# ANATOMY-GUIDED INVERSE-GRADIENT SUSCEPTIBILITY ARTIFACT CORRECTION METHOD FOR HIGH-RESOLUTION FMRI

S. T. M. Duong<sup>1</sup>, M. M. Schira<sup>2</sup>, S. L. Phung<sup>1</sup>, A. Bouzerdoum<sup>1,3</sup>, and H. G. B. Taylor<sup>2</sup>

<sup>1</sup>School of Electrical, Computer and Telecommunications Engineering, University of Wollongong, <sup>2</sup>School of Psychology, University of Wollongong, NSW, 2522, Australia <sup>3</sup>College of Science and Engineering, Hamad Bin Khalifa University, Doha, Qatar

## ABSTRACT

Functional Magnetic Resonance Imaging (fMRI) is a widely used and non-invasive technique for recording changes in brain activity. However, susceptibility artifacts are ubiquitous distortions in fMRI, especially strong in high-resolution images, causing the misrepresentation of brain function and structure in the affected regions. Here, we present a novel method for correcting these distortions in high-resolution fMRI images based on the hyper-elastic susceptibility artifact correction (HySCO) method. The novelty of the proposed method is the utilization of the easily-acquired T1-weighted  $(T_{1w})$  anatomy image as a ground-truth measurement to regularize deformations, thereby obtaining meaningful corrections. The performance of the new method is compared to that of HySCO. Results from high-resolution (1mm) EPI data are presented demonstrating the robustness of the new method for image correction and its suitability for subsequent fMRI analysis.

*Index Terms*— Susceptibility artifact, high-resolution fMRI, artifact correction, inverse-gradient, anatomy-guided.

#### 1. INTRODUCTION

Functional MRI allows researchers to non-invasively examine not only the structure of the human brain, but also its functions. Since its first demonstration twenty five years ago [1], fMRI has become a widely used tool in brain research. Many sophisticated yet robust experimental designs have been developed for analysing fMRI data. For example, the population receptive field (pRF) analysis, used in some visual fMRI experiments, reveals functional maps in early visual cortex by modelling the time course of voxels measured with fMRI, and estimating the section of the visual field to which neurons in each voxel respond [2]. Recent improvements in MRI technology have greatly increased the resolution of functional and anatomical brain images, giving researchers an unprecedented level of insight into how the human brain processes information. However, fMRI images always contain geometric and intensity distortions, known as susceptibility artifacts (SAs), which have yet to be adequately addressed. fMRI data acquired using the Echo-Planar Imaging (EPI) technique are inevitably affected by SAs [3] due to its fast imaging capability (e.g. a 3-D image in 2 seconds). The source of these artifacts is local field inhomogeneities caused by differences in magnetic susceptibilities of various tissue types (e.g. fat and blood) [3,4]. Addressing SAs is crucial, as they can confound the interpretation of results concerning the structure and function of the brain.

Several susceptibility artifact correction (SAC) methods have been proposed for multiple types of MRI images, such as structural MRI, diffusion MRI, and fMRI. The most common of these approaches involves estimating phase dispersions (phase-map), caused by the field inhomogeneities, which are then used to generate the corrected images by unwarping distorted images [4, 5], or rewinding the additional accumulated phase in k-space [6]. Another approach is modeling the distortions by a point spread function (PSF), the corrected images being results of either a deconvolution operation of distorted images with the PSF [7, 8], or an algorithm using the conjugate gradient [9]. A further approach registers the distorted images with a corrected image by using rigid [10] or non-rigid registration [11–13].

