**Unsupervised cycle-consistent network using restricted subspace field map for removing susceptibility artifacts in EPI**

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**Abstract**

**Purpose:** To design an unsupervised deep neural model for correcting susceptibility artifacts in single-shot EPI and evaluate the model for preclinical and clinical applications.

**Methods:** This work proposes an Unsupervised Cycle-consistent model based on the Restricted Subspace Field map to take advantage of both the deep neural network (UCRSF-net) and the gradient reversal method for single-shot EPI. The proposed model consists of three main components: (1) the UCRSF to obtain field maps based on a pair of images acquired with reversed-phase encoding; (2) the spin physical model-based modules to obtain the corrected undistorted images based on the learned field map; (3) the cycle-consistency loss between the input images and back calculated images from each cycle is explored to train the network. In addition, the field maps are derived using a restricted subspace to ensure the smoothness of the field maps and avoid blurring in the corrected images. This new method is trained and validated on both preclinical and clinical datasets for diffusion and functional MRI.

**Results:** The proposed network could effectively generate smooth field maps and correct for susceptibility artifacts in single-shot EPI. Simulated and in vivo preclinical/clinical experiments demonstrated that our method outperforms the state-of-the-art susceptibility artifact correction methods. Furthermore, the ablation experiments of the cycle-consistent network and the restricted subspace in generating field maps did show the advantages of UCRSF-net.

**Conclusion:** The proposed method (UCRSF-net) can effectively correct susceptibility artifacts for preclinical and clinical single-shot EPI sequences.

**Keywords:** Deep learning, EPI, susceptibility artifacts, subspace field map, diffusion-weighted MRI, cycle-consistent

# 1 | INTRODUCTION

Magnetic resonance imaging (MRI) is one of the most widely used imaging methodologies for preclinical and clinical applications.1 Specifically, single-shot Echo Planar Imaging (ssEPI) is one of the most efficient MRI acquisition schemes which can provide relatively high-definition images in 100 ms or less.2 Furthermore, the quality of ultrafast acquisition makes ssEPI immune to the motion artifacts and desirable for Diffusion Tensor Imaging (DTI),3,4 functional MRI (fMRI),5,6 and Dynamic Susceptibility Contrast MRI (DSC-MRI).7 However, due to the B0 field inhomogeneity and the low bandwidth along the phase encoding direction, ssEPI suffers from severe susceptibility artifacts, especially at tissue boundaries with different susceptibilities and high fields.

Many methods have been proposed to correct the susceptibility artifacts in ssEPI.8 Among various proposed ssEPI susceptibility correction methods, field-mapping9,10, and gradient reversal methods11 are the two most commonly used methods. The field-mapping techniques first collect two gradient-echo (GRE) images with different TE values to calculate the B0 field map10. Then, the distorted images are corrected by coordinate calculation and linear interpolation based on the field map. Although these methods are easy to implement, their performance is limited by the field map's quality. Inaccurate field maps will lead to the residual artifacts after the distortion correction. Note that the ssEPI acquisition for the full human brain takes only a few seconds, while acquiring a GRE-based image for field mapping requires several minutes.12 Furthermore, the phase unwrapping procedure in the field map calculation is vulnerable to various errors, especially near tissue boundaries or regions with high field inhomogeneity.13 The gradient reversal method relies on two reversed phase encoding images to estimate the displacement map.14 Chang et al.15 proposed the gradient reversal method, which estimates the displacement map in each line along the phase encoding direction independently by calculating the integral for every phase encoding. The main limitation of this method is the use of 1-D unwarping for every phase encoding line without considering the displacement map's smoothness, resulting in streaking or discontinuities in the corrected images. Improved implementation of the reversed gradient method by Andersson involves fitting for a smoothly-varying displacement field using discrete cosine basis functions16. This method is widely used in FSL (FMRIB Software Library) as TOPUP17. The main problem of these conventional approaches is the time-consuming optimization of the objective function, especially for large-sized input images. Moreover, the optimized objective functions often lead to a poorly conditioned, nonconvex optimization problem and fall into a local minimum.

