\sqrt{1/N \sum_{i=1}^N (x_i - \mu)^2}} \quad [15]$$

where N is the number of time points; μ is the mean of the time series; and σ is its standard deviation.

Results

The proposed reconstruction used higher resolution FLASH calibration to estimate the coil sensitivities, resulting in lower noise images compared to the use of the scanner default (EPI calibration). To ensure a fair comparison, the traditionally reconstructed images were also obtained by the offline reconstruction (using FLASH calibration) unless otherwise stated. Data-112 and Data-160 denote the EPI data sets with matrix 112×112 and 160×160 , respectively.

Phantom Studies

In Figure 2a, the 1st column shows the strong geometric distortions in the fully sampled ($R=1$) image obtained from the conventional reconstruction. The 2nd column shows that these distortions were corrected in post-processing by the voxel shift map method. The image shapes appeared mostly similar to the image obtained by the proposed Model-based reconstruction (3rd column). However, the Nyquist ghosting (2nd row, 2nd column) remained high as in the image without distortion correction (2nd row, 1st column). In contrast, the proposed Model-based reconstruction corrected both the geometric distortions and the Nyquist ghosting (3rd columns). As expected, the distortions and the ghosting were smaller in the undersampled ($R=2$) images reconstructed from either the conventional technique (4th column) or the Model-based reconstruction (6th column). Nevertheless, small residual artifacts in the white dashed boxes caused by coil sensitivity mismatch were visible. In the 3rd row, the tSNR obtained from the proposed Model-based reconstruction appeared higher than the tSNR obtained from the conventionally reconstructed images in both fully sampled and undersampled ($R=2$) data.

In Figure 2c, GSRs up to $11.20 \pm 1.50\%$ and $6.99 \pm 1.21\%$ were detected in fully sampled images (both Data-112 and Data-160) reconstructed using the conventional technique. The GSRs were strongly reduced to $1.30 \pm 0.80\%$ and $1.31 \pm 0.78\%$ when the identical data sets were reconstructed using the proposed Model-based method. For the undersampled ($R=2$) data sets, the GSRs obtained by the Model-based reconstruction were lower than for the conventional reconstruction; all GSRs were less than 2% in all the methods.

Figure 2d demonstrates that the average tSNR values obtained by the proposed Model-based reconstruction were higher than for the conventional reconstruction in all the data sets. For the fully sampled data sets, the average tSNR increased by 7.31% and 8.84% at Data-112 and Data-160, respectively. For the undersampled ($R=2$) data sets, the average tSNR increased by 3.89% and 4.12% at Data-112 and Data-160, respectively.

In Vivo Studies

Phase Difference Map—Figure 3a shows that the coil sensitivity mismatches appeared slightly raised in the phase difference images obtained by regularized CG-SENSE (1st column) compared to GRAPPA (2nd column). Note that 48 lines of the fully sampled GRE at the center of k-space were used to calculate the GRAPPA kernels. After GRAPPA reconstruction, all coil images were combined using the coil compression concept, as described in a previous section. Such artifacts were reduced efficiently by the proposed

Model-I that includes the geometric distortion correction (3rd column) and completely suppressed by the image denoising (4th column). Figure 3b shows that the slopes of the linear phase ramp vary slightly at different locations in the phase encoding direction, i.e., -0.061, -0.055, and -0.058 radians/pixel in the front (blue line), center (green line), and back (red line) of the axial brain slice, respectively. Figure 3c shows the profile plots at the corresponding black line on the 3× undersampled phase map obtained by Model-I reconstruction. The residual aliasing artifacts in the raw phase map appear dominant along the ramp (red line). These variations were reduced in the denoised phase maps and much smoother when using larger threshold values.

Model-based vs. Conventional Reconstructions—In Figure 4, strong geometric distortions were clearly visible in the fully sampled image obtained by the conventional reconstruction (a1). Although such artifacts were corrected in the post-processing step (b1), the intensities of ghost artifacts were identically high even with distortion correction (a2 vs. b2). Although parallel imaging remarkably reduced both geometric distortions and Nyquist ghosts (d2), the residual artifacts remained substantially higher compared to the Model-based reconstruction (f2). Since the residual artifacts could be minimized by the proposed method, as clearly illustrated in c1 and f1 images, the Model-based reconstruction provided higher tSNR values in both fully sampled and undersampled (R=2) data sets (c3 and f3), compared to the conventional reconstruction (a3, b3, d3 and e3).