The focus of this work is fMRI images acquired using EPI sequences, where SAs are most pronounced along the phase-encoding (PE) direction (direction that images are acquired) [14, 15]. Interestingly, two EPI fMRI images, acquired using an identical imaging sequence but inverse po*larity of PE gradients* (inverse-blip or inverse-gradient), have inverse patterns of distortions in the PE direction. Thus, some correction methods use inverse-gradient images to estimate correction matrices. Chang and Fitzpatrick proposed a simple spatial correction by finding pairs of corresponding points in inverse-gradient images [16]. An alternative approach models the field inhomogeneity as a combination of discrete cosine basis functions [17]. An integration of the inverse-gradient based approach into a registration framework was proposed in [15]. Building on this, Ruthotto et al. proposed a method, named HySCO, by introducing hyper-elastic image registration to achieve a more realistic and better constrained distor-

The authors would like to thank Dr. Alexander Puckett from Queensland Brain Institute at the University of Queensland, QLD, AU, for collecting the experimental data. This work is supported by a grant (ID: APP1086083) from the National Health and Medical Research Council and a grant (ID: DP140101833) from the Australian Research Council.

tion framework [18]. The use of an independent set of images, specifically T2-weighted  $(T_{2w})$  images, to tune the inversegradient registration has also been suggested in [19].

The essentially undistorted anatomy image, collected using a much slower image acquisition (about 6 minutes), provides an almost ground-truth image of the brain. In this paper, we propose to integrate the  $T_{1w}$  anatomy image into a stateof-the-art SAC scheme, namely HySCO [18]. The specific advantage of utilizing a  $T_{1w}$  image over a  $T_{2w}$  image is that the  $T_{1w}$  image is routinely acquired alongside of fMRI images for anatomical reference and hence does not require additional scanning time. Here we suggest a second use of  $T_{1w}$ images, aiding in creating a robust and accurate procedure for removing SA from high-resolution fMRI images. The work presented here may be considered as extending the original HySCO work in three respects: model formulation, image type, and experimental evaluation.

The paper is organised as follows. Section 2 presents the inverse-gradient correction model. Section 3 introduces the proposed SAC method. Section 4 presents experiments and analysis. Section 5 presents concluding remarks.

### 2. INVERSE-GRADIENT CORRECTION MODEL

The inverse-gradient approach is a two-step correction method. In the first step, the field inhomogeneity B is estimated using the two corresponding images  $I_1$  and  $I_2$  with inverse-blip. In the second step, the distorted images are unwarped using a distortion model, resulting in corrected images.

First, we describe the distortion model in the presence of the magnetic field inhomogeneity. Let E be the 3-D ideal image and I be the acquired but distorted image. The distortion model at every 3-D point **p** is defined [15, 16] as

$$E(\mathbf{p}) = I(\mathbf{p} + B(\mathbf{p})\mathbf{v}) [1 + \partial_{\mathbf{v}}(B(\mathbf{p}))], \qquad (1)$$

where **v** denotes the distortion direction (PE direction), and  $\partial_{\mathbf{v}}(B(\mathbf{p}))$  denotes the directional derivative of *B* at **p** along **v**. Let us assume that the PE gradient is applied in the first dimension, hence  $\mathbf{v} = (1, 0, 0)$ . In Eq. (1), the term  $(1 + \partial_{\mathbf{v}}(B(\mathbf{p})))$  denotes the intensity modulation of the acquired images. The term  $(\mathbf{p} + B(\mathbf{p})\mathbf{v})$  denotes the geometric displacement. In other words, the point **p** in the ideal image *E* is shifted to point  $(\mathbf{p} + B(\mathbf{p})\mathbf{v})$  in the acquired image *I*. Note that *B* causes distortions in acquired images, and hence it is called the deformation field.