With the development of deep learning in medical image processing, several researchers recently began to use deep learning methods to correct susceptibility artifacts in ultrafast MRI. Deep learning techniques provide a potential avenue for dramatically reducing computational time and solving nonconvex optimization problems for the field map estimation. These deep learning techniques can be divided into supervised18,19 and unsupervised methods.20,21 The supervised methods need the datasets with ground truth to train the model. Liao22 proposed to use the convolutional neural network (CNN) for gradient-echo ssEPI distortion correction based on the simulated distorted images generated by SPROM software. Hu23 proposed a 2D-Unet based network for correcting distortions in ssEPI, in which they use PSF-EPI images as targets to train the network to obtain the displacement maps. However, the displacement maps are tedious to acquire or may not be guaranteed to represent a "true" ground truth due to the phase unwrapping or regularization procedure's errors. Moreover, the displacement maps based on simulations are always different from the experimentally measured maps, especially in the temporal lobes or surroundings of the sinuses. On the other hand, unsupervised networks do not need the ground truth (the "true" displacement map or undistorted images) to train the network. Soan20 proposed an end-to-end deep learning network (S-Net) to correct the reversed-phase encoding ssEPI image pairs' susceptibility artifacts, exploring the use of deep convolutional network to estimate the displacement map from a pair of input images. Benjamin21 trained a deep convolutional U-net architecture that was previously used to estimate optic flow (Flow-Net24) between moving images to learn to predict the distortion map from an input pair of distorted ssEPI acquisitions. During the training step, the network minimizes a loss function calculated from corrected input image pairs.

This paper presents a new unsupervised cycle-consistent deep neural network that uses a restricted subspace field map25 to correct susceptibility artifacts in the reversed-phase encoding ssEPI. Firstly, the deep neural network combined with the restricted subspace technique generates the displacement map that avoids converging to local minima estimates. Then the forward and backward physical model containing both geometric and intensity correction modules is employed to obtain the cycle-consistent loss for the network training. This approach does not require explicit knowledge of the ground truth displacement map. The simulation experiments show that our method outperforms the state-of-the-art traditional and deep learning methods in qualitative and quantitative terms. Both clinical and preclinical applications are tested to demonstrate the generalization capabilities of this method. Furthermore, the ablation experiments show the advantage of the combination of the restricted subspace technique and deep learning in generating field maps and the cycle-consistent loss for correcting susceptibility artifacts.

# 2 | METHODS

## 2.2 | The overall architecture

The overall architecture of the proposed method is shown in Figure 1. Figure 1(a) shows the pulse sequence of reversed-phase encoding ssEPI. In figure 1(b), we illustrate the main idea of this method: Firstly, the field map is obtained by the UCRSF network based on the data acquired with the reversed-phase encoding ssEPI. Then the corrected images can be obtained by the physical backward model (Geometric and Intensity Correction) using the generated field map. Finally, the forward model is applied to obtain the distorted cycle back blip-UP/DOWN images to calculate cycle-consistency loss. Figure 1(c) shows the details of the respective procedures.

## 2.2 | UCRSF-Net for field map estimation

At the heart of the susceptibility artifact correction lies the accurate estimation of the B0 field map. However, estimating field maps is not a straightforward problem because the least-squares cost function with respect to field maps is always nonconvex.26 Neighborhood information is often incorporated into the reconstruction to avoid erroneous field map estimates. Motivated by the work of Tsao,26 we propose a new network (UCRSF-network) that takes both advantages of deep learning and restricts the field map to a subspace. The overall architecture of the UCRSF-network is shown in Figure 2. The main idea of the UCRSF-network is to generate the coefficients for the field map in the restricted subspace, namely, these coefficients are expected to be close to the inner product of the field map and the predefined cubic spline vectors.27 Moreover, we can notice in Figure 2 that the coefficients of field maps in the different resolution subspaces correspond to different feature layers in the network. For example, the feature maps in UCRSF-Net's bottom layer correspond to the coefficients in the restricted low-resolution subspace. In contrast, the feature maps of the upper layers correspond to the coefficients representing the higher resolution subspace of the field map.