In Figures 4h and 4i, the shapes of the conventionally and Model-based reconstructed images appeared similar due to further reduction of geometric distortion strength with higher reduction factor (R=3). However, the residual artifacts caused by an inaccuracy of the phase correction were clearly visible in the conventionally corrected images from two different subjects as highlighted by the black boxes. Consequently, the tSNR values in the corresponding regions were lower.

Figure 5a shows that the conventional reconstruction yielded higher levels of ghosting with GSR values of $7.02 \pm 1.72\%$ and $7.79 \pm 2.25\%$ in the Data-112 and Data-160 (R=1), respectively. With the proposed Model-based reconstruction method, the GSRs were reduced in the same data sets to $1.57 \pm 0.59\%$ and $1.39 \pm 0.72\%$, respectively. For the undersampled (R=2) data sets, the GSR values of $1.12 \pm 0.32\%$ and $2.68 \pm 1.42\%$ for Data-112 and of $0.61 \pm 0.31\%$ and $2.82 \pm 1.65\%$ for Data-160 were measured, respectively with the Model-based and the conventional reconstruction.

The improvements in tSNR are shown in Figure 5b. For the fully sampled data sets, the increases of average tSNR were 9.24% and 7.64% at Data-112 and Data-160, respectively. For the undersampled (R=2) data sets, the increases of average tSNR were 5.59% and 6.34% at Data-112 and Data-160, respectively.

In Figure 5c, the (geometry) g-factor maps were used to quantify the g-noise originated from same k-space data, but reconstructed using two different reconstruction schemes. These maps were calculated by using the pseudo multiple-replica method (43) that emulates acquisition of image replicas by adding complex-valued noise to the acquired k-space data before image reconstruction. In this study, we repeated 100 reconstructions using identical

data and newly synthesized noise. The g-factor maps obtained by the conventional reconstruction were mostly identical to the maps obtained by the proposed method with the denoised phase maps (both R=2 and R=3 data sets). In contrast, without denoising, the g-noise corrupted the raw phase maps and propagated into the proposed reconstructed images, which resulted in higher g-factors. When compared with the results obtained by the vendor-provided reconstruction, the improvements were even more significant, as demonstrated in Figures 5d and 5e.

Model-based vs. PAGE reconstructions—Figure 6a illustrates the magnitude images obtained from PAGE and Model-based reconstructions. Note that the individual even and odd echo images used for PAGE combinations (Eq. 8 and Eq. 9) were reconstructed using regularized SENSE without integrated distortion correction. The 2× undersampled images obtained from both techniques appear similar. However, the noise amplification is clearly visible in the 3× undersampled images obtained by PAGE, particularly in aliased regions as illustrated by the red ovals. In contrast, this artifact was suppressed by the proposed method even with a small number of iterations.

Figure 6b illustrates that PAGE can preserve phase information when combining the even and odd echo images using the complex-value summation (Eq. 9). This phase information is also well preserved by the proposed technique. Note that phase singularities were found in some regions when using the coil sensitivities obtained by Walsh's method (results not shown). This is because phase singularities in the first SVD coil sensitivity propagated into the complex result. However, such non-physical phases did not affect the φ images (Model-I) and the magnitude of the final EPI (Model-II). The ghosting level in all images shown in Figure 6c is low. Note that after applying SENSE to the separate echoes, the Nyquist ghost can be fully absent in the even image, odd image, and also their RSS (Eq. 8). However, a small residual artifact outside the brain (yellow ovals in 6c) appeared due to the geometric mismatch of coil sensitivity and the interaction of smoothed phase in the regions of large local phase changes. In Figure 6d, for 2× undersampled data, the tSNR values obtained by the Model-based reconstruction are only slightly higher than for PAGE. However, the noise amplification in 3× undersampled images obtained by PAGE causes a large decrease in tSNR compared to the tSNR obtained by the proposed technique.