Next, assume that v is the PE direction of image  $I_1$ ; thus the PE direction of image  $I_2$  is -v. By applying Eq. (1), the corrected images  $E_1$  and  $E_2$  are

$$E_1(\mathbf{p}) = I_1(\mathbf{p} + B(\mathbf{p})\mathbf{v}) [1 + \partial_{\mathbf{v}}(B(\mathbf{p}))], \qquad (2)$$

$$E_2(\mathbf{p}) = I_2(\mathbf{p} - B(\mathbf{p})\mathbf{v}) \left[1 - \partial_{\mathbf{v}}(B(\mathbf{p}))\right].$$
(3)

To generate the corrected images, the deformation field B is estimated such that the two images  $E_1$  and  $E_2$  should be as similar to each other as possible. The similarity can be measured by the sum of squared differences (SSD) over the image domain  $\Omega \subset \mathbb{R}^3$  [15, 18]:

$$D(I_1, I_2, B) = D(E_1, E_2) = \frac{1}{2} \int_{\Omega} (E_1(\mathbf{p}) - E_2(\mathbf{p}))^2 d\mathbf{p}.$$
(4)

Finding *B* by minimizing the distance function  $D(I_1, I_2, B)$  is categorized as an ill-posed problem [15,18]: multiple possible solutions exist, but only one is correct. Thus, prior knowledge about smoothness and invertibility of the geometrical transformation is introduced to regularize *B* [18]. To enforce the smoothness of the transformation, a Tikhonov regularizer  $S^{\text{diff}}$  is integrated into the objective function [15]

$$S^{\text{diff}}(B) = \int_{\Omega} \| \partial_{\mathbf{v}}(B(\mathbf{p})) \|^2 d\mathbf{p}.$$
 (5)

To ensure the invertibility, the Jacobian matrix of the geometric transformation in Eqs. (2) and (3) must be invertible. Chang and Fitzpatrick [16] demonstrated that this is equivalent to satisfying the constraint:  $-1 \leq \partial_{\mathbf{v}}(B(\mathbf{p})) \leq$ 1, for all  $\mathbf{p} \in \Omega$ .

In addition, Ruthotto *et al.* observed that the deformation field B should be as small as possible, and proposed to augment the objective function by a non-linear term  $S^{\text{hyper}}$  [18]. This term is inspired by the hyper-elastic model:

$$S^{\text{hyper}}(B) = \int_{\Omega} \phi(\partial_{\mathbf{v}}(B(\mathbf{p}))) \, d\mathbf{p}, \quad \text{with } \phi(z) = \frac{z^4}{1 - z^2}.$$
(6)

Finally, Ruthotto et al. proposed the objective function:

$$J(B) = D(I_1, I_2, B) + \alpha S^{\text{diff}}(B) + \beta S^{\text{hyper}}(B),$$
  
s.t.  $|\partial_{\mathbf{v}}(B(\mathbf{p}))| \leq 1.$  (7)

HySCO estimates B by minimizing (7) based on the Gauss-Newton method, then generates the corrected images using Eqs. (2) and (3). HySCO can provide corrected images with high similarity, however the results may not be reasonable in terms of the brain structure. For example, its results always contain blur trails, as shown later in the corrected LR image of Fig. 1. These artifacts are likely due to over-deformation in the estimated B (see under arrows of Fig. 1) as there is no constraint enforcing adherence to the correct brain structure.

#### 3. PROPOSED ANATOMY-GUIDED CORRECTION

The  $T_{1w}$  anatomy image, which has different contrast properties (modality) to EPI fMRI images, is typically regarded as a *gold standard* representation of a subject's brain anatomy. It is routinely acquired for every subject that participates in an fMRI study, and hence is readily available. Here, we propose to integrate a  $T_{1w}$  image into the HySCO registration in order to tune the deformation with respect to the brain anatomy.

The proposed anatomy-guided inverse-gradient SAC (AISAC) is described as follows. Let A denote the  $T_{1w}$  anatomy image. By incoporating the image A, the optimization problem becomes finding the deformation field B such

that images  $E_1$  and  $E_2$  (i) are as similar as possible, and (ii) fit best with the image A in terms of morphology. A similarity term  $D(I_1, I_2, B, A)$  based on the normalized gradient field (NGF) is introduced to satisfy the second condition. The NGF can provide the image structure, and it has been proven to be well-suited for the multi-modal registration problem [20].