The architecture of UCRSF-Net is similar to the most common network (U-Net28).  It has a symmetric encoder-decoder architecture, including Skip Connections, shown in Figure 2. The layers in the encoder part are skip connected and concatenated with layers in the decoder part. The skip connections promote U-Net to use fine-grained details learned in the encoder part to construct an image in the decoder part. The encoder part consists of multiple residual blocks and results in a feature map with halved resolution as the input for the next encoder. The residual blocks29 were used to replace the traditional U-Net feature extraction block. Details of the encoder are shown in the upper left part of Figure 2(a): it contains two 2D convolutional layers, two rectified linear units (ReLU), and a skip connection. The decoder block contains 2D convolutional layers, two batch normalization layers, and an upsampling layer, shown in Figure 2(a). More details of the UCRSF-Net can be found in the support information Text S1. As was mentioned above, with the number of decoding layers increasing, the dimension of the coefficient matrix also increases. The Residue Leaky ReLU(RLR) is utilized to convert the feature map to the coefficients, shown in Figure 2(c). The Leaky ReLU is introduced as the activation function to ensure that the output can be positive or negative. Then, the Back Projection Module (BPM) is applied to map the deep-learned coefficients to the field map in the image space by multiplying the predefined basis, shown in Figure 2(b).

## 2.3 | Geometric and intensity correction based on UCRSF-learned field map

In general, the susceptibility artifacts induced by field inhomogeneities in ssEPI can be assumed to be negligible along the frequency-encoding and slice-selection direction due to much higher acquisition or excitation bandwidth. Thus, susceptibility artifacts along phase-encoding (PE) in ssEPI can be considered as consisting of two parts: geometric deformations and intensity variations. It is intuitive for the geometric deformation induced by the B0 inhomogeneities to manifest as a pixel shift along the PE direction. For a pixel in position (x,y), the shift distance along the PE in terms of the number of pixels can be formulated as . More details on the theoretical background of susceptibility artifacts can be found in the Supporting information Text S2. The undistorted spatial images  can be obtained based on  mapping of the distorted domain to undistorted domain, . As the distance of pixel shifts are not necessarily integer multiples of the image resolution, the interpolation of the distorted images is usually needed.30

After the geometric deformation correction, the intensity correction should not be neglected. Theoretically, the mean intensity of any subspace should be inversely proportional to its area.31 Pixel-wise Jacobian modulation has usually been adopted to correct intensity variation, in which the contracted areas will experience increased intensity, and the dilated areas will experience decreased intensity.4 More details regarding intensity corrections using Jacobian modulation used in this paper can be found in the Supporting information Text S3. In this work, the optimized Jacobian modulation method is used based on the recent work,32 and the corrected images can be obtained by the following equation:

 (1)

If the field map derived by deep-learning is exact, the intensities in the image after correction by Jacobian modulation Jfield and "true" image pixel intensities will be the same. However, it is difficult to obtain an accurate Jacobian matrix. As the intensity accumulation and corresponding intensity dispersion in the image pair can compensate for each other to a certain degree, the intensity correction by Equation (1) has certain tolerance to field map error propagation and can obtain better images compared to traditional Jacobian modulation. After obtaining the corrected images, we need to derive the cycle back-calculated images based on the forward model to get the cycle-consistent loss for unsupervised training of the network. More details regarding cycle-consistency loss calculation can be found in the supporting information Text S4.