Model-based Reconstruction with and without Geometric Distortion

Correction—In practice, the resolution of a standard double-echo GRE used to create a field map is generally lower than high resolution EPI data (44). We evaluated the efficacy of the proposed reconstruction for matched resolution and for lower resolution field maps.

Figure 7a shows the images obtained from the acquired double-echo GRE data (1.4 mm²), and lower resolution versions (2.0 mm² and 3.0 mm² obtained by truncating the k-space data). Figure 7b illustrates the B0 field maps calculated from the corresponding images in 7a. All field maps are visually identical, since they are dominated by the smoothing Gaussian filter of FWHM=10 pixels (SPM8 default). The shapes of all images in 7c (1st -3rd columns) that were obtained by the proposed method are notably improved, using either the matched resolution or lower resolution field maps. They are well aligned with contours matching the undistorted GRE image. However, the strong distortions at frontal region of the

brain appear not completely compensated by using the smooth field map. The differences between reconstructions using lower or higher resolution field maps are nearly invisible as illustrated in 7d (1st -3rd columns). In contrast, the geometric distortion and the image difference are highly visible in the image obtained by conventional reconstruction as shown in the 4th column of 7c and 7d, respectively.

To observe solely the distortion correction effect, the distortion correction was removed from the proposed Model-based reconstruction. Specifically, the three operators in the square bracket (NUFFT type-I) in Eq. 5 were excluded. Figure 8a shows that even without the distortion correction, the Model-based reconstruction was able to provide images without ghost artifacts, which were comparable to fully corrected images (8b). However, the full correction was able to reduce geometric mismatch between EPI and reference images, particularly in the regions with the effects of inhomogeneous field up to 170 Hz (black circles in 8f). The geometric improvements furthermore resulted in higher appearance of tSNR (5e), compared to the tSNR map of the distorted images (8d).

Model-based Reconstruction from Virtual Coil Data—The processing time of the proposed method was about 15 times longer than the conventional reconstruction, since the Model-based reconstruction used NUFFT instead of FFT. Moreover, using a 32-channel receiver coil increased the data size. Therefore, we employed coil compression (45) that allows a significant reduction in the number of channels and reconstruction time.

All virtual coil images displayed in Figure 9a were obtained by the proposed Model-based reconstruction. Since all images in Figure 9a were visually indistinguishable, the image intensity differences compared to the reference (32-Ch) image were calculated and are shown in Figure 9b. The differences between 8-Ch and reference images were more clearly visible than the differences between 16-Ch and reference. As shown in Figure 9d, the processing time increased linearly with the number of virtual coils used. The histogram plots in Figure 9e show that the distributions of tSNR values obtained from 32-Ch, 16-Ch, and 8-Ch were mostly similar with mean values 60.11, 59.87, and 59.70, respectively.

In Figure 9f, the tSNR values of individual data sets different resolutions and reduction factors were somewhat stable between 12 and 28 virtual coils. The tSNR's changes between 12 and 28 virtual coils were less than 1.2% in all data sets. The maximum change was detected in undersampled (R=2) data sets with 8 virtual coils (3.2% and 2.5% at Data-112 and Data-160, respectively).

Discussion and Conclusions

In this study, we have demonstrated that more accurate EPI can be achieved when considering the physical perturbations in a forward signal model, and using the appropriate inverse operators to solve for the uncorrupted image from the redundant data samples across multi-channel receive array.

Recently, the use of a large number of coil elements has shown to improve the tSNR and provide clear benefits in functional experiments (46). Moreover, the use of multi-channel array coils allows highly accelerated parallel acquisition (47) and is also beneficial for the

proposed reconstruction scheme since the individual even and odd signals are prone to be highly undersampled. The 3rd row of Figure 3a shows that the phase maps obtained from the 6× undersampled data are still accurate, resulting in improved images as demonstrated in Figure 4h and 4i. The application of the proposed Model-I with a small number of coil elements may be limited at high reduction factors, and should be investigated further.