The NFG measure can be defined as follows. First, for a given image X, the NGF at any point **p** is defined as [20]

$$\tilde{\nabla}(X(\mathbf{p})) = \frac{\nabla X(\mathbf{p})}{\sqrt{\|\nabla X(\mathbf{p})\|^2 + \varepsilon^2}},$$
(8)

where  $\varepsilon^2$  is the edge threshold parameter. This parameter determines what is considered an edge, i.e. a point **p** with  $\|\nabla X(\mathbf{p})\|^2 > \varepsilon^2$  belongs to the edge of image X, and vice versa. The term  $\tilde{\nabla}(X(\mathbf{p}))$  is a vector which reveals the intensity change and its direction at point **p**.

Next, let  $\langle \cdot, \cdot \rangle$  denote the dot-product operator. The NGF distance between two images X and Y is defined as

$$D^{\mathrm{NGF}}(X,Y) = \frac{1}{2} \int_{\Omega} 1 - \langle \tilde{\nabla}(X(\mathbf{p})), \tilde{\nabla}(Y(\mathbf{p})) \rangle^2 \, d\mathbf{p}.$$
 (9)

The NGF similarity between two unwarped images  $E_1$ and  $E_2$  and the A is then introduced as

$$D(I_1, I_2, B, A) = D^{\text{NGF}}(A, E_1) + D^{\text{NGF}}(A, E_2).$$
(10)

Finally, we propose to minimize the objective function:

$$J(B) = D(I_1, I_2, B) + \alpha S^{\text{diff}}(B) + \beta S^{\text{hyper}}(B) + \gamma D(I_1, I_2, B, A)$$
(11)  
s.t.  $| \partial_{\mathbf{v}}(B(\mathbf{p})) | \leq 1$  for all  $\mathbf{p} \in \Omega$ .

The positive and user-defined regularization parameters  $\alpha$ ,  $\beta$ , and  $\gamma$  represent the trade-off between the smoothness of B, the deformation of the transformation, and the similarity to the anatomy image, respectively. These parameters are empirically chosen by evaluating a range of values. Small values of  $\alpha$  or  $\beta$  or large value of  $\gamma$  cause the violation of the invertible constraint in (11). Large values of  $\alpha$  or  $\beta$  reduce the fitness of the corrected images. Small value of  $\gamma$  brings less anatomy information into the registration procedure.

Here, the Gauss-Newton method with an Armajo type line search is used for minimization. In the Gauss-Newton method, starting with an initial guess, e.g.  $B^0 \equiv \mathbf{0}$ , the  $(k + 1)^{th}$  step of the iteration gives  $B^{k+1} = B^k - \lambda^k G^k (H^k)^{-1}$ , where  $G^k$  and  $H^k$  are the approximate gradient and Hessian of the objective function J at  $B^k$ , respectively, and  $\lambda^k > 0$  is the learning rate at this step. The best learning rate, which is found by the backtracking-Armijo line search, should be the maximum value providing  $B^{k+1}$  satisfying the constraint in (11), thereby improving convergence [21].

The coarse-to-fine approach is integrated with the Gauss-Newton method in minimizing J(B). This aims to avoid the local minima and to speed up the convergence [18, 22]. In implementation, a multilevel image representation is derived

first. The image representation in a coarser level is obtained simply by averaging over adjacent cells. Next, the deformation field in the coarsest level is estimated by minimizing the objective function in (11) using the image representation in this level. The estimated deformation field in the coarser level is interpolated to be the initial guess for the optimizer at a finer level. The process of interpolation and estimation is repeated until the deformation field in the finest level is obtained. The coarse-to-fine approach is summarized in Algorithm 1.