## 2.4 | The Loss function

To optimize the performance of susceptibility artifact correction, we propose a hybrid loss function that considers several knowledge priors. The first term of the hybrid loss is the cycle-consistency losses between the cycle back- -calculated blip-UP/DOWN images and original UP/DOWN images. It also consists of the field map loss that enforces similarity between the two field maps, and the structural similarity between the T2/T1 weighted imaged and the corrected EPI images. The hybrid loss function can be denoted as:

 (2)

Where  is the cycle-consistency loss represents the difference between the original and the cycle back-calculated images. denotes the loss of the difference between two field maps.  denotes the loss for the two corrected UP/DOWN images. And  means the normalized mutual information(NMI)33,34 for the structural similarity between the susceptibility artifact-corrected image and the reference image, which is defined as:

 (3)

where  and  are the corrected image and the reference image, respectively. The expression of normalized mutual information is as follows:

 (4)

where  represents the probability distribution of , which means the probability that variable  has value ,  is the joint probability distribution of  and . NMI values range from 0 (no mutual information) to 1 (completely relevant). In addition,  are the weighting factors in formula (2) that are empirically set as , and  after performing an array of optimization runs. Supporting Information Figure S1 depicts the convergence curves of UCRSF network training under different loss components.

# 3 | Experiments

## 3.1 | Datasets

The preclinical MRI data were acquired on a Bruker Biospec 7.0 T/20cm MRI scanner using a homemade modified EPI sequence with an inverse encoding gradient in the coronal view of the rat brain. (The source code of the modified EPI sequence is available in the ???) A 72-mm-diameter volume coil was used for radio-frequency (RF) transmission, and a quadrature surface coil for signal detection. The rats were anesthetized with isoflurane mixed with oxygen (4.0-5.0% for induction, 0.5-1.0% for maintenance). The respiratory rate (30~50) was continuously monitored during the scan under the anesthesia state scan. The body temperature was maintained with 37 °C water circulation. The sequence parameters are as follows: the field of view (FOV) is 28×28 mm2, the acquisition matrix's size is 80×80, TE = 30 ms, TR = 4000 ms, slice thick = 1 mm, number of slices for each rat ranged from 20 to 30, number of averages (NA) = 1. The diffusion-weighted scans were distributed equally over 1 shell defined with b-values of 1000s/mm2, diffusion gradient time δ= 3.5 ms, and gradient separation time Δ = 12 ms. In addition, each rat also has corresponding T2w images with RARE pulse sequence: The FOV is 28×28 mm2, the acquisition matrix's size is 256×256, TE = 20 ms, TR = 2500 ms, slice thick = 1 mm, the reference images' region and position are the same as for the EPI sequence.

All clinical data were acquired using multi-shell multi-band EPI sequences with an inverse encoding gradient, downloaded from the Human Connectome Project (HCP) website, including DWIdata, fMRI data, and structural data.35,36 All the images were acquired on the HCP standard 3T Siemens MRI scanner with 32 channel head coil.37 Parameters selected for DWI-EPI were: the FOV is 208×180 mm2, the acquisition matrix's size is 104×90, TE = 89.5 ms, TR = 5520 ms, nominal voxel size of 1.25 mm isotropic, and 270 diffusion-weighted scans distributed equally over 3 shells defined with b-values of 1000, 2000 and 3000 s/mm2. For fMRI images, the FOV is 208×180 mm2, the acquisition matrix's size is 104×90, TE = 89.5 ms, TR = 5520 ms, spatial resolution of 2 mm isotropic voxels. Each scan was repeated along two reverse phase encoding directions (L/R and R/L). The T1w images: FOV is 224×224 mm2, the acquisition matrix's size is 320×320, TE = 2.14 ms, TR = 2400 ms, nominal voxel size of 0.7 mm isotropic. The corresponding correction results of fMRI-3T are shown in Supporting Information Figure S2.

## 3.1 | Implementation

The UCRSF model was implemented on Pytorch for the Python 3.6 environment on an NVIDIA Geforce GTX 2080Ti with 11GB GPU memory and Intel Core CPU i7-8700 3.7GHz. The network was trained by the hybrid loss function according to section 2.4 and Adam optimizer38 with , , . Each dataset was trained for 300 epochs. The initial learning rate was set to 0.001, and it decreased by a factor of 0.95 after five epochs.