The typical 1D-Nav based phase correction is usually accurate and easy to implement on the scanner for routine use. In some cases, such as in oblique-plane imaging (48) and in the presence of cross-term eddy currents (49), however, the residual artifacts after 1D correction can yield images unsuitable for clinical use. High residual ghost artifacts in the reconstructed image were observed even in true axial imaging, particularly at longer TE and larger echo spacing (R=1 data sets). Figure 3b shows that the slopes of phase ramps vary across the axial brain in phase encoding direction. These variations clearly warrant 2D phase correction. The proposed 2D phase correction is significantly superior in suppressing the Nyquist ghosting in all data sets, as illustrated in Figures 2, 4, and 6. Previous studies have also shown that 2D approaches can be implemented more efficiently than 1D corrections (19-21,48). However, most 2D phase estimators require additional full k-space reference scans at a significant cost of temporal resolution (19-21). To avoid such acquisition time penalty, the reference-less method called 2D phase-cycled reconstruction has been recently introduced (48) and has shown robustness and reliability in single-shot EPI.

The use of parallel imaging is preferred to allow a short TE and to reduce the distortion strength, especially for high-resolution imaging at ultra-high field. For highly accelerated data acquisition, the proposed reconstruction can be superior over the PAGE method in terms of data reliability. The PAGE reconstruction becomes more ill-conditioned since the highly accelerated even and odd echo data are considered separately. In this work, after a denoising procedure for calculation of the 2D phase difference map between even and odd echoes is applied in Model-I (Fig. 3), the denoised phase map is incorporated in Model-II. We ensured that the impact of g-factor noise is negligible for 1- to 3-fold accelerated data when using the proposed reconstruction with the incorporation of phase difference map denoising (Figure 5c). In principle, the phase difference between even and odd echoes has a specific slope and intercept. The denoising technique with large thresholding may change these properties, resulting in remaining Nyquist ghosting in the corrected image. In this work, threshold values of 0.1-0.4 were appropriate. We also found that the denoising technique can be applied to the complex-value of the individual even and odd images (50) before calculating the phase map. However, the final images were mostly identical (results not shown). Alternatively, instead of using the phase maps obtained by Model-I, the 2D phase maps obtained from abovementioned techniques (19-21,48) may be incorporated with the proposed Model-II to avoid potential g-factor penalties.

In general, several factors affect tSNR maps, including the voxel size, TE, reduction factor, and the sampling bandwidth (51). Moreover, the tSNR maps can vary depending on the reconstruction used. In this study, the proposed Model-based reconstruction provided slightly higher tSNR maps compared to the conventional method for all data sets (in both phantom and in vivo brain studies). The residual phase errors are likely to be a major cause of the tSNR alterations. Figure 2d and 5b show that the increase in the residual ghosts is

associated with the decrease in tSNR as clearly demonstrated in the fully-sampled data sets. However, in principle, there is no direct relationship between the residual ghosting and tSNR. This means that if the residual ghosts are constant over time, the tSNR will be not degraded (18). Figures 2d and 5b show that although the Nyquist ghosts can be largely removed after applying the proposed reconstruction, the tSNR values are only slightly improved. This may be because the residual ghosting after the conventional reconstruction fluctuates along time series. Unlike the ghost artifacts that interfere with the entire brain/object volume, the geometric distortions that cause the mismatch of coil sensitivity and EPI alter the tSNR only in the local regions with highly inhomogeneous B₀ field, as demonstrated in Figure 8. Recently, high residual ghosting has been shown to cause false positives in functional MRI (6,52). The efficiency of the proposed method for fMRI application will need to be investigated further in future studies.

Field map based distortion correction only adjusts the shape of the EPI and does not recover missing signal due to intra-voxel dephasing. Moreover, filtering is commonly applied to the field map to reduce noise, which therefore does not accurately model local inhomogeneities such as the regions near air-tissue interfaces. As a result, residual geometric distortions can remain as seen in Figure 7c (1st-3rd columns) and 8b (see the superimposed contours). The distortion correction aspect of the proposed reconstruction could be replaced by other existing methods such as inverse phase encoding (PE) (53) or PSF methods (3,14). The performance of the distortion correction will depend on the base method. Using the explicit PSF kernel or inverse PE shift map instead of the field map may render the proposed method even more accurate.