Algorithm 1 AISAC: Anatomy-guided Inverse-gradient SAC

```
Input: I_1 and I_2: inverse-gradient EPI fMRI images,
         A: anatomy image corresponding to fMRI images,
         l_{\min}, l_{\max}: min, max level of data representation.
```

**Output:** Corrected images  $E_1$  and  $E_2$ .

- 1: Derive the multilevel image representation;
- 2:  $B_{l_{\min}-1} \leftarrow \mathbf{0};$ 3: **for**  $l = l_{\min} : l_{\max} \, \mathbf{do}$
- Interpolate  $B_{l,0}$  from  $B_{l-1}$ :  $B_{l,0} \leftarrow inter(B_{l-1})$ ; 4: 5:
- Compute the objective function as in Eq. (11): 6:  $[J, \tilde{G^k}, H^k] \leftarrow \mathbf{obj\_fnct}(I_1, I_2, B_{l,k}, A, l);$
- while not converged do 7:

8: Compute the new *B* via backtracking line search:  

$$B_{l,k+1} \leftarrow \mathbf{backtrack}_{search}(B_{l,k}, G^k, H^k);$$

- 9: Increment  $k: k \leftarrow k + 1$ ;
- Compute the objective function as in Eq. (11): 10:  $[J, G^k, H^k] \leftarrow \text{obj_fnct}(I_1, I_2, B_{l,k}, A, l);$
- end while 11:

 $B_l \leftarrow B_{l,k};$ 12:

- 13: end for
- 14: Unwarp  $I_1$  and  $I_2$  using Eqs. (2) and (3)  $E_1 \leftarrow \mathbf{unwarp}(I_1, B_{l_{\max}});$ 
  - $E_2 \leftarrow \mathbf{unwarp}(I_2, B_{l_{\max}});$

#### 4. EXPERIMENTAL RESULTS

This section presents the data acquisition and pre-processing, and then discusses the results.

## 4.1. Experimental methods

EPI fMRI data from 3 healthy subjects (1 F and 2 M) were acquired using a 2-D single-shot GRE EPI sequence in a 3T scanner with a 32-channel head coil, TR = 3 s, and TE = 30ms. An FOV of 144 mm  $\times$  192 mm, matrix size of 144  $\times$  192, 36 ascending and interleaved slices (1 mm thickness) resulted in images with 1 mm isotropic resolution. Subjects viewed a visual stimulus, while half of the scans was acquired with the left-to-right (LR) or right-to-left (RL) blip. This resulted in pairs of scans with reversed patterns of distortions in the PE direction. For each subject, a  $T_{1w}$  anatomy image of the whole brain was acquired.

In a preliminary step, all acquired fMRI data were motion and slice scan time corrected using tools in the Statistical Parametric Mapping (SPM 12) package [23]. The  $T_{1w}$  alignment image of each subject was created by aligning the  $T_{1w}$ 



Fig. 2. Left-hemisphere surface and visual field maps of Subject 3. Circles indicate the areas where the maps differ.

image to an average of two oppositely-distorted images of the subject, through SPM's co-registration procedure [24].

In the implementation of the corrections, a four-level image representation, with matrix sizes of  $18 \times 24 \times 5$ ,  $36 \times 48 \times 9$ ,  $72 \times 96 \times 18$ , and  $144 \times 192 \times 36$ , were performed. Average NGF measurements between the anatomy image and each corrected image were computed for comparison.

The proposed method with the anatomy-based regularization term was compared to HySCO, obtained by setting  $\gamma = 0$ in Eq. (11). By implementing HySCO on a validation dataset with varied ranges, the  $\alpha$  and  $\beta$  were chosen as 30 and 50, respectively, with the best measures of the SSD between corrected images and NGF similarity between the anatomy and corrected images. The  $\gamma$  was set as 75000 after implementing AISAC with the selected  $\alpha$  and  $\beta$  while varying value of  $\gamma$ .

### 4.2. Results and analysis

Table 1 summarizes the mean and standard deviation of NGF similarity measures. The results indicate that AISAC achieves a quite similar similarity rating between corrected images and Fig. 1. Results of HySCO (Row 1) and AISAC (Row 2). Columns 1 and 4 show the grid of estimated deformation. Columns 2 and 5 show the corrected LR and RL images, respectively. Column 3 shows magnification of the window in the second column focusing on the shadow artifact.

the anatomy image in comparison to that of HySCO.