Two deep learning methods (Soan's20 and Benjamin's21) and the well-known traditional method (TOPUP 16,17 in FSL6.04) are used for the comparison with UCRSF-Net. In terms of the model parameters: Benjamin's has 2.87 million, UCRSF-Net has 3.02 million, and Soan's has 2.16 million parameters. All deep learning methods (Soan's method, Benjamin's method, and UCRSF-Net method) running on the PyTorch platform have a correction time of less than 1.8 seconds per subject with GPU. With CPU, the correction times are 2.8 s, 9.6 s and 15.2 s, which are still less than the correction time of the traditional method TOPUP (598s) running on the FSL6.04 platform.

We also performed the Bloch equation-based simulation to compare the susceptibility correction results quantitatively This simulation was performed based on our preclinical dataset acquired with the FSE pulse sequence on a 7.0T scanner. Moreover, the B0 inhomogeneity maps were obtained from the field map protocol based on 3D-GRE with different TEs. The distorted ssEPI images (UP/DOWN) were simulated with different phase-encoding gradient polarities. And the reference images were simulated with zero B0 inhomogeneity, in which UP/DOWN images are identical. The quality of the outputs of the network were evaluated by two quantitative metrics: peak signal-to-noise ratio (PSNR) and structural similarity index (SSIM).39

# 4 | RESULTS

## 4.1 | Validation for Simulated EPI data acquired with reversed gradients

Figure 3 shows the corrected images for simulated EPI data acquired with the reversed gradients and the corresponding quantitative comparison. The columns from left to right show: reference images, distorted bilp-UP/DOWN images, images corrected by TOPUP16,17, Soan's,20 Benjamin's21 and the UCRSF method. The last column shows the corresponding field maps used for the simulation. Here we also show the correction results for different B0 inhomogeneities, one from -150 Hz to 150 Hz, and the other from -200 Hz to 200 Hz. Figure 3 illustrates that the UCRSF method can obtain better corrected images. This can be particularly well perceived by the zoomed regions (the second and fifth row) and by the error maps (the difference between the reference images and the corrected images). This can be appreciated even better from the zoomed regions and the absolute error map. And the last line summarizes the quantitative comparison between the results obtained by TOPUP,16,17 Soan's ,20 Benjamin's21 and the UCRSF method. Regarding PSNR/SSIM quantitative metrics, the UCRSF method is 33.6/0.92, which is higher than 28.3/0.82 for TOPUP, 29.8/0.82 for Soan, and 30.1/0.85 for Benjamin's.

## 4.2 | The correction results for the clinical dataset

Figure 4 presents comparison between correction results for b0 images of DWI-3T data with the edges extracted from the corresponding T2 images using Boundary-Based Registration (BBR)40. The images from left to right correspond to distorted blip-UP/DOWN images, images corrected by TOPUP,16,17 Soan's ,20 Benjamin's21 and the UCRSF method. The 2nd and 5th rows show the absolute error maps between cycle back-calculated blip-UP and original UP images. The 3rd and 6th rows show the absolute error maps between corrected UP and DOWN images. Figure 4 illustrates that the UCRSF method can obtain better corrected images with respect to the other assessed methods especially at the edges and in the region of the cerebrospinal fluid (CSF). The corrected images with UCRSF show the smallest error maps in both cycle back-calculated error maps, and error maps calculated between corrected UP and DOWN images. Additional corrected images for various representative slices from the human brain are shown in Supporting Information Figure S3. In addition, Figures S4, S5, S6 in the Supporting Information show the correction results for different b-values at various regions of the human brain.

We also evaluated the corresponding fractional anisotropy (FA) map41, and diffusion-encoded-color (DEC) map42, based on the images after susceptibility artifact correction. Figure 5 shows comparison of different susceptibility artifacts correction methods for two slices of the fractional anisotropy (FA) and diffusion-encoded-color (DEC) maps. We can notice that the deep learning method can obtain better b0 images, FA, and DEC maps compared to other evaluated methods. Figure S7 in the Support information shows another slice that suffers from susceptibility artifacts close to the sinus.

