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Ghost Reduction in Echo-Planar Imaging by Joint Reconstruction of Images and Line-to-Line Delays and Phase Errors

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Abstract

Purpose—To correct line-to-line delays and phase errors in echo-planar imaging (EPI).

Theory and Methods—EPI-trajectory auto-corrected image reconstruction (EPI-TrACR) is an iterative maximum-likelihood technique that exploits data redundancy provided by multiple receive coils between nearby lines of k-space to determine and correct line-to-line trajectory delays and phase errors that cause ghosting artifacts. EPI-TrACR was efficiently implemented using a segmented FFT and was applied to in vivo brain data acquired at 7 Tesla across acceleration (1x–4x) and multishot factors (1 to 4 shots), and in a time series.

Results—EPI-TrACR reduced ghosting across all acceleration factors and multishot factors, compared to conventional calibrated reconstructions and the PAGE method. It also achieved consistently lower ghosting in the time series. Averaged over all cases, EPI-TrACR reduced root-mean-square ghosted signal outside the brain by 27% compared to calibrated reconstruction, and by 40% compared to PAGE.

Conclusion—EPI-TrACR automatically corrects line-to-line delays and phase errors in multishot, accelerated, and dynamic EPI. While the method benefits from additional calibration data for initialization, it was not a requirement for most reconstructions.

Keywords

image reconstruction; EPI; parallel imaging; phase correction; eddy currents; ghosting

Introduction

Echo-planar imaging (EPI) is a fast MRI technique in which multiple lines of k-space are measured per excitation. It is widely used in functional and diffusion MRI. However, EPI

images contain ghosting artifacts due to trajectory delays and phase errors between adjacent k-space lines that result from eddy currents created by rapidly switched readout gradients.

The most common methods to correct EPI ghosting artifacts are based on the collection of calibration data from which delays and phase errors can be estimated and applied in image reconstruction [1–6]. Usually this data comes from a separate acquisition without phase encoding gradient blips, acquired before the imaging scan. Corrections can also be made by re-acquiring EPI k-space data that is offset by one k-space line so that odd k-space lines become even and vice versa [1, 7]. The gradient impulse response function can also be measured and applied to predict errors [8]. However, these methods do not address dynamic errors caused by effects such as gradient coil heating. Dynamic errors can be compensated by measuring calibration data within the imaging sequence itself, for example by reacquiring the center line of k-space within a single acquisition [9]. However, these approaches result in a loss of temporal resolution. Alternatively, dynamic errors can be measured during a scan without modifying the sequence using field-probe measurements [10–12]. However, the hardware required to make those measurements can take up valuable space in the scanner bore and is not widely available at the time of writing.

As an alternative to separate calibration measurements, many retrospective methods attempt to correct ghosting based on the EPI data or images themselves. The image-based methods [13–16] rely on the assumption that some part of the initial image contains no ghosted signal. Another group of methods makes corrections based on finding phased array combinations that cancel ghosts [17–21]. Several methods use parallel imaging to separately reconstruct images from odd and even lines and then combine them, and these have further been combined with a dynamically alternating phase encode shift or direction [18–20, 22, 23]. However, relying on undersampled data for calibration weights may make these approaches unstable, and some methods reduce temporal resolution. The method of Ref. [24] also works by reconstructing and combining images from odd and even lines, but relies on compressive sampling and matrix completion principles instead of parallel imaging. Importantly, with the exception of the multi-shot diffusion EPI phase-corrected reconstruction method of Ref. [25], most of these calibration-free retrospective methods are either incompatible or have not been validated with multi-shot EPI, and are either incompatible with parallel imaging acceleration or have only been validated with small acceleration factors of $2\times$ or less. At the same time, to our knowledge the method of Ref. [25] has not been applied to correct even/odd phase shifts and delays *within* each shot, but instead relied on calibration data for those corrections.

