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Dynamic 2D Self-Phase-Map Nyquist Ghost Correction for Simultaneous Multi-Slice EPI

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Abstract

Purpose—To develop a reconstruction pipeline that intrinsically accounts for both simultaneous multi-slice echo planar imaging (SMS-EPI) reconstruction and dynamic slice-specific Nyquist ghosting correction in time series data.

Methods—After 1D slice-group average phase correction, the separate polarity (i.e. even and odd echoes) SMS-EPI data were unaliased by slice-GRAPPA. Both the slice-unaliased even and odd echoes were jointly reconstructed using a model-based framework, extended for SMS-EPI reconstruction that estimates a 2D self-phase map, corrects dynamic slice-specific phase errors, and combines data from all coils and echoes to obtain the final images.

Results—The percentage ghost-to-signal ratios (%GSR) and its temporal variations for MB3R_y2 with a FOV/4 shift in a human brain obtained by the proposed dynamic 2D and standard 1D phase corrections were 1.37 ± 0.11 and 2.66 ± 0.16 , respectively. Even with a large regularization parameter λ applied in the proposed reconstruction, the smoothing effect in fMRI activation maps was comparable to a very small Gaussian kernel size $1 \times 1 \times 1 \text{ mm}^3$.

Conclusion—The proposed reconstruction pipeline reduced slice-specific phase errors in SMS-EPI, resulting in reduction of GSR. It is applicable for fMRI studies since the smoothing effect caused by the regularization parameter selection can be minimal in BOLD activation map.

Keywords

Nyquist ghost; slice-specific phase correction; self-phase map; SMS-EPI

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INTRODUCTION

Echo-planar imaging (EPI) (1) has been the most common imaging technique for fMRI (2) due to its high blood-oxygen-level-dependent (BOLD) sensitivity and fast acquisition speed (~tens of milliseconds per slice). To cover a whole brain with high spatial resolution, however, a long repetition time (> 3 sec.) was typically required, until the recent introduction of Simultaneous Multi-Slice (SMS) imaging (3–5) allowed reduction of the repetition time for high-resolution whole-brain coverage.

In SMS imaging, multiple slices are simultaneously excited and acquired. The superimposed slice signal is subsequently unfolded using parallel imaging techniques such as SENSE (6) and GRAPPA (7). Among various promising techniques (8–10), slice-GRAPPA reconstruction scheme (5) is the most widely-used method for blipped-controlled aliasing in parallel imaging (blipped-CAIPI) SMS-EPI. This scheme uses single band (SB) calibration data, which are mostly identical to SMS-EPI in terms of resolution, imaging contrast, Nyquist ghost level, and echo spacing (ESP) to estimate the slice-GRAPPA kernels that are subsequently used to unfold the superimposed slice signals. To further reduce artifacts that may arise from misalignment of even and odd echoes in k-space, the two-kernel slice-GRAPPA method was proposed (11). This method requires two 1D phase corrections including the slice-group average and slice-specific ghost corrections, which are performed before and after slice-GRAPPA (8,11), respectively. Note that the latter correction utilizes a 1D non-phase-encoded single slice navigator (1D-SB-Nav) which is usually acquired once prior to the SMS-EPI time series.

Alternatively, when SB-Nav data are available, they can also be incorporated with other existing slice-specific Nyquist ghost correction schemes. For example, 1) an algebraic reconstruction, which is a hybrid-space SENSE method (12), directly inverts the encoding matrix in the hybrid x - k_y - k_z -space after stripping the fully sampled x -direction (readout) and can therefore handle arbitrary, non-periodic CAIPI blip patterns. This method can also incorporate an echo and slice-specific phase ramp into the signal equation. 2) a 2D-NGC-SENSE-GRAPPA (13), where NGC stands for Nyquist ghost correction, is able to reconstruct SMS-EPI together with Nyquist ghost correction in a single step. Specifically, fully sampled ACS data are introduced and have the same zigzag pattern as the slice-aliased MB imaging data before being used for training 2D SENSE-GRAPPA kernels. However, all the above-mentioned reconstruction schemes still utilize static 1D-SB-Nav calibration data to handle the phase error in dynamic MB data as in an fMRI experiment. This may lead to increased residual ghosting artifacts in case of subject motion or eddy current variations at different time points. Although dynamic 1D-MB-Nav calibration data (obtained simultaneously from multiple slices and collapsed in the same way as the image data) are available, they cannot be used for slice-specific phase correction, because there is no known way to separate the non-phase-encoded navigator data, i.e., to create slice-specific navigator data. Furthermore, 1D-based phase correction often results in images with residual ghosting (14). Such artifacts can be suppressed more effectively by 2D correction, but at the cost of an additional full k-space reference scan (15,16).