Table 1.	Mean	and	standard	deviation	of ]	NGF	measures	for
hree cor	rected :	fMR	I datasets	S.				

BARS	Pairs of	HySCO	AISAC (proposed)
Datasets	images	$(mean \pm std)$	(mean $\pm$ std)
Subject 1	376	$0.49938 \pm 0.00006$	$0.49930 \pm 0.00007$
Subject 2	376	$0.49952 \pm 0.00007$	$0.49951 \pm 0.00007$
Subject 3	376	$0.49886 \pm 0.00023$	$0.49880 \pm 0.00024$
Average	-	$0.49925 \pm 0.00012$	$0.49920 \pm 0.00012$

Bold numbers indicate the best entry.

Figure 1 shows results of HySCO and AISAC, given the same pair of input images. Importantly, the AISAC algorithm reduces the shadow artifact seen with HySCO (see Column3). This is likely due to the deformation of AISAC being smaller than that of HySCO (see Columns 1 and 4). This suggests that the inclusion of the anatomy image adequately moderates the deformation.

The corrected fMRI images of Subject 3 are analysed using a pRF model, resulting in visual field maps [2]. pRF model results produced by AISAC corrections overall provide a higher explained variance and smaller artifacts in early visual areas than those of HySCO corrections (see circles in Fig. 2). The pRF model results further corroborate that the information provided by  $T_{1w}$  images is helpful in tuning the correction. Retinotopic mapping data was chosen here to validate the methods, however using the anatomy image as a ground-truth for correcting and guiding SAs could readily be applied to EPIs collected for other experimental paradigms.

### 5. CONCLUSIONS

This paper proposed a novel algorithm for correcting the SAs in high-resolution fMRI images. The proposed method uses the morphology information of the  $T_{1w}$  anatomy image to regularize the deformation. This ensures that the corrected images adhere to the correct brain structure. The experimental results demonstrate the accuracy and efficiency of the proposed method on high-resolution images. It also demonstrates the feasibility of the method for fMRI data analysis in future research.

## 6. REFERENCES

- S. Ogawa, T. M. Lee, A. R. Kay, and D. W. Tank, "Brain magnetic resonance imaging with contrast dependent on blood oxygenation," in *Proc. Natl. Acad. Sci. U.S.A.*, 1990, pp. 9868–9872.
- [2] S. O. Dumoulin and B. A. Wandell, "Population receptive field estimates in human visual cortex," *NeuroImage*, vol. 39, pp. 647–660, 2008.
- [3] K. M. Ludeke, P. Roschmann, and R. Tischler, "Susceptibility artifacts in NMR imaging," *Magn. Reson. Imaging*, vol. 3, pp. 329343, 1985.
- [4] P. Jezzard and R. S. Balaban, "Correction for geometric distortion in echo planar images from B0 field variations," *Magn. Reson. Med.*, vol. 34, pp. 65–73, 1995.
- [5] P. J. Reber, E. C. Wong, R. B. Buxton, and L. R. Frank, "Correction of off resonance related distortion in echoplanar imaging using EPI-based field maps," *Magn. Reson. Med.*, vol. 39, pp. 328–330, 1998.
- [6] Y. M. Kadah and X. Hu, "Simulated phase evolution rewinding (SPHERE): a technique for reducing B0 inhomogeneity effects in MR images," *Magn. Reson. Med.*, vol. 38, pp. 615–627, 1997.
- [7] M. D. Robson, J. C. Gore, and R. T. Constable, "Measurement of the point spread function in MRI using constant time imaging," *Magn. Reson. Med.*, vol. 38, pp. 733–740, 1997.
- [8] H. Zeng and R. T. Constable, "Image distortion correction in EPI: comparison of field mapping with point spread function mapping," *Magn. Reson. Med.*, vol. 48, pp. 137–146, 2002.
- [9] P. Munger, G. R. Crelier, T. M. Peters, and G. B. Pike, "An inverse problem approach to the correction of distortion in EPI images," *IEEE Trans. Med. Imag.*, vol. 19, pp. 681–689, 2000.
- [10] D. H. Wu, Y. Guo, C. C. Lu, and J. Suri, "Improvement to functional magnetic resonance imaging (fMRI) methods using non-rigid body image registration methods for correction in the presence of susceptibility artifact effects," in *Proc. Inter. Conf. IEEE Eng. Med. Biol. Soc.*, 2006, pp. 1018–1020.
- [11] J. Kybic, P. Thevenaz, A. Nirkko, and M. Unser, "Unwarping of unidirectionally distorted EPI images," *IEEE Trans. Med. Imag.*, vol. 19, pp. 80–93, 2000.
- [12] C. Studholme, R. T. Constable, and J. S. Duncan, "Accurate alignment of functional EPI data to anatomical MRI using a physics-based distortion model," *IEEE Trans. Med. Imag.*, vol. 19, pp. 1115–1127, 2000.
- [13] M. Wu, L. C. Chang, L. Walker, H. Lemaitre, A. S. Barnett, S. Marenco, and C. Pierpaoli, *Comparison of EPI*