## 4.3 | Correction results for preclinical data

We also applied the different susceptibility artifact correction methods to correct artifacts in the preclinical DWI-7T dataset. Figure 6 shows a comparison of the results after applying corrections using different methods, including TOPUP16,17, Soan's,20 Benjamin's21, and UCRSF. Figure 6 shows that the UCRSF method can obtain better corrected images compared to the rest of assessed methods. Supporting Information Figure S8 shows another diffusion-weighted slice of the rat after applying corrections using various methods. Figure 7 presents comparison between the results after applying corrections for fractional anisotropy (FA) maps,41 and diffusion-encoded-color (DEC) maps42 arising from images after applying different correction methods. As can be seen from Figure 7, the deep learning method can obtain better b0 corrected images, diffusion-weighted images, fractional anisotropy (FA) map,41 and diffusion-encoded-color (DEC) map42, compared to other evaluated methods. Supporting Information Figure S9 shows diffusion-weighted results and corresponding FA and DEC maps for some additional slices of rats.

# 5 | DISCUSSION

This work has introduced a new method for distortion correction in EPI images that arise from magnetic field inhomogeneities. Quantitative metrics on all examined data sets demonstrate, along with qualitative image assessment, that our proposed method outperforms widely employed TOPUP method and some of the recently introduced DL-based methods. At the same time, the method introduced herein is orders of magnitude faster than TOPUP method while using the same input, namely, so-called "UP" and "DOWN" images.

Particular effort has been dedicated to address one of the main challenges when deriving field maps: overcoming discontinuities introduced through the fitting process. In TOPUP, this has been addressed by fitting a field map to a set of discrete cosine functions. In line with this idea, we chose spline functions as our basis set. Firstly, this helps to avoid discontinuities in the derived field maps, and secondly, this reduces the space in which the field map is expected to lie by constraining it to a subspace spanned by the basis functions. While some of the methods try to enforce smoothness on the field map by penalizing total variation of the field map, using a set of smooth basis functions ensures this by definition. Impact of the usage of spline subspace on simulated EPI-7T mice data set and HCP DWI-3T data dataset is illustrated in Figure 8 where SSIM is significantly reduced when directly using extracted feature maps without projecting them to the spline basis set, i.e., by ablating the BPM module. This is particularly well exemplified by preclinical images, where a spline basis set helps to reduce dimensionality of the solution space and improves the convergence, particularly well perceivable in the vicinity of structures with sharp intensity changes, where model without spline basis does not converge to one solution.

The ablation experiments were also performed to evaluate the advantage of the cycle loss and the NMI loss terms. Firstly, the improvements of the cycle loss term is shown in Figure 9 both for the simulated EPI data and real in vivo DWI-3T data. In Supporting Information, Figure S10 results from ablation experiment are shown with and without NMI loss. As can be seen, the CSF region and the edge region were better corrected when using NMI loss. Moreover, we demonstrated that our proposed model can perform shift correction with high fidelity and the more challenging task of intensity correction. We assign this asset to adoption of an optimized method to calculate intensity correction as described by Eq. 1. This approach tries to alleviate the limited accuracy of the derived field maps. The benefits of Eq. 1 are emphasized in Figure. 10 comparing it to the classical Jacobian correction method.

One advantage of the TOPUP method is the fast acquisition of input image pairs from which the field map will be derived. This allows for minimizing the impact of motion, which is much more of a concern for alternative distortion correction methods based on time-consuming field mapping7. Nonetheless, to define cost function as physically realistic as possible we accounted for potential impact of motion or field drift and derived two field maps allowing differences in field maps corresponding to "UP" and "DOWN" images, respectively, but applying a slight penalty on these differences to force maximal similarity between them when no or negligible amount of motion is present. The benefits of this approach in the presence of motion based on simulations are illustrated in Supporting Information Figure S11.