The advantage of the NUFFT type-II over the conventional gridding is visually indistinguishable in this study. This may be due to the ramp sampling that introduces the non-uniformity only at the peripheral part of k-space data. These corrupted data still satisfy the Nyquist criterion (no undersampling effect), for which conventional gridding appears to be sufficient. However, the proposed method is expected to be applicable for arbitrary k-space trajectories, such as spiral, PROPELLER (54), and radial acquisitions, which generally result in more non-uniform and undersampled k-space data.

A few challenges require further investigation. First, care should be taken when multiple receiver coils are used for reconstructing the phase image. For a single coil, the signal phase includes the phase of the magnetization added to the phase of the coil sensitivity. For multiple coils, each coil could be used for determination of the magnetization phase, but this would require removal of the receiver coil phase. Various methods have been introduced to optimally combine magnitude and phase images. The method of Roemer (55) and SENSE (11) can be used when the coil sensitivities are known. Because the coil sensitivities are usually not known, methods for estimating the coil sensitivities from the complex-valued images have been developed (39,56). Recently, Chatnuntawech et al. (41) proposed a novel coil sensitivity estimation that is fully automated and allows high-quality parallel imaging whilst preserving the image phase. This method is a combination of SVD compression (42) and ESPIRiT (40), and has shown to be largely beneficial for phase sensitive QSM at 3T. In this study, however, a global SVD appeared not local enough to create a smooth, singularity-free virtual body coil at 7T, resulting in phase singularities (results not shown). Fortunately,

this non-physical phase did not impact the φ images as shown in Figure 3a. However, if the phase wraps remain in the φ images, the phase singularities may inhibit the efficiency of the phase unwrapping techniques, and may result in errors in the final images (Model-II). In this study, although the standard coil sensitivity estimation (11) provided singularity-free phase images at 7T equipped with a 32-channel coil, it may not be guaranteed to work with different coil geometries or at even higher field. To address this challenge more advanced methods could be applied, e.g. (i) birdcage mode reception as reference “body coil” if this is a transceive array (41), or (ii) block coil compression (57). Second, the successful application also depends on proper selection of regularization parameter (λ) that controls the degree of smoothness imposed on the reconstruction. A heuristic method such as the L-curve method (58) could be used to select λ . Third, the proposed iterative reconstruction is much more time consuming than conventional reconstruction even after employing coil compression. The application of highly parallel computing and/or graphics processing units (GPUs) (59) may be ideally suited to improve the reconstruction speed. Finally, the proposed reconstruction may be limited when motion occurs between the pre-scan calibration and EPI acquisitions. In general, when the subject moves, the local field will also change (60). As a result, the pre-scan field map would no longer be accurate. In this case, EPI-based B0 field maps at any time points (61) could be utilized. The relative motion of coil sensitivities is another concern. However, this effect is negligible in fMRI (62) where only small movements occur.

In conclusion, this study demonstrates that an improved EPI quality can be achieved by using the proposed Model-based reconstruction scheme that corrects for physical perturbations during the reconstruction rather than before or after the image reconstruction. The stable reduction in Nyquist ghosting and distortion can improve the tSNR of EPI time series. Finally, using fewer virtual coils can speed up the reconstruction and still provide acceptable results with very small loss in tSNR.

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Fig. 1.
The pipeline of the proposed single-shot EPI reconstruction.

Fig. 2.

(a) (*1st row*) Images with the superimposed red contours illustrated the image geometries, (*2nd row*) images displayed to show ghost intensities outside the object, (*3rd row*) the tSNR maps calculated from EPI time-series at the corresponding slices in (*1st row*). The small air bubbles in the black oval (R=1) create a susceptibility artifact, compromising the tSNR in the corresponding regions. (b) (*upper*) The reference GRE image, (*bottom*) the B0 field map at the corresponding slices in (a). (c) The average GSR $\pm$ SD% over 30 slices. (d) The average tSNR $\pm$ SD inside the object ROI over 30 slices. The difference within each group in (c) and (d) is statistically significant (pair t-test **P<0.01, *P<0.05).

