Learning-based solution to phase error correction in T2*-weighted GRE scans

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Abstract

Long-TE gradient recalled-echo (GRE) scans are prone to phase artifacts due to B0 inhomogeneity. We propose a learning-based approach that does not rely on navigator readouts and allows to infer phase error offsets directly from corrupted data. Our method does not need to be pre-trained on a database of medical images that match a contrast/acquisition protocol of the input image. A sufficient input is a raw multi-coil spectrum of the image that needs to be corrected. We train a convolutional neural network to predict phase offsets for each *k*-space line of a 2D image. We synthesize training examples online by reconvolving the corrupted spectrum with point spread functions (PSFs) of the coil sensitivity profiles and superimposing artificial phase errors, which we attempt to predict. We evaluate our approach on "in vivo" data acquired with GRE sequence, and demonstrate an improvement in image quality after phase error correction.

1 Introduction:

High-field magnetic resonance imaging is prone to the problems related to undesirable spatiotemporal magnetic field variations. When measuring in vivo, a dominant source of the temporal fluctuations are physiology related e.g. breathing. In long echo time T2*-weighted gradient-recalled echo (GRE) scans, temporal B0 variations lead to phase errors that appear as ghosting and blurring artifacts in spatial domain. Such errors are caused by additive phase offsets that vary from readout to readout and occur because of the phase accumulation in imaged voxels due to off-resonance shifts.

A common solution to estimate the errors is to use non-phase-encoded navigators to measure phase offsets at each repetition [1]. During the image reconstruction, offsets are subtracted from respective frequency domain segments to correct for the errors. Although such navigators are usually inexpensive to acquire, it is still advantageous, to develop a method that does not require extra navigator readouts and thus does not increase a repetition time.

2 Methods:

We formalize an image acquisition process in the presence of the temporal B0 variations as

$$\mathbf{y}_m = \mathbf{F}(\mathbf{s}_m \odot \mathbf{u}) \exp(i\boldsymbol{\theta}),$$

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Algorithm 1 Learning to predict phase errors

Input: $\mathbf{Y} \in \mathbb{C}^{M \cdot N_x \cdot N_y}$ **// Raw data acquired with *M* coil elements**
$\mathbf{S} \in \mathbb{C}^{M \cdot N_x \cdot N_y}$ **// Coil sensitivity profiles**
Output: $\mathbf{u} \in \mathbb{C}^{N_x \cdot N_y}$ **// Corrected image in spatial domain**
For $e = 1, ..., E$ **do** **// Training loop, E is the number of training epochs**

For each sample in the batch, draw from a uniform distribution: $\boldsymbol{\psi}, \boldsymbol{\theta} \in (-\pi/2, \pi/2)^{N_y}$

Generate a phase-perturbed image: $\hat{\boldsymbol{u}} = \sum_m^M (\overline{\boldsymbol{s_m}} \odot \mathbf{F}^{\mathsf{H}}(\boldsymbol{y}_m \odot exp(i\boldsymbol{\psi})))$

For each *m*, reconvolve with sensitivities: $\hat{\boldsymbol{y}}_{\boldsymbol{m}} = (\mathbf{F}(\boldsymbol{s}_m \odot \hat{\boldsymbol{u}})) \odot \exp(i\boldsymbol{\theta})$

Prepare a batch for CNN and train for one step. Input: $\{sin(\angle\hat{\boldsymbol{Y}}), cos(\angle\hat{\boldsymbol{Y}})\}$; target: $\boldsymbol{\theta}$

End

Predict $\boldsymbol{\theta}$ using the trained network with $\{sin(\angle\boldsymbol{Y}), cos(\angle\boldsymbol{Y})\}$ as input

Reconstruct phase-corrected image with sum-of-squares $\boldsymbol{u} = \sqrt{\sum_m^M |\mathbf{F}^{\mathsf{H}}(\boldsymbol{y}_m \odot \exp(-i\boldsymbol{\theta}))|^2}$

where $\odot$ denotes element-wise multiplication, $\mathbf{u} \in \mathbb{C}^N$ is an unknown artifact-free 2D image with $N = N_x \cdot N_y$ pixels, $\mathbf{y}_m \in \mathbb{C}^N$ a spectrum acquired by the coil element *m*, $\mathbf{s}_m$ a respective coil sensitivity profile, $\mathbf{Y}$ a matrix of size $M \times N$ containing raw data from all coil elements, $\mathbf{F} \in \mathbb{C}^{N \times N}$ the orthonormal Fourier matrix, $\boldsymbol{\theta} = [0, 2\pi)^T$ a vector of B0 inhomogeneity-induced phase offsets, and $T = N_y$ the number of repetitions (phase encode steps). Please note, that we use $\exp(i\boldsymbol{\theta})$ as a shorthand for the outer product $\exp(i\mathbb{1}\boldsymbol{\theta}^{\mathsf{T}})$. If phases $\boldsymbol{\theta}$ are known, the solution to the problem is straightforward and amounts to multiplying the spectrum with $\exp(-i\boldsymbol{\theta})$.