The simulated and in vivo preclinical/clinical experiments show the advantages of the susceptibility artifact correction method introduced in this work. However, this method is designed for the single pairs of UP/Down images without taking advantage of the whole diffusion-weighted dataset. Eddy-current-induced-distortions caused by the rapid switching of diffusion gradients are ignored, these distortions may cause misalignment between different DWI volumes, thereby affecting the quality of the FA and DEC MAP. However, the existing eddy-current-distortion correction based on affine transformations is not enough. Our next direction is to further correct the eddy-current-distortion between different volumes of DWI based on the susceptibility artifact correction.

# 6 | CONCLUSIONS

This paper presents a cycle-consistent deep neural network that combines the deep neural network and the gradient reversal method for correcting susceptibility artifacts. The model can be applied with unsupervised training without explicit knowledge of the ground truth field map. Results using clinical and preclinical datasets demonstrate that our method outperforms state-of-the-art methods, and the speed is an order of magnitude faster than the traditional iterative TOPUP method.

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**List of figure**

**Figure 1.** (a) The pulse sequence and k-space acquisition trajectory of reversed-phase encoding ssEPI; (b) the cycle-consistency idea of this method, Firstly, the field map is obtained by the UCRSF network based on the pairs of images acquired by the reversed-phase encoding ssEPI. Then the corrected images can be obtained by the physical backward model (Geometric and Intensity Correction) with the generated field map. Finally, the forward model is applied to obtain the distorted cycle back blip-UP/DOWN images to explore the consistent cycle loss. (c) The whole detailed procedure of the proposed learning framework for the ssEPI susceptibility artifacts correction. The total loss for training the network is shown at the bottom.

**Figure 2.** (a) The overall architecture of the UCRSF-Net. (b) The Back Projection Module multiplies the pre-generated bases and the coefficients map generated by the network to obtain the components of the final field map. (c) The Residue Leaky ReLU is introduced as the activation function to ensure that the output can be positive or negative.

**Figure 3.** Comparison of different susceptibility artifact correction methods for simulated EPI-7T mice data set and the quantitative results of PSNR, SSIM, correction time, and amount of parameters. Columns from left to right correspond to reference images (no B0 inhomogeneity), distorted blip-UP/DOWN images, corrected images based on TOPUP,16,17 Soan's ,20 Benjamin's21 and herein proposed method (UCRSF) along the field map used for simulation.

**Figure 4**. The susceptibility artifact correction results were compared for b0 images of DWI-3T data. The edges extracted from the corresponding T1 reference images are overlaid over the corrected images. The 2nd and 5th rows show the corresponding absolute error maps between cycle back blip-UP and original UP. The 3nd and 6th rows show the corresponding absolute error maps between corrected UP and corrected DOWN.

**Figure 5**. The comparison of different susceptibility artifact correction methods for two slices of the fractional anisotropy (FA) and diffusion-encoded-color (DEC) maps. The rows from up to down show the b0 images, diffusion-weighted images, the FA and DEC maps.The bottom four rows show theb0 images, diffusion-weighted images, the FA and DEC maps for the slice that suffers from susceptibility artifacts close to the sinus.

**Figure 6.** Comparison of the correction results obtained by the different methods, including TOPUP16,17, Soan's,20 Benjamin's21, and UCRSF.

**Figure 7.** Comparison of the correction results for fractional anisotropy (FA) maps, and diffusion-encoded-color (DEC) maps based on different correction methods.

**Figure 8.** The comparison of our proposed method with or without BPM module.

**Figure 9.** The comparison of our proposed method with and without the cycle-consistency loss for our laboratory DWI-7T and HCP DWI-3T test data. On the far right is the reference and the corresponding Quantitative comparison (SSIM) for a slice of HCP DWI-3T test data

**Figure 10.** Different density compensation results are shown in the first row: a shows the corrected image without density compensation; b and c show the corrected image obtained with Jfield and JRPG, density compensation method, respectively. In addition, in d FSE image is presented for reference. The second row presents a quantitative comparison between no weight, Jfield weight and JRPG weight density compensation methods.