In this work, a flexible EPI-trajectory auto-corrected image reconstruction (EPI-TrACR) is proposed that alleviates ghosting artifacts by exploiting data redundancy between adjacent k-space lines in multicoil EPI data. It is an extension of a previously described method for automatic non-Cartesian trajectory error correction (TrACR-SENSE) [26] to the joint estimation of images and line-to-line delays and phase errors in EPI. In the following we describe the method, including an efficient segmented FFT algorithm for delayed EPI k-space trajectories. The method is then validated in vivo at 7 Tesla, at multiple acceleration and multishot factors and in a time series. It is demonstrated that EPI-TrACR reduces dynamic ghosting and is compatible with multishot EPI and acceleration. Furthermore, the

method benefited from initialization with calibration data but did not require it at moderate acceleration and multishot factors.

Theory

Problem Formulation

EPI-TrACR jointly estimates images, delays and phase errors by fitting an extension of the SENSE MR signal model [27] to EPI k-space data:

$$y_c[m, n] = \sum_{i=1}^{N_s} e^{-i2\pi((k_m^x + \Delta k_n^x)x_i + k_n^y y_i)} e^{i\Delta\phi_n} s_{ci} f_i, \quad (1)$$

where $y_c[m, n]$ is the signal measured in coil c at the m th time point of the n th phase-encoded echo, k_m^x is the k-space coordinate in the readout/frequency encoded dimension and Δk_n^x is the trajectory delay in that dimension for the n th echo (out of N echoes), k_n^y is the n th echo's k-space coordinate in the phase-encoded dimension, ϕ_n is the phase error of the n th echo resulting from zeroth-order eddy currents, s_{ci} is coil c 's measured sensitivity at (x_i, y_i) , f_i is the image at (x_i, y_i) , and N_s is the number of pixels in the image. The unknown parameters in this model are the image f and the delays and phase errors $\{(\Delta k_n^x, \Delta\phi_n)\}_{n=1}^N$, which are determined by fitting the model to measured data $\tilde{y}_c[m, n]$ by least squares. Assuming additive Gaussian noise in the k-space data, this corresponds to a maximum likelihood (ML) estimation of the parameters. The delays and phase errors are constrained so that a single delay and phase error pair applies to all of a shot's odd echoes and another pair applies to all of its even echoes, with separate parameters for each shot. Without loss of generality, the first shot's odd echoes serve as a reference and are constrained to have zero delay and phase error. Overall, a total of $2(2N_{shot} - 1)$ delay and phase error parameters are fit to the data along with the image. We note that EPI-TrACR implicitly estimates phase error maps for each shot's even and odd echoes that are constrained to contain only zeroth and first order spatial variations; this represents an alternative to estimating spatially-resolved phase maps for each set of echoes, which would typically require spatial regularization.

Algorithm

The EPI-TrACR algorithm minimizes the data-model error by alternately updating the estimated image f , the k-space delays $\{\Delta k_n^x\}_{n=1}^N$, and the phase errors $\{\Delta\phi_n\}_{n=1}^N$. The image is updated with a conjugate-gradient (CG) SENSE reconstruction [28]. The delay and phase error updates are both performed using a nonlinear Polak-Ribière (CG) algorithm [29], which requires computation of the derivatives of the sum of squared data-model errors with respect to those parameters. Denoting the sum-of-squared data-model errors as the function Ψ , the derivative with respect to each delay Δk_n^x is:

$$\frac{\partial \Psi}{\partial \Delta k_n^x} = \sum_{c=1}^{N_c} \sum_{m=1}^M \sum_{i=1}^{N_s} \Re \left\{ -\iota 2\pi x_i e^{-\iota \Delta \phi_n} e^{\iota 2\pi ((k_m^x + \Delta k_n^x)x_i + k_n^y y_i)} s_{ci}^* f_i^* r_{cmn} \right\}, \quad (2)$$

and the derivative with respect to each phase error ϕ_n is:

$$\frac{\partial \Psi}{\partial \Delta \phi_n} = \sum_{c=1}^{N_c} \sum_{m=1}^M \sum_{i=1}^{N_s} \Re \left\{ \iota e^{-\iota \Delta \phi_n} e^{\iota 2\pi ((k_m^x + \Delta k_n^x)x_i + k_n^y y_i)} s_{ci}^* f_i^* r_{cmn} \right\}, \quad (3)$$

where $\Re$ denotes the real part, $*$ is complex conjugation, and r_{cmn} is the residual error between the measured data and the model given the current parameter estimates, $\hat{\mathbf{f}}$, $\hat{\Delta k_n^x}$, and $\hat{\phi_n}$:

$$r_{cmn} = \tilde{y}_c[m, n] - \sum_{i=1}^{N_s} e^{-\iota 2\pi ((k_m^x + \hat{\Delta k_n^x})x_i + \hat{k_n^y} y_i)} e^{\iota \hat{\Delta \phi_n}} s_{ci} \hat{f}_i. \quad (4)$$

To constrain the delays and phase errors to be the same for the set of odd or even echoes of each shot, the derivatives above are summed across the echoes in that set, and a single delay and shift pair is determined for the set each CG iteration. The updates are alternated until the sum-of-squared data-model error stops changing significantly.

Segmented FFTs

Since a delayed EPI trajectory is non-Cartesian, the model in Equation 1 corresponds to a nonuniform discrete Fourier transform (DFT) of the image. Non-uniform fast Fourier transform (FFT) algorithms (e.g., Ref. [30]) are typically used to efficiently evaluate non-uniform DFTs, but they use gridding, which would result in long compute times in EPI-TrACR, since Equation 1 is repeatedly evaluated by the algorithm. Figure 1 illustrates a segmented FFT algorithm that applies the delays as phase ramps in the image domain, instead of gridding the delayed data in the frequency domain. In addition to eliminating gridding, this also enables the data to be FFT'd in the frequency-encoded dimension before starting EPI-TrACR, so that the algorithm only needs to compute 1D FFTs in the phase-encoded dimension. The figure shows an inverse segmented FFT (k-space to image space) for a 2-shot dataset with delays and phase errors, which comprises the following steps:

1. The data in each set of odd or even echoes of each shot are collected into $2N_{shot}$ submatrices of size $M \times (N/(2 \times N_{shot}))$, and the 1D inverse FFT of each submatrix is computed in the phase-encoded dimension.
2. The estimated phase errors are applied to each submatrix.
3. A phase ramp is applied in the phase-encoded spatial dimension of each submatrix to account for that set's relative position in the phase-encoded k-space

dimension. This is necessary since the inverse FFTs assume all the submatrices are centered in k-space.

4. The phase ramp corresponding to each set's estimated delay is applied to its submatrix in the frequency-encoded spatial dimension.
5. For each submatrix entry, the inverse DFT across submatrices is computed to obtain $2N_{shot}$ subimages of size $M \times (N/(2 \times N_{shot}))$, which are concatenated in the column dimension to form the final $M \times N$ image.

For efficiency, the phase errors of steps 2 through 4 are combined into a single precomputed matrix that is applied to each submatrix by elementwise multiplication. To perform the forward segmented FFT (image space to k-space), the steps are reversed, with the phase ramps and shifts negated. Steps 1 and 5 dominate the computational cost, and respectively require $O(MNN_{shot})$ and $O(MN \log(N/(2N_{shot})))$ operations.