Fig. 3.

(a) The differences between even and odd phases (ϕ) (matrix size 160×160) obtained by regularized SENSE (1st column), GRAPPA (2nd column), and Model-I (3rd column). The superimposed values on the last column images indicate the threshold values used for denoising. (b) The profile plots of the phase ramps along the readout direction at three different locations that correspond to the same color lines in the denoised image. (c) The profile plots at the same corresponding black line in (a), but different threshold values used for the denoising technique.

Fig. 4. Reconstructed images with the superimposed red contours demonstrating the image geometries (**a1-f1**) and with image contrast adjustment to highlight ghost intensities outside the brain (**a2-f2**), corresponding tSNR maps (**a3-f3**), and a reference GRE (**g**). In **h** and **i**, the images ($R=3$) are displayed to show residual artifacts in the black boxes (*upper left*), the improvements (*upper right*), and corresponding tSNR maps (*bottom*).

Fig. 5.

(a) The average GSR $\pm$ SD% over whole brain volume (30 slices) of seven subjects. (b) The average tSNR $\pm$ SD inside the brain ROI (over 30 slices) of seven subjects. The difference within each group in (a) and (b) is statistically significant (pair t-test $**P < 0.01$, $*P < 0.05$). (c) The masked g-factor maps at the corresponding slice displayed in Figure 4a-4h. (d and e) *upper row*; the 2 $\times$ undersampled images obtained from the scanner vendor reconstruction, in which the GRAPPA kernel was calculated from EPI based auto calibration signal (ACS), *bottom row*; the images obtained by the Model-based reconstruction from the same raw data.

Fig. 6.

(a) Images obtained from PAGE and the proposed Model-based reconstructions. (b) Phase images corresponding to the magnitude in (a). (c) Images displayed to show ghost intensities outside the brain regions. (d) The tSNR maps calculated from EPI series data.

Fig. 7.

(a) The different resolution GRE images used for calculating the B0 field maps. (b) The B0 field maps obtained from the corresponding images in (a). (c) 1st - 3rd columns; the images obtained by the Model-based reconstruction with the corporation of the corresponding B0 field maps, 4th column; the conventional reconstructed image. (d) Each image in (c) subtracted from the 1st column image in (c).

Fig. 8. (a and b) The undersampled ($R=2$) images (matrix 160×160) obtained by the Model-based reconstruction without (a) and with (b) the geometric distortion correction. (c) The reference GRE image. (d and e) the tSNR maps calculated from EPI series data. (f) The B_0 field map at the corresponding slice in (a and b).

Fig. 9.

(a) Three different virtual coil images ($R=2$, matrix 160×160) reconstructed using the Model-based. (b) The identical windowed difference images, i.e., each image was subtracted by the image obtained from 32-Ch data. (c) The tSNR maps calculated from EPI series data at the corresponding slice in (a). (d) The plot for a number of virtual coils against a processing time per iteration of CG for the matrix size 160×160 . (e) The histogram plots displayed the tSNR distributions inside brain ROI corresponding to the tSNR maps in (c). (f) The plots for a number of coils against the average $tSNR \pm SD$ values inside the brain ROI of seven subjects. The tSNR of four groups at different reduction factor and resolution are obviously different. However, the differences within each group are not statistically significant as measured by one-way ANOVA ($P > 0.05$).

Table 1

Parameters of the MR imaging sequences.

Sequence	R	Matrix size	TR (ms)	TE ₁ /TE ₂	p.F.	Readout BW (Hz/pixel)	Effective ESP (μs.)
FLASH	1	112×112	367	3.6/4.6	off	1540	-
EPI	1	112×112	2350	26	6/8	1540	710
	2	112×112	2000	26	off	1540	365
	1	160×160	3080	35	6/8	2230	700
	2	160×160	2310	35	off	2230	360
	3	160×160	2000	26	off	2230	180

* R: reduction (acceleration) factor; p.F: partial Fourier; BW: bandwidth; ESP: echo spacing; 1 mm. slice thickness, 30 slices, and 224 mm² FOV for all scans.