In this study, we propose a dynamic 2D slice-specific phase correction to address the slice-specific phase error. This correction scheme does not require additional time for acquiring 2D phase difference scans. We introduce two sequential steps consisting of slice unfolding and in-plane reconstruction to reconstruct SMS-EPI data accounting for the slice-specific Nyquist ghosting using 2D self-phase maps. For *slice unfolding*, even- and odd-kernel slice-GRAPPA (5) were applied to the individual even- and odd-echo SMS-EPI data, respectively. For *in-plane reconstruction*, the individual slices of even and odd echoes were jointly reconstructed by using a model-based framework (17), which includes slice-specific phase difference estimation and coil combination. These phase difference maps, referred to as 2D self-phase maps, were estimated from the imaging data itself. They were also employed during the coil combination process. The effectiveness of the proposed method was evaluated in phantom and human brain experiments.

METHODS

Data Acquisition

All data sets were acquired on a 3T MR (80 mT/m gradients) (Prisma, Siemens Healthineers, Erlangen, Germany) using a 64-channel head/neck coil. Two healthy volunteers were scanned after informed consents according to the IRB-approved protocol. All scans were performed using a 2D blipped CAIPI multiband EPI sequence from the Center for Magnetic Resonance Research, University of Minnesota. This sequence sets the FOV shift automatically, in which FOV/3 and FOV/4 are the default values for in-plane acceleration factors of one and two, respectively.

For testing the proposed algorithm, both phantom and in vivo brain data sets were investigated. The imaging parameters were as follows:

Data set 1(Phantom)

- Multiband factor 4, in-plane acceleration factor 1, and TE/TR =30/3000 ms.

Data set 2(Phantom)

- Multiband factor 6, in-plane acceleration factor 2, and TE/TR =30/2050 ms.

Data set 3 (in vivo)

- Multiband factor 3, in-plane acceleration factor 2, and TE/TR =30/3200 ms.

Data set 4 (fMRI)

- An fMRI experiment using SMS-EPI with MB3R_y2 was performed on the second volunteer. The entire brain was covered using 78 slices with 1.5 mm isotropic resolution and the following parameters: matrix size = 140 × 140, FOV = 210 × 210 mm², partial Fourier = 6/8, TE/TR = 40.6/2000 ms, echo spacing = 0.93 ms, flip angle = 84°, FLASH-ACS with 48 central k-space lines, and 180 measurements. A standard four-finger tapping task was performed. The volunteer was instructed when to tap and rest using a visual cue. The tasks were carried out in block design with each block comprising

30 seconds of rest followed by 30 seconds of right hand finger tapping. The blocks were repeated six times for a total of six minutes of scanning.

Note that the data sets 1–3 were acquired using 50 measurements with the following identical parameters: 24 slices with 2 mm slice thickness, matrix size = 128×128 , FOV = $192 \times 192 \text{ mm}^2$, partial Fourier = 6/8, echo spacing = 0.67 ms, flip angle = 90° , and FLASH-ACS with 32 central k-space lines. Data sets (1 and 2) were reconstructed using the same sensitivity maps.

Proposed Reconstruction Pipeline

The reconstructions were performed offline using MATLAB (version 2015b, The MathWorks Inc.). Figure 1 depicts the proposed reconstruction pipeline. The re-gridding (18) and 1D slice-group average phase correction (PC) were applied to both SB calibration and MB aliased data prior to the following image reconstructions.

The multiband data reconstruction—Slice-GRAPPA (5) was applied to the even and odd multiband data (s_{MB}^{l+} and s_{MB}^{l-}) separately using the following formulations to mitigate slice-aliasing:

$$S^{j,z}(k_x, k_y)^{+/-} = \sum_{l=1}^L \sum_{b_x=-B_x}^{B_x} \sum_{b_y=-B_y}^{B_y} w_{j,z,l}^{b_x, b_y, +/-} s_{MB}^{l+/-}(k_x - b_x \Delta k_x, k_y - b_y \Delta k_y) \quad [1]$$

where $S^{j,z+}$ and $S^{j,z-}$ are the slice-unaliased even and odd k-space data of the j -th coil at the z -th slice. $w_{j,z,l}^{b_x, b_y, +}$ and $w_{j,z,l}^{b_x, b_y, -}$, the even and odd weight coefficients at location (b_x, b_y) in the slice-GRAPPA kernels of coil l are estimated from the even and odd echoes of the SB calibration data, respectively. To avoid signal leakage between the simultaneously acquired slices after unaliasing, the slice-blocking technique (19) was incorporated during the kernel calculation. A kernel size of 5×5 was used in all experiments. The CAIPI FOV shift and zero-padding (partial Fourier) were performed prior to the individual slice reconstruction. Note that two separated slice-GRAPPAs are analogous to the two-kernel slice-GRAPPA (11).