Methods

Algorithm Implementation

The EPI-TrACR algorithm was implemented in MATLAB 2016a (The Mathworks, Natick, MA, USA) on a workstation with dual 6-core 2.8 GHz X5660 Intel Xeon CPUs (Intel Corporation, Santa Clara, CA) and 128 GB RAM. For each iteration of the algorithm's outer loop, CG-SENSE image updates were initialized with zeros to prevent noise amplification, and were performed using MATLAB's lsqrfunction and a fixed tolerance of 10^{-1} , capped at 25 iterations. CG delay and phase updates were each fixed to a maximum of 5 iterations per outer loop iteration, and terminated early if all steps were less than 10^{-6} cm^{-1} (for delays) or 10^{-6} radians (for phase errors). The maximum permitted delay step in a single iteration was limited to $1/FOV$, and the maximum permitted phase step in a single iteration was limited to $\pi/10$ radians. Enforcing these maximum step sizes mitigated the effects of phase wraps in the calculated delay derivatives, by preventing the algorithm from taking large steps that may cause it to become stuck in local minima. Outer loop iterations stopped when the change in squared error was less than the previous iteration's error times 10^{-6} . Code and example data for EPI-TrACR can be downloaded at <https://bitbucket.org/wgrissom/tracr>.

Experiments

A healthy volunteer was scanned on a 7T Philips Achieva scanner (Philips Healthcare, Best, Netherlands) with the approval of the Institutional Review Board at Vanderbilt University. A bird-cage coil was used for excitation and a 32-channel head coil was used for reception (Nova Medical Inc., Wilmington, MA, USA). EPI scans were acquired with $24 \times 24 \text{ cm}$ FOV, $1.5 \times 1.5 \times 3 \text{ mm}^3$ voxels, TR 3000 ms, TE 56 ms, flip angle 60° . They were repeated for 1–4 shots, acceleration factors of 1–4x, and the 2-shot/1x scan was collected with 20 time points. The TE of 56 ms was chosen to facilitate side-by-side comparisons between images with different multishot and acceleration factors by maintaining the same contrast and matrix size between images, and was the shortest possible TE for the single-shot/1x acquisition, which had a readout duration of 102 ms. A calibration scan with phase encodes turned off was acquired in each configuration, and delays and phase errors were estimated

from it using cross-correlation followed by an optimization transfer-based refinement [31]. SENSE maps were also collected using the vendor's mapping scan.

Images were reconstructed to 160×160 matrices using CG-SENSE with no corrections, and with phase error and delay estimates from the calibration scans; the latter reconstructions are hereafter referred to as 'conventional calibrated reconstructions.' Images were also reconstructed using EPI-TrACR initialized with the delays and phase errors from the calibration scans, and with zeros. EPI-TrACR was further compared to the calibration-free PAGE EPI correction method [17]. Since EPI-TrACR's compute time depends on image and data size, the amount of k-space data necessary to estimate delays and phase errors was characterized by repeating the algorithm on 2-shot/1x in vivo data that was truncated in both k-space dimensions, across a range of truncation factors. The reconstructed image matrix sizes within EPI-TrACR were correspondingly reduced, so that the image matrix size matched the data matrix size. The final estimated delays and phase errors were then applied in a full-resolution CG-SENSE reconstruction. Except where indicated, displayed images shown are windowed down to 20% of their maximum amplitude for clear display of ghosting, and ghosted signals were measured in all images as the root-mean-square (RMS) signal outside an elliptical region-of-interest that excluded the brain and skull.

Results

Figure 2 shows reconstructed images across multishot factors. Ghosting was lowest with EPI-TrACR in all cases. Supporting Information Figure S1 further shows that EPI-TrACR achieved lower ghosting than PAGE in all cases, and that the differences between zero initialization and calibrated initialization EPI-TrACR images are negligible: averaged across multishot factors, the RMS difference between EPI-TrACR-estimated delays and phase errors with and without calibrated initialization was 0.014%. EPI-TrACR RMS ghosted signals were on average 37% lower than for conventional calibrated reconstructions, and 36% lower than for PAGE reconstructions. In addition, EPI-TrACR suppressed a strong aliased edge inside the brain which appeared in the 4-shot conventional calibrated reconstruction (indicated by the yellow arrow). Due to the long readout duration of the 1-shot acquisition, all the 1-shot reconstructions contain a similar off resonance-induced geometric distortion at the back of the brain (indicated by the green arrow in the conventional calibrated reconstruction). The uncorrected 1-shot acquisition also contains much dimmer ghosts than the multishot acquisitions, so the corrected 1-shot images are more similar than the multishot corrected images.

