Direct Diffusion Tensor Estimation Using Joint Sparsity Constraint Without Image Reconstruction

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INTRODUCTION:

Diffusion tensor imaging (DTI) provides a non-invasive method for in vivo evaluation of tissue water mobility [1]. In practice, DTI suffers from low SNR and long acquisition time. To accelerate the imaging speed, there are mainly two strategies to obtain diffusion tensor **D** from undersampled k-space. The first one is to reconstruct all diffusion weighted images (DWI) first and then estimate **D** by conventional least squares fitting. Compressed sensing (CS) has been applied to reconstruct all DW images under the total variation constraint [2]. However, too many unknowns need to be solved and the CS reconstruction error may lead to fitting errors in diffusion tensors. The second strategy is the model-based (MB) method which fits diffusion tensors directly and nonlinearly to the acquired data based on the data consistency in the DTI model without image reconstruction [3]. This strategy is sensitive to the initial diffusion tensor, because the measured data correspond to the continuous Fourier transform whereas the estimation is discrete[4]. In this work, we propose a novel model-based method using a joint sparsity constraint [5] (MB-JSC). This novel method not only has the benefits of fewer unknowns and no error propagation in MB method, but also utilizes the joint sparsity penalty to reduce the number of measurements and improve robustness to initial diffusion tensor.

THEORY AND METHOD:

The j-th diffusion-weighted image $\mathbf{f}_j$ can be represented as $\mathbf{f}_j = \mathbf{I}_0 e^{-b g_j^T \mathbf{D} g_j} e^{i\phi_j}$, where **D** is the diffusion tensor, $\mathbf{I}_0$ is reference image, b is the diffusion weighting factor, g_j is the diffusion encoding directional vector, and ϕ_j is the image phase. Since the diffusion weightings only modulate the intensity of each diffusion-weighted image, $\mathbf{f}_j$'s fit the joint sparsity model , that exploit both intra- and inter-signal correlation structures in distributed compressed sensing (DCS) theory [5]. It means the diffusion-weighted images are not only transform-sparse, but also share the common sparse support. Then the direct reconstruction of diffusion tensor from undersampled k-space using joint sparsity constraint can be formulated as

$$\arg\min_{\mathbf{D}}\{\sum_j \|\mathbf{d}_j - \mathbf{PFf}_j\|_2^2 + \lambda\|\mathbf{C}\|_{1,2} \ (1), \quad \mathbf{C} = \mathbf{\Psi}[\mathbf{f}_1, \mathbf{f}_2, \cdots, \mathbf{f}_J]$$

where $\mathbf{d}_j$ is the measured k-space data for the j-th diffusion direction, **P** is undersampling mask, **F** is Fourier transform, **C** is the sparse coefficients matrix with size N (# image pixel) × J (# diffusion direction), $\| \ \|_{1,2}$ is the mixed L_1-L_2 norm of matrix, which applies the L_2 norm to rows of **C** (to promote nonsparsity) and then applying the L1 norm to the resulting vector (to promote sparsity). **Ψ** is the sparsifying transform and represents finite difference in our work. The experiments were conducted on a 7T Bruker Scanner (Bruker BioSpin). A spin echo diffusion tensor imaging (SE-DTI) was performed on an adult SD rat to acquire one B0 image and six diffusion-weighted images, all of size 256×256. TR/TE = 1500/29 ms, b value = 1000 s/mm2, NEX=10. Variable-density random undersampling with net reduction factors R=2, 3 and 4 was applied on the phase encoding direction. Fractional anisotropy (FA) map and mean diffusivity (MD) calculated from the reconstruction of full data were used as the gold standard. In our work, $\mathbf{I}_0$ was reconstructed separately and then used to estimate **D**.

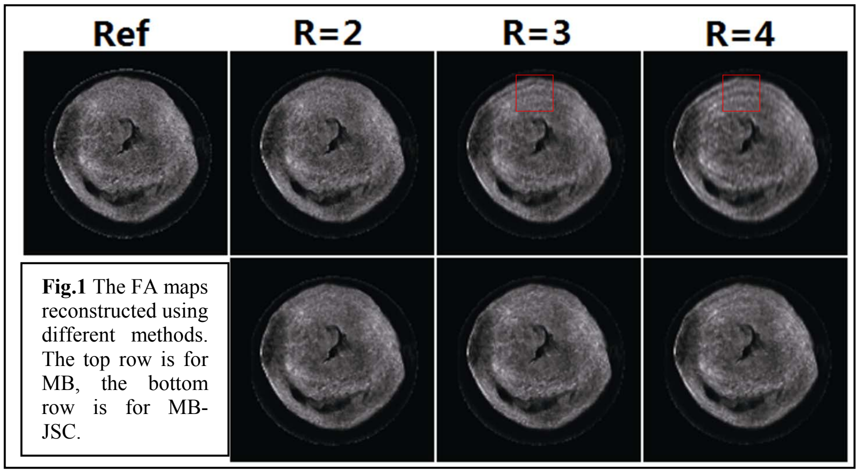


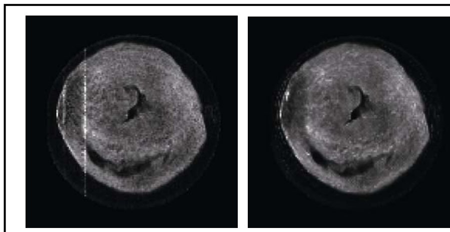
Fig.1 The FA maps reconstructed using different methods. The top row is for MB, the bottom row is for MB-JSC.

RESULTS AND DISCUSSION:

Fig.1 shows the FA maps estimated using MB and MB-JSC methods with R=2, 3 and 4. We can see that the FA map estimated using the proposed MB-JSC at R=2 is less noisy than that from the full data and MB method. When R= 3, the artifacts show up in the map from MB, but are negligible in that from MB-JSC. When the k-space was heavily undersampled with R=4, the FA map estimated using the MB-JSC method still only shows negligible artifacts while the MB method exhibits severe artifacts (indicated by red boxes). The improvement of MB-JSC over MB is also demonstrated in the root-mean-squared errors (RMSE) of FA and MD listed in Table 1. The estimated maps using a random initial **D** with R=2 are shown in Fig.2. We can see the MB method is sensitive to the initial **D,** which is consistent with the observations in [3]. In contrast, MB-JSC doesn't exhibit large variations with different initial **D**. It suggests that the introduction of the joint sparsity constraint can improve the robustness of model-based methods.

Tab.1 Quantified performance of different methods.

	MB		MB-JSC	
RMSE	FA	MD	FA	MD
R=2	0.0245	5.09e-5	0.0322	5.27e-5
R=3	0.0447	8.15e-5	0.0422	7.02e-5
R=4	0.0546	9.28e-5	0.0489	8.01e-5



MB **MB-JSC**

Fig. 2 FA maps using random initial D with R=2.

CONCLUSION:

We propose a novel model-based method with joint sparse constraint for estimating the diffusion tensor directly from undersampled k-space data. Experimental results demonstrate that the proposed method can improve the estimation accuracy of the model-based method. The method has potential to be applied in biological tissue characterization, such as neural, muscle and heart.

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