The individual slice reconstruction

Iterative SENSE: This step aimed to reconstruct the even and odd complex-valued images that will then be used to estimate the residual phase difference map. In principle, when the even and odd echoes are separated, its individual complex-valued image can be obtained using standard parallel imaging reconstruction (7,20). Here, the iterative SENSE was chosen, since it provides flexibility in modeling the physical effects directly, which may be convenient when non-Cartesian sampling or spatial distortions are considered. In this step, two optimization problems were formulated and solved using the conjugate gradient (CG) method (20):

$$\min_{v^{+/-}} \left\{ \|s^{+/-} - A_1^{+/-}(v^{+/-})\|_2^2 + \lambda \|L v^{+/-}\|_2^2 \right\}, \text{ with } A_1^{+/-} = \sum_{j=1}^{N_c} M^{+/-} F C^j \quad [2]$$

where $v^+ = p \cdot e^{-i\phi^+}$, and $v^- = p \cdot e^{-i\phi^-}$ are complex-valued images, comprising magnitude (p) and phase ($e^{i\phi^+}$, $e^{i\phi^-}$), respectively. M^+ and M^- are the binary sampling masks (1=sampled, 0=otherwise). F denotes the discrete Fourier transform. The Tikhonov regularization with a tri-diagonal (1-2 1) regularization matrix (L) was used to reduce noise and stabilize the solution at high iteration counts (21). The regularization parameter (λ) is a positive real number. Coil sensitivity C^j of the channel j was calculated from FLASH-ACS, since it can improve the SNR and tSNR of EPI time series (22). In this work, ESPIRiT (23), which is available within the Berkeley Advance Reconstruction Toolbox (BART) (24), was employed to estimate the coil sensitivities from the FLASH-ACS data.

2D phase difference map estimation for even and odd echoes: After solving Eq. 2, the 2D residual phase difference map (ϕ) can be estimated as follows:

$$\Delta\phi = \text{angle}(v^+ * v^-). \quad [3]$$

The notation $*$ denotes the complex conjugate. Due to the effective doubling of the under-sampling factor in this reconstruction, g-factor noise enhancement in the raw ϕ images occurs. Such noise can propagate into the final reconstructed image (17). To address this issue, we applied 2D polynomial least squares fitting to the estimated phase maps. Specifically, in two dimensions, a complete n^{th} order polynomial is given by,

$$\Delta\phi_n(x, y) = \sum_{\substack{p, q \\ p+q \leq n}} a_{p, q} x^p y^q \quad [4]$$

Only the values at masked regions were used to estimate the coefficients $a_{p, q}$ in Eq. 4. Note that a binary mask was constructed using a threshold of 60% of the mean pixel value of the magnitude image which was obtained by Eq. 2. Optionally, within a noisy region, where the polynomial technique may provide inaccurate results due to overfitting, a smoothing filter can be used instead. In this work, a cosine taper with a kernel size 7×7 was chosen for a convolution in image space (see Figure 2).

Iterative Augmented SENSE: To prevent excessive undersampling when the even and odd echoes are considered separately, we formulate an optimization problem with a single forward operator (A_2) that includes both echoes. Specifically, to estimate the artifact-free EPI (v), we solve the following optimization problem using the CG method:

$$\min_v \{ \|s - A_2(v)\|_2^2 + \lambda \|L v\|_2^2 \}, \text{ with } A_2 = \sum_{k=1}^2 \sum_{j=1}^{N_c} M^k F C^j \Phi^k \quad [5]$$

where Φ^k consists of a set of phase information $\{e^{i\phi}$ for $k=1$, and $e^{i\varphi}$ for $k=2$. M^k is the binary sampling mask (1=sampled, 0=otherwise), where $k=1$ is for the even echo and $k=2$ is for the odd echo. Note that we assessed the residual artifacts from the 1st reconstructed slice (near to base of the skull), since it presents the highest noise level (for the whole brain data), to ensure the convergence of CG before choosing the number of iterations and using it for all slices. In addition, the number of iterations was set to 20, except for $\lambda = 1 \times 10^{-1}$ where slower convergence was detected and, therefore, the number of iterations was set to 25 instead.

Ghost-to-Signal Ratio and Temporal Signal-to-Noise Ratio

To calculate the ghost-to-signal ratio (GSR), three ROIs of size 15^2 pixels within the ghost, object and noise regions were drawn (see Figure 4a). The ghost was drawn in the Nyquist ghost region outside the object with highest ghost intensity (G). The image signal was drawn inside the corresponding object region (S). The GSR was calculated as, $GSR = \frac{G - N}{S}$, where N is the standard deviation of the background noise intensity (outside the Nyquist ghost and the object regions). Finally, a tSNR map of the EPI time-series was calculated as $tSNR = \frac{\mu}{\sigma}$, where μ is the pixel-wise mean of the time series; and σ is its standard deviation.