Figure 3 shows reconstructed 2-shot EPI images with 1–4× acceleration. Compared to conventional calibrated reconstruction, EPI-TrACR with calibrated initialization again reduced ghosting up to 4× acceleration, and RMS ghosted signals were 18% lower on average. Supporting Information Figure S2 expands this comparison to include PAGE, and EPI-TrACR with zero initialization. Compared to PAGE, EPI-TrACR with calibrated initialization had 44% lower ghosting on average. Furthermore, EPI-TrACR estimates matched with and without calibrated initialization up to 3× acceleration: averaged across factors of 1–3×, the RMS difference between estimated delays and phase errors with and without calibrated initialization was 0.024%.

Figure 4a plots RMS ghosted signal across repetitions for the 2-shot/ $1\times$ scan, for conventional calibrated reconstruction, PAGE, and EPI-TrACR. The signal levels are normalized to that of the first repetition's EPI-TrACR reconstruction. On average, residual ghosted signals in the conventional calibrated and PAGE reconstructions were respectively 80% and 20% higher than in the EPI-TrACR reconstructions. Figure 4b shows a Weisskoff plot [32] for all three reconstructions compared to the theoretical ideal; the coefficient of variation over repetitions is plotted for an ROI of increasing size. The EPI-TrACR time series had a radius of de-correlation (RDC) of 12.94 which was much higher than for the conventional calibrated and PAGE reconstructions, which had RDC's of 1.46 and 1.08, respectively. This indicates that, while PAGE reduced ghosting compared to conventional calibrated reconstruction, it was less temporally stable; i.e. residual ghosting was lower, but the image less consistent over time.

Figure 4c shows conventional calibrated reconstruction, PAGE, and EPI-TrACR (with zero initialization) images at the 14th repetition. The conventional, PAGE, and EPI-TrACR images at the 14th repetition respectively have 190%, 35%, and 16% higher RMS ghosted signal compared to the first repetition's EPI-TrACR reconstruction. A video of the full time series reconstructions produced by the three methods is provided as Supporting Information.

The truncated 2-shot EPI-TrACR results are shown in Figure 5. Figure 5a shows that delay and phase error estimation errors relative to full-data EPI-TrACR estimates are low up to very high truncation factors, and Figure 5b shows that compute time can be reduced up to 90% by truncating the data by 90%. Figures 5c and d show that images reconstructed with full data and 90%-truncated data delay and phase estimates are indistinguishable: RMS ghosted signal was 8% higher in the truncated EPI-TrACR image versus the full-data reconstruction, but still 40% lower than the conventional calibrated reconstruction (which appears in Figure 2). For greater than 90% truncation though, the compute time starts to increase again due to increasing iterations. For full data, EPI-TrACR reconstruction times using the described segmented FFT's ranged from one minute (for 1 shot, $1\times$ acceleration, and calibrated initialization) to 88 minutes (for 2 shots, $4\times$ acceleration, and zero initialization). In comparison, reconstructions using NUFFTs [30] in place of the segmented FFTs ranged from 8 minutes (for 1 shot, $1\times$ acceleration, and calibrated initialization) to 269 minutes (for 2 shots, $4\times$ acceleration, and zero initialization).

Discussion

EPI-TrACR is an iterative ML algorithm that jointly estimates EPI echo delays and phase errors, along with images that are compensated for them. While ML frameworks for MR image reconstruction are a classical approach [33], we are not aware of any ML method that simultaneously estimates an image and EPI trajectory delays and phase shifts, with any optimization approach. To our knowledge, the original TrACR method [26] was the first ML algorithm to jointly estimate an image and trajectory errors, but was originally developed and applied to non-Cartesian imaging (spiral and radial). In this work, we extended it to estimate both trajectory errors (delays) and phase shifts, and we introduced a segmented FFT for efficient computation. These advances were required for the method to be effective in suppressing ghosts in EPI images.

