DeepSTI: Towards Tensor Reconstruction using Fewer Orientations in Susceptibility Tensor Imaging

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Abstract

Susceptibility tensor imaging (STI) is a magnetic resonance imaging technique that can provide important information for reconstruction of neural fibers and detection of myelination changes in the brain. However, the application of STI in human in vivo has been practically infeasible because of its time-consuming acquisition that requires sampling at multiple (usually more than six) head orientations and the challenging dipole inversion problem involved in image reconstruction. Here, we tackle these issues by presenting a novel image reconstruction algorithm for STI that leverages data-driven priors. Our method, called DeepSTI, learns the data prior implicitly via a deep neural network that resembles the proximal operator of a regularizer function. The dipole inversion problem is then solved iteratively using the learned proximal network. Experimental results demonstrate superior performance of DeepSTI over state-of-the-art methods for STI reconstruction and fiber tractography. DeepSTI is the first to achieve high quality results for in vivo human STI with fewer than six orientations.

1 Introduction

Susceptibility tensor imaging (STI) [14] is an emerging magnetic resonance imaging technique that characterizes the anisotropic tissue magnetic susceptibility with a second-order tensor model. It can provide information for both the reconstruction of white matter fiber pathways and detection of myelin changes in the brain at millimeter resolution or less [10, 9], which would be of great value for understanding brain structure and function in healthy and diseased brain [5, 21, 19, 11, 20, 7, 15]. However, the application of STI in vivo has been hindered by its cumbersome and time-consuming acquisition requirement of measuring susceptibility induced MR phase changes at multiple (usually more than six) head orientations to obtain sufficient information for the ill-posed STI dipole inversion. Existing methods for STI reconstruction have used hand-crafted priors to regularize the dipole inversion problem [14, 16, 2, 3, 6, 14, 18], but the performance is still not sufficient for stable reconstruction from in vivo human measurements. Moreover, all of them require a large number of head orientations for satisfactory reconstruction, which is infeasible in practice. In this work, we tackle these issues by developing a new machine learning based method for STI image reconstruction that allows for stable reconstruction from a reduced number of head orientations, closing the gap to deploying STI in vivo in clinical settings.
2 Methodology

To start with, we formulate the STI dipole inversion problem as the following regularized linear inverse problem:

$$\min_x \frac{1}{2} \| M(y - F^{-1} A F x) \|_2^2 + R(x),$$

where $x \in \mathbb{R}^{6n}$ is the underlying tensor image (symmetric 2nd order tensor of size $3 \times 3$, therefore requiring 6 coefficients per voxel, $n$ is the number of voxels), and $y \in \mathbb{R}^{mn}$ denotes the observed local field change ($m$ is the number of head orientations). The operator $F^{-1} A F$ is the forward model of STI, where $F$ denotes discrete Fourier Transform and $A$ is the dipole kernel, and $M$ is a brain mask. The function $f(x) = \frac{1}{2} \| M(y - F^{-1} A F x) \|_2^2 : \mathbb{R}^{6n} \rightarrow \mathbb{R} \geq 0$ is a data fidelity term that promotes the solution to match observed measurements $y$. The regularizer, $R(x) : \mathbb{R}^{6n} \rightarrow \mathbb{R}$, is a suitable function that introduces prior knowledge and allows a robust reconstruction for the ill-posed inverse problem [2]. In order to minimize the problem in Eq. (1), we follow a proximal gradient descent approach by taking the gradient of the differentiable function $f(x)$ and the proximal of the regularizer function, defined as $\mathcal{P}_R$, allowing for potentially non-smooth functions $R(x)$. To leverage the advantage of deep neural networks for learning powerful priors from large amounts of data, we parameterize the proximal operator $\mathcal{P}_R$ by a deep neural network $G_\theta$, which produces the learned proximal iterates given by:

$$x_{k+1} = G_\theta(x_k - \alpha_k \nabla f(x_k)),$$

where $\alpha_k \in \mathbb{R}$ is the step size at the $k$-th iteration and $\theta$ denotes all trainable parameters of the neural network. Importantly, this parameterization decouples the learned prior from the forward operator, allowing it to be applied with a variety of forward models. More precisely, a new forward model can be naturally incorporated in our algorithm by adjusting the forward function in Eq. 2 (i.e., by modifying the function $f(x)$), without any modifications to $G_\theta$. In the context of STI, this is particularly beneficial because it allows our model to deal with an arbitrary number of measurements at arbitrary head orientations without any retraining or adaptation of the network.

To train the network, we leveraged a supervised learning framework by minimizing the $l_1$ distance between estimated and ground-truth STI over all training samples. Since ground-truth STI samples cannot be easily obtained from human in vivo, we generated realistic brain phantoms using a combination of in vivo Quantitative Susceptibility Mapping (QSM) [17] and Diffusion Tensor Imaging (DTI) [8] measurements collected from human subjects, and synthesized local field measurements using the STI forward model. The so-obtained simulated measurements and phantom data pairs are used as training samples for the learned proximal network.