Functional MRI Data Processing

Applying the proposed reconstruction, two data sets were generated using small λ and with large λ in order to observe the smoothing effect on BOLD activation maps. The fMRI analysis was carried out using SPM version 12. Standard preprocessing steps were performed. The data were motion realigned and high-pass filtered over the EPI time series before applying the general linear model (GLM) analysis. Note that the small λ data was analyzed twice (i.e. with and without a Gaussian kernel for smoothing).

RESULTS

Residual Phase Differences and g-factor Evaluations

In Figure 2, the MB3Ry2 SMS-EPI brain data were reconstructed by two different in-plane reconstruction techniques (i.e. standard SENSE and proposed augmented SENSE). The standard SENSE was applied after 1D slice-group average phase correction and slice-GRAPPA. As a result, the image intensities appear slightly non-uniform as highlighted by red ellipses in Figure 2d and 2k. The residual phase maps corresponding to the above images are illustrated in Figure 2a and 2h. Alternatively, the 2D slice-specific phase map was incorporated into augmented SENSE and the artifacts were notably suppressed, as shown in Figure 2e–2g and 2l–2n. However, due to the ill-conditioning problem of the raw phase maps obtained from effectively double-undersampled images (even and odd), noise

amplification propagated into Figure 2e and 2l, resulting in high g-factor values (25) (small superimposed images). This problem has been mitigated when either the smoothed or polynomial-fitted phase maps were incorporated. With the improved phase correction, both image intensity variations in local areas and the fluctuations over repetitions were reduced, as shown in Figures 2o and 2p.

Conventional 1D versus Proposed 2D Phase Corrections

In Figure 3a, standard SENSE reconstruction without slice-specific phase correction resulted in residual artifacts (red boxes) and Nyquist ghosting (red ellipses) leading to tSNR reduction of the corresponding regions. In Figure 3b, the Nyquist ghosting artifacts in a more homogeneous slice were reduced when the 1D slice-specific phase correction was also applied before the standard SENSE. Nevertheless, the phase interferences were still unchanged in the regions of field inhomogeneities (red boxes). These artifacts were mitigated with the proposed 2D slice-specific phase correction (Figure 3c), resulting in increased tSNR.

CMRR-provided versus Proposed Reconstructions

Figure 4a shows that the Nyquist ghost levels on the images obtained by the CMRR-provided reconstruction remained high in both phantom and in vivo brain. In the chosen ROIs (appearance of highest ghost intensity), mean $\pm$ standard deviation of GSR over all time points of in vivo brain (180 measurements) is $2.66 \pm 0.16\%$. Moreover, in the phantom studies (50 measurements), GSR values for both MB4 and MB6 are larger than 6%. In contrast, Figure 4b shows that the proposed reconstruction can reduce the GSR values for phantom and in vivo brain images to be less than 3% and 2%, respectively. The tSNR maps obtained by either the CMRR-provided or the proposed reconstruction were mostly identical (in vivo results), except when larger λ values were incorporated to the proposed reconstruction, resulting in an increase of tSNR values as shown in MB4 and MB6 phantom data sets.

Influence of Regularization Parameters

Figures 5a shows that with regularization ($\lambda > 0$) the noise was suppressed, resulting in higher tSNR values and lower standard deviation values. If the noise levels are different across a time series, different lambda values should be used for different time points. However, we observed that the noise levels were very similar across the time series; we thus reduced the number of regularization parameters by using the same value for all time points. Note that the λ values shown in the 3rd and 4th columns were obtained by using the L-curve method (26). Figure 5b and 5c show the smoothing effect of the proposed reconstruction with the regularization parameter λ in an fMRI data. The highest t-score value in the BOLD activation map was increased when the fMRI dataset was reconstructed using a larger λ value due to the effective image smoothing. At a small λ , the highest t-score value was 28.70, whereas the value of 31.81 was detected when the large λ was used. However, the activation map (5c) appears to be slightly smoothed similar to using a Gaussian filter (with small $1 \times 1 \times 1 \text{ mm}^3$ kernel size) (5d). Therefore, a loss of spatial specificity caused by the regularization can be minimal in the proposed approach by using small λ .