distortion correction methods in diffusion tensor MRI using a novel framework, Med. Image. Comput. Assist. Interv. Springer Berlin Heidelberg, 2008.

- [14] C. Hutton, A. Bork, O. Josephs, R. Deichmann, J. Ashburner, and R. Turner, "Image distortion correction in fMRI: a quantitative evaluation," *NeuroImage*, vol. 16, pp. 217–240, 2002.
- [15] D. Holland, J. M. Kuperman, and A. M. Dale, "Efficient correction of inhomogeneous static magnetic fieldinduced distortion in echo planar imaging," *NeuroImage*, vol. 50, pp. 175–184, 2010.
- [16] H. Chang and J. M. Fitzpatrick, "A technique for accurate magnetic resonance imaging in the presence of field inhomogeneities," *IEEE Trans. Imag. Process.*, vol. 11, no. 3, pp. 11, 1992.
- [17] J. L. R. Andersson, S. Skare, and J. Ashburner, "How to correct susceptibility distortions in spin-echo echoplanar images: application to diffusion tensor imaging," *NeuroImage*, vol. 20, pp. 870888, 2003.
- [18] L. Ruthotto, H. Kugel, J. Olesch, B. Fischer, J. Modersitzki, M. Burger, and C. H. Wolters, "Diffeomorphic susceptibility artifact correction of diffusion-weighted magnetic resonance images," *Phys. Med. Biol.*, vol. 57, pp. 5715–5731, 2012.
- [19] M. O. Irfanoglu, P. Modia, A. Nayaka, E. B. Hutchinson, J. Sarllsc, and C. Pierpaoli, "DR-BUDDI (Diffeomorphic Registration for Blip-Up blip-Down Diffusion Imaging) method for correcting echo planar imaging distortions," *NeuroImage*, vol. 106, pp. 284–299, 2015.
- [20] E. Haber and J. Modersitzki, "Intensity gradient based registration and fusion of multi-modal images," *Methods Inf. Med.*, vol. 46, pp. 292–299, 2007.
- [21] J. Nocedal and S. J. Wright, *Numerical optimization*, Springer, New York, 1999.
- [22] J. Macdonald and L. Ruthotto, "Efficient numerical optimization for susceptibility artifact correction of EPI-MRI," *Opt. Ctrl.*, pp. 1–29, 2016.
- [23] W. Penny, K. Friston, J. Ashburner, S. Kiebel, and T. Nichols, *Statistical Parametric Mapping: The Analysis of Functional Brain*, Academic Press, 1 edition, 2006.
- [24] A. Collignon, F. Maes, D. Delaere, D. Vandermeulen, P. Suetens, and G. Marchal, "Automated multi-modality image registration based on information theory," in *Inf. Process. Med. Imaging*, 1995, pp. 263–274.