Compared to conventional calibrated corrections, EPI-TrACR consistently reduced image ghosting across multishot factors, acceleration factors, and a time series, by 27% on average. It also reduced image ghosting compared to PAGE in all cases, by 40% on average. In most cases it was able to do so without being initialized with calibrated delays and phase errors. Because EPI-TrACR leverages data redundancy between nearby lines of k-space, its performance is expected to degrade as the distance between k-space lines increases with increasing acceleration factor, which was observed here in the zero-initialized 4 $\times$ -accelerated case. However, when initialized with calibrated delays and phase errors, the method always reduced ghosting compared to conventional calibrated reconstruction. In addition to these results, Supporting Information Figure S3 shows errors in final delay and phase shift estimates and ghosting, as a function of initial values for the 1-shot/1 $\times$ data. The figure shows that when the initial delay values are too far from the global minimum, due to phase wraps in the calculated derivatives the algorithm becomes stuck in a suboptimal local minimum with high ghosting. However, the figure also indicates the ranges of phase shifts and delays encountered in our data, which are within the region that converged to the global minimum. It may also be possible to expand the region of convergence using phase unwrapping or regularization [34]. A further validation experiment comparing EPI-TrACR estimates (1-shot/1 $\times$) to a full k-space trajectory measurement [35] in a phantom at 3 Tesla is shown in Supporting information Figure S4. The EPI-TrACR bulk line delay estimate was similar to the median measured delay (13% difference), and the EPI-TrACR image contained 19% lower RMS ghosted signal than the measured trajectory reconstruction.

We chose the Polak-Ribière conjugate-gradient (CG) algorithm to update the delays and phase errors because it efficiently finds a local minimizer of the data-model error with respect to these parameters. Related methods could be used such as gradient or steepest descent, which may have simpler formulations but would generally converge more slowly, and would still require the derivatives to be computed. Global optimization approaches such as genetic algorithms may be more robust to local minima than derivative-based methods, but would be impractical for more than one or two shots due to the number of dimensions that must be searched over while jointly estimating the image. Furthermore, we showed that the CG-based updates robustly converged to solutions that reduced image ghosting compared to conventional methods, especially when initialized with calibrated values.

Off-resonance is not currently modeled in EPI-TrACR, and may degrade delay and phase error estimates. While a full study of EPI-TrACR's off-resonance sensitivity is beyond the scope of this work, we note that: a) A measured field map could be incorporated in the signal model of Equation 1 [33]; b) Figure 5 showed that EPI-TrACR can accurately estimate delays and phase errors from a small number of k-space lines, over which there would be very little phase accrual due to off-resonance; and c) One of the main advantages of EPI-TrACR over previous image databased methods is that it can be directly applied to multishot and accelerated acquisitions, which have inherently reduced off-resonance sensitivity.

Compared to reconstruction with a fixed calibrated trajectory, the main tradeoff for EPI-TrACR's improved delay and phase shift estimates is increased computation, but this can be mitigated in several ways. First, we showed that compute time can be reduced by truncating

the data matrix down to the low frequencies, without compromising the delay and phase shift estimates. Compute times are also shorter when the algorithm is initialized with calibrated estimates, since fewer iterations are required to reach a solution. The algorithm could be applied in parallel across repetitions or slices, or within the algorithm the FFTs could be parallelized across receive coils.