DISCUSSION AND CONCLUSIONS

In this study, we have demonstrated that more accurate Nyquist ghost correction in SMS-EPI is possible when the slice-specific 2D-phase correction is considered. The phase difference maps and improved reconstructed images can be achieved from the redundant data samples across multi-channel receive arrays by using parallel imaging reconstruction. In practice, using a large number of phase-array coil elements can potentially increase the imaging speed, improve the SNR and tSNR, and provide accurate fMRI (27). This also allows highly accelerated parallel acquisition (28,29), which is directly beneficial for the proposed reconstruction scheme, since the individual even and odd signals are effectively double-under-sampled during the phase difference estimation. Note that since the proposed pipeline employed standard slice-GRAPPA for slice unfolding, it allows reconstruction of data with different FOV shifts or multiband factors. However, the proposed reconstruction may be limited in case of large in-plane reduction factors due to the effective double under-sampling of the phase encoding. The proposed reconstruction has been demonstrated for data with multiband factors of three and six in human brain and phantom studies, respectively, but only in-plane reduction factor of two was employed. The effectiveness of the proposed method on SMS-EPI data with larger in-plane reduction factors requires further investigation.

For SENSE-based reconstruction, accurate coil sensitivity estimation is crucial. In this study, the well-extrapolated coil sensitivities were estimated from the FLASH-ACS data using E-SPiRiT (23). A common issue such as coil sensitivity mismatch (30) between the ACS and EPI data was not observed in this study. However, at higher field strengths where magnetic field in-homogeneity is dominant, the geometric mismatch may become relevant (17,31). An alternative calibration scan based on the Fast Low-angle Excitation Echo-planar Technique (FLEET), which is distortion-matched to the EPI, has shown unaliasing performance in the presence of strong field inhomogeneity (31). Using coil sensitivities estimated from FLEET data may improve the proposed reconstruction at higher field strengths. Optionally, our recent work (17) that considers EPI distortion correction during the reconstruction process can potentially resolve this mismatch, but a B0 field map is required.

In Figure 3 and 4, the dynamic 2D-self phase map correction provided images with a relatively lower Nyquist ghost and its temporal variation compared to the standard 1D approach. Although the proposed phase maps appear corrupted by g-factor-related noise amplification, the smooth 2D phase maps obtained by either polynomial fitting or filtering address this issue as indicated by the g-factor maps in Figure 2(f–g) and 2(m–n). In general, high order polynomial fitting is usually prohibited due to potential over-fitting if the data are noisy. In this study, 2nd or 3rd order polynomial models provided a good fit to the support points within the object and also provided reasonable extrapolation beyond the object boundary as illustrated in Figure 2c and 2j, respectively. However, the fitting model or smoothing filter generally removes high spatial frequency components, potentially resulting in residual phase errors particularly in high susceptibility regions where high-order phase variations may be present (15,32,33). In such cases, two frames of calibration data with equal but opposite polarity readout gradients, known as the GESTE method (33), may allow calculation of high quality 2D phase maps. Since these maps are obtained from fully

sampled k-space data, fitting or smoothing methods may be not required. Consequently, all phase information is maintained and may be used to correct high-order phase errors.

Besides the coil sensitivity estimation, regularization also plays an important role in iterative reconstructions. It not only enables noise suppression, but also stabilizes the convergence at high iteration counts (21). Moreover, our results in Figure 5c show that the smoothing effect caused by large λ appears relatively small, and the activation is only slightly broadened compared to the activation map obtained from the small λ . However, the selection of proper λ is still challenging. Although automatic selection such as with the L-curve method (26), can provide reasonable λ values, it requires long computation times to estimate the λ values for every time point. The computation time may be minimized by estimating the λ value only once and then applying an identical value to all measurements as demonstrated in Figure 5a. This approach may be practical when the noise is independent and the noise levels are comparable across repetitive measurements, as expected in typical fMRI time series. Alternatively, Lin F.H. et al. (34) introduced a computationally efficient and robust approach to estimate the regularization parameters. This so-called variance partitioning regularization was claimed to provide more robust regularization parameter estimation than the L-curve method.

In this study, the imaging parameters for data sets 1–2 were set up similarly in order to maintain the image contrast and allow direct result comparison. SMS-EPI enables a significant reduction in repetition time (TR) as a function of the multiband factor, and to maximize MR signal at relatively short TR, the optimal flip angle (Ernst angle) can be used without reducing BOLD sensitivity (35). One category of fMRI studies that can benefit from temporal resolution improvement is high-resolution whole brain fMRI, which is gaining widespread interest because of its ability in reducing partial volume effects, thereby resulting in more localized and stronger BOLD activation (36,37). To acquire such data, however, a high readout bandwidth or large echo spacing may be also required. A recent study (38) showed that these two parameters can increase the intensity of Nyquist ghosting and its temporal variation depending on the MR scanner's characteristics, and EPI sequence calibrations (eddy current, shimming, etc.). In addition, several studies (15,39,40) show that in conditions such as strong subject movement and/or the use of oblique imaging planes, residual Nyquist ghosting can increase, thereby resulting in false-positive activation in fMRI maps (41). For those cases, the proposed dynamic 2D phase correction may be particularly useful. In Figure 2o and 2p, the temporal variations of image intensity obtained by either the standard 1D or the proposed 2D phase corrections appear only slightly different. This is likely due to very small motion of the volunteer's head in this example.