Data STI measurements were acquired from 8 human subjects, including 3 subjects on a 3T scanner with 1.5 mm isotropic resolution as in [12] and 5 subjects on a 7T scanner with 1 mm isotropic resolution, reconstructed to 0.98 $\times$ 0.98 $\times$ 1 mm$^3$ resolution as in [13]. The data was split in to 5, 1 and 2 subjects for training, validation and testing, respectively, in each fold of five-fold cross validation.

Figure 1: Magnetic susceptibility anisotropy (MSA) weighted principal eigenvector (PEV) maps estimated from simulation (a) and in vivo measurements (b) from a human subject at 3T with 1.5 mm resolution. Numbers in (a) show the eigenvector cosine similarity error (ECSE) of the estimated PEV.
3 Results

We evaluated DeepSTI on both simulation and in vivo data and compared it with state-of-the-art methods including STIimag [9], MMSR [12] and aSTI+ [18]. Fig. 1 shows the principal eigenvector (PEV) maps estimated from simulation (a) and in vivo measurements (b) acquired from a testing subject at 3T and 1.5 mm isotropic resolution. A significant improvement can be observed in the results yielded by DeepSTI. Note that with only a few (e.g., 1∼2) head orientations, DeepSTI can still yield a reasonable estimation of the PEV map, while the other methods fail to provide any reasonable estimation. Table 1 summarizes the quantitative metrics for STI reconstruction from all 8 subjects using cross validation, where our method consistently outperforms other methods in various metrics. Fig. 2 depicts STI-based fiber tracking results using in vivo data from a 7T subject. It is clear from these that our method offers more coherent and complete tracking results than other alternatives. Local tracking results further show that the fibers passing through the corpus callosum (i.e., the fibers connecting the left and right brain hemispheres) can be nicely recovered by our method from very few orientations, demonstrating the potential of STI-based fiber tractography with DeepSTI.

| Number of orientations | Method     | PSNR     | SSIM     | ECSE     | wPSNR     |
|------------------------|------------|----------|----------|----------|-----------|
|                        | STIimag    | 40.26(1.16) | 0.88(0.01) | 0.25(0.03) | 15.78(1.24) |
|                        | MMSR       | 44.14(0.82) | 0.91(0.01) | 0.26(0.03) | 16.98(0.70) |
|                        | aSTI+      | 41.00(1.26) | 0.90(0.01) | 0.28(0.03) | 17.65(0.91) |
|                        | DeepSTI (ours) | 47.52(0.80) | 0.96(0.01) | 0.08(0.01) | 23.20(1.00) |
| 3                      | STIimag    | 39.24(1.24) | 0.87(0.01) | 0.30(0.03) | 15.07(1.51) |
|                        | MMSR       | 42.76(0.98) | 0.90(0.01) | 0.32(0.03) | 15.94(0.83) |
|                        | aSTI+      | 39.99(1.25) | 0.89(0.01) | 0.32(0.03) | 17.64(0.81) |
|                        | DeepSTI    | 44.88(1.19) | 0.95(0.01) | 0.12(0.02) | 21.97(1.00) |
| 1                      | STIimag    | 38.27(1.13) | 0.87(0.01) | 0.38(0.02) | 16.92(0.81) |
|                        | MMSR       | 40.77(0.88) | 0.89(0.01) | 0.39(0.01) | 16.86(0.43) |
|                        | aSTI+      | 38.65(1.13) | 0.89(0.01) | 0.38(0.02) | 17.60(0.64) |
|                        | DeepSTI    | 40.13(1.33) | 0.91(0.01) | 0.25(0.03) | 19.61(0.76) |

Table 1: Quantitative metrics of STI reconstructed from simulated measurements obtained from 8 subjects using cross validation. PSNR and SSIM are evaluated on the reconstructed tensor images. The Eigenvector Cosine Similarity Error (ECSE) measures the Principal Eigenvector (PEV) dissimilarity in anisotropic regions. wPSNR measures the PSNR in anisotropy-weighted PEV maps.

Figure 2: STI-based fiber tractography results from in vivo measurements of a human subject at 7T with 0.98×0.98×1 mm³ resolution. Row 1: whole brain tracking results overlaid on DTI FA. Rows 2 and 3: 3D volume rendering (row 2) and 2D visualization (row 3) of local tracking results for fibers passing corpus callosum. Column 1 shows the DTI result as a reference.
4 Conclusion

We proposed DeepSTI, a new method for STI dipole inversion that enables reliable reconstruction with measurements at much fewer head orientations than previously needed by leveraging data-driven priors. Experimental results from both simulation and in vivo human brain data demonstrate the superiority of DeepSTI compared to state-of-the-art methods for susceptibility tensor reconstruction, fiber direction (PEV) estimation and fiber tractography. Our method is the first to provide high quality reconstruction results for STI in human in vivo with limited number of head orientations, demonstrating the potential of STI for large-scale clinical applications and enabling new STI-based fiber tractography techniques of human brain in vivo.

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6 Potential Negative Societal Impact

To the best of our knowledge, we do not foresee any potential negative societal impact of our research.

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