The key idea of proposed Alg. 1 is to reconvolve phase corrupted data in the frequency domain with PSFs associated with coil sensitivity profiles. We perform the convolution by element-wise multiplication in the spatial domain. Such reconvolution introduces characteristic dependencies in neighboring *k*-space lines, which are in disagreement with the additive phase offsets $\boldsymbol{\theta}$ that we apply after reconvolution. We use phases of perturbed spectrum $\angle\hat{\boldsymbol{Y}}$ as input to the network and offsets $\boldsymbol{\theta}$ as the target. During the training, we force the network to be insensitive to initial phase errors in the input spectrum. For this purpose before reconvolution we perturb the input spectrum with an additional phase vector $\boldsymbol{\psi}$, which we treat as noise. Proposed framework allows to generate an arbitrary number of training examples and avoid overfitting. As a proxy to actual complex-valued coil sensitivities we use an approximation obtained with an adaptive combine approach [4].

We acquired conventional T2*-weighted GRE data of a healthy volunteer after obtaining informed consent and approval by the local ethics committee. Images were acquired at 9.4T using a custom-built head coil with *M*=30 receive channels [3]. We used a 2D acquisition with the following parameters: TR=356 ms, TE=30 ms, flip angle = 45°, matrix = 512x512, resolution = 0.4x0.4 mm², slice thickness = 1mm, 9 slices. A non-phase-encoded navigator was acquired after each imaging readout. To speedup the training we crop the spectrum in frequency-encode direction around the center, which results in the input dimension of 64x512x60. The architecture of our network features 6x repetition of a block of [convolution (3x3), batch normalization, ReLu, maxpooing in X direction]. In each repetition we increase the number of neurons by 10, starting with 30 in the first layer. The last layers of the network are two convolution layers with 20/1 neurons. The dimensionality of the target is thus 1x512, which matches the size of the vector $\boldsymbol{\theta}$. We use MSE as a loss function, a batch size of 32 samples, adadelta optimizer, and a learning rate of 0.1. We train the network for 2000 epochs, which requires two hours on a single Tesla K80 GPU device. To speedup reconvolution and phase perturbation we perform all operations in Alg. 1 on the GPU with the use of CuPy [2].

3 Results:

We show five out of nine slices in Fig. 1. Phase errors make spectral data along the phase-encoding direction inconsistent causing characteristic ghosting artifacts. We compare the results obtained

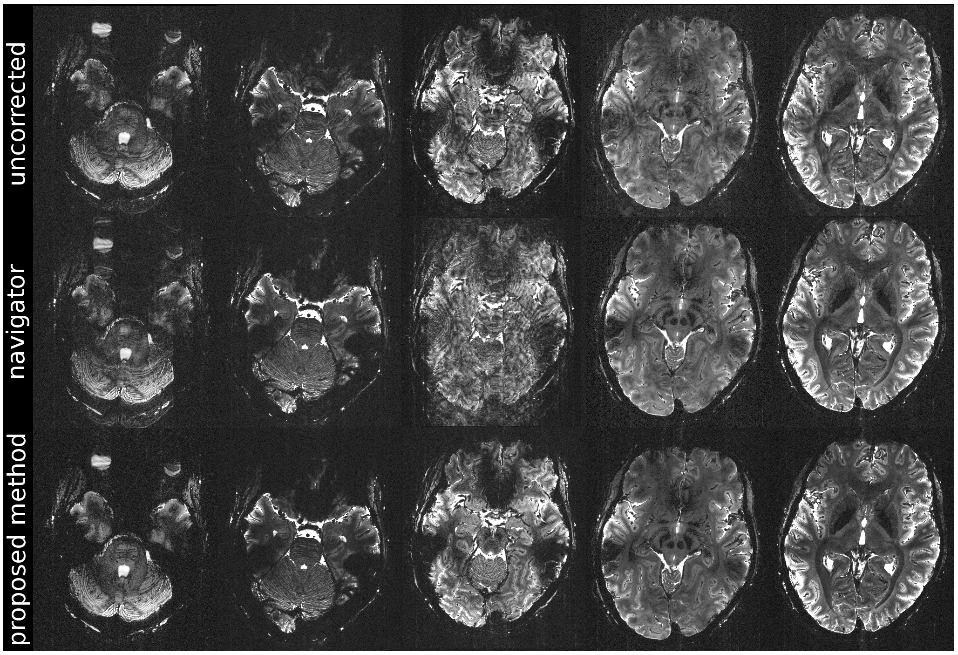

Figure 1: Five slices acquired with a 2D FLASH sequence are corrected for phase errors. The proposed CNN-based method is compared against a conventional navigator-based approach. As a reference, uncorrected images are shown. Ghosting artifacts most severe in the lower brain regions.

using our method with navigator-based reconstructions, and uncorrected images. The reconstruction pipeline of the vendor (Siemens) was used to obtain a navigator-corrected image. Phase distortions are most severe in the ventral portions of the brain due to proximity to body parts affected by B0 fluctuations (mostly caused by breathing). In slices 2,4 and 5 the proposed method achieves similar results to a navigator-based correction. In slices 1 and 3 the navigator-based correction is unstable, while our method is still capable of estimating the phase errors and correct for the artifacts.

4 Discussion:

We have demonstrated an ability of our method to learn to predict phase errors from a single corrupted scan. The key insight that is an enabling factor for our method is the discrepancy between phase error vectors and spectral data after convolution with PSFs associated with coil sensitivities. We approximate coil sensitivity profiles with an adaptive combine approach directly on the phase-corrupted data. Interestingly, we did not observe any significant difference in performance compared to the case where the profiles were estimated on the artifact-free data (acquired with TE=10ms). In future work, we aim to extend the method to 3D and accelerated acquisitions. Furthermore, we aim to predict phase error vectors for each coil element, which can result in better reconstructions.

References

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