In conclusion, this study demonstrates that improved SMS-EPI quality can be achieved when a slice-specific 2D phase correction is performed. This phase correction step is fully integrated into the image reconstruction. The proposed reconstruction can successfully reduce the SMS-EPI phase errors, thereby resulting in reduced Nyquist ghosting. The proposed SMS-EPI reconstruction can be applied to fMRI time series since the smoothing effect caused by the regularization parameter selection can be minimal in BOLD activation maps.

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References

1. Mansfield P. Multi-planar image formation using NMR spin echoes. *Journal of Physics C: Solid State Physics*. 1977; 10(3):55–58.
2. van der Zwaag W, Francis S, Head K, Peters A, Gowland P, Morris P, Bowtell R. fMRI at 1.5, 3 and 7 T: characterising BOLD signal changes. *Neuroimage*. 2009; 47(4):1425–1434. [PubMed: 19446641]
3. Moeller S, Yacoub E, Olman CA, Auerbach E, Strupp J, Harel N, Ugurbil K. Multiband Multislice GE-EPI at 7 Tesla, With 16-Fold Acceleration Using Partial Parallel Imaging With Application to High Spatial and Temporal Whole-Brain FMRI. *Magn Reson Med*. 2010; 63(5):1144–1153. [PubMed: 20432285]
4. Nunes RG, Golay X, Larkman DJ. Simultaneous slice excitation and reconstruction for single shot EPI. *Proceedings of the 14th Annual Meeting of ISMRM*; Seattle, USA. 2006; Abstract 293
5. Setsompop K, Gagoski BA, Polimeni JR, Witzel T, Wedeen VJ, Wald LL. Blipped-controlled aliasing in parallel imaging for simultaneous multislice echo planar imaging with reduced g-factor penalty. *Magn Reson Med*. 2012; 67(5):1210–1224. [PubMed: 21858868]
6. Pruessmann KP, Weiger M, Scheidegger MB, Boesiger P. SENSE: sensitivity encoding for fast MRI. *Magn Reson Med*. 1999; 42(5):952–962. [PubMed: 10542355]
7. Griswold MA, Jakob PM, Heidemann RM, Nittka M, Jellus V, Wang J, Kiefer B, Haase A. Generalized autocalibrating partially parallel acquisitions (GRAPPA). *Magn Reson Med*. 2002; 47(6):1202–1210. [PubMed: 12111967]
8. Blaimer M, Breuer FA, Seiberlich N, Mueller MF, Heidemann RM, Jellus V, Wiggins G, Wald LL, Griswold MA, Jakob PM. Accelerated volumetric MRI with a SENSE/GRAPPA combination. *J Magn Reson Imaging*. 2006; 24(2):444–450. [PubMed: 16786571]
9. Blaimer M, Choli M, Jakob PM, Griswold MA, Breuer FA. Multiband phase-constrained parallel MRI. *Magn Reson Med*. 2013; 69(4):974–980. [PubMed: 23440994]
10. Moeller SVA, Auerbach E, Ugurbil K, Yacoub E. RO extended FOV SENSE/GRAPPA for multiband imaging with FOV shift. *Proceedings of the 23rd Annual Meeting of ISMRM*; Milan, Italy. 2014; Abstract 4396
11. Setsompop K, Cohen-Adad J, Gagoski BA, Raij T, Yendiki A, Keil B, Wedeen VJ, Wald LL. Improving diffusion MRI using simultaneous multi-slice echo planar imaging. *Neuroimage*. 2012; 63(1):569–580. [PubMed: 22732564]
12. Zhu K, Dougherty RF, Wu H, Muddione MJ, Takahashi AM, Zhang T, Pauly JM, Kerr AB. Hybrid-Space SENSE Reconstruction for Simultaneous Multi-Slice MRI. *IEEE Trans Med Imaging*. 2016; 35(8):1824–1836. [PubMed: 26915118]
13. Koopmans PJ. Two-dimensional-NGC-SENSE-GRAPPA for fast, ghosting-robust reconstruction of in-plane and slice-accelerated blipped-CAIPI echo planar imaging. *Magn Reson Med*. 2017; 77(3):998–1009. [PubMed: 26932565]
14. Poser BA, Barth M, Goa PE, Deng W, Stenger VA. Single-shot echo-planar imaging with Nyquist ghost compensation: interleaved dual echo with acceleration (IDEA) echo-planar imaging (EPI). *Magn Reson Med*. 2013; 69(1):37–47. [PubMed: 22411762]
15. Chen NK, Wyrwicz AM. Removal of EPI Nyquist ghost artifacts with two-dimensional phase correction. *Magn Reson Med*. 2004; 51(6):1247–1253. [PubMed: 15170846]
16. Xiang QS, Ye FQ. Correction for geometric distortion and N/2 ghosting in EPI by phase labeling for additional coordinate encoding (PLACE). *Magn Reson Med*. 2007; 57(4):731–741. [PubMed: 17390358]