There are a number of ways the method could be extended. First, in the present work it was assumed that all the echoes within a set of even or odd echoes of a shot had the same delay and phase shift. However, it is also possible to estimate different delays and phase shifts for different echoes within a set by expressing them as a weighted sum of basis functions. We have previously tested this extension by expanding the delays and phase shifts of each set of odd and even k-space lines across multiple triangular basis functions, but found little improvement with our data. Nevertheless, as others may find it useful this functionality is included in the provided code. Second, the method could be extended to jointly estimate a single set of delays and phase shifts over a whole stack of slices simultaneously, which would increase the effective signal-to-noise ratio for estimation. This could in particular help for highly accelerated acquisitions where the method is currently more sensitive to poor initialization. Finally, we note that in its current form, EPI-TrACR is not suitable for correcting shot-to-shot phase errors caused by bulk and physiological motion in multishot diffusion-weighted EPI, since these errors are generally higher than first order. It may however be useful as a preprocessing step to correct even/odd delays and phase shifts within each shot individually, which would then be followed by higher order inter-shot phase correction using a method such as Ref. [25]. It may also be possible to estimate higher order phase error maps using EPI-TrACR by increasing its polynomial order, or to estimate a spatially resolved phase error map for each shot and set of even or odd lines; the latter approach would likely require spatial regularization of the estimated phase error maps [34].

Conclusions

The EPI-TrACR method alleviates ghosting artifacts by exploiting data redundancy between adjacent k-space lines in multicoil EPI data. It benefits from initialization with calibration data but does not require it at moderate acceleration and multishot factors. EPI-TrACR reduced dynamic ghosting without sacrificing temporal resolution, is compatible with multishot and accelerated acquisitions, and does not rely on a ghost-free image region. It was validated in vivo at 7T, at multiple acceleration and multishot factors and in a time series.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

Acknowledgments

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Figure 1.

Illustration of the inverse segmented FFT, starting with 2-shot x - k_y EPI data corrupted by line-to-line delays and phase errors. First the data are segmented into $2N_{shot}$ submatrices and individually inverse Fourier transformed. Then each image-domain submatrix is phase shifted to account for its offset in k_y , its phase error, and its delay. Finally, an inverse Fourier transform is calculated across the segments, and the result is reshaped into the image.

Figure 2.

Multishot echo-planar images (no acceleration) reconstructed with no correction, conventional calibrated reconstruction, and EPI-TrACR with calibrated initialization. The length and color of the horizontal bars beneath each image represent the residual RMS ghosted signal as a percentage of maximum image intensity, as defined by the color scale on the right. The green arrow in the conventional calibrated 1-shot reconstruction indicates off resonance-induced geometric distortion at the back of the head which appears in all of the 1-shot reconstructions. The yellow arrow in the conventional calibrated 4-shot reconstruction indicates an edge that aliased into the brain, which is not visible in the EPI-TrACR reconstruction.

Figure 3.

1x–4x 2-shot echo-planar images reconstructed with no correction, conventional calibrated reconstruction, and EPI-TrACR with calibrated initialization. The length and color of the horizontal bars beneath each image represent the residual RMS ghosted signal as a percentage of maximum image intensity, as defined by the color scale on the right.

Figure 4.

2-shot echo-planar images over 20 repetitions reconstructed using conventional calibrated reconstruction, PAGE, and EPI-TrACR with zero initialization. (a) Percentage increase in RMS ghosted signal versus repetition, normalized to that of the EPI-TrACR reconstruction of the first repetition. (b) Weisskoff plot showing the normalized coefficient of variation over repetitions for an ROI of increasing size, for conventional calibrated reconstruction, PAGE, and EPI-TrACR compared to the theoretical ideal. (c) Windowed-down conventional calibrated reconstruction, PAGE, and EPI-TrACR reconstructions, at the 14th repetition (indicated by the arrow in (a)).

Figure 5.

2-shot, 1x-accelerated EPI-TrACR reconstructions from truncated data. The plots show (a) combined root mean square error (RMSE) in the estimates of DC and linear phase shifts compared to full-data EPI-TrACR estimates and (b) compute time as a percentage of a full-data EPI-TrACR compute time; both are shown as a function of percentage of degree of data reduction in each dimension. (c-d) Images reconstructed using the full data EPI-TrACR estimates using 90%-truncated EPI-TrACR estimates (16 PE lines) (d) (the red data point in a-b).