17. Yarach U. Model-based iterative reconstruction for single-shot EPI at 7T. In: Chatnuntawech MHI, Bilgic B, Godenschweger F, Mattern H, Sciarra A, Speck O, editors *Magn Reson Med*. 2017.
18. Jackson JI, Meyer CH, Nishimura DG, Macovski A. Selection of a convolution function for Fourier inversion using gridding [computerised tomography application]. *IEEE Trans Med Imaging*. 1991; 10(3):473–478. [PubMed: 18222850]
19. Cauley SF, Polimeni JR, Bhat H, Wald LL, Setsompop K. Interslice leakage artifact reduction technique for simultaneous multislice acquisitions. *Magn Reson Med*. 2014; 72(1):93–102. [PubMed: 23963964]
20. Pruessmann KP, Weiger M, Bornert P, Boesiger P. Advances in sensitivity encoding with arbitrary k-space trajectories. *Magn Reson Med*. 2001; 46(4):638–651. [PubMed: 11590639]
21. Yarach U, Luengviriya C, Stucht D, Godenschweger F, Schulze P, Speck O. Correction of B0-induced geometric distortion variations in prospective motion correction for 7T MRI. *Magn Reson Mater Phy*. 2016; 29(3):319–332.
22. Talagala SL, Sarlls JE, Liu S, Inati SJ. Improvement of temporal signal-to-noise ratio of GRAPPA accelerated echo planar imaging using a FLASH based calibration scan. *Magn Reson Med*. 2016; 75(6):2362–2371. [PubMed: 26192822]
23. Uecker M, Lai P, Murphy MJ, Virtue P, Elad M, Pauly JM, Vasanawala SS, Lustig M. ESPIRiT - an eigenvalue approach to autocalibrating parallel MRI: where SENSE meets GRAPPA. *Magn Reson Med*. 2014; 71(3):990–1001. [PubMed: 23649942]
24. Uecker MOF, Tamir JI, Bahri D, Virtue P, Cheng JY, Zhang T, Lustig M. Berkeley Advanced Reconstruction Toolbox. Proceedings of the 24th Annual Meeting of ISMRM Annual Meeting ISMRM; Toronto, Canada. 2015; Abstract 2486
25. Robson PM, Grant AK, Madhuranthakam AJ, Lattanzi R, Sodickson DK, McKenzie CA. Comprehensive quantification of signal-to-noise ratio and g-factor for image-based and k-space-based parallel imaging reconstructions. *Magn Reson Med*. 2008; 60(4):895–907. [PubMed: 18816810]
26. Hansen PC. Analysis of Discrete Ill-Posed Problems by Means of the L-Curve. *SIAM Review*. 1992; 34(4):561–580.
27. Salomon R, Darulova J, Narsude M, van der Zwaag W. Comparison of an 8-channel and a 32-channel coil for high-resolution FMRI at 7 T. *Brain topography*. 2014; 27(2):209–212. [PubMed: 23749257]
28. Schmitt M, Potthast A, Sosnovik DE, Polimeni JR, Wiggins GC, Triantafyllou C, Wald LL. A 128-channel receive-only cardiac coil for highly accelerated cardiac MRI at 3 Tesla. *Magn Reson Med*. 2008; 59(6):1431–1439. [PubMed: 18506789]
29. Wiggins GC, Polimeni JR, Potthast A, Schmitt M, Alagappan V, Wald LL. 96-Channel receive-only head coil for 3 Tesla: design optimization and evaluation. *Magn Reson Med*. 2009; 62(3):754–762. [PubMed: 19623621]
30. Griswold MA, Breuer F, Blaimer M, Kannengiesser S, Heidemann RM, Mueller M, Nittka M, Jellus V, Kiefer B, Jakob PM. Autocalibrated coil sensitivity estimation for parallel imaging. *NMR in biomedicine*. 2006; 19(3):316–324. [PubMed: 16705632]
31. Polimeni JR, Bhat H, Witzel T, Benner T, Feiweier T, Inati SJ, Renvall V, Heberlein K, Wald LL. Reducing sensitivity losses due to respiration and motion in accelerated Echo Planar Imaging by reordering the auto-calibration data acquisition. *Magn Reson Med*. 2016; 75(2):665–679. [PubMed: 25809559]
32. Buonocore MH, Gao L. Ghost artifact reduction for echo planar imaging using image phase correction. *Magn Reson Med*. 1997; 38(1):89–100. [PubMed: 9211384]
33. Hoge WS, Polimeni JR. Dual-polarity GRAPPA for simultaneous reconstruction and ghost correction of echo planar imaging data. *Magn Reson Med*. 2016; 76(1):32–44. [PubMed: 26208304]
34. Lin F-H, Huang T-Y, Chen N-K, Wang F-N, Stuffelbeam SM, Belliveau JW, Wald LL, Kwong KK. Functional MRI using regularized parallel imaging acquisition. *Magn Reson Med*. 2005; 54(2):343–353. [PubMed: 16032694]
35. Preibisch C, Castrillon GJ, Buhner M, Riedl V. Evaluation of Multiband EPI Acquisitions for Resting State fMRI. *PloS one*. 2015; 10(9):e0136961. [PubMed: 26375666]

36. Goense J, Bohraus Y, Logothetis NK. fMRI at High Spatial Resolution: Implications for BOLD-Models. *Frontiers in computational neuroscience*. 2016;10–66. [PubMed: 26903851]
37. Todd N, Moeller S, Auerbach EJ, Yacoub E, Flandin G, Weiskopf N. Evaluation of 2D multiband EPI imaging for high-resolution, whole-brain, task-based fMRI studies at 3T: Sensitivity and slice leakage artifacts. *Neuroimage*. 2016; 124(A):32–42. [PubMed: 26341029]
38. Giannelli M, Diciotti S, Tessa C, Mascalchi M. Characterization of Nyquist ghost in EPI-fMRI acquisition sequences implemented on two clinical 1.5 T MR scanner systems: effect of readout bandwidth and echo spacing. *Journal of applied clinical medical physics*. 2010; 11(4):3237. [PubMed: 21081879]
39. Zaitsev M, Akin B, LeVan P, Knowles BR. Prospective motion correction in functional MRI. *Neuroimage*. 2017; 154:33–42. [PubMed: 27845256]
40. Chen NK, Avram AV, Song AW. Two-dimensional phase cycled reconstruction for inherent correction of echo-planar imaging Nyquist artifacts. *Magn Reson Med*. 2011; 66(4):1057–1066. [PubMed: 21446032]
41. van der Zwaag W, Marques JP, Lei H, Just N, Kober T, Gruetter R. Minimization of Nyquist ghosting for echo-planar imaging at ultra-high fields based on a “negative readout gradient” strategy. *Journal of magnetic resonance imaging*. 2009; 30(5):1171–1178. [PubMed: 19856451]

Fig. 1.
The pipeline of the proposed SMS-EPI reconstruction.

Fig. 2. (a–c and h–j) 2D residual phase differences for even and odd echoes obtained from MB3R_y2 data, their smoothed and polynomial fitted versions (3rd order in c, and 2nd order in j). (d and k) The images reconstructed by standard SENSE without slice-specific phase correction. (e–g and l–n) The images reconstructed by the proposed augmented SENSE with the incorporation of the above corresponding 2D phase difference maps. (o–p) The plots for the mean and standard deviation of the image intensities in the ROI #1 and #2, respectively shown in (d) and (f) and the variations over the entire 50 measurements. Note that the g-factor maps superimposed at the left corner of their corresponding images were calculated by using pseudo multiple-replica method (25) with 100 repetitions of newly synthesized noise.

Fig. 3.

Comparison of SMS-EPI (MB3Ry2) images obtained from three different phase correction schemes including (a) 1D slice-group average, (b) 1D slice-group average + 1D slice-specific, and (c) 1D slice-group average + proposed 2D slice-specific phase corrections. The second column shows the magnitude images with 10× enhanced (to show the Nyquist ghost level). The tSNR maps corresponding to each reconstruction scheme are illustrated in the last column.

Fig. 4.

Comparison of Nyquist ghost levels and tSNR maps of the SMS-EPI images obtained by the CMRR-provided (a) and the proposed reconstruction (b). Note that the dual kernel and LeakBock options were turned on for the CMRR-provided online reconstruction, but the slice-specific phase correction was not available.

Fig. 5.

(a) The tSNR and standard variation maps obtained from the proposed reconstruction with non-regularization (1st column), regularization using large single λ (2nd column), small single λ (3rd column), and different λ (4th column) for each measurement over the entire time-series. (b and c) The motor task activation maps obtained from MB3R_y2 data that were reconstructed by using different λ values. (d) The motor task activation maps obtained from the same data in (b), but with a Gaussian smoothing kernel size of $1 \times 1 \times 1$ mm³.